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# A Simulation Framework for Analyzing the Impact of Stochastic Occupant Behaviors on Demand Flexibility in Typical Commercial Buildings

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## ABSTRACT

*As one of the primary users of the electric grid, buildings and building equipment, including heating, ventilation, and air conditioning (HVAC) systems, can be leveraged to provide the flexible demand needed to balance the grid. Typical strategies to achieve demand flexibility are to reduce electricity use during peak or critical periods by shutting down equipment or relaxing system setpoints, which will inevitably impact the occupants' comfort. When occupants feel uncomfortable, they may take actions to regain their comfort, and some of those actions (such as turning on a personal fan) may have a negative impact on meeting the demand response goal. Therefore, it is important to incorporate occupant behaviors into the assessment of the building demand flexibility potential. In this study, a simulation framework that includes simulation of zone thermal loads, an HVAC system, and occupant behaviors, was developed to investigate the impact of occupant behaviors on demand flexibility.*

*A case study was conducted using a small office model from the U.S. Department of Energy (DOE) Commercial Prototype Building Models to simulate the building envelope and zone loads. An agent-based occupant thermal behavior model was adapted to forecast occupants' thermal comfort and their resulting thermal behaviors. An artificial neural network (ANN) based airflow model trained from a computational fluid dynamics (CFD) model of the zone was adopted to better predict the ambient environment of each occupant. An air-source heat pump simulation model that was calibrated from a real two-stage air-source heat pump system was used as the HVAC system. A typical load shedding event during peak hours was studied. Repeated simulations*

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*were conducted to capture the stochastic effects of occupant behaviors. The interplay between the demand flexibility, occupant comfort and behavior were analyzed by evaluating key performance indicators, including the energy use, occupant discomfort duration, and occupant behavior duration during the peak period. The results suggest that this framework can be used to analyze typical commercial buildings and their HVAC systems in terms of demand flexibility potential under the impact of occupant behaviors.*

## **INTRODUCTION**

With the increase of renewable energy and the development of the smart grid, it is important to improve the flexibility of both the supply-side and demand-side of the electric grid to meet the needs of power generation, transmission, distribution, and dispatch. As one of the primary users of the electric grid, buildings and building equipment, including heating, ventilation, and air conditioning (HVAC) systems, can be leveraged to provide flexible demand (Rohmund et al. 2008). Typical strategies to increase demand flexibility are to reduce electricity use during peak or critical periods by shutting down equipment or relaxing system setpoints. However, these strategies can have a significant impact on occupant comfort, leading to decreased productivity, elevated complaints, and potential harm to health. Additionally, when occupants feel uncomfortable, they may resort to personal comfort solutions such as portable heating or cooling units, negatively impacting the overall goal of demand response. As such, it is crucial to consider the impact on occupant comfort and behavior when evaluating a building's potential for demand flexibility.

