Advanced Co-simulation Framework for Assessing the Interplay between Occupant Behaviors and Demand Flexibility in Commercial Buildings

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With buildings contributing significantly to electricity usage, enabling demand flexibility becomes a challenge, especially when accounting for occupant comfort. This study introduces an innovative co-simulation framework integrating multiple models: heating, ventilation, and air conditioning (HVAC) system, building zone load, indoor airflow, supervisory control, and occupant comfort and behavior. Uniquely, this framework allows for a comprehensive and dynamic analysis of building systems and occupant interactions in demand response events. Using this framework, we conducted a case study using a typical small office building model. Specifically, we focused on three areas: (1) the impact of indoor airflow modeling on energy use, occupant comfort, and behaviors forecasting, (2) the impact of occupant behaviors on demand flexibility, and (3) occupant comfort and behaviors under demand response events. Key performance indicators such as energy use, flexibility factor, durations of occupant discomfort and occupant behaviors were analyzed. Our findings indicated variations in energy usage and occupant comfort within demand flexibility events, marked by uncertainty boundaries, with variability in demand shedding up to 57.9%. We concluded that this framework is suitable for analyzing typical commercial buildings and their HVAC systems in terms of demand flexibility potential under the impact of occupant behaviors.

Keywords: demand flexibility, occupant behavior, commercial buildings HVAC, grid-interactive efficient buildings, thermal comfort

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 (also referred to as energy flexibility throughout this paper) are to reduce electricity use during peak or critical periods by shutting down equipment or relaxing system setpoints. These measures are viable due to the building's passive energy storage capacity, which allows for the temporary reduction in energy consumption while the stored energy maintains environmental conditions. For example, Sun et al. (2013) summarized peak load shifting control strategies using thermal energy storage facilities, which includes the use of building thermal mass to store thermal energy through precooling or preheating. Nyholm et al. (2016) demonstrated that optimizing the pre-conditioning time and the system operating time can provide considerable load shifting capacity of the heating system.

Nonetheless, such strategies, though potentially impactful in reducing or shifting energy consumption, may significantly affect occupant comfort. In response to the strategies aimed at increasing flexibility in building electricity use, it is challenging to guarantee that the indoor environment will always be maintained at a desirable level. This may then lead to decreased productivity, elevated complaints, and potential harm to health. On the other hand, when occupants feel uncomfortable, they may engage in behaviors to alleviate their discomfort, such as adjusting thermostat setpoints, using personal heating or cooling equipment, etc. These behaviors can in turn negatively impact the overall goal of demand response (DR) and fail to increase demand flexibility. 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) investigated the impact of occupancy, interactions, and behavioral efficiency on building energy consumption. Their study found that the implementation of occupancy-based demand response control in real building operation can significantly reduce energy consumption. Jia, Srinivasan, and Raheem (2017) summarized behavior-related data collection techniques and occupant behavior modeling methods. Among many models, they concluded that agent-based modeling approaches have better potential for behavior modeling and energy simulation.

Meanwhile, a few studies have specifically analyzed the influence of occupant behaviors on demand flexibility in buildings. For example, Olawale, Gilbert, and Reyna (2022) explored the relationship between residential occupant behaviors and demand flexibility. They used machine learning models to predict occupant behaviors in activities relevant to demand flexibility using the American Time Use Survey data (Bureau of Labor Statistics 2020). This study provides valuable insights into understanding when and who might adopt demand flexibility technologies based on their daily routine activities. Vellei, Martinez, and Le Dréau (2021) developed a novel framework to model the interactions between occupants and thermostats during 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 thermostat overrides during DR events using data from 6,389 connected

North American 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. Morales-Valdés, Flores-Tlacuahuac, and Zavala (2014) analyzed the effect of comfort relaxation on the energy flexibility of building control systems through two main paradigms: economic-based control strategies and tracking control strategies. The article recommended that building energy flexibility could be more accurately assessed using economic-based control strategies and optimization strategies that use occupant comfort related metrics, i.e., predicted mean vote (PMV) and predicted percentage dissatisfaction (PPD), as constraints. Hu and Xiao (2020) used a stochastic occupancy model to quantify the uncertainty in the overall energy flexibility of the residential building stock, including uncertainty in building envelope parameters, building energy system performance, occupancy, and occupant behavior. They found that the energy flexibility potential stabilized at around 12.4 % with the scaling up of building clusters. Olawale, Gilbert, and Reyna (2023) assessed user behavior related to residential demand flexibility through a survey. They identified the activity priorities of U.S. residential occupants during different demand flexibility-related times (critical peak, peak, and off-peak), which showed that a high level of overrides was exhibited by participants of DR programs.

Although strides have been made in recognizing how occupant behavior influences building energy flexibility, a significant knowledge deficit persists concerning the specific effects of these behaviors on demand flexibility within commercial buildings. Additionally, occupant behavior is inherently unpredictable due to its randomness — individuals do not exhibit identical behavior patterns daily. Moreover, there is a diversity of behaviors reflecting varying comfort needs and tolerances, meaning that even within identical environments, behavior differs significantly (Ahmed et al. 2023; Belazi et al. 2018; Wagner, O'Brien, and Dong 2018; Gunay, O'Brien, and Beausoleil-Morrison 2013). This unpredictability poses challenges for directly quantifying the impact of occupant behaviors on building demand flexibility. In this context, probability-based or stochastic models can be used to tackle the complexity. For example, Baetens and Saelens (2016) explored the role of occupant behaviors in building energy conservation and district energy simulation, and proposed a stochastic behavior model to quantify and analyze different types of uncertainty for residential occupants. Similarly, Langevin, Wen, and Gurian (2015) developed an agent-based occupant behavior model to simulate stochastic occupant thermal behaviors in office buildings.

Building on the foundational work of Langevin, Wen, and Gurian (2015), this study seeks to develop an advanced co-simulation framework that assists the investigation of human-building interaction, with a focus on demand flexibility in commercial buildings. This intricate framework encompasses simulations of control strategies, zone thermal loads, HVAC systems dynamics, and granular indoor airflows, alongside a detailed modeling of occupant thermal behaviors. Through this multifaceted and bottom-up simulation approach, we aim to glean more profound insights into how occupants perceive and react to DR events in commercial buildings. The ultimate goal of this framework is to delineate the bounds of uncertainty in the demand flexibility of commercial buildings, thereby informing the development of effective policies and control strategies that optimize energy flexibility and occupant comfort in dynamic building environments. It is important to note that while many models have been developed to study occupant behaviors, our framework uniquely integrates comprehensive models across several dimensions. These include a control model, a zone load model, an airflow model, an occupant behavior model, and an HVAC system model, which collectively offer a more holistic view of building dynamics as demonstrated in this study. To the best of our knowledge, this is the first co-simulation framework that offers such a detailed and integrated view of the multiple aspects influencing building performance and occupant comfort.

This paper is organized as follows: The following presents the development of the co-simulation framework and its components, providing an overview of the methodology employed. The subsequent section constitutes the core of this paper, where a detailed case study is employed not just as an application, but as a vital demonstration of the framework's capabilities and functionalities. This section delves into the simulation settings, statistical rationale, and presents results along with a thorough discussion, thereby providing a deeper insight into the framework's effectiveness. Finally, the paper concludes with a summary of the findings, their implications, and suggestions for future directions.

Development of the co-simulation framework

In this section, the simulation framework for analyzing the impact of occupant behaviors on demand flexibility, including 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. And Figure 2 depicts the architecture of the co-simulation script reflecting the overall concept presented in Figure 1. The integration of this framework is achieved through co-simulation among various software environments including MATLAB & Simulink (The MathWorks 2020) and EnergyPlus (Crawley et al. 2001). Data storage and exchange is facilitated via MongoDB (MongoDB 2018). The framework is structured into two primary parts: the simulation of HVAC system and the simulation of building and control. These parts can operate at different timesteps, and a master script controls the timing of data exchanges between them. The minimum data exchange timestep is determined by the longest simulation timestep between the two parts. For our case study, we have chosen a 1-minute timestep for all components in the framework to ensure that the transient dynamics within the simulated environment are adequately captured and reflected across the integrated components. Figure 3 provides an illustrated example of the Simulink model specifically designed for the Virtual Building Model as referenced in Figure 2. This visual representation highlights the intricate details and the functional interconnectivity within the model. For an in-depth exploration and further technical insights, readers are invited to consult our GitHub repository (Chen 2023), where the full simulation settings and additional resources related to this framework are comprehensively documented. Below, we provide a concise overview of the functionality of each key component in the framework. Further details regarding the simulation settings of each component will be discussed in the case study section.

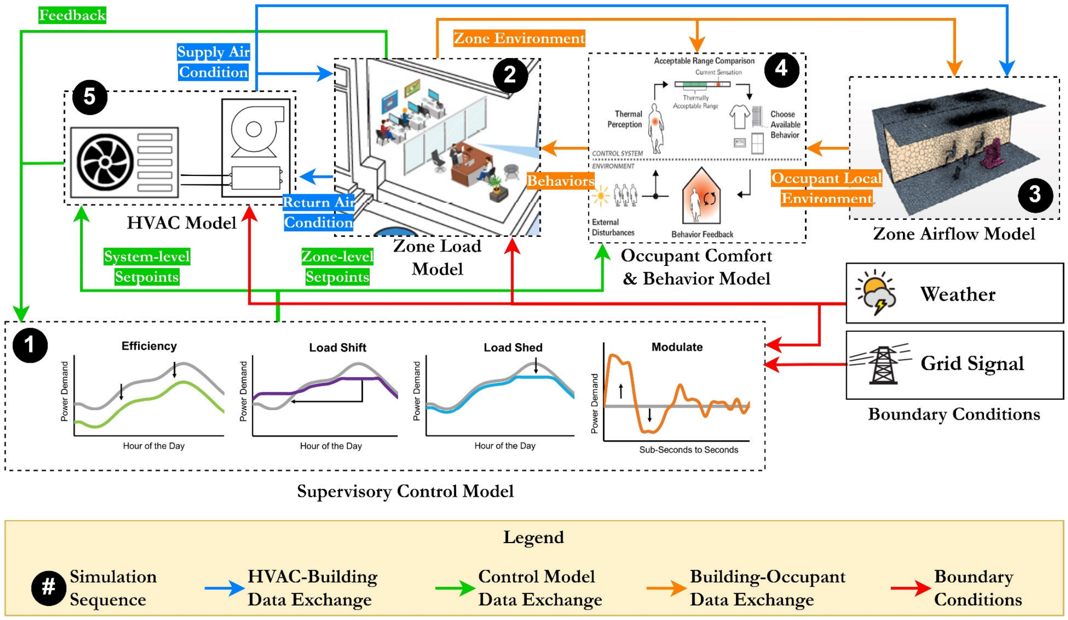

Figure 1 An overview of the occupant behavior and demand flexibility simulation framework. Figures in Supervisory Control Model are adapted from Neukomm, Nubbe, and Fares (2019) and the figure for Occupant Comfort & Behavior Model is adapted from Langevin, Wen, and Gurian (2015).

