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Methodology and analytical approach to investigate the impact of building temperature setpoint schedules

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ABSTRACT

This paper presents a method for generating a large set of stochastically varying temperature setpoint schedules for building performance simulations. It analyses tradeoffs resulting from specific changes to those schedules in terms of three quantities: total electricity consumption per day; maximum hourly electricity consumption per day and predicted percentage dissatisfied (occupant thermal comfort). The method for generating schedules requires a single base schedule as the starting point and, using a few clearly defined parameters, transforms it into a set of schedules that can be used for modelling an existing building stock or for performing parametric studies. Temperature setpoint schedules are generated and simulated for a small office building in a cool-dry climate in three different case studies pertaining to changing temperature setpoint schedules. Tradeoffs between the three output metrics are significant and vary based on the temperature setpoint schedules and the time of the year.

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Building energy modelling; temperature setpoints; building schedules

Nomenclature

T	Shift in temperature for heating/cooling setpoint with respect to base schedule
λ_1	Computed parameter in exponential distribution used to sample t_p
λ_2	Computed parameter in exponential distribution used to sample t_{ramp}
$\mu_{no\text{-}sb,cool}$	Mean of normal distribution from which $T_{no\text{-}sb,cool}$ is sampled
$\mu_{no\text{-}sb,heat}$	Mean of normal distribution from which $T_{no\text{-}sb,heat}$ is sampled
$\sigma_{no\text{-}sb,cool}$	Standard deviation of normal distribution from which $T_{no\text{-}sb,cool}$ is sampled
$\sigma_{no\text{-}sb,heat}$	Standard deviation of normal distribution from which $T_{no\text{-}sb,heat}$ is sampled
σ_{cool}	Standard deviation of normal distribution using which $T_{dst,cool}$ and $T_{sb,cool}$ are sampled
σ_{heat}	Standard deviation of normal distribution using which $T_{dst,heat}$ and $T_{sb,heat}$ are sampled
3-σ	Three standard deviations with respect to the mean value
N_{occ}	Length of time for occupied hours – used to compute *ppd*
p_{thresh}	Probability with which a given building setpoint is likely to have a setback
$T_{no\text{-}sb,cool}$	Cooling setpoint temperature value of a no-setback profile (cooling setpoint)
$T_{no\text{-}sb,heat}$	Heating setpoint temperature value of a no-setback profile (heating setpoint)
$T_{lo,dst,cool}$	Lower threshold limit for cooling setpoint during hours of cooling operation
$T_{lo,dst,heat}$	Lower threshold limit for heating setpoint during hours of heating operation
$t_{p,thresh}$	Upper threshold time period for t_p
t_p	Duration of time for which early-morning heating/cooling is extended (relative to 6 AM)
$t_{ramp,thresh}$	Threshold value for t_{ramp}
t_{ramp}	Duration of time over which heating/cooling setpoints are ramped
$T_{sb,cool}$	Setback temperature for cooling setpoint in a setback schedule
$T_{sb,heat}$	Setback temperature for heating setpoint in a setback schedule
t_{start}	Time of day when heating/cooling setpoint schedule transitions from setback to operation
$T_{up,sb,cool}$	Upper threshold limit for cooling setpoint during hours of cooling setback

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$T_{up,sb,heat}$	Upper threshold limit for heating setpoint during hours of heating setback
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CBECS	Commercial Buildings Energy Consumption Survey
DOE	Department of Energy
HVAC	Heating, Ventilation and Air Conditioning
IDF	Input Data File
PNNL	Pacific Northwest National Laboratory
PPD	Predicted Percentage Dissatisfied
TMY	Typical Meteorological Year
$E_{day,tot}$	Change in median of $E_{day,tot}$ (total electricity consumption per day [kWh]) due to a given setpoint modification
E_{max}	Change in median of E_{max} (maximum hourly consumption per day [kWh]) due to a given setpoint modification
ppd	Change in median of *ppd* (mean hourly predicted percentage of dissatisfied [PPD, %] in the core zone per day) due to a given setpoint modification
$E_{day,tot}$	Total electricity consumption per day (kWh)
E_{max}	Maximum hourly consumption per day (kWh)
ppd	Mean hourly predicted percentage dissatisfied (PPD) in the core zone per day (%)
$T_{dst,cool}$	Daytime setpoint temperature for cooling setpoint in a setback schedule
$T_{dst,heat}$	Daytime setpoint temperature for heating setpoint in a setback schedule
$T_{lo,sb,cool}$	Lower threshold limit for cooling setpoint during hours of cooling setback
$T_{lo,sb,heat}$	Lower threshold limit for heating setpoint during hours of heating setback
$T_{up,dst,cool}$	Upper threshold limit for cooling setpoint during hours of cooling operation
$T_{up,dst,heat}$	Upper threshold limit for heating setpoint during hours of heating operation

1. Introduction

Residential and commercial buildings contributed to approximately 75% of retail sales of electricity in the USA in 2020 (Administration 2021). Heating, ventilation and air-conditioning (HVAC) is often responsible for a large fraction of building energy use – for instance, in office buildings HVAC contributes to ~35% to 45% of the energy consumption (U.S. Department of Energy 2015). Thermostat setpoints, i.e. heating and cooling setpoints, are a key driver of HVAC energy consumption behaviour in an office building. Changing these setpoints can significantly reduce overall energy consumption (Oldewurtel, Sturzenegger, and Morari 2013; Yang and Becerik-Gerber 2014; Huang et al. 2021); however, measures to improve overall energy savings by adjusting temperature setpoints can have adverse effects on thermal comfort (Papadopoulos et al. 2019; Ghahramani, Dutta, and Becerik-Gerber 2018) and peak electricity consumption (Cai et al. 2018).

The extent to which any potential energy savings occur due to changes in temperature setpoint schedules can depend on the building type and construction, and the climate zone it is located in (Hoyt, Arens, and Zhang 2015). For instance, performing EnergyPlus simulations using a medium office DOE prototype building model (gas-heated) under different HVAC configurations, a previous study concluded that a widened temperature setpoint range used in conjunction with personal controls can reduce the annual HVAC consumption by 32–73%, depending on the climate zone (Hoyt, Arens, and Zhang 2015). Researchers also investigated the impact of optimal temperature setpoints on energy savings in small, medium and large office buildings; concluding that the potential energy savings for the simulated buildings could be 10–37%, 11.5–21%, 7–11.5% respectively (where the ranges indicate the variation in results with respect to climate zone) (Ghahramani, Dutta, and Becerik-Gerber 2018; Ghahramani et al. 2016).

Peak/maximum hourly electricity consumption (computed on a per day basis) is a critical metric to evaluate, as it can be significantly more expensive (by a factor of 2–10) to meet on the generation side compared to meeting the average demand (Putra, Andrews, and Senick 2017). Previous work (Faruqui, Hledik, and Palmer 2012) has indicated that power plants often operate outside their highest efficiency ranges during the peak hours. Using eQuest simulations, researchers identified that increasing the cooling setpoint can increase the instantaneous peak demand (kW) during summer season (Cai et al. 2018). The relative increase in peak demand was as much as 6.3% for an HVAC setback of 2.8 °C (5 °F).

Thermal comfort of occupants in an office building needs to be considered when evaluating the effects of changing temperature setpoints, as the primary purpose of HVAC energy consumption in a commercial building is to provide an appropriate thermal environment for its occupants. The thermal indoor environment has been shown to affect occupant productivity (Geng et al. 2017); however, previous work has indicated that only a small number of buildings in the USA are likely to achieve 90% occupant satisfaction (Huizenga et al. 2006). Note that in ASHRAE 55-2017, the 90% acceptability is based on 10% dissatisfaction for general thermal comfort. Previous research has shown that a given setpoint modification

strategy – for instance, increasing the cooling setpoint temperature during building operational periods can adversely affect thermal comfort of building occupants in cooling seasons (Aghniaey and Lawrence 2018). In an effort to control moisture in moist regimes (type 'A' ASHRAE climate zones) (Baechler et al. 2015), commercial buildings often overcool buildings during summer days (Derrible and Reeder 2015). Previous studies (Derrible and Reeder 2015; Mendell and Mirer 2008; Aghniaey and Lawrence 2017) have shown that overcooling often results in increased electricity consumption with minimal improvement in thermal comfort. There has been detailed work in the controls community on optimizing temperature setpoint to maximize thermal comfort in high performance buildings (Gunay 2016); however, there remains a need to generate temperature setpoints for large-scale building energy modelling and parametric analysis to investigate impact of setpoint modifications in a typical building stock.

Therefore, it is important to jointly analyse the effects of temperature setpoint profiles on electricity consumption, peak demand (or an indicator thereof) and thermal comfort (Silva, Duplessis, and Adnot 2011), and how modification to the temperature setpoints can affect these three output metrics. However, while there are guidelines from policymakers on selection of temperature setpoint schedules for energy simulation and code improvement purposes, these schedules are not universally applied to all buildings in an actual building stock (Ueno and Meier 2020). To estimate how modifications to temperature setpoint schedules can affect a collection of buildings (e.g. districts, campuses, cities or the national building stock), it is critical to perform this analysis using a distribution of setpoint schedules that can be representative of schedules employed in actual commercial buildings. As such, there is a need for a systematic method to generate a *distribution* of stochastic temperature setpoint schedules to capture the diversity present in actual schedules in commercial buildings.

The automatic generation of large numbers of temperature setpoint schedules can support improved building stock energy modelling. Several researchers have pointed out the benefits of stochastic occupancy modelling (Feng, Yan, and Hong 2015; Hu and Xiao 2019; Bianchi et al. 2020) to improve building stock models. Bianchi et al. (2020) recently demonstrated the use of stochastic, auto-generated occupancy models with an aggregated urban-scale building energy model and compared a subset of their simulated buildings against observed electrical meter data. They found that their procedure guaranteed diversity in the operating times of buildings and reduced calibration error between modelled and observed data by about 1%.

In this study, we focus on the specification of the temperature setpoint control value that would be provided to the building's cooling or heating system, such as through control signals provided by a building automation system. These setpoints are directly controllable by building operators and closely tied to both HVAC energy consumption and to the occupants' thermal comfort. While some commercial buildings provide occupants with the ability to alter temperature setpoints within a particular space, the occupants typically have a very limited range of temperature variation available for adjustment. We do not attempt to represent individual occupant-controlled thermostats in this work, which is focused on evaluating impacts of temperature setpoints in aggregate. Large-scale data sources for building stock modelling usually provide only high-level parameters and not detailed schedules for the sampled buildings (Ye, Zuo, and Wang 2019). To perform an aggregated building energy analysis with models derived from a common set of prototypes, any diversity in temperature setpoint values and in the change of temperature setpoints over time (i.e. temperature setpoint schedules/profiles) must be added systematically by the modeller. While previous researchers have created methods for deriving temperature setpoint values using high-resolution observations of energy and temperature data (Gianniou et al. 2018; Bienvenido-Huertas, Sánchez-García, and Rubio-Bellido 2020), no publicly available method exists for stochastically generating temperature setpoint profiles using only a small set of parameters defined by the modeller. We provide an open-source, automated method for generating large numbers of temperature setpoint profiles in heating and cooling seasons using only simple transformations applied to a base schedule extracted from the U.S. Department of Energy's Commercial Prototype Building model for a small office building based on ASHRAE Standard 90.1-2004 (U.S. Department of Energy 2020a).

Aside from supporting large-scale building energy simulation, the proposed methodology also supports parametric analysis of how a given modification to a setpoint schedule can affect a single building. A modification to a given setpoint schedule can include employing a nighttime setback, changing the daytime setpoint/setback temperature, employing pre-cooling/pre-heating, employing a gradual morning ramp-up or a given combination of the above.

In this study, we analyse the impacts of temperature setpoint modifications on three output metrics of interest: total electricity consumption per day (kWh), maximum hourly consumption computed per day (kWh) and mean predicted percentage dissatisfied (PPD). Total electricity consumption per day provides information about

the electricity used due to a given setpoint schedule throughout a full diurnal cycle. Maximum hourly electricity consumption provides information about the electricity needed in the hour of highest demand throughout the day. It is provided in kWh for consistency with peak hourly electricity usage, since electrical power will vary within this hour and short-timescale electrical dynamics are not the focus of this work. PPD provides information about the likelihood of providing thermal comfort to building occupants under the given setpoint schedule by quantifying the portion of occupants who would be likely to report themselves as dissatisfied with the building's thermal conditions. We are interested in how the impacts to these three variables generalize across a distribution of schedules. Note that we are not producing an optimal set of setpoint schedules and that our setpoint schedules will not represent advanced control systems; rather, we aim to generate a set of feasible schedules that could be observed in an existing office building with simple rule-based temperature setpoint control.

