eSim 2018
«BUILDING SIMULATION TO SUPPORT BUILDING SUSTAINABILITY»
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Characterizing Smart Thermostats Operation in Residential Zoned Heating Systems and its Impact on Energy Saving Metrics

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Abstract: *The emergence of line-voltage communicating thermostats (LVCT) prompts for new opportunities for energy management in homes equipped with heating systems such as baseboard heaters. To capture either energy savings or demand response opportunities, one should first determine how the technology is actually used in homes where each room is in a different thermal zone. This study takes advantage of data collected from about 300 LVCTs over a heating season. In this paper, the occupants' preferences in terms of comfort set-points and habits of performing temperature setbacks are analyzed. Such knowledge is valuable for building energy simulation and allows to discuss how the EnergyStar Smart Thermostats energy savings metric, designed with single zone central HVAC systems in mind, would perform for baseboard heaters or other heating systems zoned at the room level. Accordingly, this paper investigates the impact of the selection of a zone-based reference temperature versus a home-based reference temperature.*

Keywords: *Baseboard heaters, thermostats utilization, energy savings, EnergyStar*

HVAC	Heating, Ventilation and Air-Conditioning
PT	Programmable Thermostats
PCT	Programmable Communicating Thermostats
LVCT	Line-Voltage Communicating Thermostats
DR	Demand Response
BCT	Baseline Comfort Temperature
BD	Business Days
WE	Weekend and Holidays
ATR	Acceptable Temperature Range
LCR	Low Comfort Range
UNR	Uncomfortable Range
HTR	High Temperature Range

Introduction

In Quebec, Canada, where this study was conducted, heating systems account for 63% of the total energy consumption of the residential sector (Office of Energy Efficiency, 2016). Particularly in Quebec, 80% of dwellings use electricity as their main heating source (Office of Energy Efficiency, 2011) compared to 38% usage for Canada as a whole. The amount of energy spent on heating justifies the emergence of energy management technologies and services targeting household thermal energy solutions (Zipperer et al., 2013).

Regarding the type of main heating system, 26% of Canadian houses use electric baseboards whereas in Quebec this amount reaches 60%. Homes heated with baseboard heaters are often zoned at the room level. Each room has its own thermostat and heater, allowing set-points to be adjusted independently. This case differs from homes heated with central HVAC systems where there is seldom more than one thermal zone. Zoned heating provides additional energy management possibilities by allowing the individual adjustment of rooms' temperature settings according to their usage (Ibrahim et al., 2016; Beizaee et al., 2015).

Customer's interest in enhanced energy management has caused a significant uptake of programmable thermostats (PT) in Canada. In fact, more than 45% of households in Canada and 47% of houses in Quebec use programmable thermostats(Office of Energy Efficiency, 2011). Programmable thermostats can apply scheduled temperature set-points changes to save energy during periods of occupants absence or when comfort temperature levels are not required. These schedules may vary according to the hours of the day, the days of the week, as well as specific days.

ISBN 978-2-921145-88-6

Typically, "comfort" set-points are applied when occupants are present while "savings" or reduced set-points are used for either non-occupancy or sleeping periods. The amount of energy savings is related to the depth of the setback. Nonetheless, according to several studies, the low usability of programmable thermostats has hindered the technology from delivering the expected savings (Meier et al., 2010; Meier et al., 2011).

Interest in connected technologies has led to a growing adoption of smart thermostats which support advanced applications and extended integration in the context of smart homes (Zipperer et al., 2013). Adding two-way communication to thermostats resulted in the creation of Programmable Communicating Thermostats (PCT). PCTs have the ability to communicate, often through the web, to enable remote monitoring and control as well as interaction with other devices. PCTs can monitor different variables such as room temperature, set-point temperature, HVAC system runtime, and energy use. Smarter devices provide benefits such as feedback to users, remote diagnosis and alarms. Indeed, smart thermostats can improve customers experience, engagement, and services by reporting useful actionable information. Furthermore, PCTs can play a significant role in future utility initiatives where their remote control and data collection capabilities can improve participation in energy efficiency and load management programs such as demand response (DR) (Energetics Incorporated and Vermont Energy Investment Corporation, 2016).