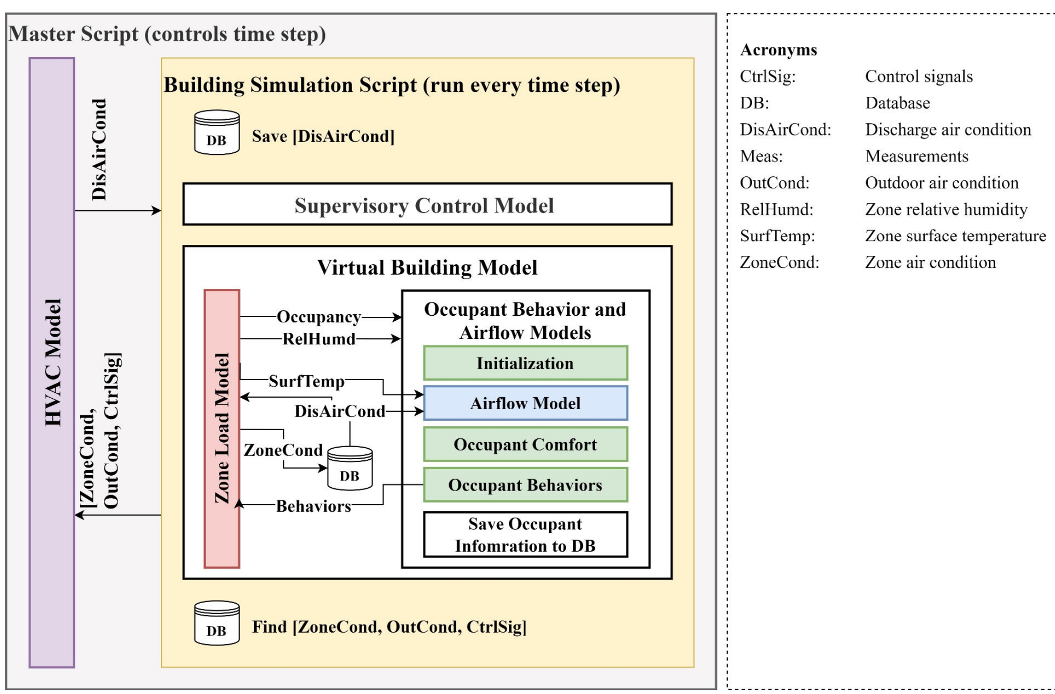

Figure 2 Architecture of the Co-Simulation Script and Data Flow

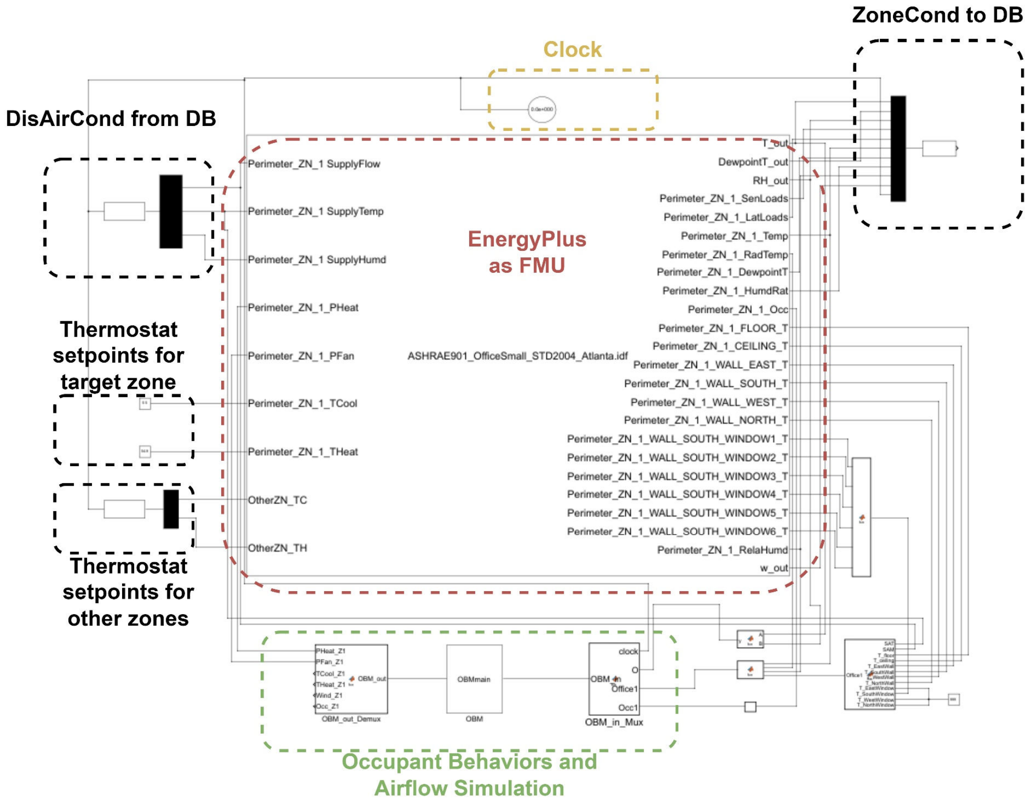

Figure 3 An Example of the Virtual Building Model in the Simulink Environment

The supervisory control model is designed to mimic how a supervisory control strategy would generate zone-level or system-level setpoints to optimize building operations. This model employs either rule-based control (RBC) with 'if-then' logic or model predictive control (MPC) that is configured in a Simulink environment. It adeptly generates supervisory control signals that respond to a variety of DR signals, such as electricity price and demand limit.

The zone load model simulates the thermal load and zone environment in each zone of a building, considering various factors such as solar radiation, building envelope heat conduction, air infiltration, occupancy, lighting, and equipment usage. EnergyPlus models (Crawley et al. 2001) are well-suited for this purpose. To enable co-simulation, the EnergyPlus model can be exported as a functional mock-up unit (FMU) using the

EnergyPlusToFMU package developed by Lawrence Berkeley National Laboratory (2020). Specifically, important simulation results, such as zone mean air temperature, humidity, mean radiant temperature, and surface temperature, can be exported from EnergyPlus using the *External Interface: Functional Mockup Unit Export: From: Variable* object. For inputs, *External Interface: Functional Mockup Unit Export: To: Schedule* object is used to input control signals (i.e., schedule) for personal equipment or thermostat schedules if the HVAC system is simulated within EnergyPlus. For an HVAC system that is modeled outside of EnergyPlus, which is the case for this study, the *Ideal Loads Air System* and the *External Interface: Functional Mockup Unit Export: To: Actuator* objects (referred to as Actuator Object hereafter) of EnergyPlus is employed. Specifically, the Actuator Object enables overriding the discharge air conditions, such as *Air Mass Flow Rate*, *Air Temperature*, and *Air Humidity Ratio* of the *Ideal Loads Air System*. It is important to note that the ideal load system will disengage if the zone air temperature enters the deadband established by the thermostat's setpoint, potentially nullifying any external overrides. Hence, while the externally determined discharge air conditions supplant the zone temperature control mechanism within EnergyPlus, the thermostat setpoints for these ideal load systems are still critical. They must be set strategically to ensure that EnergyPlus continuously uses externally determined discharge air conditions. For instance, in a zone where the typical temperature is around 78 °F (25.56 °C), setting a substantially higher heating setpoint, such as 122 °F (50 °C) can force the system to operate continuously. This strategy effectively guarantees the successful override of the zone's thermal conditions with externally determined discharge air parameters.

The behavior of occupants in a building plays a crucial role in the buildings thermal load and energy use. The agent-based occupant behavior model (referred to as

OBM hereafter) developed by Langevin, Wen, and Gurian (2015) has been adapted into this framework. This model forecasts the thermal behaviors of occupants and sends them to the zone load model. It was validated via a year-long longitudinal survey (Langevin, Gurian, and Wen 2015) 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 equipment, adjusting thermostats, opening/closing windows/doors/blinds, taking clothes on/off, consuming hot/cold drinks, and walking. Originally developed as a MATLAB script, the OBM required significant reworking and adaptation for compatibility with the Simulink environment. Unlike MATLAB scripting, which provides a more lenient approach to coding without strict variable definitions, Simulink demands precise specification of variable data types and explicit declarations of persistent and global variables. After a thorough conversion process, the OBM was successfully integrated into Simulink as a Level-2 MATLAB S-Function block. This integration entailed detailed definition of the variables' data types and clear identification of global and persistent variables, thus ensuring a robust and efficient simulation within the Simulink environment. Again, readers may refer to the GitHub repository (Chen 2023) for more technical details.