The key focus of our work is to develop a methodology to generate feasible heating and cooling temperature setpoints in commercial buildings using only a limited set of available parameters, such that they can be used in large-scale building energy simulation, and to perform parametric analysis to analyse tradeoffs between total electricity consumption, maximum hourly electricity consumption and thermal comfort. To summarize, this paper describes the following unique contributions to the research literature:

- Develop a methodology to stochastically generate a distribution of heating and cooling setpoint schedules, starting from a base schedule and a small set of parameter choices.
- Propose an approach to quantify the tradeoffs between total electricity consumption, maximum hourly electricity consumption and thermal comfort due to a given setpoint modification.
- Demonstrate how the proposed analytical approach can be used to assess the impact of a given setpoint modification across a distribution of schedules generated using the methodology mentioned above.

The methodology is implemented as a Python package called 'TEMPSET'. The code implementing the methodology and analysing the result is provided here: https://github.com/IMMM-SFA/tempset.

2. Methodology and analysis approach

In this section, we provide details of the proposed methodology for generating a large, diverse set of schedules and an analytical approach to quantify the tradeoffs between the three output variables mentioned in Section 1. We have developed this methodology based on data from the existing literature, ASHRAE guidelines, data from CBECS, and conversations with building energy professionals at PNNL. Details on how this data was used for the selection of schedule parameters used in our methodology is provided in Supplementary Information.

Figure 1 provides a schematic of the overall workflow. The two key components of the workflow are:

- A methodology to generate a distribution of schedules from a base schedule. These schedules are processed as text objects that can be placed directly into Input Data Files (IDFs) for EnergyPlus simulations. Each stochastic schedule will provide the full annual schedule of heating and cooling setpoints for a single building energy model's IDF. The IDFs are subsequently used to perform simulations in EnergyPlus (U.S. Department of Energy 2020b).
- An approach to analyse the tradeoffs caused by a given setpoint modification between the three output metrics of interest: total electricity consumption per day (kWh), maximum hourly electricity consumption per day (kWh) and mean PPD in the core zone (averaged per day during occupied hours, %). The PPD estimates the number of occupants dissatisfied with the thermal environment at a given time.

2.1. Methodology for schedule generation

The proposed methodology starts with a base/reference schedule and generates a distribution of temperature setpoint schedules based on stochastic perturbations to the base schedule. The time-of-day operation of the buildings is a key driver of actual building consumption. In building energy simulation, the operating hours in real buildings are expressed as schedules and the schedules consist of information pertaining to building operation (such as whether HVAC system is on or off, values of temperature setpoints) at different times during a day.

We used the DOE Small Office Prototype building model for ASHRAE Standard 90.1-2004, as an example in this study. The DOE Commercial Prototype buildings (Thornton et al., 2011) were developed based on DOE's Commercial Reference Building Models (Deru et al. 2011). CBECS 2018 microdata suggests that the small office (as shown in Figure 2) is well-represented in the commercial building stock (U.S. Energy Information Administration 2020). Office buildings comprise 16.4% of all commercial buildings surveyed in CBECS 2018 – more than any other commercial building type. The median floor area of these office buildings is 455 m^2 – lower than the

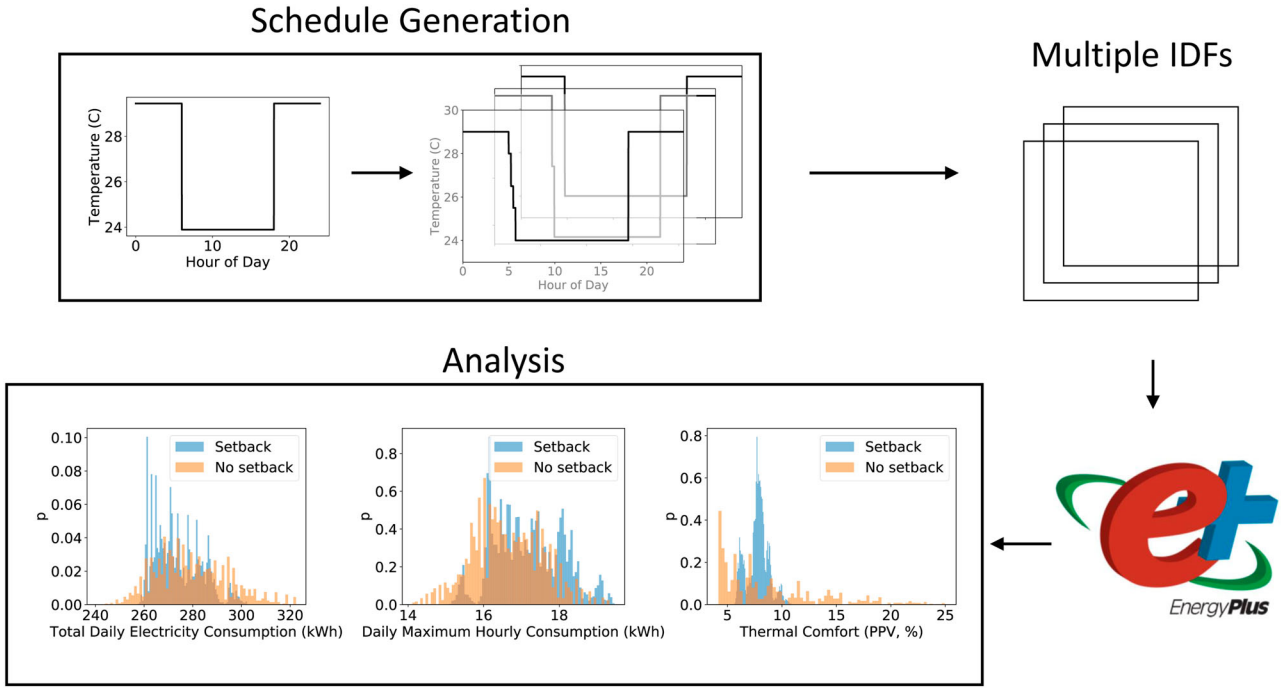

Figure 1. Schematic diagram of overall workflow.

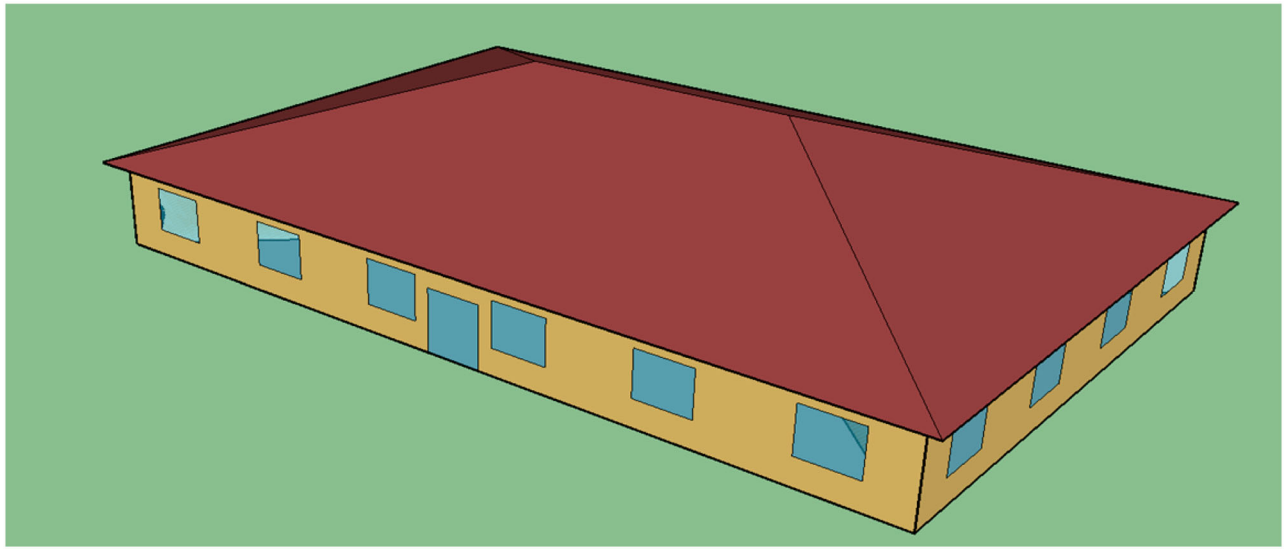

Figure 2. Image of DOE small office prototype (U.S. Department of Energy 2020a).

floor area for the DOE Prototope Small Office (511 m^2). We have selected ASHRAE 90.1-2004 as our vintage, as a 'representative' existing commercial building in the USA is more likely to follow an older energy code compared to a newer code. The base schedule used in this study was extracted from the DOE Small Office Prototype for ASHRAE Standard 90.1-2004. Figure 3 presents the schedules for cooling setpoints on weekdays and weekends/holidays respectively, as used in the DOE Small Office Prototype for ASHRAE Standard 90.1-2004. While we have selected the base schedule from the DOE Small Office Prototype, the methodology can be implemented with different base schedules as well. In this study, we have looked at the impact of modifying weekday schedules *only*; however, the methodology presented here can be used to generate weekend schedules as well. We are considering weekdays only, as the occupancy is typically significantly higher in commercial buildings on weekdays and as such, the tradeoffs between our output variables of interest are only pertinent on weekdays. Details of the prototype small office building used in this analysis are provided in Section 2.2.

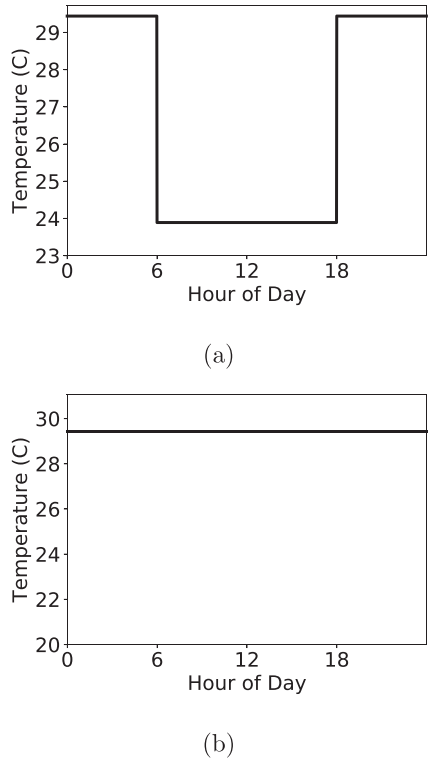

Figure 3. Cooling setpoint schedule used in the DOE small office prototype for ASHRAE Standard 90.1-2004 during (a) weekdays and (b) weekends/holidays.

Figure 4 provides a schematic diagram of the methodology used to generate schedules that are used as inputs to EnergyPlus. We enforce a set of parameters and assumptions, which will allow us to generate a broad range of plausible schedules. CBECS microdata has shown that 23% of the commercial buildings (for which survey responses were available) do not employ a nighttime setback. Therefore, in this methodology we randomly select, with probability p_{thresh}, whether a given generated schedule will have a nighttime setback for a given sample schedule. We have implemented p_{thresh} as a user-modifiable input. However, for this study, we based p_{thresh} on CBECS 2012 data (U.S. Energy Information Administration 2020) – determined as the number of sampled buildings in CBECS that contain setback divided by the total number of sampled buildings that included information on whether or not a setback was employed. The value of p_{thresh} was computed based on the CBECS data to be 0.77.

A given realization of a schedule will have a no setback schedule with probability $1 - p_{thresh}$ and a setback schedule with probability p_{thresh}. In the following sections, we describe the procedures to generate no setback and setback schedules respectively. Note that both the no-setback and setback profiles are profiles for control temperatures, not the actual zone temperatures.