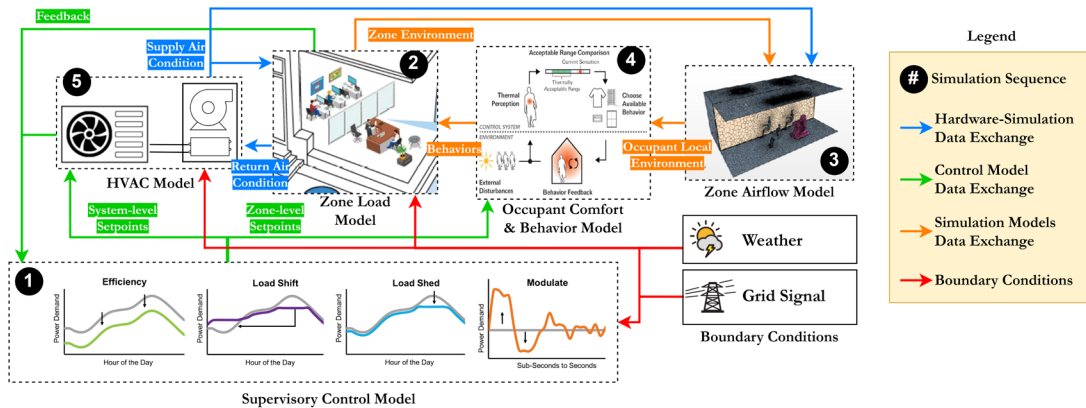
Recent studies have explored the impact of occupant behavior on energy consumption in buildings, but the focus has mainly been on energy efficiency and conservation (Chen et al. 2021; Jia et al. 2017). Meanwhile, a few studies have specifically analyzed the influence of occupant behaviors on demand flexibility in buildings. For example, Olawale et al. (2022) explored the relationship between residential occupant behavior and demand flexibility. They used machine learning models to predict occupant behavior in activities relevant to demand flexibility using the American Time Use Survey data. This study provides valuable insights into understanding when and who might adopt demand flexibility technologies based on their daily routine activities. Vellei et al. (2021) developed a novel framework to model the interactions between occupants and thermostats during demand response (DR) events. The framework was calibrated using data from approximately 9,000 connected Canadian thermostats and was used to predict occupant override rates as a function of indoor temperature and the time since the start of the DR event. Similarly, Sarran et al. (2021) conducted a data-driven study on the thermostat overrides during DR events using data from 6,389 connected North America thermostats in the summer of 2019. Both studies provide insight to the design and control of setpoint modulations in residential buildings. Chen et al. (2019) proposed a systematic approach to quantify electricity flexibility of an office building by considering contributions from building thermal mass, lights, HVAC systems, and occupant behaviors. In this study, the impact of occupant behaviors on the HVAC system was quantified by assuming occupants can accept a wide range of temperatures rather than a fixed temperature setpoint. Li et al. (2017) developed a co-simulation framework that couples an EnergyPlus model with Java-based occupancy and occupant behavior models through Functional Mock-up Units (FMU). This framework was then used to compare two scenarios for lighting, personal computer, and air-conditioner control, namely occupant control and sensor-based control for demand flexibility.

Despite recent progress in understanding the impact of occupant behavior on building energy flexibility, there remains a critical gap in our knowledge regarding the role of occupant behaviors on demand flexibility in commercial buildings. This study seeks to fill that gap by developing a novel simulation framework that includes the simulation of zone thermal loads, HVAC systems, and occupant thermal behaviors. By explicitly using a stochastic model to represent the inherent uncertainty in occupant behavior, this framework will provide a more comprehensive understanding of how occupants feel and behave during DR events in commercial buildings.

This paper is organized as follows: Section 2 presents the development of the simulation framework and its components, providing a comprehensive overview of the methodology employed. Section 3 is the heart of the paper, presenting a detailed case study using the simulation framework. The simulation settings, results, and discussions are described in this section, providing insight into the effectiveness of the framework. Finally, in Section 4, the paper concludes with a summary of the findings and their implications.

## DEVELOPMENT OF THE SIMULATION FRAMEWORK

In this section, the simulation framework for analyzing the impact of occupant behaviors on demand flexibility as well as its major components is introduced. The framework is designed to integrate multiple component models to simulate real-world building operations, including the HVAC systems, zone loads, occupant comfort and behaviors, indoor airflow, and supervisory control strategies. Figure 1 provides an overview of the framework, highlighting its major components, data flow schema, and the simulation sequences. The integration of the simulation framework is achieved through co-simulation among various software environments including MATLAB & Simulink (The MathWorks 2020), and EnergyPlus (via FMU) (Crawley et al. 2001; Lawrence Berkeley National Laboratory 2020). Data storage and exchange is facilitated by MongoDB (MongoDB 2018). Details about the key components are introduced in the following subsections.



**Figure 1** An overview of the occupant behavior and demand flexibility simulation framework.

**Zone Load Model.** The zone load model simulates the thermal load and zone environment in each zone of the building, considering various factors such as solar radiation, building envelope heat conduction, air infiltration, occupancy, lighting, and equipment usage. The EnergyPlus model is exported as an FMU using the EnergyPlusToFMU package (Lawrence Berkeley National Laboratory 2020) for co-simulation with other models in the framework.

**HVAC Model.** The HVAC model is responsible for simulating the performance of an air-based HVAC system in the building and providing the supply air condition required to meet the zone demand. With the return air condition and weather condition as inputs, the HVAC model returns the supply air condition needed to meet the zone demand. Note that EnergyPlus is capable of modeling both the zone and the HVAC system at the same time, however, the proposed simulation framework separates these two tasks to demonstrate a general approach. This separation allows the HVAC system to be modeled by other software or dynamic system simulation platforms, such as Modelica, HVACSIM+, and TRNSYS (Chen et al. 2022a). Additionally, the framework provides the potential interfaces to integrate real HVAC systems through hardware-in-the-loop simulation (Chen et al. 2023). This study uses an air-source heat pump model written in a MATLAB script.