EnergyPlus offers zone air modeling for both well-mixed air conditions and a limited selection of non-uniform air temperature distributions (U.S. Department of Energy 2020). However, it typically falls short in accurately capturing the real-world dynamic, particularly in large spaces like open offices or conference rooms. To accurately estimate the thermal conditions surrounding occupants for a large space, a zone airflow model is incorporated into the framework. The local indoor air environment surrounding an occupant is simulated using a computationally efficient artificial neural network (ANN) model trained from computational fluid dynamics (CFD) simulation data (Zhang, Lo, and Grajewski 2022). Specifically, the ANN model was trained using the mean radiant temperature of an occupant, computed as the average mean radiant temperature of an occupant's head and chest surfaces by a surface-to-surface radiation model, and the air temperature and air velocity, sampled by a 1.2-meter cube centered on the occupant. Examples of a CFD simulation and the associated ANN model can be seen in Figure 4 and Figure 5. Compared to CFD simulations, the ANN model offers significantly enhanced computational and time efficiency. At each simulation timestep, the ANN model takes various inputs including the discharge air conditions from the simulated HVAC system, zone surface temperatures from EnergyPlus simulation, and predefined occupancy and occupant's location within the zone, to estimate the local thermal conditions (i.e., air temperature, radiant temperature, and air velocity) near each 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 sub-function prior to the assessment of occupant comfort. It is important to note that the ANN model is specifically designed to function within the co-simulation framework presented in this study or frameworks with similar setups. For applications where certain boundary conditions, such as zone surface temperatures, are unavailable, adaptations are necessary. Nevertheless, the methodology of using an ANN model to leverage CFD simulation data may still be applicable in different contexts.

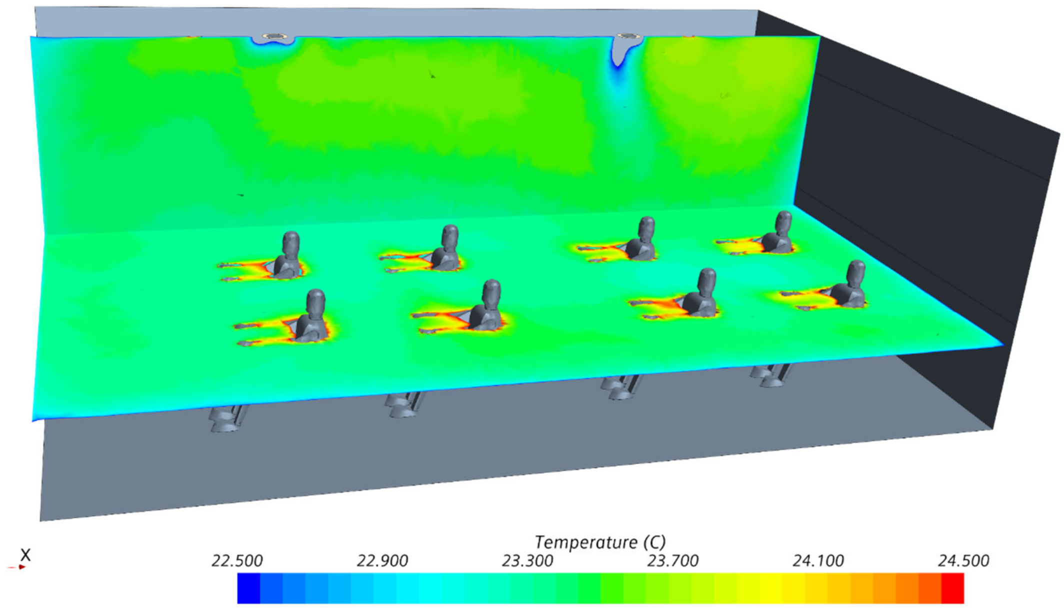

Figure 4 An Example CFD Simulation for an Office Room (Zhang, Lo, and Grajewski 2022)

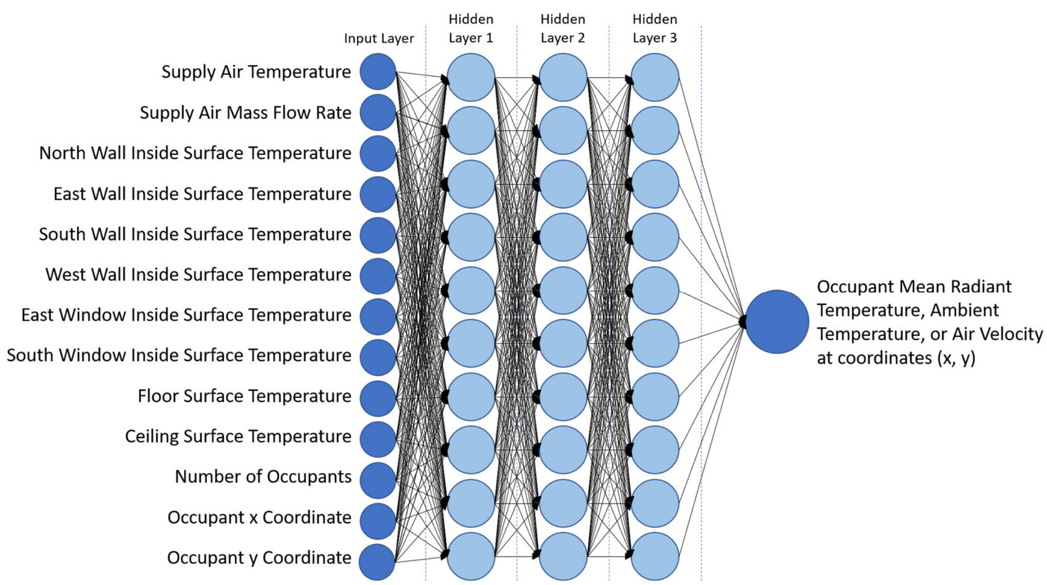

Figure 5 An Example ANN Developed for Fast Indoor Airflow Simulation (Zhang, Lo, and Grajewski 2022)

With the return air condition and weather condition as inputs, the HVAC model in the proposed framework is responsible for simulating the performance of an air-based

HVAC system in the building and providing the discharge air condition required to meet the zone demand. Although EnergyPlus includes HVAC system simulation capabilities, it assumes a steady-state behavior of the HVAC system, which may not be sufficient for studies that focus on the dynamics of the HVAC system. Therefore, the proposed simulation framework separates the task of simulating the zone load and the HVAC system. This separation facilitates the integration of various external modeling tools for enhanced and flexible HVAC system representation. For instance, in the case study below, we utilize an empirical heat pump model developed in MATLAB. Additionally, the same framework is directly applicable if real HVAC systems are used through a hardware-in-the-loop approach (Chen, Wen, Bushby, Lo, O'Neill, et al. 2022; Calfa et al. 2023).

Case study

In this section, a comprehensive case study is presented, leveraging the developed framework to explore the complex interplay between occupant behaviors and demand flexibility in commercial buildings. This case study builds upon a preliminary investigation that was introduced in a prior conference paper by Chen et al. (2023). The case study begins with an overview of the general simulation settings, detailing the fundamental characteristics of the building and its occupants. Building upon the general settings, the discussion progresses to cover a range of test scenarios. Each scenario comes with its tailored simulation settings, enabling a nuanced exploration of different conditions. Following this, the Key Performance Indicators (KPIs) for evaluating the results are presented. Subsequently, the rationale for the selected number of simulation repetitions is discussed, emphasizing its statistical underpinnings to ensure result reliability and validity. Finally, the results are presented and discussed.

General simulation settings

To ensure a robust and realistic simulation, a set of general simulation settings are firstly defined, which include aspects like the weather condition, building envelope, occupant attributes, and HVAC operations. The focus of this study is to illustrate how occupant behavior affects a building's load flexibility. Considering that an occupant behavior is a stochastic process, repeated simulation is needed to understand the probability of a behavior's impact. An open office of a small commercial building with an air-source heat pump is simulated for its computation simplicity. The same framework can be used for other buildings and HVAC types with higher complexity. The zone and HVAC system selection for this case study would also allow the usage of an air source heat pump model that is validated with real system operation data to ensure the accurate reflection of real-world load flexibility.

Boundary conditions and simulation settings

For this study, August 28th was selected from the TMY3 dataset for Atlanta, GA, USA, to represent a typical summer day in a typical climate zone. The occupied period was from 5 AM to 9 PM, mirrors the typical occupancy patterns found in the small office model from the Commercial Prototype Building Models (U.S. Department of Energy 2023). The peak period was from 1 PM to 6 PM according to Georgia Power Co. (Georgia Power 2021), the utility company serving the Atlanta area. The simulation timestep was set at 1-minute to ensure sufficient tracking of the transient nature of indoor environmental conditions and airflow dynamics. This finer resolution is vital for understanding the subtle changes in indoor thermal environment conditions that directly influence occupant comfort and behavior. Since the study aims to investigate the impact of occupants on demand flexibility, accurately capturing these dynamic profiles is essential for obtaining precise and insightful results. Furthermore, while HVAC simulation and airflow simulation may benefit from even finer timesteps to capture dynamics further, it is deemed unnecessary for this study. The indoor environment and occupant behavior typically remain steady within a larger timeframe, such as 5 to 10 minutes, thus the choice of a universal 1-minute timestep provides an optimal balance.

Zone load model

For zone load simulation, the small office EnergyPlus model (Figure 6) from the 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 air systems. Given that the main objective of this study is to verify the behavior of the co-simulation framework, which does not handle occupants' movement across different zones, focusing on one zone is deemed sufficient. This approach ensures computational simplicity while still adequately testing the framework's behavior. In addition, in order 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 prototype EnergyPlus model was modified to 8, according to the findings of Chen, Wen, Bushby, Lo, O'Neill, et al. (2022), and Lee and Hong (2018).