2.1.1. No setback schedules

A no setback schedule will have a constant temperature for the entire 24 h period – similar to one shown in Figure 3(b). Here, we present a procedure to select this constant temperature value. We assume that the no setback temperature (for either a cooling or a heating setpoint profile) will be drawn from a truncated normal distribution. To define this distribution, we need to decide on the mean of this distribution ($\mu_{cool,no\text{-}sb}$ for cooling and $\mu_{heat,no\text{-}sb}$ for heating setpoint) and its standard deviation. To compute the standard deviation, we selected the upper and lower threshold values (corresponding to three standard deviations) of this truncated normal distribution ($T_{up,dst,cool}$ and $T_{lo,dst,cool}$ for cooling setpoints; $T_{up,dst,heat}$ and $T_{lo,dst,heat}$ for heating setpoints). The actual values of each of these temperature parameters (Table 1) are based on conversations

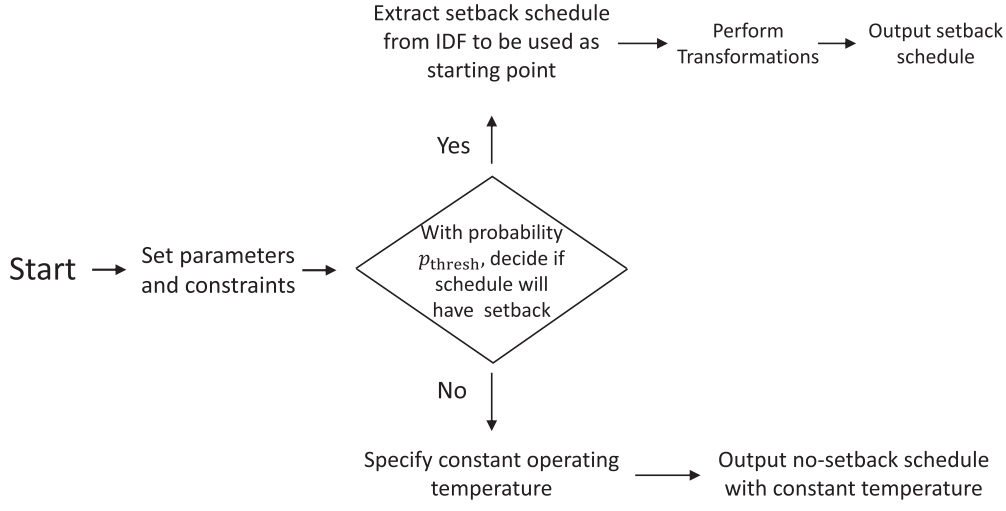

Figure 4. Schematic diagram of process to generate stochastic schedules.

Table 1. Parameters needed to generate no setback schedule. Please refer to Supplementary Information for justifications on selection of these parameters.

Parameter	Parameter value
Mean temperature for cooling setpoints, $\mu_{cool,no\text{-}sb}$	24 °C
Mean temp. for heating setpoints, $\mu_{heat,no\text{-}sb}$	21 °C
Upper threshold value of temp. for cooling setpoints, $T_{up,dst,cool}$	28 °C
Upper threshold value of temperature for heating setpoints, $T_{up,dst,heat}$	23.5 °C
Lower threshold value of temperature for cooling setpoint, $T_{lo,dst,cool}$	20 °C
Lower threshold value of temperature for heating setpoint, $T_{lo,dst,heat}$	17 °C

with building science professionals at PNNL. Additional notes justifying these parameter selections are provided in Supplementary Information.

Once the parameters are set, we can generate the no setback cases as presented in Table 1. The constant temperatures used for no-setback schedules are sampled from a truncated normal distribution using these parameters, so as to reflect the diversity in no-setback schedules.

- We set the standard deviation ($\sigma_{no\text{-}sb}$) of our truncated normal distribution, which we will use to sample the no setback temperature ($T_{no\text{-}sb}$). ($\sigma_{no\text{-}sb}$) is computed in a way such that while we can get a diverse range of ($T_{no\text{-}sb}$), a given sample of $T_{no\text{-}sb}$ is likely to fall within the upper and lower threshold values:

$$\sigma_{no\text{-}sb,i} = \min\left[\frac{(T_{up,dst,i} - \mu_{no\text{-}sb,i})}{3}, \frac{(\mu_{no\text{-}sb,i} - T_{lo,dst,i})}{3}\right] \quad (1)$$

  In Equation (1), the subscript $i \in \{cool, heat\}$ indicates whether the corresponding schedule is a cooling or a heating setpoint and $T_{up,dst,i}$ and $T_{lo,dst,i}$ denote the upper and lower threshold values for daytime setpoint temperatures ($T_{dst,cool}$ or $T_{dst,heat}$). Equation (1) indicates that we take the minimum of the two values: ($T_{up,dst,i} - \mu_{i,no\text{-}sb}$) and ($\mu_{i,no\text{-}sb} - T_{lo,dst,i}$), and set corresponding value as the $3-\sigma$ bounds of our truncated normal distribution.
- Subsequently, we sample from the distribution: $T_{no\text{-}sb} \sim \mathcal{N}(\mu_{no\text{-}sb}, \sigma_{no\text{-}sb})$ to get the constant temperature at which the setpoint schedule is set. We round off the constant temperature value to the nearest 0.5 °C, which we assume as the minimum increment to which the temperature setpoint can be set.

Based on the values in Table 1, the no setback standard deviations for cooling and heating setpoints ($\sigma_{no\text{-}sb,cool}$ and $\sigma_{no\text{-}sb,cool}$) were computed to be 1.33°C and 0.83°C, respectively.

2.1.2. Setback schedules

Here, we describe the procedure to generate setback profiles (i.e. schedules with a nighttime setback) for cooling and heating setpoint derivations from the base schedule. The aim of this procedure is to generate a diverse set of setback schedules that are plausible and do not deviate significantly from the base schedule. Figure 3(a) shows an example of a cooling setpoint schedule with nighttime setback. The procedure for generating the setback schedules requires more parameters than the procedure used to generate no setback profiles.

Before describing the process we used to generate setback schedules, we describe the relevant terms we will use to generate new schedules:

- **Daytime setpoint temperature, $T_{dst,i}$**: (°C) For a given heating setpoint schedule, this would correspond to the maximum temperature within the 24 h period, whereas for a given cooling setpoint schedule, it would correspond to the minimum temperature over the 24 h period.
- **Setback temperature, $T_{sb,i}$**, (°C): This is the temperature when the heating or the cooling mode is in 'setback' mode. For a given heating setpoint schedule, this would correspond to the minimum temperature within the 24 h period, whereas for a given cooling setpoint schedule it would correspond to the maximum temperature over the 24 h period.
- **Setback hours (*hr*)**: Duration of time during which the heating or cooling setpoint temperature is equal to the setback temperature. $T_{sb,i}$.
- **Hours of daytime operation (*hr*)**: Duration of time during which the heating or cooling setpoint temperature is equal to the daytime setpoint temperature $T_{dst,i}$.
- **Occupied hours (*hr*)**: Duration of time during which building occupancy is greater than 20%. As will be described later in this section, this duration will be used to compute the mean PPD in the core zone.
- **Length of pre-heating/pre-cooling time, $t_{p,i}$ (*hr*)**: This is the length of time, measured backwards from 6 AM, over which pre-heating or pre-cooling is employed. In the base schedule, the transition from setback to operation for both cooling and heating setpoints starts at 6 AM. When pre-heating/pre-cooling is employed in a given setback schedule this transition starts at (6 – $t_{p,i}$) AM.
- **Time period for morning ramp-up, $t_{ramp,i}$ (*hr*)**: In a setback schedule, we need to transition from the setback temperature $T_{sb,i}$ to the daytime setpoint temperature $T_{dst,i}$ in the morning. It may be beneficial for a building's equipment and/or demand charges to do

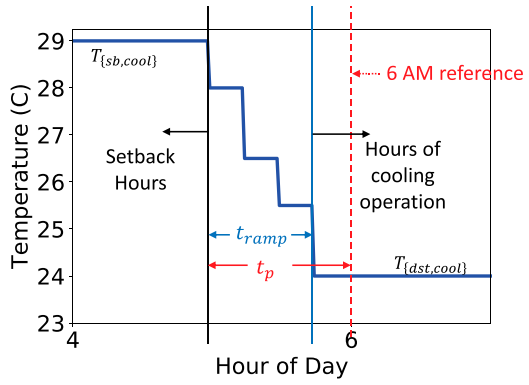

Figure 5. Schematic diagram of one stochastic sample of cooling setpoint schedule to describe key terms used to generate setback schedules. The red vertical line at 6 AM corresponds to the transition from setback to operation in the base schedule, which is subsequently used to determine the transition time from setback to operation in the generated schedule.

this gradually rather than all at once. $t_{ramp,i}$ indicates the time taken to transition from $T_{dst,i}$ to $T_{sb,i}$.

- **Morning ramp-up rate, γ, (°C/ h)**: This is the rate indicating how quickly the morning transition from $T_{sb,i}$ to $T_{dst,i}$ occurs. In a setback profile, we need to transition from the setback to the daytime setpoint temperature. It may be beneficial to do this gradually rather than instantaneously. The morning ramp-up rate is expressed as

$$\gamma = \frac{|T_{sb,i} - T_{dst,i}|}{t_{ramp,i}} \tag{2}$$

Figure 5 shows a schematic representation of a cooling setpoint schedule to clarify the terminology used to generate setback schedules. Note that the figure presented is just one stochastic sample of a cooling setpoint schedule.

In this procedure, we generate a given setback schedule from the base schedule by changing the following variables for either cooling or heating setpoint: (a) daytime setpoint temperature (or temperature for daytime operation), $T_{dst,i}$; (b) setback temperature, $T_{sb,i}$; (c) length of time for morning pre-heating/ pre-cooling, $t_{p,i}$ and (d) length of time for morning ramp-up, $t_{ramp,i}$, We assume that daytime setpoint temperature, $T_{dst,i}$ and setback temperature $T_{sb,i}$ both follow truncated normal distributions with identical standard deviations. We also assume that the length of time for morning pre-heating/pre-cooling, $t_{p,i}$ and the length of time for morning ramp-up $t_{ramp,i}$ follow truncated exponential distributions, as we assume that a longer duration of pre-heating/pre-cooling (relative to reference 6 AM), and a slow morning ramp-up are less common in practice. To specify these distributions, we define the following parameters:

- Mean daytime setpoint and setback temperatures for cooling and heating setpoints: for cooling setpoint, the mean daytime setpoint temperature, $\mu_{dst,cool}$, and the mean setback temperature, $\mu_{sb,cool}$, represent the mean values of the truncated normal distribution from which $T_{dst,cool}$ and $T_{sb,cool}$ will be sampled. Similarly, for heating setpoint, $\mu_{dst,cool}$ and $\mu_{dst,heat}$ represent the mean values using which $T_{dst,cool}$ and $T_{sb,cool}$ are sampled.
- Upper threshold value of setback temperature for cooling setpoints: We assume that both the daytime setpoint temperature $T_{dst,i}$ and the setback temperature $T_{sb,i}$ follow a truncated normal distribution with an identical standard deviation, σ_i. To compute this standard deviation for cooling setpoints (σ_{cool}), we use the upper threshold value (corresponding to three standard deviations) of cooling setpoint during setback, $T_{up,sb,cool}$.
- Lower threshold value of setback temperature for heating setpoints: As mentioned above, both $T_{dst,i}$ and $T_{sb,i}$ have a common standard deviation, σ_i. To compute this standard deviation for heating setpoints (σ_{heat}), we use the lower threshold value (corresponding to three standard deviations) of cooling setpoint during setback, $T_{lo,sb,heat}$.
- Threshold length of time for pre-heating/pre-cooling: To compute a plausible $t_{p,i}$ for schedule, we define a threshold time duration, $t_{p,thresh}$, as an upper extreme for the time duration of the pre-heating or pre-cooling period. Therefore, 99% of the generated heating/cooling setpoint schedules with setback will have a pre-heating/pre-cooling period that is shorter than this time duration.
- Threshold morning ramp-up rate: We define a threshold morning ramp-up rate, γ_{thresh}, which is an extreme case of a slow/gradual morning ramp-up. We subsequently use γ_{thresh} to compute the threshold $t_{ramp,thresh}$ – an upper extreme for the time duration of $t_{ramp,i}$. 99% of the generated schedules will have $t_{ramp,i} < t_{ramp,thresh}$.