Improving the knowledge about behavior and dynamics of zones heating set-points can help to reduce differences between simulated and monitored energy building performance. In fact, building energy simulation tools can be used for evaluating the potential of new thermostats for energy management strategies. However, appropriate schedules must be provided in order to recreate realistic scenarios (Urban et al., 2012). Accordingly, in buildings with multiple zones, the number of set-point schedules needed by the model is increased and additional information is required for proper stochastic representation of the actual technology utilization.

Scope of the study and contribution

This paper presents several experimental results regarding the occupants' habits in performing setbacks in residences heated with baseboard heaters. In this work, we propose a methodology based on statistical methods of pattern recognition to analyze set-point temperatures provided by communicating thermostats in buildings zoned at the room level. Accordingly, the contributions of this paper can be defined as follows:

1. Developing an automatic statistical characterization of set-point temperature profiles using historical data collected by thermostats.
2. Providing statistical information on the realization of temperature setbacks by LVCTs in heating dominated area.
3. Discussing an existing energy-savings metric in the context of homes zoned at the room level.

Related works

Several studies have been conducted to explore occupants' habits in using residential thermostats (Peffer et al., 2011; Meier et al., 2011). The main goals of these studies are evaluating the performance of PTs in delivering energy savings, as well as customers engagement in employing such technologies. In fact, knowledge about users' preferences is a key factor to grasp the impact of thermostat features on energy management. In order to collect information about thermostat utilization, three types of methodology can be used: crowd-sourcing, dedicated data acquisition, and direct data logging from communicating thermostats.

In their work, (Pritoni et al., 2015) used the Amazon Mechanical Turk on-line crowd-sourcing service. They investigated thermostat settings and behavior in households by asking the respondents about their preferences, and complementary information like providing pictures of thermostats for verifying self-reported data. The results showed that about 40% of programmable thermostats were not programmed and 33% included overridden programming features. Crowd-sourcing can be an efficient method for identifying trends and public preferences in thermostats' operation. Additionally, it can be adequate for detecting possible drawbacks which make their utilization difficult. In fact, usability issues and misunderstandings of thermostats operation are recognized as the main factors causing the differences between theoretical and measured energy-saving strategies. Such issues could worsen in a multi-zone topology where there are multiple, and possibly interacting, thermostats to operate. It should be noted that it is possible that occupants do not have enough information to establish an adequate set-point configuration to optimize energy usage and comfort. In this regard, new approaches are sought to improve programmable thermostat usability in zoned configurations.

The second approach based on measured data was described in (Andersen et al., 2011). Data were collected with dedicated data acquisition equipment installed within each monitored dwelling. This work used a linear regression in order to infer a model of occupants' heating set-point selection. The method aimed to estimate the set-point of thermostats through an inverse model considering indoor/outdoor environmental variables over four time periods per day. Almost half of the variance was explained by nominal variables, indicating that set-points are as dwelling (and room) dependent as their are influenced by environmental variables. To explain such variabilities one should include a more accurate occupant representation within the energy simulation, as comprehensively exposed in (Vorger, 2014).

ISBN 978-2-921145-88-6

Data logging is a prominent feature of new communicating thermostats. The approach of modeling observed set-point histories of smart thermostats with a prototypical energy model was used by (Urban and Gomez, 2012; Urban et al., 2014). They developed a method for estimating the energy consumption associated with the real thermostat usage profile. For comparison, they also computed a baseline heating consumption related to a constant Baseline Comfort Temperature (BCT). This BCT is arbitrarily chosen to match the 90th percentile value of the room historical temperature data, and deemed to be the occupants' preferred comfort temperature for the heating period. This method is prescribed by EnergyStar in its Connected Thermostat Program Requirements for calculation of the energy savings metric (Epa and Star, 2018). Accordingly, a minimum metric value of 8% savings compared to the baseline consumption for heating is required in order to qualify as an EnergyStar device. Although EnergyStar has settled on this metric, additional improvements and adjustments are needed for covering particularities and new features of household heating technologies (Daken et al., 2016).