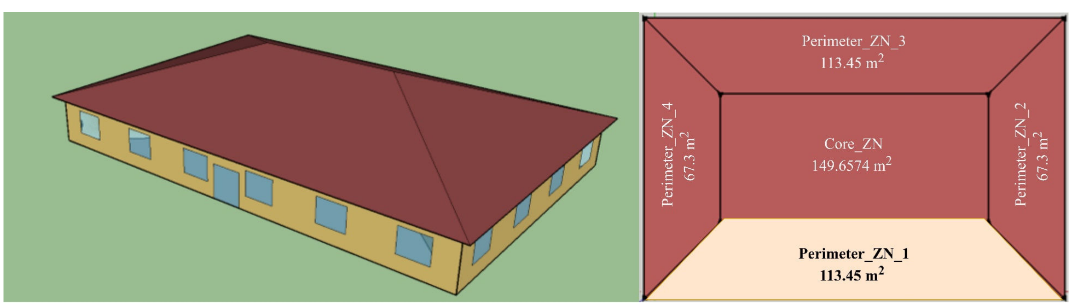

Figure 6 Standard 90.1 Prototype Building Models – Small Office (U.S. Department of Energy 2023)

Occupant behavior model

The selected zone was occupied by eleven simulated occupants, each assigned a unique ID number ranging from 1 to 11, as shown in Figure 7. This section offers an in-depth look at the behaviors, thermal acceptability, and constraints of these occupants, all depicted in the figure. These occupants were generated using a stochastic approach prior to the case study and remained consistent across all scenarios and repeated simulations. Their thermal acceptability ranges, corresponding to the seven-point ASHRAE thermal sensation scale (ASH) (ASHRAE 2004), are presented on the right of each occupant icon. Their acceptability ranges, while inherently subjective, were sampled from the summer season PMV-PPD curve for RP-884 HVAC buildings (De Dear 1998; Langevin, Wen, and Gurian 2013). The PMV-PPD curve reflects the percentage of occupants that are dissatisfied with different thermal sensations. The PMV-PPD curve is an objective representation based on a large sample of data and is used here to approximate the subjective ASH vote acceptability ranges for the simulated occupants. This approach assumes that the distribution of thermal sensations (ASH votes) within the occupants' acceptability ranges can be aligned with the PMV values from the RP-884 curve.

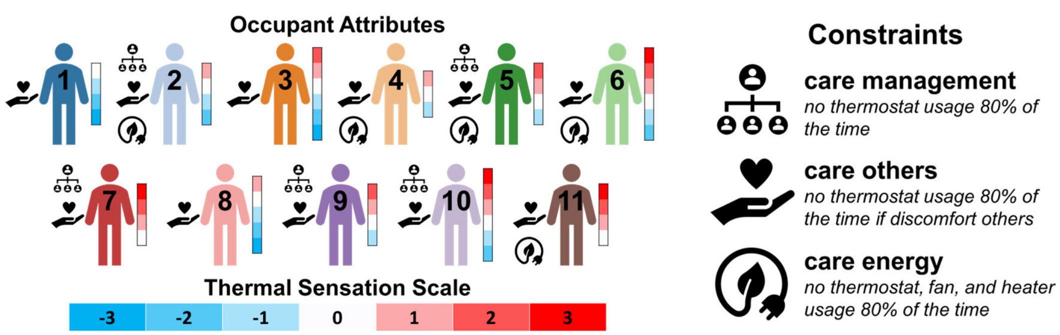

Figure 7 Occupant Attributes – Same Occupants in All Scenarios

Figure 8 demonstrates the summer season PMV-PPD curve provided by RP-884 and the curve according to the thermal acceptability ranges of the sampled occupants in this study. The data from our sampled group reveals a discernible trend towards a preference for warmer conditions, diverging slightly from the trend implied by the RP-884 curve, which serves as a benchmark for the general population. Although our occupants' thermal preferences were informed by the RP-884 dataset, the small sample size of eleven individuals inherently restricts the fidelity of the match with the extensive RP-884 curve. Nonetheless, the fundamental architecture of our curve resonates with established patterns, showing increased dissatisfaction as the PMV diverges from the neutral midpoint. Through the above-described process, we attempt to create a group of occupants that represent a typical population observed in commercial buildings.

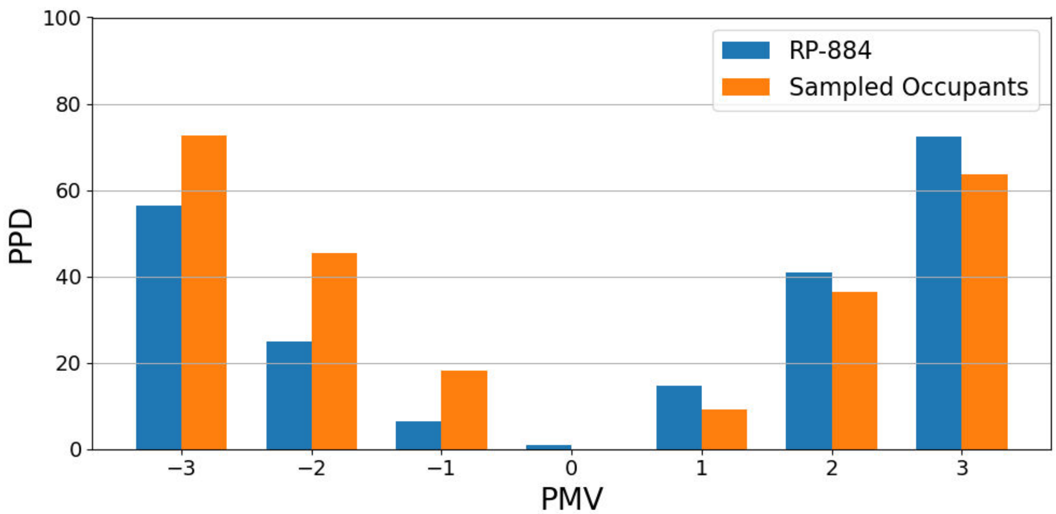

Figure 8 The Summer Season PMV-PPD Curves (RP-884 and Sampled Occupants of the Case Study)

As described by Langevin, Wen, and Gurian (2015), the OBM determines whether an occupant is comfortable by comparing an occupant's thermal sensation (i.e., ASH vote) with the occupant's thermal acceptability range. The probability that an occupant will experience discomfort is equivalent to the likelihood of their ASH vote falling outside their acceptable thermal range. In this study, we adopted the distribution of ASH Vote by PMV from RP-884 (De Dear 1998; Langevin, Wen, and Gurian 2013) as shown in Figure 9. This figure visualizes the probability of experiencing various ASH votes at specific PMV values. For example, Occupant #4, whose thermal acceptability range spans from -1 to 1 on the ASH scale, would face cold discomfort for any ASH vote below -1 and warm discomfort for any ASH vote above 1. These probabilities are visually represented in Figure 9 with *Cold (-3)* in red and *Cool (-2)* in blue for cold discomfort, and *Warm (+2)* in yellow and *Hot (+3)* in pink for warm discomfort. Specifically, when PMV is -1, this occupant has approximately a 20 % chance (the combined probability of *Cold* and *Cool*) of feeling cold discomfort, and about a 2 % chance (the combined probability of *Warm* and *Hot*) of feeling warm discomfort.

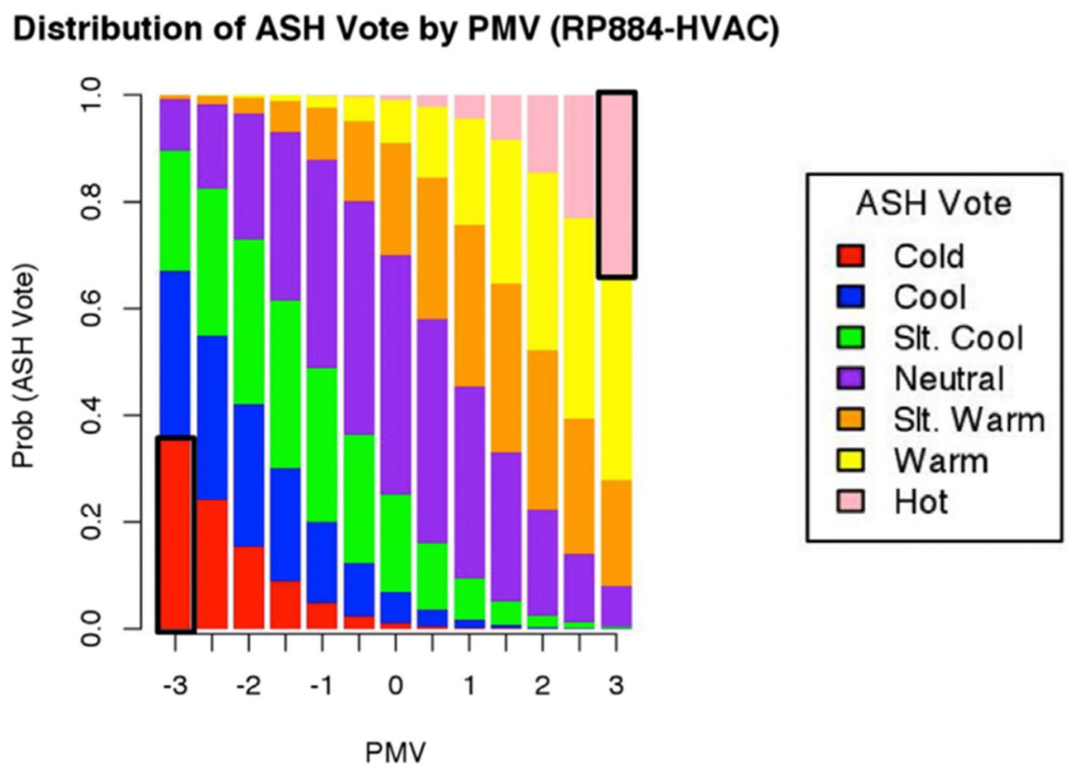

Figure 9 ASH Vote Distribution by PMV for RP-884 (Langevin, Gurian, and Wen 2015)

In this study, occupants were provided with a selection of six behaviors to mitigate thermal discomfort: adjusting clothing-level, using a personal fan, using a personal heater, adjusting the thermostat, drinking, and walking. We adopted the sequencing of these six behaviors as recommended by Langevin, Wen, and Gurian (2015), as they were validated in a one-year longitudinal study. If no constraints were placed on the available behaviors, the hierarchy of these behaviors began with the adjustment of clothing-level. If thermal discomfort persisted, the use of a personal heater or fan was the subsequent choice, followed by adjusting the thermostat. Consuming a hot/cold drink or walking were considered the final options. In terms of reversing actions previously taken to alleviate discomfort in the other direction, the initial step was to turn off any personal heating or cooling equipment. This was followed by the adjustment of clothing to its original state. The last option was to reset the thermostat to its previous setting. Drinking and walking did not have a reversal counterpart. To adapt the OBM for a smaller timestep in this study, an additional setting was implemented. At every timestep (1-min), each occupant was only allowed to perform one behavior. If an occupant performed a behavior at a specific timestep, the occupant was not allowed to perform another behavior within the next 10 timesteps (10-min).