The selections of these parameters are provided in Table 2. Additional notes justifying the selection of these parameter values are provided in Supplementary Information. The parameters defined in Sections 2.1.1 and 2.1.2 are user-modifiable inputs in the workflow.

Having defined the parameters to generate a setback schedule, we now present the operations performed to generate a given schedule. In Figure 6, as an example, we present one instance of a schedule generated with this methodology. The specific operations to generate this particular schedule are illustrated as follows:

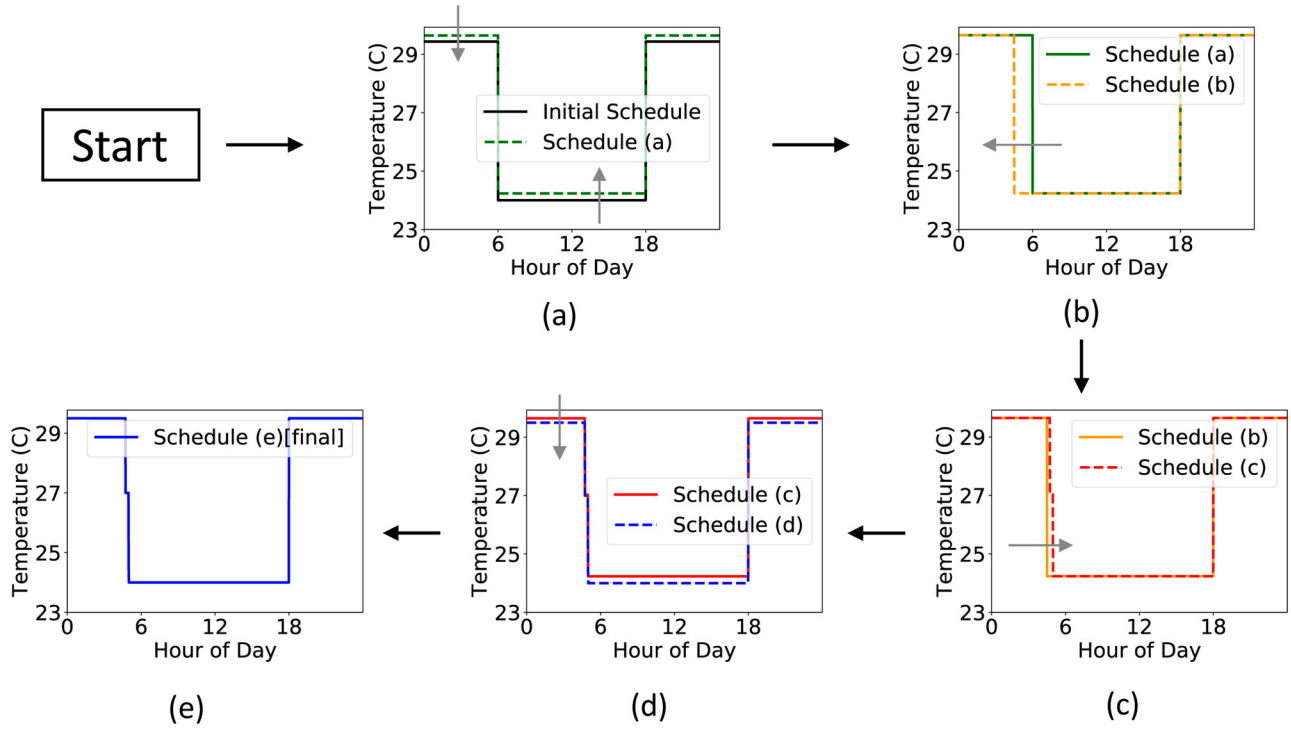

Figure 6. Schematic diagram of the procedure to modify the setback profile. Note that the schematic diagram corresponds to generation of one realization of a schedule generated through our proposed methodology and not the exact sequence for *all* setback schedules. The process consists of the following operations: (a) changing the maximum and minimum temperatures of the heating/cooling setpoint schedule; (b) adding a pre-heating/pre-cooling period; (c) modifying the gradient of morning ramp-up; (d) rounding off the temperatures to the nearest 0.5°C. (e) The final schedule obtained for one stochastic 'run' of the setback schedule generation process.

Table 2. Parameters to generate a setback schedule (in addition those specified in Table 1). Please refer to Supplementary Information for justifications on selection of these parameters.

Parameter	Parameter value
Mean value of daytime setpoint temperature for cooling setpoints $\mu_{dst,cool}$	24 °C
Mean value of setback temperature for cooling setpoints, $T_{sb,cool}$	29.5 °C
Mean value of daytime setpoint for heating setpoints, $\mu_{dst,heat}$	21 °C
Mean value of setback temperature for heating setpoints, $\mu_{sb,heat}$	15.5 °C
Upper threshold value for cooling setpoints during unoccupied hours, $T_{up,dst,cool}$	30 °C
Lower threshold value for heating setpoints during unoccupied hours, $T_{lo,dst,heat}$	14 °C
Threshold time period for pre-heating/pre-cooling, $t_{p,thresh}$	4 h
Threshold ramp-up rate, $\gamma_{ramp,thresh}$	0.5°C/h
Maximum allowable length of time for morning rampup	3 h

- *Step (a):* First, we change the maximum and minimum temperatures of our setpoint schedule. Step (a) in Figure 6 shows how this is performed in the case of a cooling setpoint – where the maximum and minimum temperatures correspond to setback temperature and operating temperature, respectively. For both heating and cooling setpoints, the setback and daytime setpoint temperatures are modified by shifting the initial mean values by T, as shown in Equation (3):

$$T_{sb,i} = \mu_{sb,i} + T_{sb,i}, \text{ and}$$
$$T_{dst,i} = \mu_{dst,i} + T_{dst,i} \quad (3)$$

Here, Equation (3), $T_{sb,i}$ and $T_{dst,i}$ correspond to the setback and daytime setpoint temperatures for both heating and cooling setpoints.

As mentioned earlier in this section, we aim to generate a diverse range of setback schedules that are plausible in practice. To achieve this balance, we assume that the values of change in temperature (T) are not necessarily the same for both $T_{sb,i}$ and $T_{dst,i}$, but the T values are drawn from an identical distribution for both $T_{sb,i}$ and $T_{dst,i}$. The shifts in these temperatures, $T_{sb,i}$ and $T_{dst,i}$ are determined as follows:

$$T_{sb,i}, \quad T_{dst,i} \sim \mathcal{N}(0, \sigma_i) \quad (4)$$

Now, we compute the standard deviation of this distribution, σ_i (i.e. σ_{cool} or σ_{heat}) so that the resulting values of $T_{sb,i}$ and $T_{dst,i}$ are plausible and are likely to fall within the upper and lower threshold values during both setback and operation. Later in the section, we will describe how we can account for 'outlier' schedules that do not fall within the threshold values. For a

cooling setpoint (for which $T_{dst,cool} < T_{sb,cool}$), we consider the minimum of the two differences: ($T_{up,sb,cool} - T_{sb,cool}$) and ($T_{dst,cool} - T_{lo,dst,cool}$) and set the corresponding value to three standard deviations. Considering the minimum of the two values provides a more conservative estimate of σ_{cool}, ensuring that the threshold values $T_{up,sb,cool}$ and $T_{lo,dst,cool}$ are likely to be maintained, i.e. $T_{sb,cool} \leq T_{up,sb,cool}$ and $T_{dst,cool} \geq T_{lo,dst,cool}$.

$$\sigma_{cool} = \min\left(\frac{T_{up,sb,cool} - T_{sb,cool}}{3}, \frac{T_{dst,cool} - T_{lo,dst,cool}}{3}\right) \tag{5}$$

We follow a similar process to compute the standard deviation for heating setpoints, σ_{heat}. For heating setpoints, $T_{dst,heat} > T_{sb,heat}$ and so σ_{heat} can be expressed as

$$\sigma_{heat} = \min\left(\frac{T_{up,dst,heat} - T_{dst,heat}}{3}, \frac{T_{sb,heat} - T_{lo,sb,heat}}{3}\right) \tag{6}$$

σ_{cool} and σ_{heat} were computed to be 0.17 °C and 0.5 °C respectively. The standard deviation for cooling setpoints is lower than heating setpoints, because the mean setback temperature for cooling setpoints $\mu_{sb,cool}$ was set to 29.5 °C (obtained from the base schedule), which is close to the upper threshold value for setback temperature of 30°C. More details on the possible implications of a low value of σ_{cool} are discussed later in this section.

While the conservative estimates of σ_{cool} and σ_{heat}, as computed from Equations (5) and (6), ensure that the sampled T values (i.e. $T_{sb,i}$ and $T_{dst,i}$) are likely to fall within the threshold values, it is possible that a given outlier sample of T might take values that are not plausible in practice. To ensure that the sampled T is plausible, we 'hard-set' $T = 3.0$ °C if the sampled $T > 3.0$ °C; and $T = -3.0$ °C if the sampled $T < -3.0$ °C.

- *Step (b):* After changing the setback temperature, we modify the schedule to add a period of pre-heating/pre-cooling. Step (b) in Figure 4 shows how this operation is performed for a cooling setpoint. We make the following assumptions about the pre-heating/pre-cooling operation:
  - We assume that the distribution of pre-heating/pre-cooling period in buildings is truncated exponential.

$$t_{p,i} \sim \exp(\lambda_1) \tag{7}$$

Here, $t_{p,i}$ is the sampled length of pre-heating/pre-cooling duration. Since $t_{p,thres}$ corresponds to the upper limit corresponding to 1% of profiles generated, we can compute the parameter λ_1 as

$$\lambda_1 = -\frac{\ln(0.01)}{t_{p,thresh}} \tag{8}$$

The value of λ_1 was computed to be 1.15 h^{-1}.

- *Step (c):* The next step is to modify the morning ramp-up rate as shown in step (c) in Figure 4. Slow/gradual ramp-up rates (≈0.5° to 0.6°C/h) can occasionally be employed in buildings, but are not likely to be commonplace. We make the following considerations modifying the ramping gradients:
  - We compute the threshold ramp-up rate as follows:

$$t_{ramp,thresh} = \frac{|T_{sb,i} - T_{dst,i}|}{\gamma_{thresh}} \tag{9}$$

The numerator corresponds to the absolute difference between the setback and the daytime setpoint temperatures for either a heating or a cooling setpoint, after they were assigned in step (a). γ_{thresh} is the 'extreme limit' for slow ramp-up rates, as described earlier. $t_{ramp,thresh}$, therefore, will serve as an upper limit for $t_{ramp,i}$. Since $t_{ramp,thresh}$ depends on $T_{sb,i}$ and $T_{dst,i}$, it is computed dynamically for each stochastic schedule. We assume that a given schedule will have $t_{ramp,i} < t_{ramp,thresh}$ with 99% probability.

  - We assume that the distribution of $t_{ramp,i}$ follows an exponential distribution, as slower ramp-ups are less significantly likely than steep ramp-ups:

$$t_{ramp,i} \sim exp(\lambda_2) \tag{10}$$

Here, λ_2 is computed as

$$\lambda_2 = -\frac{\ln(0.01)}{t_{ramp,thresh}} \tag{11}$$

  - Even though we constrain our ramp-up gradients using Equations (9) and (10), in certain instances a given schedule might have an excessively long ramp-up duration $t_{ramp,i}$. In practice, $t_{ramp,i} > 3$ h is unlikely. Therefore, we 'hard-set' $t_{ramp,i} = 3$ h if the sampled $t_{ramp,i}$ in Equation (10) is greater than 3 h.
  - We use the start-time (t_{start}) for the ramp-up that we obtained at the previous step (step (b) in Figure 4), where $t_{start} = (6 - t_p)$ AM. The end-time for the ramp-up is $(6 - t_{p,i} + t_{ramp,i})$.
- *Step (d):* Subsequently, we round off the temperature profile to the nearest 0.5°C, a common temperature increment in commercially available thermostats, as shown in step (c) in Figure 4. Performing this operation gives us the final profile, as shown in step (d).