Line-voltage thermostats are currently excluded from the scope of the EnergyStar Smart Thermostat program. If they were to be included, the metric validity (and its threshold value) should be reassessed since it undergoes limitations in a multi-zone context. It associates energy savings to a reduction in set-point values relative to a BCT determined using the same thermostat historical temperature readings. Thermostats operating at constant set-point should therefore return negligible savings. In fact, in a house where each room is an individual thermal zone, a thermostat located in a usually unoccupied room may never apply a set-point value corresponding to a comfortable temperature level. If this thermostat operates at a constant low set-point, it uses less energy than being set with a comfortable set-point even for only a specific part of the day. The current metric could not accurately account for this case as it is computed for each thermostat individually rather than considering the thermostat in the global house context.

Data Collection

Data used in this study were gathered from a collection of 30 standard detached houses located near Trois-Rivières in Quebec, Canada. This region corresponds to climate zone 7 i.e. very cold according to the ASHRAE International Climate Zone Definitions. It was part of a DR demonstration project where set-points were remotely modulated on specific days to reduce peak demand. However, data from these specific days were excluded from the analysis. The electricity tariff is not time dependent in Quebec.

All studied houses use electric baseboards or convectors with wall-mounted thermostats as their primary heating system. Each line-voltage thermostat was replaced with a Line-Voltage Communicating Thermostat (LVCT). Secondary heating devices that had built-in thermostats were not retrofitted and left without monitoring.

The used LVCTs manage discrete ranges of temperature set-points and time steps for programming changes. In this regard, temperature set-point variations are allowed in steps of 0.5 ^{o}C, while for time, the set-back and set-up events can be programmed at 15 minute discrete time intervals. Furthermore, the resolution of temperature readings is 0.1 ^{o}C. Additionally, logged data-sets contain energy consumption readings at the kWh granularity for each thermostat at hourly sampling periods.

The installed thermostats had no initial set-point programs. Data started to be considered for analysis about one month after the installation in order to allow enough time for the users to program set-point schedules if desired. They had access to the standard, mobile-friendly, manufacturer website to program set-point schedules or alternatively switch all their thermostats between an "away" and a "home" mode. Temperature set-points could be configured independently for each of these modes for each thermostat. The website also allows to change set-points on demand and to visualize heating energy consumption.

Figure 1 shows the distribution of the number of rooms per house that are controlled by individual thermostats. There were an average of ten installed thermostats per house.

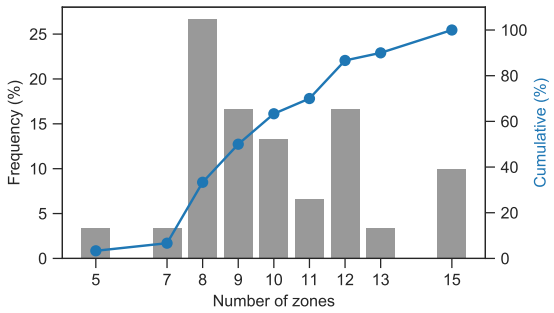

Figure 1: Distribution of the number of rooms per house that are controlled by individual LVCT.

Methodology

Preferred set-point profile

The proposed method segments data according to the type of day. The first group consists of Business Days (BD), and the second class comprises Weekends and public Holidays (WH). The statistical analysis of each group is performed for all thermostats in the house. Two types of programmed set-points are identified: comfort and setback set-points. Another process allows to identify weekdays and weekends recurrent usage patterns during heating days. The process for characterizing a thermostat is carried out based on the following steps:

ISBN 978-2-921145-88-6

1. The relative frequency or empirical probability of temperature set-points according to the time of day is estimated. The empirical probability is the ratio of the number of observations of a certain set-point to the total number of observations during the same time interval.
2. The set-point with the highest empirical probability for each time-step is then selected to form the preferred set-point profile.
3. The time fraction of usage for each set-point is estimated using the preferred set-point profile which is the ratio of the duration of the set-point to the total time of the day.
4. The set-points having a low time fraction of usage are removed from the preferred profile.
5. The highest value of the preferred profile is selected as the comfort set-point, and the rest of the set-point values are considered as setbacks.
6. The setback difference is defined as the difference between comfort set-point and the setback values.