Behavioral constraints that can restrict certain occupant behaviors are presented on the left of each occupant icon in Figure 7. This study assumed three constraints provided by the OBM (Langevin, Wen, and Gurian 2015): *care management*, *care others*, and *care energy use*. With respect to *care management*, without specific literature to draw from, it was assumed that approximately half of the occupants were expected to comply with building management policies that may restrict the use of certain devices. Through randomly sampling with a 50 % probability, 5 out of 11 occupants were assigned with the *care management* constraint. These occupants were restricted from adjusting the thermostat 80 % of the time in this study. Similarly, those with the *care others* constraint tend to prioritize the comfort of others over their own. Since the studied zone was a shared office, it was assumed that all occupants had the *care others* constraints. These occupants were restricted from adjusting the thermostat 80 % 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. According to the survey conducted by Xu et al. (2017), 56.33 % of the participants reported their willingness to save energy in the workplace. Through random sampling with a 56.33 % probability, 5 out of the 11 occupants were assigned with the *care energy use* constraint. These occupants were restricted from adjusting the thermostat and using personal equipment 80 % of the time. Note that the assignment of *care management* and *care energy use* constraints to the occupants was independent of each other. This implies that being assigned one constraint does not influence the likelihood of being assigned the other. Consequently, it is possible for an occupant to have both constraints simultaneously, with each constraint being applied based on its respective sampling probability.

Airflow model

Following the methodology provided by Zhang, Lo, and Grajewski (2022), a CFD model for the studied zone, *Perimeter_Zn_1*, was developed. This model was then used to run 972 steady-state simulations covering various combinations of occupancy and boundary conditions (i.e., discharge air conditions and zone surface temperatures). These CFD boundary conditions were determined using typical values derived from annual EnergyPlus simulations of the small office model (U.S. Department of Energy 2023). These simulations were conducted under various climate conditions, including those specific to Atlanta, which was the selected test location for the case study. Figure 10 presents the zone temperature distribution from one of the CFD simulations.

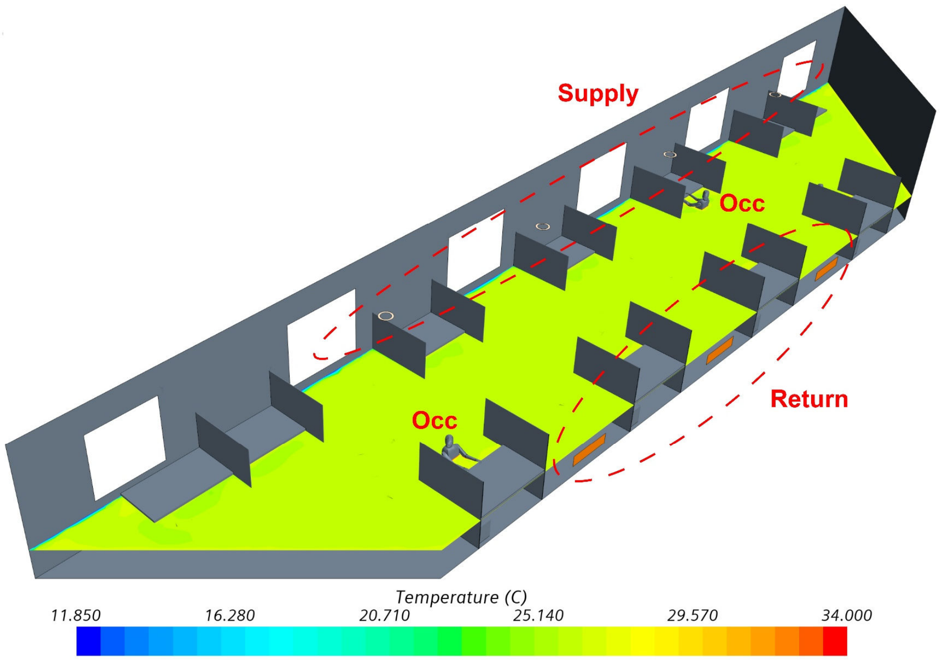

Figure 10 An Example of the CFD Simulation for Perimeter_Zn_1

The CFD simulation results were used to develop an ANN model in Tensorflow (Abadi et al. 2016) using the Adam optimizer with a 40 % split for each epoch. This model was trained to accept inputs such as occupancy level, occupant location within the zone, discharge air conditions, and zone surface temperatures to predict outputs including air temperature, radiant temperature, and air velocity around each occupant. By the end of the training, the testing and the training errors were very close, differing by no more than 1 %. The resulting model, trained with all the data, demonstrated high accuracy, with mean absolute percentage error for the air temperature, radiant temperature, and air velocity predictions of 0.69 %, 0.34 %, and 6.48 %, respectively. These errors were found to cause no more than 5 % error in predictions of occupant comfort.

HVAC system

In this study, the HVAC system was represented by a model of a two-stage air-source heat pump, which was calibrated using empirical data from a series of controlled experiments at the heat pump testing laboratory of the National Institute of Standards and Technology (NIST) (Payne, Yoon, and Domanski 2017). The performance curves of this model can be described using Equation (1), where x_1, x_2, and x_3 represent zone air temperature T_z, zone air dewpoint temperature $T_{z,dp}$, and outdoor air temperature T_o with unit °C, respectively. The values of y representing sensible heat capacity Q_s with unit Btu/hr, total heat capacity Q_{tot} with unit W, and electric power P with unit W, are calculated using the parameters a_0 to a_9 shown in Table 1.

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_1x_2 + a_5x_1x_3 + a_6x_2x_3 + a_7x_1^2 + a_8x_2^2 + a_9x_3^2 \tag{1}$$

Table 1 Two-Stage Air-Source Heat Pump Fitted Parameters

y	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
Low-Speed										
Q_s	2023.06	293.38	-55.24	-63.36	-33.02	6.43	-10.06	3.23	37.69	0.14
Q_{tot}	5751.88	38.18	-114.71	29.73	-43.24	7.55	-9.89	7.18	61.05	-2.23
P	1247.44	-48.54	93.13	-8.25	-17.58	2.00	-3.36	4.77	15.40	0.77
High-Speed										
Q_s	829.56	752.48	-415.18	-45.18	70.54	-5.82	10.54	-25.02	-69.19	-0.18
Q_{tot}	4224.29	180.44	480.31	-52.02	45.80	-4.24	3.93	-11.44	-58.59	0.18
P	3448.18	-206.14	206.90	-33.81	-6.76	0.73	-1.07	5.99	-0.91	1.25

At each timestep, given zone air temperature T_z, zone air humidity ratio ω_z, outdoor air temperature T_o, and operating mode (off, low-speed, or 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 ω_s for the next timestep by solving Equations (2) and (3) simultaneously. In these equations, $c_{pa} = 1.006$ kJ/kg°C (0.24 Btu/lb°F) is the specific heat of the air, $c_{pw} = 1.86$ kJ/kg°C (0.44 Btu/lb°F) is the specific heat of water vapor, h_{we} = 2501 kJ/kg (1075 Btu/lb) is the heat of evaporation, T_z and ω_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.

$$Q_{tot} = m_s\left[c_{pc}(T_z - T_s) + c_{pw}(T_z\omega_z - T_s\omega_s) + h_{we}(\omega_z - \omega_s)\right] \tag{2}$$

$$Q_s = m_s\left[c_{pc}(T_z - T_s) + c_{pw}\omega_s(T_z - T_s)\right] \tag{3}$$

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

Test scenarios and scenario-based settings

Various scenarios were designed in this case study to demonstrate the impact of two factors on demand flexibility: (1) demand response strategies and (2) energy consuming occupant behaviors. Additionally, it is of interest to observe if the usage of the detailed airflow model, which is often not available for a typical building simulation framework, significantly affects the conclusions. Each test scenario is represented by a unique label, which is constructed by selecting one term from each of the three categories (i.e., demand response strategy, airflow simulation model usage, and occupant behaviors), then connecting these terms with dashes. For instance, a scenario combining the "no demand response strategy", "without using the airflow model", and "thermostat adjustment" would be labeled as "noDR-noAF-T". Table 2 presents the detailed descriptions of each term used in the test scenarios. This study examines all possible combinations of these categories, with the exception of scenarios that pair "Shed" with "noAF".

Table 2 Description of terms in the test scenarios

Category	Term	Description and Settings
Demand Response Strategy	noDR	No demand response strategy - Unoccupied time cooling setpoint: 32.22 °C (90 °F) - Occupied time cooling setpoint: 25.56 °C (78 °F)
	Shed	Load shedding strategy - Follows noDR setpoints, but cooling setpoint is 26.67 °C (80 °F) during peak window (1 PM to 6 PM)
Airflow Model Usage	noAF	Without the airflow model - Same indoor environment for all occupants - Indoor environment including temperature, radiant temperature, humidity ratio are determined by EnergyPlus - Air velocity is assumed to be 0.05 m/s (0.16 ft/s)
	AF	With the airflow model - Different local indoor environment, except humidity ratio, for each occupant - Indoor environment including temperature, radiant temperature, and velocity are determined by the airflow model - Zone air humidity ratio is determined by EnergyPlus
Allowed Occupant Behaviors	T	Thermostat adjustment - Thermostat adjustment by +/- 0.56 °C (+/- 1 °F) - Thermostat resets to supervisory setting every 1 hour
	F	Personal fan usage - 0.015 kW electricity usage and heat generation per fan
	H	Personal heater usage - 1.2 kW electricity usage and heat generation per heater
	TFH	- A combination of T, F, and H

Key performance indicators

The key performance indicators used in this case study are summarized in Table 3. In the table, t_i represents a specific timestep, $Q(t_i)$ is the power demand at t_i, and N_{ts} is the total number of timesteps for a specific time period. $PMVact(t_i)$ is the thermal sensation of an occupant. $PMVact(t_i) = 1$ indicates that the occupant is feeling warm at t_i, and $PMVact(t_i) = -1$ indicates that the occupant is feeling cold at t_i. I is the indicator function, such that $I(condition) = 1$ if the condition is true, and 0 otherwise.