Note that after step (d), the daytime setpoint and setback temperatures are extremely likely (i.e. with $\approx$ 99% probability) to take only discrete values of $24 \pm 0.5\,^{\circ}$C and $29.5 \pm 0.5\,^{\circ}$C respectively. This occurs because σ_{cool}, as computed using Equation (5), has a low value. We get this low value because the schedule we selected as the base schedule has an aggressive setback, such that the setback temperature is close to the upper threshold value of 30°C. With a different base schedule that has a slightly lower setback temperature, we probably would have seen more diversity in operating and setback temperatures. Thus, for the selected base schedule, the diversity in cooling setpoint schedules with setback is primarily brought about by the variability in pre-cooling period and the period for morning ramp-up.

- *Step (e):* This final setpoint schedule is presented here, which is used as input to the IDF file. The generated schedules are for weekdays only, and the temperature setpoint schedules for weekends and holidays were left unchanged.

Note that the chronology of the method to generate setback schedules (i.e. steps (a) to (e)) ensure that combinations of schedule parameters that are impracticable are less likely to be generated. For instance, in step (c), Equation (9), we calculate the time period for morning ramp-up based on setback and daytime operating temperatures calculated in step (b).

2.2. Simulation details

Using each new schedule generated using the methodology described in Section 2.1, we performed simulations using the building model and weather data described later in this section. We used EnergyPlus version 9.0 (U.S. Department of Energy 2020b), released in 2018, as the building simulation engine. We performed the EnergyPlus simulations at a 10-min timestep and aggregated the outputs at 1 h resolution for each realization of a schedule generated through our proposed methodology.

The key output metrics of interest, with respect to which the impact of a given setpoint modification is analysed, are provided as follows:

- Total electricity consumption per day, $E_{day,tot}$ (kWh): $E_{day,tot}$ is the total *weekday* electricity consumed by the whole building, in kWh, over a 24 h period – considering weekdays only.
- Maximum hourly electricity consumption per day, E_{max} (kWh): E_{max} is the maximum *weekday* hourly electricity consumption, in kWh, over a 24-h period – considering weekdays only.
- Mean hourly percentage of person dissatisfied (PPD) per day, *ppd* (%): This is the mean PPD in the core zone during occupied hours only, computed on a daily basis. In this analysis, we consider 'occupied hours' to be a fixed duration of time from 7 AM to 6 PM on weekdays only – when the occupancy of the building is greater than 20%. Thus *ppd* is computed as

$$ppd = \frac{\sum_{t=t_1}^{t=t_2} PPD(t)}{N_{occ}} \tag{12}$$

In the equation above, t_1 and t_2 correspond to 7:00 AM and 6:00 PM, $PPD(t)$ denotes the computed PPD value at a given hour t after the outputs are aggregated, and N_{occ} is the number of hours (i.e. 11 h) between 7:00 AM and 6:00 PM. Note that the 'occupied' hours (N_{occ}) defined above is not the same as hours of daytime operation defined in Section 2.1.2. The occupied hours are a fixed time during weekdays used to compute *ppd*, whereas hours of daytime operation is the period of time when the setpoint temperature is equal to the daytime setpoint temperature $T_{dst,i}$. The hours of daytime operation can therefore vary from one schedule to the next.

To compute *ppd*, we assume that the heat gain per person is 120 W, as defined in the DOE Prototype model. We also assume that the representative surface area of an average person (corresponding to weight 70 kg and height 1.73 m) is 1.8 m^2, as specified in EnergyPlus (U.S. Department of Energy 2020b). The values of heat gain per person and surface area correspond to a metabolic rate of 1.15 (in Met units), which can be considered typical for office activities (ANSI/ASHRAE 2017). We also assumed a constant airspeed of 0.2 m/s (40 fpm), as suggested in ASHRAE 55-2017 (ANSI/ASHRAE 2017). Note that we used the calculated zone temperatures and not the setpoint temperature as inputs to the thermal comfort model.

We simulate a commercial building representing a small office located in Denver, CO (ASHRAE/IECC Climate Zone 5B). The basis for this model is the DOE Commercial Prototype Building Model for a Small Office, developed by Pacific Northwest National Laboratory (PNNL) (U.S. Department of Energy 2020a). The weather file used to drive the simulations was a TMY3 (TMY stands for Typical Meteorological Year) weather file for Denver, CO (U.S. Department of Energy 2020c). Table 3 presents the key features of the small office building model.

2.2.1. HVAC system details

The overall goal of this study is to generate a distribution of schedules to understand the impact of heating and

Table 3. Key features of small office building (90.1-2004).

Feature	Parameter details
Number of floors	1
Total floor area	511 m^2
Aspect ratio	1.5
Floor-to-ceiling height	3.05 m
Roof construction	Attic roof with wood joist (roof insulation and 1.6 thick gypsum board)
Exterior wall construction	Mass wall construction
Interior partition	Construction: 2 × 4 insulated stud wall Dimensions: Based on floor area and aspect ratio
Internal mass	15.2 cm standard wood (81.0 kg/m^2)
Exterior wall construction	Mass wall construction (Wood-frame walls: 2.5 cm thick stucco, 1.6 cm thick gypsum, wall insulation, 1.6 cm thick gypsum board)
Occupant density	16.6 m^2/person
Lighting power density	10.76 W/m^2
Electric plug loads	6.78 W/m^2
Heating system	Either electric resistance or gas furnace
Cooling system	Vapor compression system
Air distribution system	Single-zone constant air volume

cooling setpoint schedules on electricity use and thermal comfort. For analysing heating temperature setpoint schedules, we are interested in comparing the effect of modifying the setpoint schedule on a small office where space heating is provided by gas furnace (HVAC system A) vs. one provided by electric-resistance heating (HVAC System B). This would allow us to compare an extreme scenario where the heating is provided by gas furnace against one where heating is provided by electricity. Comparing electric resistance vs. gas-heating would also allow us to compare two heating systems, while keeping an identical cooling unit. In this paper, we are looking at total daily electricity consumption and maximum hourly electricity consumption as our energy metrics. We considered a building with gas furnace as our 'reference case' for comparison, to demonstrate the impact of setpoints in buildings with electric heating. For analysing cooling temperature setpoint schedules, a packaged single zone vapor compression air conditioning unit (system C, as provided in the DOE prototype model) is used to provide cooling loads for each zone.

We generated 3000 schedules each for three small office buildings – all identical except for the HVAC system employed. The three HVAC systems in question are: (i) heating system with gas furnace (system A); (ii) heating system with electric-resistance heating (system B) and (iii) cooling system with vapor compression air-conditioning unit (system C). We ran simulations for each of the 3000 × 3 = 9000 schedules. As will be described later in this section, we will perform multiple case studies to analyse the tradeoffs in $E_{day,tot}$, E_{max} and *ppd* due to different setpoint modification strategies. Each case study will use a subset of these simulations.

Table 4. Table describing case studies I, II and III performed in this paper.

Case study I	**Objective**: Comparing the impact of heating temperature setpoint profiles with a nighttime setback to setpoint profiles with no nighttime setback between two small office buildings, identical except for their heating systems: one with *electric resistance* heating and one with *gas heating*
	Baseline case: All schedules without setback (701 schedules)
	Modified case: All schedules with a setback (2299 schedules)
	Analysis period: November to April (heating season)
Case study II	**Objective**: Comparing the impact of heating temperature setpoint modifications on a small office building using *electricresistance heating* by:
	(i) decreasing the daytime setpoint temperature:
	Baseline case: Setback schedules with $T_{dst,heat} >$ 21 °C (724 schedules)
	Modified case: Setback schedules with $T_{dst,heat} \leq$ 21 °C (1575 schedules)
	Analysis period: November to April (heating season)
	(ii) employing pre-heating.
	Baseline case: Setback schedules with $t_{p,heat} = 0$ (440 schedules)
	Modified case: Setback schedules with $t_{p,heat} > 0$ (2560 schedules)
	Analysis period: November to April (heating season)
Case study III	**Objective**: Comparing the impact of cooling temperature setpoint profiles with a nighttime setback to setpoint profiles with no nighttime setback. Cooling is provided by a *vapor compression system*.
	Baseline case: All schedules without setback (701 schedules)
	Modified case: All schedules with a setback (2299 schedules)
	Analysis period: May to September (cooling season)

The HVAC equipment sizing was identical across all our simulations. The heating and air conditioning systems were autosized in EnergyPlus using winter and summer design days. As specified in the DOE Prototype Building model, the heating and cooling temperature setpoint schedules on the two design days were assumed to be constant-temperature schedules. For heating setpoints, the constant temperatures for winter and summer design days were 21.1°C and 15.6 °C respectively. For cooling setpoints, the constant temperatures for winter and summer design days were 29.4°C and 23.9 °C respectively. A summary of the HVAC equipment sizing is provided in Supplementary Information.

2.3. Analysis approach

The goal of the analytical approach is to quantitatively evaluate the impact of a given setpoint modification strategy across a wide range of temperature setpoint schedules. Before detailing the analysis approach, we present specifics of the three case studies we will employ to demonstrate our approach. The details of the three case studies are presented in Table 4.

For a given case study, the steps in the analysis approach are:

- We identify the HVAC system in question and we start with the set of 3000 simulations corresponding to that HVAC system (as mentioned in Section 2.2.1).
- We decide whether the analysis is to be performed for heating or cooling setpoints, and we set the other to the DOE Commercial Prototype schedule. Thus, during heating season, the cooling setpoints are 'kept constant' and vice versa.
- For a given month in the heating/cooling season (depending on whether the analysis is being performed for heating or cooling setpoints):
  - We identify the set of simulations corresponding to the baseline and modified cases (as detailed in Table 4).
  - For each of the baseline and the modified cases, we compute the output metrics $E_{day,tot}$, E_{max}, and *ppd*, as described in Section 2.2. Each data point $\mathbf{y_d} = \{y_{1,d}, y_{2,d}, y_{3,d}\}$ is specific to a given realization of a schedule and a given weekday of the month *d*. Thus, for the baseline case, the total number of data points will be equal to the number of schedules for the baseline case (presented in Table 4 for each of the three case studies) multiplied by the total number of weekdays in the given month. The total number of data points for the modified case can be computed similarly.
  - Thus, for a given output metric ($E_{day,tot}$, E_{max} or *ppd*), we have two distributions to compare – one for the baseline and one for the modified case. Each distribution is constructed using the data points for the baseline and modified case respectively. We can compare the two distributions using the metrics: ($E_{day,tot}$, E_{max}, *ppd*). $E_{day,tot}$ and E_{max} are computed as follows:

$$y_i = \frac{\tilde{y_{i,mod}} - \tilde{y_{i,baseline}}}{\tilde{y_{i,baseline}}} \tag{13}$$

    Here $\tilde{y_{i,mod}}$ and $\tilde{y_{i,baseline}}$ correspond to the medians of 'modified' and 'baseline' distributions respectively, and $y_i \in \{E_{day,tot}, E_{max}\}$. We consider the median instead of the mean, as the median is less likely to be skewed by an outlier data point (i.e. a data point corresponding to an outlier schedule or extreme weather on a given day).
  - For the metric *ppd* (mean hourly PPD (%) in core zone per day), we compute *ppd* as follows:

$$ppd = \tilde{ppd_{mod}} - \tilde{ppd_{baseline}} \tag{14}$$

Evaluating $E_{day,tot}$, E_{max} and *ppd* in conjunction allows us to analyse the potential tradeoffs due to a specific setpoint modification. Section 3 presents the results obtained from implementing this approach on three case studies.

3. Results and discussion

In this section, we demonstrate how the methodology and analytical approach described in Section 2 can be applied to the three case studies described in Section 2.3. In each case study, the schedules with which the analysis was performed were generated using the methodology in Sections 2.1.1 and 2.1.2. The distribution of parameters used to generate these schedules are provided in Supplementary Information. The analyses to achieve objectives in each case study were based on comparing the 'baseline' and 'modified' cases, which are defined in Table 4. The key finding from the results was that the nature of the tradeoffs between $E_{day,tot}$, E_{max} and *ppd* is not only dependent on the specific setpoint schedule modification being implemented, but can also vary depending on the month of the year.