The result of the proposed statistical analysis for BD data is shown in Figure 2. On the left, a 2D color-map histogram is presented in which the doted cyan curve is the preferred set-point schedule. On the right, the horizontal gray bars illustrate the time duration of each set-point of the preferred profile and arrows are the setbacks difference related to the comfort set-point.

Set-points categorization

In order to provide general information about preferences in temperature set-points, the frequent set-points of each thermostat are classified according to the Thermal Comfort Conditions of ASHRAE Standard 55 (Chandel and Aggarwal, 2012). This standard defines the Acceptable Temperature Range (ATR) for winter season in a range of 20-23 $^{\circ}C$. This range is depicted in Figure 3 which also includes specific temperature reference values of human comfort. Supplementary categories are used for set-points outside of the ATR. Generally, four categories are defined:

- Uncomfortable Range (UNR) : $T_{sp} < 18\ ^{\circ}C$
- Low Comfort Range (LCR) : $18\ ^{\circ}C \leq T_{sp} < 20\ ^{\circ}C$
- Acceptable Temperature Range (ATR) : $20\ ^{\circ}C \leq T_{sp} \leq 23\ ^{\circ}C$
- High Temperature Range (HTR) : $T_{sp} > 23\ ^{\circ}C$

It is expected to find set-points in the lower ranges when comfort requirements are lowered, i.e. when unoccupied and during night. For example, the classification of the weekday set-points of a living room presented in Figure 2 shows that comfortable set-points are programmed in the morning and evening from 6 to 8AM and from 5 to 10PM, respectively. Furthermore, LCR is programmed during the day and a UNR set-point is applied during the night. Thermostats having their highest set-point in the UNR are presumably in rooms that are normally unoccupied while the highest set-point in rooms that get occupied should occur in higher ranges. We also intend to corroborate if there is a relationship between thermostats operating at steady set-points and the mentioned temperature ranges.

Metric Assessment for Heating Savings

In the EnergyStar metric, the heating run-time is taken as a proxy to the heating energy. This methodology infers that the daily heating energy demand is calculated by multiplying an equivalent heating run-time *hrt* with a constant power heating capacity. Hence, the percentage of energy savings related to a baseline energy consumption should be estimated as a function of baseline heating run-time : $\Delta E[\%] = 100(hrt^{base} - hrt)/hrt^{base}$. In order to provide hrt^{base} and *hrt* estimations, the prescribed method uses a linear model with an hourly temperature input data defined by (1)[1]:

$$\hat{hrt}_{(d)} = \alpha \sum_{h=1}^{24} \left(T_{d,h}^{in} - T_{d,h}^{out} - \tau\right) \tag{1}$$

Where the parameters α and τ are the slope and the temperature offset related to zero heating demand during the cold season. These parameters are unique to each house and determined by minimizing the sum of quadratic error $\sum_d (\hat{hrt}_{(d)} - hrt_{(d)})^2$, where $hrt_{(d)}$ is the observed daily heating run time and d is the day index.