Table 3 A summary of key performance indicators

KPI	Description	Equation
Energy Use	The total electricity used during a period of time	$E = \sum_{1 \le i \le N_{ts}}[Q(t_i) \cdot (t_{i+1} - t_i)]$
Absolute Energy Saving	Absolute electricity saving against a reference case	$\Delta E_{abs} = E_{ref} - E$
Relative Energy Saving	Relative electricity saving against a reference case	$\Delta E_{rel} = \frac{\Delta E_{abs}}{E_{ref}}$
Flexibility Factor (Li et al. 2023)	A measure that illustrates the ability to shift the (electric) energy use from high to low price/demand periods	$FF = \frac{\sum_{t_i \in nonpeak} Q(t_i) - \sum_{t_i \in peak} Q(t_i)}{\sum_{t_i \in nonpeak} Q(t_i) + \sum_{t_i \in peak} Q(t_i)}$
Warm Discomfort Duration	The accumulated duration of an occupant feeling warm discomfort during a period of a time	$d_{warm,Occ_k} = \sum_{\substack{1 \le i \le N_{ts}, \\ PMVact(t_i)=1}} PMVact(t_i)$
Cold Discomfort Duration	The accumulated duration of an occupant feeling cold discomfort during a period of a time	$d_{cold,Occ_k} = \sum_{\substack{1 \le i \le N_{ts}, \\ PMVact(t_i)=-1}} -PMVact(t_i)$
Personal Fan Duration	The accumulated duration of a personal fan usage during a period of a time	$d_{fan,Occ_k} = \sum_{1 \le i \le N_{ts}} I(fan\ is\ on)$
Personal Heater Duration	The accumulated duration of a personal fan usage during a period of a time	$d_{heater,Occ_k} = \sum_{1 \le i \le N_{ts}} I(heater\ is\ on)$

Statistical rationale for simulation repetitions

Due to the stochastic nature of occupant behavior simulation, achieving consistent and reliable results necessitates multiple repetitions of the simulation. The randomness inherent in such simulation can lead to wide variations in outcomes, which might not be evident in a single run or even a few runs. These variations can greatly influence key performance indicators, potentially leading to skewed perceptions or misguided decisions if not adequately addressed.

Recognizing the pivotal role of repetition in capturing the inherent variability within the co-simulation framework, it becomes paramount to ascertain the number of repetitions that will offer a comprehensive understanding. Each repetition unveils a fresh scenario of occupant behaviors, offering insights into different possible outcomes. To determine the adequacy of the simulation repetitions, we employ a convergence test complemented by a stability check. The convergence test monitors the progression of cumulative metrics, such as the mean and standard deviation, as the number of repetitions grows. When these metrics stabilize, it suggests that further repetitions might have a minimal impact on the outcomes, indicating that the simulation has reached convergence.

For instance, Figure 11 showcases the cumulative mean, median, and standard deviation from 100 repetitions for the scenario “noDR-AF-TFH”. The subplots include KPIs for daily energy use and flexibility factor, accounting for both HVAC and personal equipment energy consumption. It is observed that these critical statistics stabilize within a 5 % error range after approximately 60 repetitions of the same scenario. For this case study, we opted for 100 repetitions per scenario, aiming for an error margin of less than 5 % for these vital statistics. Across the spectrum of scenarios assessed, the maximal observed discrepancies in mean, median, and standard deviation – when comparing the values at the 100th repetition to those seen in the final 10 iterations – are minimal, at 1.26 %, 1.31 %, and 3.69 %, respectively. It is concluded that all test scenarios have reached convergence.

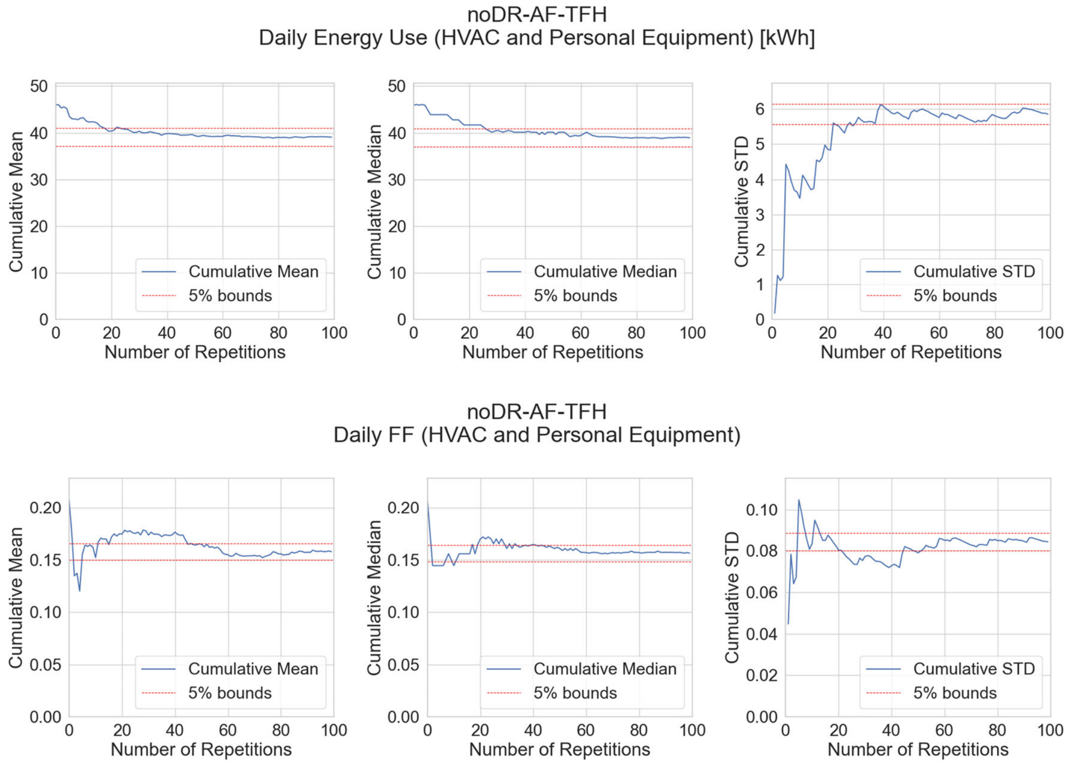

Figure 11 Cumulative Results for Scenario “noDR-AF-TFH”

Results and discussions

In this section, the results are discussed from various aspects. Firstly, we demonstrate the impact of having an airflow model within the framework. Secondly, we demonstrate the impact of different occupant behaviors and how they may affect conclusions about the demand flexibility potential. And finally, we delve deeper into each occupant’s comfort and their behaviors.

Impact of the airflow model on the simulation results

To determine the influence of the airflow model on our study, we paired and compared multiple scenarios. Each pair comprised one scenario with "AF" in its name, indicating the presence of the airflow model, and its counterpart with "noAF", indicating its absence. Notice again that for each scenario, 100 repetitions have been performed. The daily energy use, flexibility factor, and daily average discomfort durations are graphically represented in Figure 12 using boxplots. Upon initial observation, the inclusion or exclusion of the airflow model seems to exert only a marginal influence on the results.