**Occupant Comfort & Behavior Model (OBM).** The behavior of occupants in a building plays a crucial role in the building's thermal load and energy use. An agent-based OBM (Langevin et al. 2015a) is adapted in this study. This model forecasts the thermal behaviors of occupants and sends them to the zone load model. This model was validated via a year-long longitudinal survey (Langevin et al. 2015b) in an office building and it is capable of simulating various occupant behaviors with given probabilities (i.e., action frequency) and behavioral constraints (i.e., allowed actions), including turning on/off personal heaters/fans, adjusting thermostats, opening/closing windows/doors/blinds, taking clothes on/off, consuming hot/cold drinks, and changing activity levels from sitting to walking. The OBM is integrated into the Simulink environment as a Level-2 MATLAB S-Functions block.

**Zone Airflow Model.** To accurately estimate the thermal comfort conditions surrounding occupants, a zone airflow model has been incorporated into the framework. The local environment is simulated using a computationally efficient artificial neural network (ANN) model trained using computational fluid dynamics (CFD) simulation data (Zhang et al. 2022). Compared to CFD, the ANN model saves significant simulation time when running repeated simulations. The ANN model takes various inputs including the supply air conditions from the HVAC model, the zone surface temperatures from the zone load model, and the occupant's location within the zone, to estimate the local thermal conditions (e.g., air temperature, radiant temperature, air velocity) near the occupant. These conditions are then used in the assessment of occupant comfort in the OBM. The zone airflow model is integrated into the OBM as a MATLAB function prior to the assessment of occupant comfort.

**Supervisory Control Model.** The supervisory control model is designed to generate zone-level or system-level setpoints to optimize building operations. In this study, our control model is capable of generating supervisory control signals in response to different demand response signals, such as electricity price, demand limit, and emergency events, using either rule-based control (RBC) or model predictive control (MPC).

## A CASE STUDY

A case study is presented in this section to demonstrate the application of the simulation framework developed in the previous section. In the following subsections, the test settings will be introduced, and then the results are analyzed and discussed to provide insights into the interplay between occupant behaviors and demand flexibility.

### Test Settings and Assumptions

This case study compares two cooling mode simulation scenarios to demonstrate the interplay between occupant behaviors and demand flexibility: a baseline scenario with no DR event, and a load shedding scenario (i.e., a DR scenario with a load shedding event). All test settings for the two scenarios in the following subsections are the same, except the supervisory control strategy.

**Simulation Settings.** This case study simulates a typical summer day in Atlanta, on August 28th, using a 1-minute time step. The occupied period was from 5 AM to 9 PM. The weather data for the selected date was taken from the TMY3 weather file. To capture the stochastic effects of occupant behaviors, each scenario was repeated 100 times, which was determined to be sufficient based on the results of preliminary tests.

**Supervisory Control Strategy.** In both scenarios, the cooling setpoint for the unoccupied period was 32.22 °C (90 °F). For the baseline scenario, the zone cooling setpoint was 25.56 °C (78 °F) for the entire occupied period. In the load shedding scenario, the zone cooling setpoint was temporarily set to 26.67 °C (80 °F) during a load shedding window (1 PM to 6 PM). The supervisory control signal reset the cooling setpoint every 15 minutes, overriding any adjustments made by the occupants in the OBM during the 15-minute time frame.

**Zone Load Model.** For zone load simulation, the small office model from the existing Commercial Prototype Building Models (U.S. Department of Energy 2023) was adapted. The south-facing zone, Perimeter\_Zn\_1, was selected for this study. Other zones were served by the ideal load system. To accurately reflect the air temperature dynamics of a zone with typical thermal mass under a thermostat setpoint reset strategy, the temperature capacity multiplier in the model was set to 8, according to the findings of Chen et al. (2022b) and Lee and Hong (2018).