For LVCT, heating energy could be readily available from the thermostat. However, to use as much as possible the published code from EnergyStar, the heating energy is herein converted to heating run-time. Because a LVCT transfers power to a constant electric resistance baseboard, the *hrt* can be calculated directly using either thermostat energy consumption data or duty cycle data. Accordingly, the daily $hrt_{(d)}$ in minutes can be estimated as the ratio between the daily electric energy consumption $E_{(d)}$ in kilowatt-hour (kWh) and the baseboard nominal power $P_{(th)}$ in kilowatts (kW) expressed by (2).

$$hrt_{(d)} = 60\frac{E_{(d)}}{P_{(th)}} \tag{2}$$

The percent of heating run time reduction is calculated as a ratio between observed and baseline run times given by (3).

$$\Delta hrt[\%] = 100\left(1 - \frac{\sum_d hrt_{(d)}}{\sum_d \hat{hrt}_{(d)}^{base}}\right) \tag{3}$$

Where $\hat{hrt}_{(d)}^{base}$ is the daily baseline heating run time estimated in equation (1) in which T_h^{in} is substituted by the baseline comfort temperature (BCT).

[1] `http://epathermostat.readthedocs.io`

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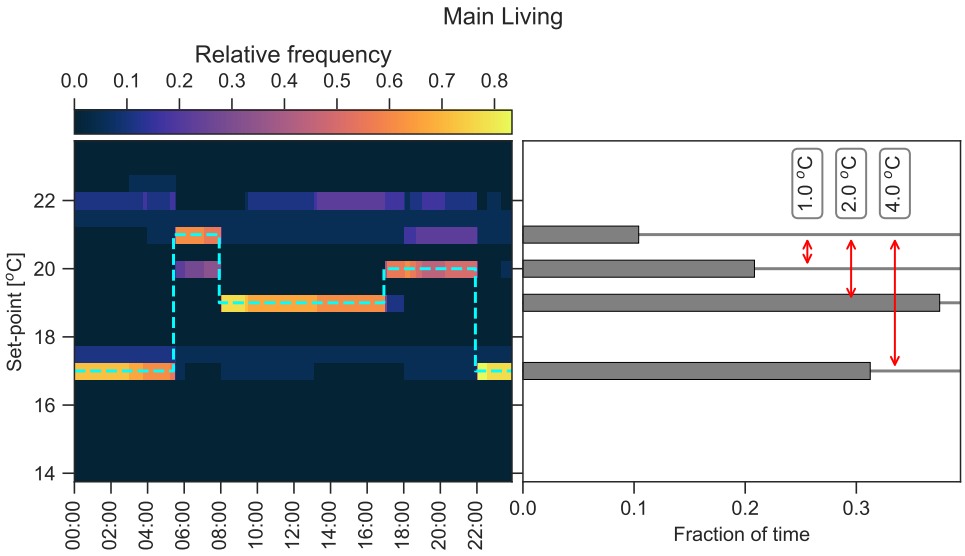

Figure 2: Daily thermostat set-point analyses for BD data located in the "main living" zone.

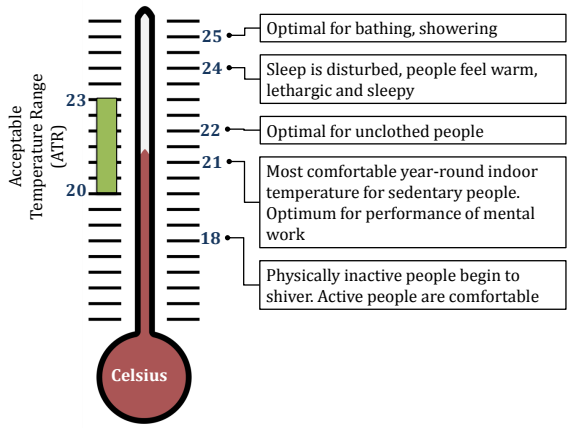

Figure 3: Comfort zones in accordance with the Canadian Center for Occupational Health and Safety, ASHRAE Standard-55-2004. Diagram adapted from (Chandel and Aggarwal, 2012).

RESULTS

In the following, the results and related discussion are presented in terms of set-points statistical analyses, and energy-savings metric calculations.

Set-point preferences

The purpose of this analysis is to expose the most frequently applied set-points and their variations according to the time of the day for a number of 301 thermostats. Likewise, we explore trends in the collection of all houses by analyzing aggregated information from their respective thermostats.