3.1. Case study I: impact of implementing heating setpoint with setback

In case study I, we investigate the tradeoffs in $E_{day,tot}$, E_{max} and *ppd* associated with implementing a setback in heating setpoints in a small office with electric resistance heating (system A) compared to temperature setpoint profiles that don't employ a nighttime setback ('no setback' profiles). Table 5 quantifies the impact of setback using the evaluation metrics ($E_{day,tot}$, E_{max} and *ppd*) during the heating season (i.e. November–April), across a diverse set of heating setpoint schedules. The table shows that $E_{day,tot}$ (percent change in total energy consumption) ranges from −11.5% to −7.1%, E_{max} (percent change in maximum hourly consumption) ranges between +4.5% and +46.7% and *ppd* (absolute change in *ppd*) ranges from −0.04% to +2.52%. Note that negative values of $E_{day,tot}$, E_{max} and *ppd* indicate savings in energy consumption, savings in maximum hourly consumption, and an improvement in thermal comfort respectively.

The results, therefore, indicate that the key tradeoff is between total daily electricity consumption, $E_{day,tot}$, and daily maximum hourly consumption, E_{max}, as they move in opposite directions to one another. As we would expect, employing a setback reduces the electricity consumption during nighttime operation (thereby reducing $E_{day,tot}$). However, the lower nighttime zone temperatures associated with a setback may lead to an increased early-morning heating load, although the tradeoff between

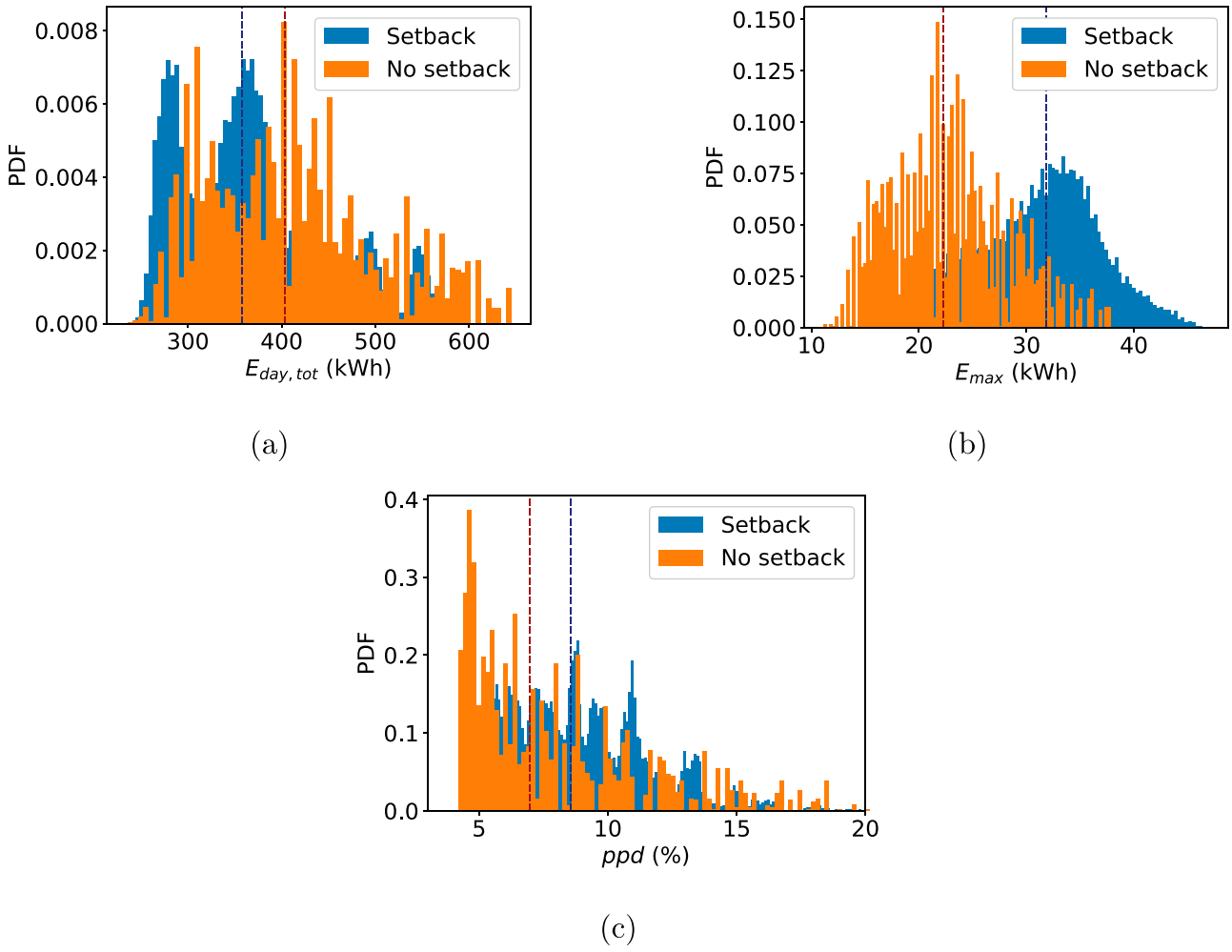

Figure 7. Probability density functions (PDFs) of (a) total electricity consumption per day, $E_{day,tot}$ (kWh); (b) daily maximum hourly consumption, E_{max} (kWh); and (c) daily mean PPD in core zone (%), *ppd* with setback vs. *ppd* without setback during the month of February for a small office using electric resistance heating. The vertical lines indicate the medians of the respective distributions.

Table 5. Table showing the results on the impact of setback in heating setpoint profiles on total electricity consumption (kWh), $E_{day,tot}$, maximum hourly electricity consumption per day (kWh), E_{max} and mean PPD in the core zone (%), *ppd*. – when space heating is provided by electric resistance heating. A negative value indicates savings in $E_{day,tot}$ or E_{max}, or a reduction in *ppd*. The corresponding results for a gas-heated small office is provided in Supplementary Information.

Month	$E_{day,tot}$	E_{max}	*ppd*
Nov	−11.4	+30.7	+0.57
Dec	−9.2	+41.6	+1.99
Jan	−10.9	+46.7	+1.98
Feb	−11.3	+42.3	+2.52
Mar	−10.8	+44.0	+0.77
Apr	−7.1	+4.5	−0.04

$E_{day,tot}$ and E_{max} can be reduced with gradual morning ramp-up. Table 5 also shows that this tradeoff in employing a setback is more severe during the months November to March. In April, a more temperate month, implementing a setback is likely to result in moderate gains ($E_{day,tot} = -7.1\%$) in total electricity, with relatively minimal cost in E_{max} ($E_{max} = +4.5\%$).

Figures 7(a–c) show the plots of probability density functions of $E_{day,tot}$, E_{max} and *ppd*, comparing setback vs. no setback cases for the month of February when space heating is provided by electric resistance heating. The figure affirms our observations from Table 5: $E_{day,tot}$ reduces from a median value of 403.7 to 358.0 kWh when switching from a setback to no setback while E_{max} increases from 22.3 to 31.8 kWh. Figure 7 also shows that there is an increase in the median value of *ppd* from 7.6% to 10.1%. Table 5 indicates that there is a small increase ($\approx$2.5% or lower) in *ppd* when going from no setback to setback, and the increase is highest in the month of February, which has the highest number of heating degree-days. While the marginal increase in *ppd* due to implementing a setback profile is relatively small ($\approx$2.5% or lower), it should be noted that implementing a setback profile is more likely to result in the PPD in the core

zone exceeding the acceptable threshold of 10% (as specified in ASHRAE 55-2017) during the cold winter months. Thus the tradeoff between total electricity consumption vs. thermal comfort when implementing a nighttime setback may only be pertinent during cold winter months (specific to climate zone 5B).

Figures 8(a–c) show the corresponding plots of probability density functions of $E_{day,tot}$, E_{max} and *ppd* for a building heated by a gas furnace (HVAC system B) for the month of February. A complete table quantifying $E_{day,tot}$, E_{max} and *ppd* is provided in Supplementary Information. The figure shows that, for a gas-heated building in February, there is a very minor improvement in $E_{day,tot}$ ($E_{day,tot} \approx -1.4\%$) with no tradeoff in E_{max}. Figure 8(a) shows that the range of $E_{day,tot}$ is significantly smaller compared to what we observed for the electric resistance-heated small office (Figure 7 a). In Figure 8(b), we observe that the distribution of maximum hourly peak consumption is concentrated within a very narrow interval, as E_{max} is not affected by heating setpoints in February for a small office heated by gas furnace. As we expect, even in a cold winter month, the heating setpoint has minimal impact on electricity consumption in a gas-heated small office. The gain of 1.4% in total electricity consumption with using a setback is due to the reduction in afternoon cooling (which, in climate zone 5B, is likely to occur sporadically during February) when building zones are not heated during nighttime. Figure 8 shows that E_{max} remains unchanged when a setback is implemented – the maximum hourly electricity consumption, which usually occurs in the morning on weekdays in February, is unaffected by heating setpoints in a gas-heated small office.

3.2. Case study II: impact of reducing daytime setpoint temperature and implementing pre-heating in heating setpoints in small office with electric resistance heating

In case study II, we investigate the tradeoffs in $E_{day,tot}$, E_{max} and *ppd* due to: (i) changing the daytime setpoint temperature and (ii) implementing pre-heating. We consider a small office with electric resistance heating.

3.2.1. Impact of reducing daytime setpoint temperatures in heating setpoint profiles with a setback

Table 6 presents the impact of reducing daytime setpoint temperature $T_{dst,heat}$ on $E_{day,tot}$, E_{max}, and *ppd* in a small office with electric resistance heating (HVAC system A). As we expect, median values of both $E_{day,tot}$ and E_{max} decrease for $T_{dst,heat} \leq 21\,^{\circ}$C vs $T_{dst,heat} > 21\,^{\circ}$C, $E_{day,tot}$ ranging from −3.4% to −5.9%, whereas E_{max} is between −4.5% to −12.0%. The thermal comfort penalty (i.e. increasing *ppd*) due to reduced daytime setpoint temperatures is most noticeable in the month of February. Figure 9 shows a comparison of PDFs of *ppd* with $T_{dst,heat} \leq 21\,^{\circ}$C vs. $T_{dst,heat} > 21\,^{\circ}$C. Note that the total electricity consumption ($E_{day,tot}$) and the maximum hourly electricity consumption (E_{max}) are higher in February compared to other months in the heating season. In February, the median *ppd* increases from 8.2% to 11.4% when daytime setpoint temperatures are reduced to $\leq 21\,^{\circ}$C, whereas in March the respective values are 5.5% and 6.6%. This indicates that an aggressive reduction in daytime setpoint temperature is more likely to be feasible in November, March and April, when the tradeoff between total electricity consumption/maximum hour electricity consumption per day vs. thermal comfort is likely to be minimal (specific to climate zone 5B).

Table 6. Results on the impact of daytime setpoint temperature, $T_{dst,heat}$ ($T_{dst,heat} > 21^{\circ}$C vs. $T_{dst,heat} \leq 21\,^{\circ}$C) on total electricity consumption (kWh), $E_{day,tot}$, maximum hourly electricity consumption per day (kWh), E_{max} and mean PPD in the core zone (%), *ppd*.

Month	$E_{day,tot}$ (%)	E_{max} (%)	*ppd* (%)
Nov	−5.9	−12.0	+0.66
Dec	−5.4	−9.3	+2.07
Jan	−5.0	−8.6	+2.36
Feb	−5.3	−8.5	+3.24
Mar	−5.1	−10.0	+1.10
Apr	−3.4	−4.5	+0.04

Table 7. Results on the impact of implementing pre-heating on $E_{day,tot}$, E_{max}, and *ppd*, (i.e. $t_p > 0$ vs. $t_p = 0$). The baseline corresponds to distributions with a setback and pre-heating implemented, i.e. $t_p > 0$ h, whereas the modified case corresponds to distributions with a setback and no pre-heating, i.e. $t_p = 0$.

Month	$E_{day,tot}$ (%)	E_{max} (%)	*ppd* (%)
Nov	+6.7	−15.4	−0.38
Dec	+5.0	−17.7	−1.22
Jan	+6.5	−14.0	−1.19
Feb	+5.1	−12.0	−1.28
Mar	+5.8	−18.2	−0.99
Apr	+3.7	−2.0	≈ 0

3.2.2. Impact of implementing pre-heating in heating setpoint schedules with a setback

In this section, we investigate the effect of implementing pre-heating ($t_p > 0$ vs. $t_p = 0$) on $E_{day,tot}$, E_{max} and *ppd* in a small office with electric resistance heating (HVAC system A). Table 7 presents the corresponding results.