**HVAC System.** A two-stage air-source heat pump simulation model serves as the HVAC system in this study. This model was calibrated using real experimental data from the heat pump testing facility at the National Institute of Standards and Technology (NIST). At each time step, given zone air temperature  $T_z$ , zone air humidity ratio  $\omega_z$ , outdoor air temperature  $T_o$ , and operating mode (off/low-speed/high-speed), this model first calculates the sensible heat capacity  $Q_s$ , total heat capacity  $Q_{tot}$ , and the electric power  $P$  of the heat pump by using the calibrated curves, then calculates supply air temperature  $T_s$  and humidity ratio  $\omega_s$  for the next time step by solving Equations (1) and (2) simultaneously. In these equations,  $c_{pa} = 1.006$  kJ/kg°C (0.24 Btu/lb°F) is the specific heat of the air,  $c_{pw} = 1.86$

$\text{kJ/kg}^\circ\text{C}$  (0.44 Btu/lb $^\circ\text{F}$ ) is the specific heat of water vapor,  $h_{we} = 2501 \text{ kJ/kg}$  (1075 Btu/lb) is the heat of evaporation,  $T_z$  and  $\omega_z$  are the zone return air temperature and humidity ratio provided by the zone load model, and  $m_s$  is the supply air mass flow rate, which is equal to 0.40 kg/s (52.91 lb/min) at low-speed and 0.62 kg/s (82.01 lb/min) at high-speed.

$$Q_{tot} = m_s [c_{pa}(T_z - T_s) + c_{pw}(T_z\omega_z - T_s\omega_s) + h_{we}(\omega_z - \omega_s)] \quad (1)$$

$$Q_s = m_s [c_{pa}(T_z - T_s) + c_{pw}\omega_s(T_z - T_s)] \quad (2)$$

This heat pump system is controlled based on the zone return air temperature. When return air temperature is 0.28  $^\circ\text{C}$  (0.5  $^\circ\text{F}$ ) higher than the cooling setpoint, the heat pump operates in low-speed mode until the temperature drops below the cooling setpoint. When return air temperature exceeds 0.56  $^\circ\text{C}$  (1  $^\circ\text{F}$ ) above the cooling setpoint, the heat pump operates in high-speed mode until the temperature drops below 0.28  $^\circ\text{C}$  (0.5  $^\circ\text{F}$ ) above the cooling setpoint and then switches back to low-speed mode.

**Zone Airflow Model.** During the CFD simulation, it was assumed that there were four air terminals evenly spread on the east-west central line of the zone and three return air grilles evenly spread at the bottom of the south-facing wall.

**OBM.** The selected zone was occupied by seven simulated occupants whose attributes (as shown in Table 1) were generated randomly prior to testing and remained consistent across all repeated simulations. These occupants are identified by their unique ID, listed in the first column, and their thermal acceptability ranges, corresponding to the seven-point ASHRAE thermal sensation scale (ASH) (ASHRAE 2004), listed in the second column. Their acceptability ranges were sampled from the summer season Predicted Mean Vote (PMV) – Predicted Percentage Dissatisfied (PPD) curve for RP-884 HVAC buildings (De Dear 1998; Langevin et al. 2013), which reflects the percentage of occupants that are dissatisfied with different thermal sensations. It is worth noting that about 20%-30% of the population can accept extreme thermal sensations, either cold (-3) or hot (+3), based on the curve. Details about the sampling process and occupant thermal comfort determination process are further explained in the appendix of Langevin et al. (2015a).

Columns 3 to 5 shows the behavioral constraints applied to each occupant. This study assumes three constraints that can restrict occupant behaviors: *care management*, *care others*, and *care energy use*. The occupants with the *care management* constraint tend to follow building management regulations that restrict the use of certain devices. In this case study, these occupants were restricted from adjusting the thermostat 80 % of the time. Similarly, those with the *care others* constraint tend to prioritize the comfort of others over their own. These occupants were restricted from adjusting the thermostat 100 % of the time if the adjustment would potentially make more than half of the occupants in the same zone feel uncomfortable. Lastly, those with the *care energy use* constraint tend to avoid behaviors that consume energy. These occupants were restricted from adjusting the thermostat and using personal equipment 80 % of the time.