Figure 4 shows the percentage of programmed thermostats in each house on BD according to discrete percentage bins. Each house is categorized into one of these bins by evaluating the ratio between the number of programmed thermostats (more than one set-point) and the total number of installed thermostats in the house. By analyzing the shape of this distribution, two categories of houses can be highlighted. The first one is related to a group of houses with a low percentage of programmed thermostats (less than 50% of the thermostats of the house are programmed). This class encompasses about 50% of houses and has a peak at the first bar which means that 24% of all houses had less than 10% of their thermostats with normally applying setbacks. The second group comprises the houses reporting a higher proportion of programmed thermostats. This category includes the houses with more than 60% of their devices applying a time varying schedule. Moreover, by adding the fraction of homes where none (24%) or all (16%) of the thermostats applied more than one set-point during a day, it can be seen that no more than 40% of the houses used the same kind of set-back strategy for all thermostats. This number only considers the number of set-points and does not reflect differences in set-point levels or between two or more set-points per day.

On the other hand, Figure 5 (A) shows the histogram of the number of set-points found for each thermostat. Thermostats having a single set-point are further classified regarding the different temperature ranges. It is shown that 47% of devices during the BD and 53% during the WE operate at constant set-point. Furthermore, about 40% of the monitored devices apply two different set-points per day. In such cases, the average temperature setback is 2.8 ^{o}C and the most common ranges are ATR and LCR.

ISBN 978-2-921145-88-6

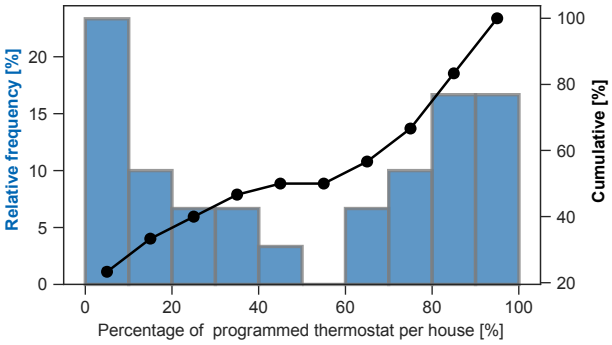

Figure 4: Distribution of the percentage of thermostats programmed per house.

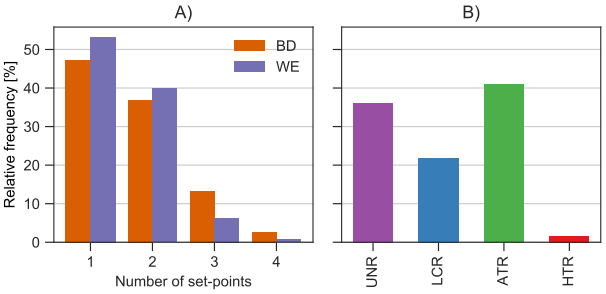

Figure 5: Figure A): Distribution of the number of set-points in the preferred schedule profile of 301 programmable thermostats. Figure B): Distribution of the set-point values for thermostats having only one set-point during business days.

Moreover, Figure 5 (B) shows that the percentage of thermostats operating at a constant set-point greater or equal to 20 ^oC is about 20% (0.47x0.42). It means that about 1/5th of the thermostats are used to maintain steady comfort conditions. On the other hand, 17% of thermostats apply a constant set-point lower than 18 ^oC . This is possibly a lower limit to the fraction of the rooms where comfort conditions are never deemed necessary.

The results of the set-point categorization is illustrated in Figure 6. The histogram presents the distribution of the highest values of the preferred set-points profile among the 301 monitored thermostats. 19% of thermostats are in the UNR class which is close to the 17% value of the previous paragraph which means that thermostats used to maintain uncomfortable temperatures seldom had set-points that varied in time. It should be underlined that 64 % of thermostats have their highest value of preferred set-point in the ATR class, where 21 ^oC is the most common value.