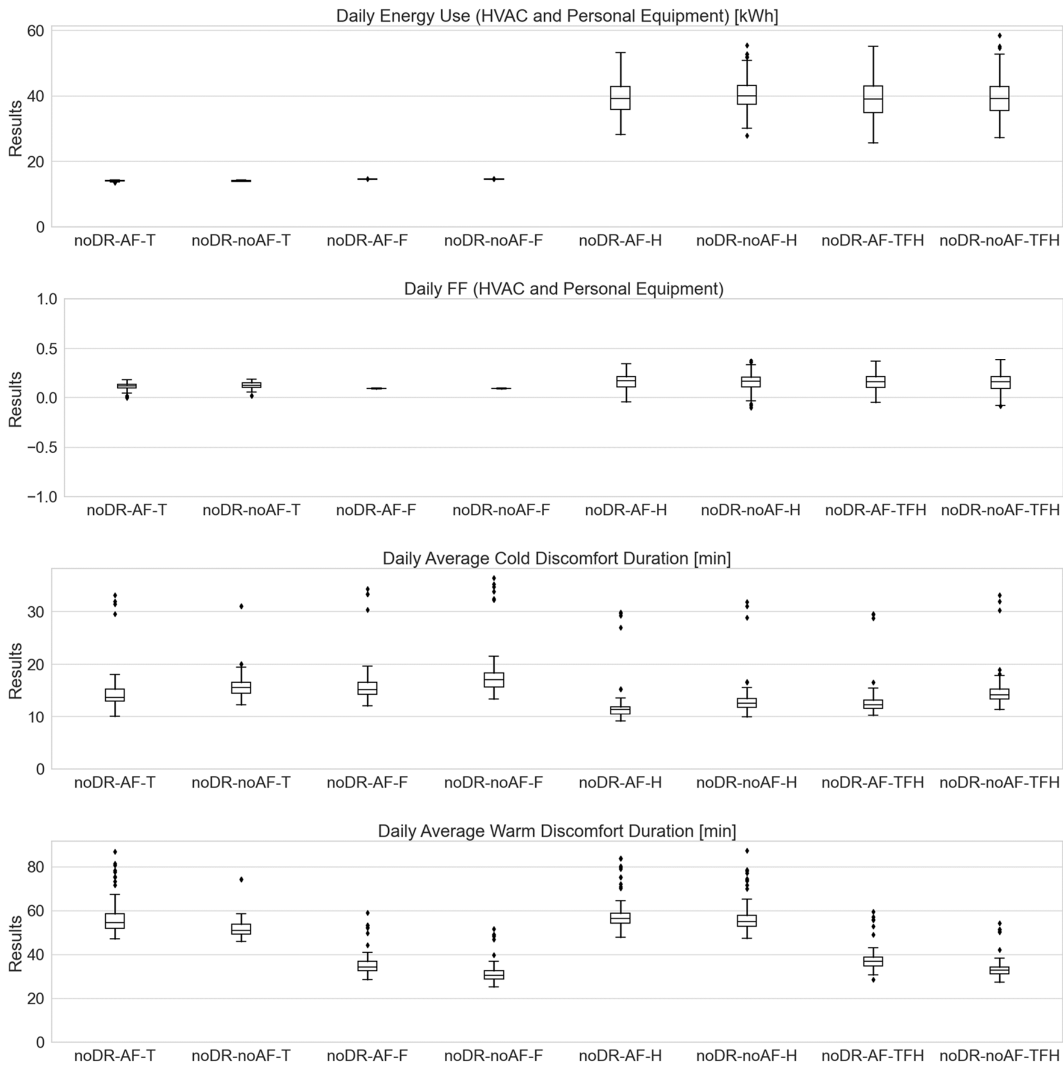

Figure 12 Boxplot Comparison of KPIs: With and Without Airflow Model

Table 4 provides a summary of the statistical differences observed due to the inclusion of the airflow model. Specifically, it presents the mean, median, first quartile (Q1), and third quartile (Q3) percentages for the daily energy use, flexibility factor, and daily average discomfort durations. Inspection of these results indicates that while there are differences in energy use, these differences remain relatively minor, with the mean and median both under 3 %. The FF showcases more pronounced percentage variations, notably a value up to 9.5% in the first quartile. However, given the inherent range of FF from -1 to 1, even though these differences might appear substantial at first glance, the actual difference is small. The maximum absolute difference is around 0.01.

Table 4 Maximum Percentage Difference of KPIs: With and Without Airflow Model

	Daily Energy Use	Flexibility Factor	Daily Average Cold Discomfort Duration	Daily Average Warm Discomfort Duration
Mean	1.7 %	7.2 %	13.3 %	17.5 %
Median	1.9 %	4.1 %	13.5 %	12.8 %
First Quartile (Q1)	4.4 %	9.5 %	13.9 %	15.4 %
Third Quartile (Q3)	1.0 %	8.9 %	13.5 %	16.4 %

To gain a more comprehensive understanding of the potential disparities between each paired distribution, we applied statistical tests. As the distributions are not typically normal, the Mann-Whitney U (MWU) test (focusing on the sample median) (Mann and Whitney 1947) and the Kolmogorov–Smirnov (KS) test (emphasizing the shape of the distribution) (Kolmogorov 1933; Smirnov 1948) were deemed appropriate. The density plot comparison between each pair is showcased in Figure 13 together with the p-values from the two statistical tests. In terms of energy-related KPIs, i.e., energy use and flexibility factor, the results suggest that for every tested scenario pair, the null hypothesis, positing identical distributions between scenarios with and without the airflow model, cannot be rejected at a 0.05 significance level, except for the comparison between “noDR-AF-T” and “noDR-noAF-T” under the KS test. In terms of the comfort related KPIs, i.e., occupant discomfort duration, the results suggest that for most of the tested pairs, the null hypothesis can be rejected at a 0.05 significance level, except for the comparison between “noDR-AF-T” and “noDR-noAF-T”.

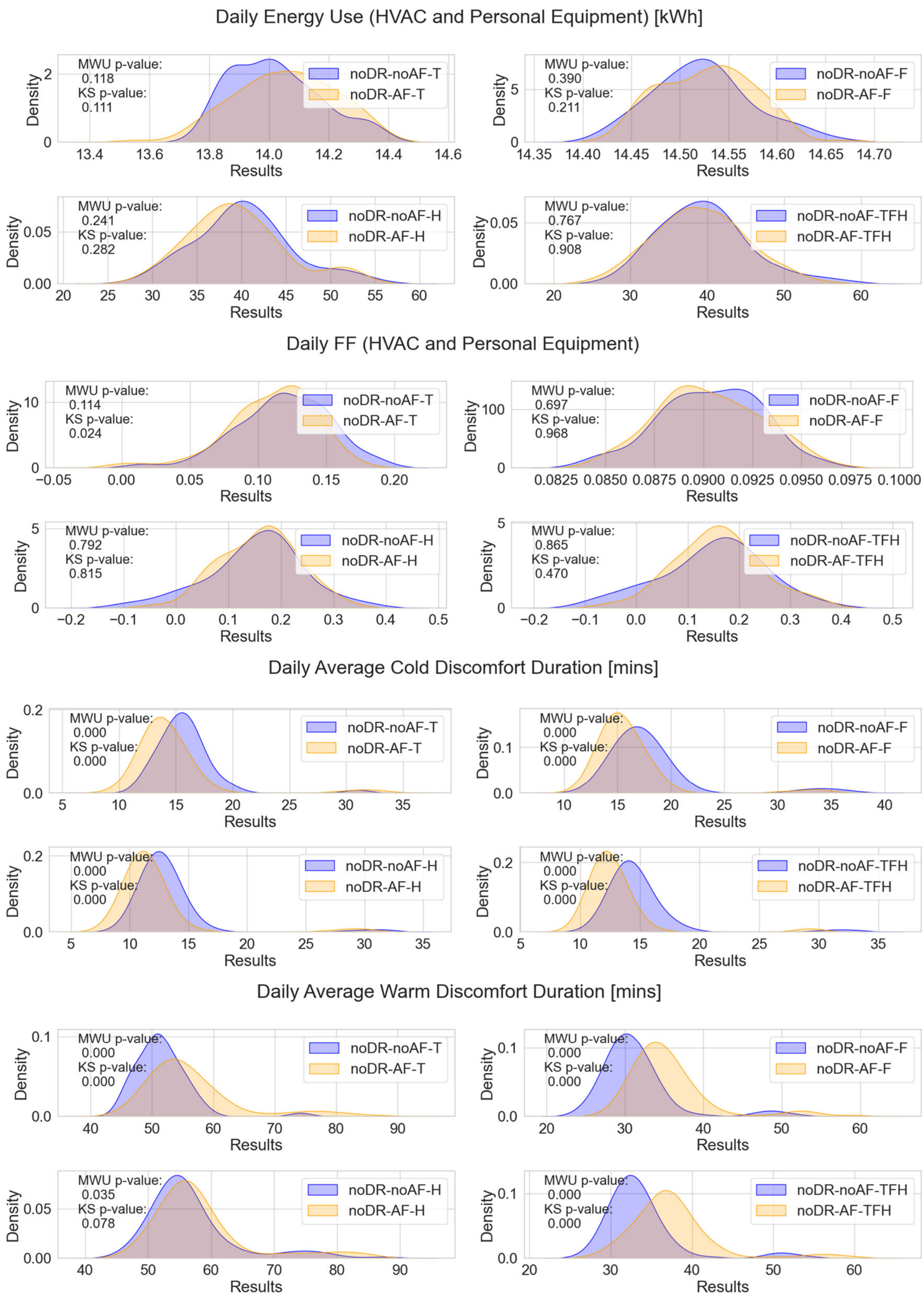

Figure 13 Density Plot Comparison of KPIs: With and Without Airflow Model

In essence, the distributions between scenarios with and without the airflow model demonstrate a high degree of consistency regarding the energy use, with only one notable exception. However, they show statistically significant differences in the distributions related to discomfort duration. When using this framework to study the demand flexibility of extensive building stocks in the future, the decision to incorporate the airflow model requires careful deliberation. At a high-level, where the main focus in on the energy efficiency and demand flexibility of the buildings, it may be more pragmatic to omit the airflow model. This recommendation is underscored by the substantial time and resources required for the airflow model's development and simulation, further emphasizing its relatively subtle differential influence.

Impact of occupant behaviors on demand flexibility

The results of the scenarios with and without a load shedding strategy are discussed in this subsection to illustrate how occupant behaviors may impact demand flexibility. Figure 14 presents the energy related KPIs, peak energy use and flexibility factor. It can be observed that, among the three energy related behaviors, the usage of the personal heater introduces the largest variation in energy use, followed by thermostat adjustment, and then the usage of the personal fan. The combination of the three behaviors further increases the variation of the distribution. These observations are consistent with the predefined simulation settings. Specifically, it is expected that the power demand from a personal heater (1.2 kW) would greatly outstrip that of a personal fan (0.015 kW). Moreover, the lesser influence of thermostat adjustments on power variability can be attributed to the simulation constraints, which only allow for a minor 0.56 °C (1 °F) modification and include an hourly reset of the thermostat setpoint to comply with the supervisory control signal. Note that this kind of restriction on the thermostat is common in commercial buildings, especially for a shared space.

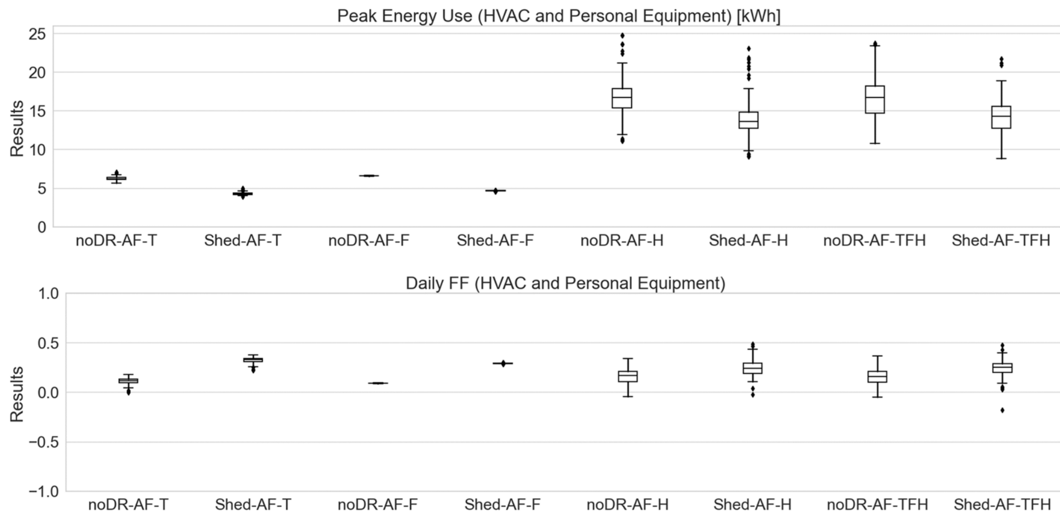

Figure 14 Boxplot Comparison of Energy Related KPIs: With and Without Load Shedding Strategy

Figure 15 and Figure 16 offer a more granular view of the uncertainties underlying our demand flexibility assessment by presenting density plots that articulate both the absolute and relative energy savings as well as the enhancement of flexibility factors associated with the load shedding strategy. Generally speaking, the load shedding strategy, which employed a 1.11 °C (2 °F) higher cooling setpoint during the peak hours, resulted in a noticeable contribution to the peak energy savings and the flexibility factor boost. The medians of the absolute and relative energy savings are about 1.9 kWh to 2.6 kWh and 14 % to 32 %, respectively, while the medians of the flexibility factor boost are about 0.08 to 0.21.