The table shows that the key tradeoff is again between $E_{day,tot}$ and E_{max}. $E_{day,tot}$ is typically between +3.7% to +6.7% between November and April. However, we observe that E_{max} ranges between −12.0% and −18.2% between November and March, but from March to April,

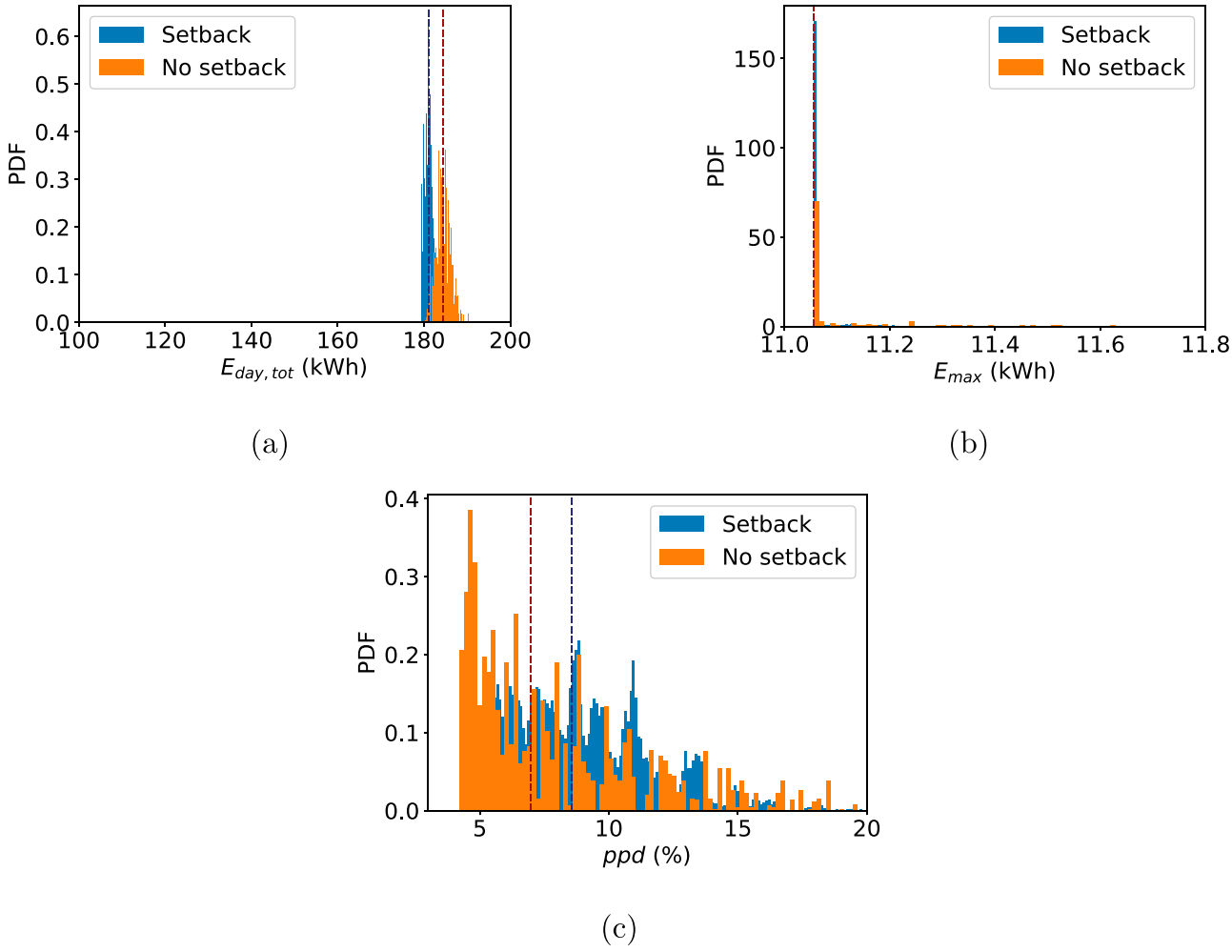

Figure 8. PDFs of (a) total electricity consumption per day, $E_{day,tot}$ (kWh) with setback vs. $E_{day,tot}$ without setback; (b) daily maximum hourly consumption, E_{max} (kWh) with setback vs. E_{max} without setback; and (c) daily mean PPD in core zone (%), *ppd* with setback vs. *ppd* without setback during the month of February for a small office using gas furnace heating.

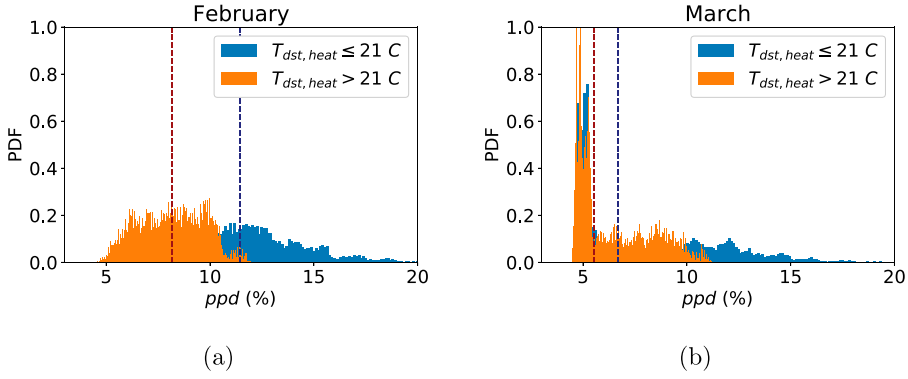

Figure 9. Comparison of probability density functions (PDFs) of *ppd* obtained with $T_{dst,heat} \leq 21\,^{\circ}$C vs. that obtained with $T_{dst,heat} > 21\,^{\circ}$C during the period of (a) February and (b) March.

E_{max} changes drastically from −18.2% to −2.0%. The magnitude of the change in PPD is less than 2% across all months, indicating that implementing pre-heating is unlikely to result in a significant tradeoff in thermal comfort. Figures 10(a,b) show the probability density functions of E_{max} during the months of March and April respectively. In March, the median of E_{max} decreases from 26.8 to 21.6 kWh, whereas in April, the median in E_{max} changes from 14.3 to 14.0 kWh. This indicates that it may not be beneficial to employ a heating setback beyond

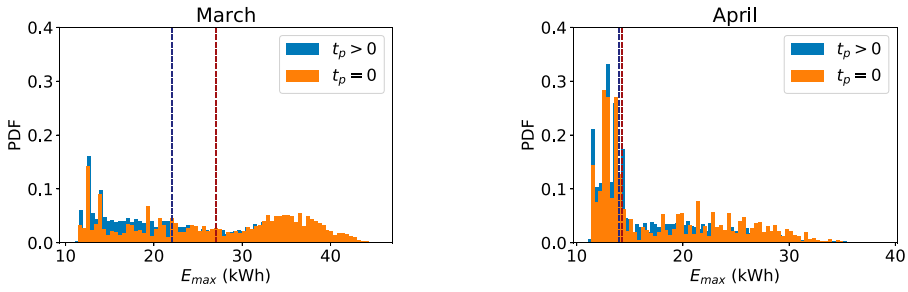

Figure 10. PDFs of E_{max} with $t_p > 0.25$ h vs $t_p \leq 0.25$ h during the month of (a) March and (b) April.

Table 8. Results on the impact of setback in cooling setpoint profiles on $E_{day,tot}$, E_{max}, and *ppd*. The baseline case corresponds to distributions with no setback, whereas the modified case corresponds to distributions without a setback.

Month	$E_{day,tot}$ (%)	E_{max} (%)	*ppd* (%)
May	≈ 0	≈ 0	-0.27
June	-1.0	$+1.8$	$+0.56$
July	-2.2	$+3.0$	$+0.95$
Aug	-2.3	$+3.3$	$+0.80$
Sep	-0.6	$+2.1$	$+0.46$

March. This finding also highlights that the benefits of implementing a setpoint modification can vary significantly from one month to the next, which suggests that it is important to analyse the tradeoffs in $E_{day,tot}$, E_{max} and *ppd* at a sub-annual timescale.

3.3. Case study III: impact of implementing a cooling setpoint with setback

In case study III, we investigate the impact of implementing a setback in cooling setpoints. Table 8 presents the results analysing the impact of setback in a cooling setpoint on $E_{day,tot}$, E_{max} and *ppd*, during the cooling season (May to September), when space cooling is provided by a vapor compression system (HVAC system C). The results show that $E_{day,tot}$ ranges between -2.3% and $+0.3\%$ during the cooling season, and E_{max} between 0 % and $+3.2\%$. . The increase in *ppd* with implementation of nighttime setback is less than 1% for all months in the cooling season, indicating that there is almost no tradeoff in thermal comfort in implementing a setback for cooling setpoints.

Table 8 shows that for climate zone 5B, there may be a limited benefit to employing a setback in May, June and September (the edges of the cooling season). Figures 11(a–c) show the PDFs of $E_{day,tot}$, E_{max} and *ppd* comparing the setback vs. no setback cases for the month of August. Figure 11 shows that, during the month of August, the median value of $E_{day,tot}$ decreases from 278.0 kWh with no setback to 271.6 kWh with setback, with a $\approx 3\%$ increase in the median of E_{max} from 16.6 to 17.1 kWh. From Table 8, we observe that the tradeoffs between $E_{day,tot}$ and E_{max} are most pronounced during the months of July and August when the cooling season traditionally peaks. The results suggest that it may not be as beneficial to employ a cooling setpoint setback during May, June and September as the decrease in $E_{day,tot}$ is 1% and utilizing a setback can increase maximum hourly electricity consumption. Thus, specific to climate zone 5B, it may only be beneficial to implement a cooling setback in the months of July and August.

3.4. Implications of presented work

We demonstrated that the proposed methodology can be used to support parametric analysis to evaluate the impact of a given temperature setpoint schedule modification on total electricity consumption, maximum hourly electricity consumption and thermal comfort. The proposed methodology can also enable improved large-scale building energy modelling. A large and diverse set of building stock models will be more likely to capture the wide range of variation in operations among actual buildings when compared with stock modelling that represents all buildings with the same, or very similar, temperature setpoint schedule profiles. To represent large numbers of buildings for bottom-up energy modelling at urban, regional or national scales, researchers typically begin with a set of prototype or archetype models to populate the building stock that will be simulated. Although actual observed control setpoint temperature values from the current building stock are not available, future users may adjust a few parameters in the existing framework to represent the type of schedule most appropriate for the building or suite of buildings being modelled.