Figure 7 shows the distribution of the time of occurrence of set-backs and set-up events. In the morning, the most likely times to increase and decrease the set-points are respectively 6 and 8 AM. For other periods of the day, these

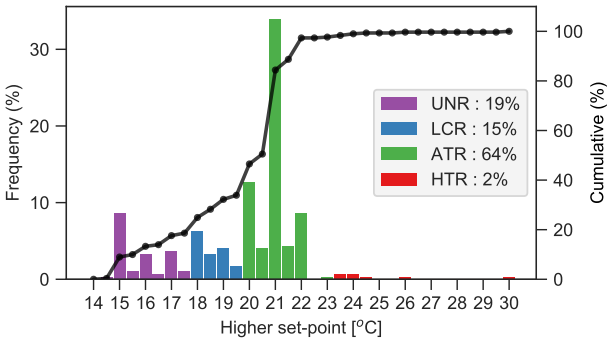

Figure 6: Distribution and categorization into temperature ranges of the highest set-points utilized in the 301 monitored thermostats.

times are 4 and 10 PM. These occurrences are compatible with the expected times of occupation change in a house: waking-up, leaving to and returning from work, and going to bed. Furthermore, Gaussian distributions were fitted over the histogram bars while neglecting relative frequencies of less than 2%. According to the results, standard deviations are close to 1 hour for the four distributions.

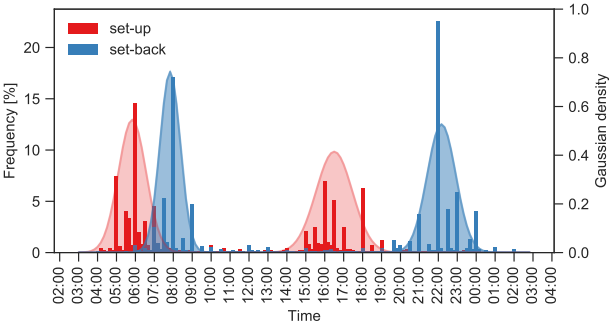

Figure 7: Distribution of set-back and set-up events of the 300 monitored thermostats.

Energy-savings metric

The results of the EnergyStar energy-savings metric applied to LVCTs in a zoned heating context are analyzed in this section. For metric calculations, the Python module developed for EnergyStar is used[2]. First, the metric is evaluated for each thermostat individually, as stipulated in the EnergyStar code. Subsequently, we compare the scenario of utilizing distinct baseline comfort temperatures for each zone versus the scenario of using a common baseline comfort temperature for all thermostats in the house.

The impact of the setback schedule complexity on the energy-saving metric is evaluated by grouping the thermostats according to the number of values detected in their

[2] https://github.com/EPAENERGYSTAR/epathermostat

ISBN 978-2-921145-88-6

preferred set-point profile of BD. The mean values and standard deviations of heating run-time reduction as a function of number of set-points are shown in Figure 8. The group having a single set-point (time invariant) had an average run-time reduction of about 5%, where a near zero value was expected. A possible factor is the fact that the BCT value is computed from measured room temperatures rather than set-points. Spurious heat gains (ex. solar and appliances) would sometimes raise the temperature over the comfort set-point, creating a setback from the metric point of view. Moreover, the increase in the number of set-points in the preferred profile does not make a significant difference in the metric value.

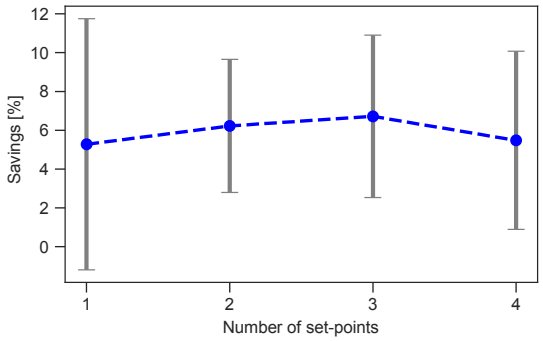

Figure 8: Heating run-time reduction as a function of the number of set-points in the preferred profile.