**Table 1. Occupant Attributes**

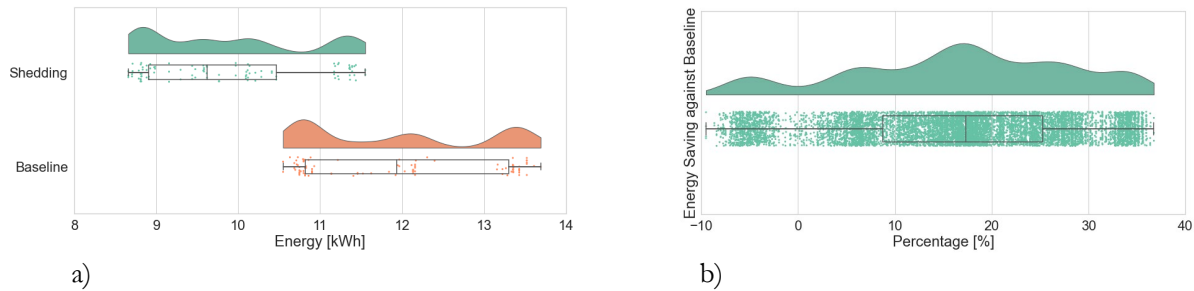
ID	Acceptability Range	Care Management?	Care Others?	Care Energy Use?
1	[-3,0]		✓	
2	[-2,1]	✓	✓	✓
3	[-3,2]		✓	
4	[-1,1]		✓	✓
5	[-1,2]	✓	✓	✓
6	[-2,3]		✓	✓
7	[0,3]	✓	✓	

In this case study, when occupants felt uncomfortable, they could choose behaviors in the following sequence if they were not restricted by the constraints: (1) take clothing on/off, (2) use personal equipment (fan or heater), (3) adjust thermostat setpoints, or (4) consume a hot/cold drink or change activity level from sitting to walking. In the

simulation, each fan consumed 0.015 kW of electricity, generated 0.015 kW of heat, and increased occupant local air velocity by 0.75 m/s. Each heater consumed 1.2 kW of electricity, generated 1.2 kW of heat, increased occupant local air temperature by 2 °C (3.6 °F), and set the local radiant temperature equal to the local air temperature. The heat generated by the personal equipment was included in the Zone Load Model as the equipment radiation heat gain, and their local effects were directly applied to the outputs of the Zone Airflow Model.

## Results and Discussions

The results of the two scenarios during peak hours are analyzed and are discussed in this subsection. The results are visualized using the raincloud plot (Allen et al. 2019), which is an effective visualization method that combines a density plot (i.e., cloud), a jittered raw data plot (i.e., rain), and optionally a box plot. Figure 2 compares the total energy use (including both the heat pump and the personal equipment) between the baseline and the load shedding scenarios. The total energy use results from the 100 repeated simulations of each scenario are shown on the left and the relative changes between all 10,000 possible pairs between the two scenarios are shown on the right. Observe that the cooling setpoint reset strategy (shedding) is an effective strategy in general, resulting in a 17.3% median savings during the peak period. However, the difference between the potential maximum and minimum savings is more than 40 %.