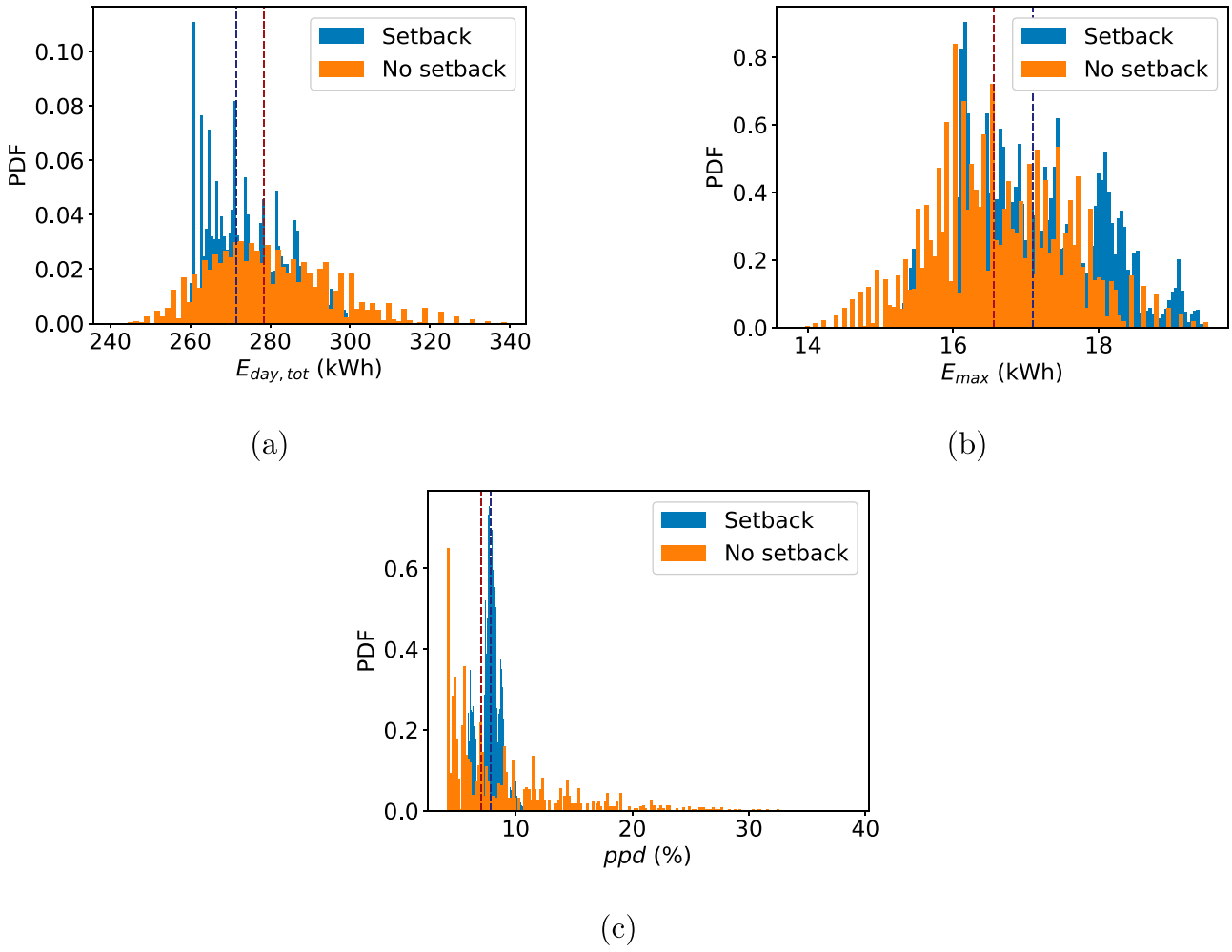

Figure 11. Probability density functions of (a) total electricity consumption per day, $E_{day,tot}$ (kWh) with setback vs. $E_{day,tot}$ without setback; (b) daily maximum hourly consumption, E_{max} (kWh) with setback vs. E_{max} without setback and (c) daily mean PPD in core zone (%), *ppd* with setback vs. *ppd* without setback during the month of August for a small office using a vapor compression system.

4. Conclusion

In this study, we developed a methodology to generate a distribution of heating and cooling setpoint schedules in commercial buildings and an analytical approach to evaluate the impact of building temperature setpoints (cooling and heating setpoints). The key takeaways from this study are:

- We demonstrated that a methodology can be utilized to generate a distribution of plausible heating and cooling setpoint schedules starting from a base schedule, and a small set of user-modifiable schedule parameters. These parameters were selected based on data from the published literature and discussions with building science professionals. This distribution of schedules, which aims to capture the diversity of building setpoint schedules that are plausible, can potentially be used for large-scale building energy modelling of a specific building stock, or to study a range of possible temperature setpoint choices on a single modelled building.
- We demonstrated an analytical approach to quantify the impact of changing the heating and cooling setpoint schedules on the total daily electricity consumption, maximum hourly electricity consumption and mean PPD in the core zone. We performed multiple case studies to investigate how a specific modification to temperature setpoint can affect these three output variables. Specific to a small office building in climate zone 5B, we made the following observations:
    - A nighttime setback can result in a reduction in electricity consumption (a relative decrease in median value of $\approx$7 to 11.5%) during heating season (November to April). From November to March, this comes at a significant expense in maximum hourly electricity consumption (a relative increase in median value of $>$30%).

Compared to other months in the heating season, it is more likely that, in February, implementing a nighttime setback might result in a severe tradeoff in thermal comfort.

- During the heating season, reducing the daytime setpoint temperature for heating setpoint is more likely to be only feasible in the months of November, March and April.
- During the months from November to March, employing a period of pre-heating is likely to result in a tradeoff between total electricity consumption (a relative increase in median value between $\approx$5.0 % and 6.5%) and maximum hourly electricity consumption (a reduction in median of 14–18%). Such a tradeoff is less likely in April (a relative increase in median total electricity consumption of 3.5% vs. a reduction in median maximum hourly electricity consumption of 2.0%), when implementing pre-heating is not likely to be beneficial.
- For cooling season, it may only be beneficial to implement a setback in cooling setpoint schedules in July and August.

Future work based on methods and results presented in this study could focus on expanding the analysis to a larger set of commercial building types and climate zones. Subsequent research can also focus on developing methods to calibrate parameters defined in the proposed methodology based on actual building electricity consumption data and to optimize temperature setpoint schedules. A sensitivity study to investigate the impact of each parameter on output metric can also be focus of future work. The code to perform future research is modifiable and available open source at https://github.com/IMMM-SFA/tempset.

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References

Administration, U. E. I. 2021. *Annual Energy Outlook 2021*. (Tech. Rep.). U.S. Department of Energy.

Aghniaey, S., and T. Lawrence. 2017. "Cooling Season Demand Response and the Real World." *ASHRAE Journal* 59 (4): 68–70.

Aghniaey, S., and T. M. Lawrence. 2018. "The Impact of Increased Cooling Setpoint Temperature During Demand Response Events on Occupant Thermal Comfort in Commercial Buildings: A Review." *Energy and Buildings* 173: 19–27.

ANSI/ASHRAE. 2017. *Standard 55-2017 – Thermal Environmental Conditions for Human Occupancy* (Tech. Rep. No.55-2017). ASHRAE. Retrieved from https://www.techstreet.com/ashrae/standards/ashrae-55-2017?product_id = 1994974.

Baechler, M. C., T. T. Gilbride, P. C. Cole, M. G. Hefty, and K. Ruiz. 2015. *Building America Best Practice Series: Volume 7.3 – Guide to Determining Climate Regions by County* (Tech. Rep.). Pacific Northwest National Laboratory.

Bianchi, C., L. Zhang, D. Goldwasser, A. Parker, and H. Horsey. 2020. "Modeling Occupancy-driven Building Loads for Large and Diversified Building Stocks Through the Use of Parametric Schedules." *Applied Energy* 276: 115470.

Bienvenido-Huertas, D., D. Sánchez-García, and C. Rubio-Bellido. 2020, October. "Adaptive Setpoint Temperatures to Reduce the Risk of Energy Poverty? A Local Case Study in Seville." *Energy and Buildings* 231: 110571. doi:10.1016/j.enbuild.2020.110571.

Cai, M., S. Ramdaspalli, M. Pipattanasomporn, S. Rahman, A. Malekpour, and S. R. Kothandaraman. 2018. Impact of HVAC Set Point Adjustment on Energy Savings and Peak Load Reductions in Buildings. In *2018 IEEE International Smart Cities Conference (ISC2)* (pp. 1–6).

Derrible, S., and M. Reeder. 2015. "The Cost of Over-cooling Commercial Buildings in the United States." *Energy and Buildings* 108: 304–306.

Deru, M., K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, and B. Liu, et al. 2011. U.S Department of Energy Commercial Reference Building Models of the National Building Stock.

Faruqui, A., R. Hledik, and J. Palmer. 2012. Time-varying and Dynamic Rate Design. : Regulatory Assistance Project.

Feng, X., D. Yan, and T. Hong. 2015, January. "Simulation of Occupancy in Buildings." *Energy and Buildings* 87: 348–359. doi:10.1016/j.enbuild.2014.11.067.

Geng, Y., W. Ji, B. Lin, and Y. Zhu. 2017. "The Impact of Thermal Environment on Occupant IEQ Perception and Productivity." *Building and Environment* 121: 158–167.

Ghahramani, A., K. Dutta, and B. Becerik-Gerber. 2018. "Energy Trade Off Analysis of Optimized Daily Temperature Setpoints." *Journal of Building Engineering* 19: 584–591.

Ghahramani, A., K. Zhang, K. Dutta, Z. Yang, and B. Becerik-Gerber. 2016. "Energy Savings from Temperature Setpoints and Deadband: Quantifying the Influence of Building and System Properties on Savings." *Applied Energy* 165: 930–942.

Gianniou, P., C. Reinhart, D. Hsu, A. Heller, and C. Rode. 2018, July. "Estimation of Temperature Setpoints and Heat Transfer Coefficients Among Residential Buildings in Denmark Based on Smart Meter Data." *Building and Environment* 139: 125–133. doi:10.1016/j.buildenv.2018.05.016

Gunay, H. B. 2016. *Improving Energy Efficiency in Office Buildings through Adaptive Control of the Indoor Climate* (Unpublished Doctoral Dissertation). Carleton University.

Hoyt, T., E. Arens, and H. Zhang. 2015. "Extending Air Temperature Setpoints: Simulated Energy Savings and Design Considerations for New and Retrofit Buildings." *Building and Environment* 88: 89–96.

Hu, M., and F. Xiao. 2019, December. "Quantifying Uncertainty in the Aggregate Energy Flexibility of High-rise Residential Building Clusters Considering Stochastic Occupancy and Occupant Behavior." *Energy* 194: 116838. http://www.sciencedirect.com/science/article/pii/S0360544219325332.

Huang, S., Y. Ye, D. Wu, and W. Zuo. 2021. "An Assessment of Power Flexibility From Commercial Building Cooling Systems in the United States." *Energy* 221: 119571.

Huizenga, C., S. Abbaszadeh, L. Zagreus, and E. A. Arens. 2006. "Air Quality and Thermal Comfort in Office Buildings: Results of a Large Indoor Environmental Quality Survey." *Proceeding of Healthy Buildings 2006* 3: 393–397.

Mendell, M., and A. Mirer. 2008. *Indoor Thermal Factors and Symptoms in Office Workers: Findings from the US EPA Base Study* (Tech. Rep.). Lawrence Berkeley National Lab. (LBNL), Berkeley, CA.

Oldewurtel, F., D. Sturzenegger, and M. Morari. 2013. "Importance of Occupancy Information for Building Climate Control." *Applied Energy* 101: 521–532.

Papadopoulos, S., C. E. Kontokosta, A. Vlachokostas, and E. Azar. 2019. "Rethinking HVAC Temperature Setpoints in Commercial Buildings: The Potential for Zero-cost Energy Savings and Comfort Improvement in Different Climates." *Building and Environment* 155: 350–359.

Putra, H. C., C. J. Andrews, and J. A. Senick. 2017. An Agent-based Model of Building Occupant Behavior during Load Shedding. In *Building Simulation* (Vol. 10, pp. 845–859).

Silva, D., B. Duplessis, and J. Adnot. 2011. A Methodology for Evaluating the Energy, Peak Load and Comfort Effects of Demand Response Control Strategies for Electric Heating. présenté à ECEEE.

Ueno, T., and A. Meier. 2020. "A Method to Generate Heating and Cooling Schedules Based on Data from Connected Thermostats." *Energy and Buildings* 228: 110423.

U.S. Department of Energy. 2015, September. Quadrennial Technology Review: An Assessment of Energy Technologies and Research Opportunities (Tech. Rep.). U.S. Department of Energy.

U.S. Department of Energy. 2020a. *Building Energy Codes Program*. Retrieved 2021-01-11 from https://www.energycodes.gov/development/commercial/prototype_models#90.1.

U.S. Department of Energy. 2020b. *Energyplus*. Retrieved 2021-05-04 from https://www.energyplus.net/.

U.S. Department of Energy. 2020c. *Weather data*. Retrieved 2021-01-11 from https://energyplus.net/weather.

U.S. Energy Information Administration. 2020. *Commercial Buildings Energy Consumption Survey (CBECS)*. Retrieved 2021-02-18 from https://www.eia.gov/consumption/commercial/data/2012/.

Yang, Z., and B. Becerik-Gerber. 2014. "The Coupled Effects of Personalized Occupancy Profile Based HVAC Schedules and Room Reassignment on Building Energy Use." *Energy and Buildings* 78: 113–122.

Ye, Y., W. Zuo, and G. Wang. 2019, March. "A Comprehensive Review of Energy-related Data for U.S. Commercial Buildings." *Energy and Buildings* 186: 126–137. 10.1016/j.enbuild.2019.01.020.