Figure 9 depicts the distribution of the heating run time reduction for the set of thermostats according to two different scenarios. In the first, shown in red, energy savings metrics are calculated using individual BCT as proposed by the Energy Star methodology while in the second scenario, shown in blue, a common BCT for all thermostats of a house is applied. In the second case, the 90th percentile is taken over the combined temperature records of all the thermostats of a house. In this scenario, the 95% confidence limit of the heating run time reduction distribution increases from 5% to 12%, exceeding the 8% threshold value.

The discrete distribution of the house BCT of the 30 monitored sites is shown in Figure 10. It can be seen that the distribution of BCT determined at the house level fits well with the Acceptable Temperature Range. The average BCT value is one degree higher than the most common comfort set-point (21^oC).

Conclusions

This paper investigated how communicating thermostats were used in 30 houses heated primarily with baseboard heaters and zoned at the room level. A statistical approach was used to extract recurrent set-point patterns from the data collected by the thermostats.

It was shown that about 3 out of 4 homes used set-backs

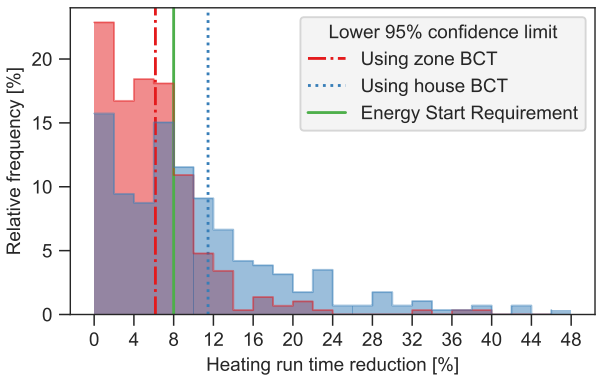

Figure 9: Distribution of heating run time reductions for both proposed scenarios: Red distribution for zonal BCT and blue distribution for entire household BCT.

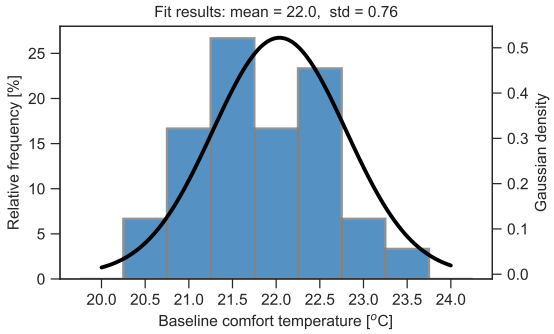

Figure 10: Distribution of BCT determined at the house level.

for at least one of their thermostats. However, no more than 40% of the houses used the same set-back strategy for all of their thermostats. Overall, 1 out of 5 thermostats ran at a steady comfort level set-point while about the same proportion maintained a steady set-point in the uncomfortable range (UR). The distribution of the highest set-points, the average setback depth, and the preferred time of occurrence of changes in set-points were also provided. This information, ideally confirmed with data gathered over a larger sample, could be used to guide the construction of stochastic set-point schedule sets, each set being composed of the schedules of each thermostat of a house. Such schedule sets could be used in building energy simulations to represent the actual use of LVCTs in a house zoned at the room level. This could allow a better estimation of the impact of different load management strategies in such buildings.

The metric used to assess energy savings in the EnergyStar Smart Thermostats certification was built with central HVAC systems in mind and links savings to the reduction of set-points in comparison to a baseline comfort temperature determined at the same thermostat. This definition of baseline comfort temperature could not capture the sav-

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ings of maintaining a room at a constant low set-point, a common practice in the studied sample. It was proposed to rather determine the baseline comfort temperature over the aggregated temperature readings of all the thermostats of a house. Although this was shown to increase the resulting metric value, it should also be compared to actual field evaluations of energy savings for the LVCT technology, which are actually scarce.

ACKNOWLEDGEMENT

The authors would like to acknowledge the Laboratoire des technologies de l'énergie (LTE) d'Hydro-Québec and Mitacs Accelerate Program for the financial support of this research.

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ISBN 978-2-921145-88-6