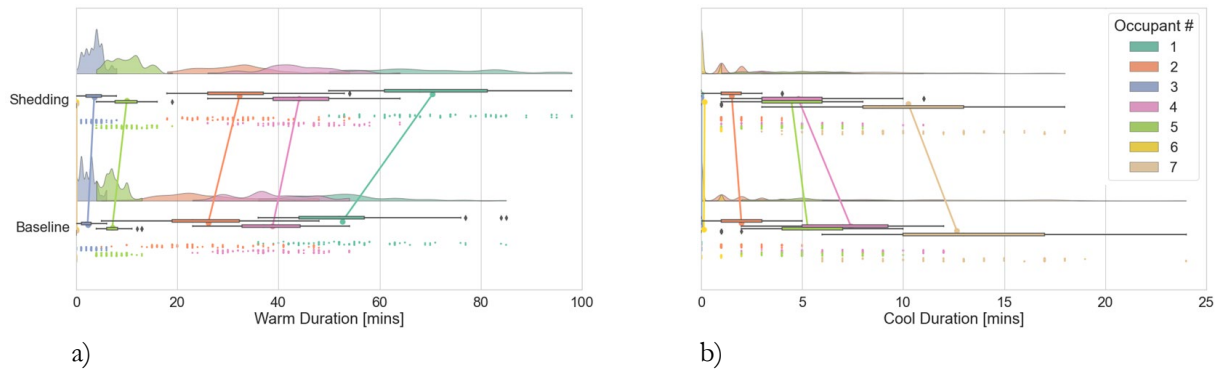


**Figure 2** (a) Energy use and (b) load shedding energy savings against baseline scenario during the peak period.

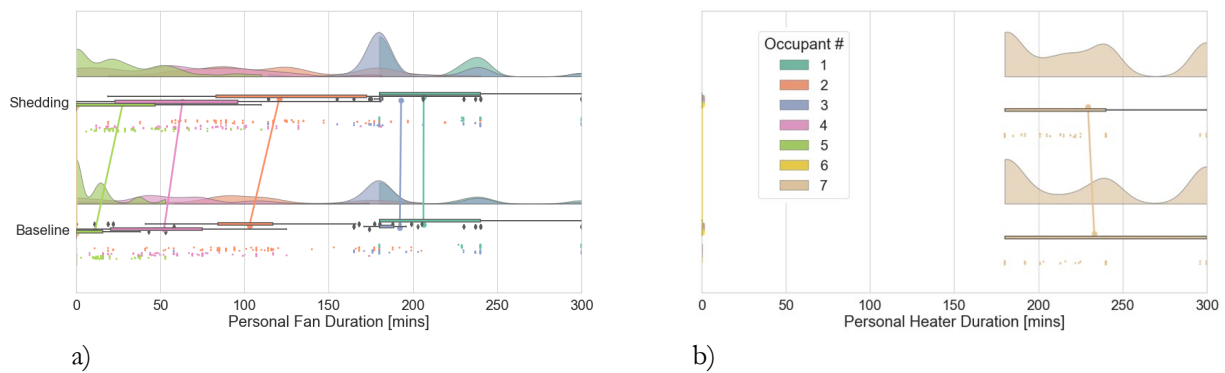
Figure 3 presents the duration of discomfort of each occupant during the peak period, where warm/cool duration is defined as the length of time that an occupant feels discomfort due to being warm or cool, respectively. In the figure, each solid line between the two scenarios connects the average value of the data distribution for each occupant. Observe that relaxing the zone temperature setpoint during the peak period can result in a longer warm duration and a shorter cool duration. According to Table 1, among the seven occupants, Occupant #1 prefers a cooler environment than others, while Occupant #7 prefers a warmer environment than others. Therefore, relaxing the cooling setpoint has a more significant effect on their comfort.

Figure 4 shows the personal fan and heater usage durations for each occupant. Note that the behaviors of some occupants are not clearly shown because the duration is 0. The figure reveals that for certain occupants (Occupants #1, #3, and #7), relaxing the zone cooling setpoint during the peak period does not have a significant impact on their behaviors despite the fact that their comfort has been affected significantly (as shown in Figure 3). These occupants share similar attributes as they all can accept extreme sensations, either cold (-3) or hot (+3). According to the ASH vote distribution by PMV graph from RP-884 HVAC buildings (Langevin et al. 2013), these occupants are unlikely to turn off their personal equipment once they turn it on until they leave the office, leading to long personal equipment runtime. As a result, the runtime of their personal equipment depends more on their presence in the office than their thermal comfort. Note that the peak duration of their behaviors is closely related to the possible duration of their presence in the office (i.e., 180, 240, or 300 minutes). Additionally, Occupants #1, #3, and #7 do not care about energy use, thus, they are more likely to use personal equipment when feeling uncomfortable. For example, Occupant #2 has a longer warm duration than Occupant #3, but since Occupant #2 cares about energy use, their personal fan runtime

is shorter than for Occupant #3. The duration of cooling setpoint adjustments is short due to the 15-minute setpoint reset frequency in this case study. Thus, their results are not reported here. Finally, it is worth noting that the shape of the energy use during the peak period (as shown in Figure 2) is similar to the personal heater duration of Occupant #7. This suggests that the uncertainty of the overall energy use is heavily influenced by the personal heater of Occupant #7. This result is reasonable as one 1.2 kW heater is responsible for nearly half of the energy use during the peak period.



**Figure 3** (a) Occupant warm duration and (b) occupant cool duration during peak period.



**Figure 4** (a) Personal fan duration and (b) personal heater duration during the peak period.

## CONCLUSION

In conclusion, the simulation framework developed in this study offers a valuable means for evaluating demand flexibility in commercial building with consideration of occupant comfort and behaviors. The case study demonstrates that increasing the cooling setpoint by 1.11 °C (2 °F) can result in significant demand shedding during a typical summer peak in Atlanta, with a median shedding of 17.3 %. However, the uncertainty boundary of the demand flexibility can be influenced greatly by occupant thermal preference, presence, and personal equipment use. Overall, the results of this study provide valuable insights into the demand flexibility uncertainty due to occupant behaviors, which can inform the development of effective supervisory control strategies for office buildings. Future studies could expand on this work by employing large-scale and long-term simulations that incorporate a broader range of occupant attributes in demand flexibility analysis, as well as exploring data-driven control strategies that leverage stochastic occupant behavior data.

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