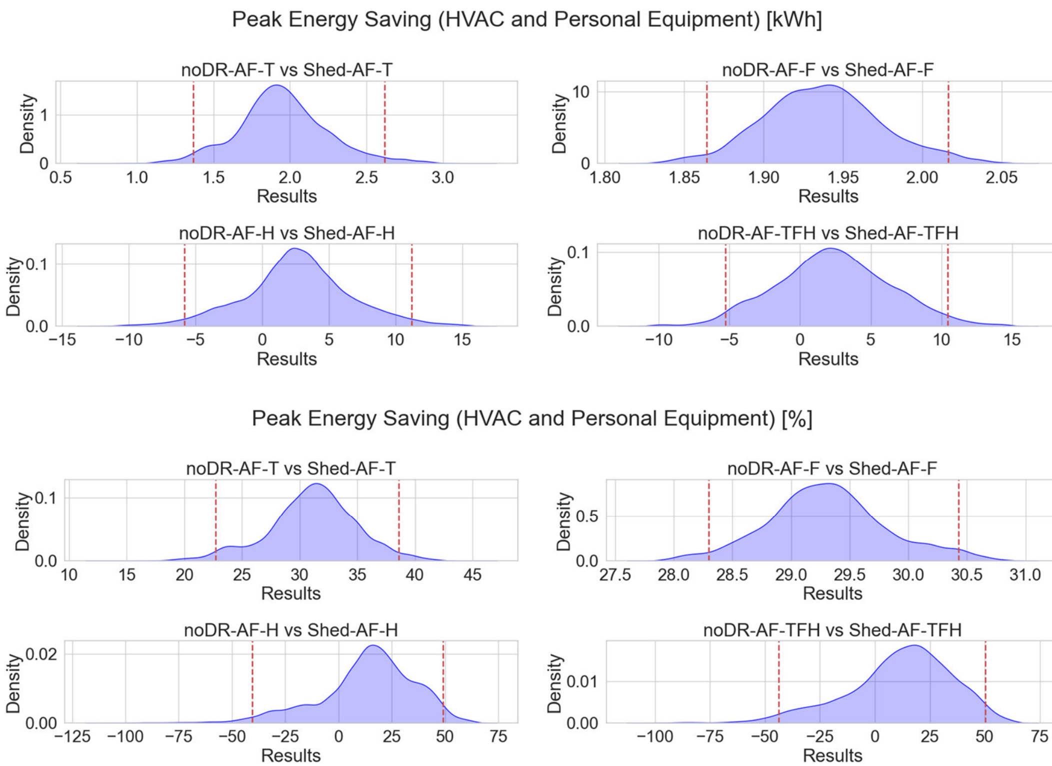

Figure 15 Density Plots for Absolute and Relative Peak Energy Saving, with Red Dashed Lines Marking the 2.5 % and 97.5 % Quartiles.

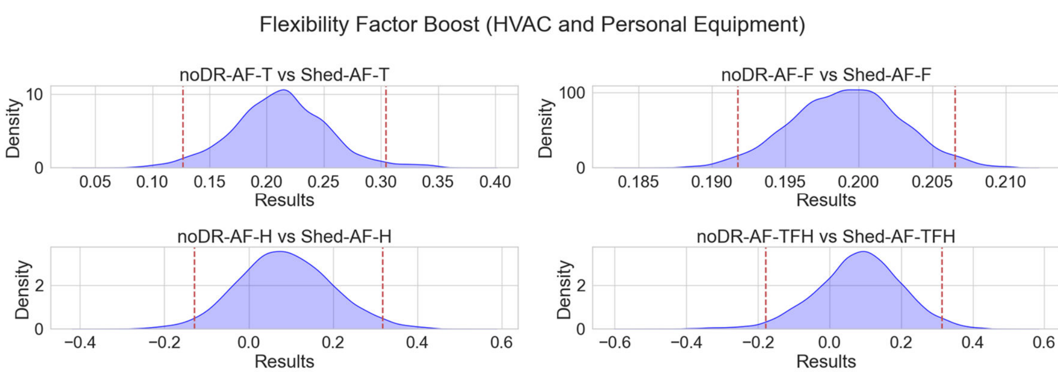

Figure 16 Density Plots for Flexibility Factor Boost, with Red Dashed Lines Marking the 2.5 % and 97.5 % Quartiles.

Nevertheless, the variance in occupant behavior introduces a layer of uncertainty in the potential energy savings. Personal fans introduce minor uncertainties, affecting the median energy savings by only 1 %. Thermostat adjustments present a wider range, altering medians by up to ±0.68 kWh and ±8.6 % for energy savings and ±0.09 for flexibility factor. Personal heaters lead to the greatest variability, with a 95 % CI of -8.43 to +8.60 kWh for absolute energy savings, -56.5 % to +33.2 % for relative energy savings, and significantly impacting the flexibility factor by ±0.23. When all three behaviors are considered, the 95 % CIs are -7.56 to +8.16 kWh for absolute energy savings, -57.9 % to +36.0 % for relative energy savings, and -0.26 to +0.22 for flexibility factor. These results highlight that occupant behaviors significantly influence energy savings and flexibility factors, but with varying degrees of impact. Personal heaters, in particular, present a notable risk due to their high variability, potentially undermining the effectiveness of demand response programs. For utility program designers, this necessitates prioritizing risk mitigation strategies specifically for electric heat devices, even in the summer season.

Variations of occupant comfort and behaviors in demand response events

In this subsection, we examine the impact of demand response events on occupant comfort and the resulting behaviors adopted to maintain their comfort. Specifically, we compare the "noDR-AF-TFH" (i.e., no demand response strategy but with airflow model and occupants are allowed to adjust thermostat, fan, and heater) and "Shed-AF-TFH" (i.e., load shedding strategy with airflow model and occupants are allowed to adjust thermostat, fan, and heater) scenarios. Figure 17 presents the discomfort duration of each occupant during the peak period; the results of some occupants are not shown because they are zero, which means that their thermal sensations are neutral during the evaluated period. The "Shed-AF-TFH" scenario results in a longer warm discomfort duration and a shorter cold discomfort duration. These changes are attributed to the elevation of the zone temperature, which is a consequence of a 1.11 °C (2 °F) increase in the cooling setpoint during the peak period.

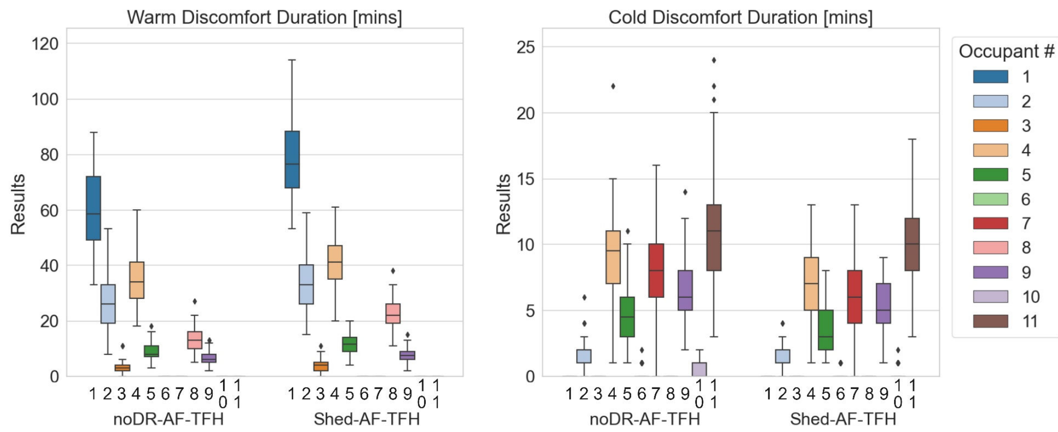

Figure 17 Occupant Discomfort Duration during the Peak Period

Figure 18 shows the personal fan and heater runtime for each occupant. Again, the results of some occupants are not visible because the runtime of their personal fan or heater is zero. The figure reveals that for certain occupants (Occupants #1, #3, #7, #8 and #11), relaxing the zone cooling setpoint during the peak period does not substantially alter their behavior despite the impact on their comfort (as shown in Figure 17). These occupants share similar attributes as they all tolerate extreme ASH votes, either cold (-3) or hot (+3). According to Figure 9, these occupants do not experience one extreme of discomfort at any PMV value. Consequently, once they activate personal equipment, they do not engage in the opposite action (turning it off) until they depart the office, as they never feel discomfort on the contrasting thermal extreme. This leads to prolonged personal equipment runtime among these occupants, with runtime being more dependent on their office presence than on thermal comfort. Figure 19 corroborates this finding by presenting the Spearman correlation coefficient between personal equipment runtime and occupant presence, with significant coefficients for Occupants #1, #3, #7, #8, and #11. Although one may argue that many occupants would turn off their personal heater/fan once their thermal comfort falls within an acceptable range, our simulations are consistent with real-world behaviors observed in office spaces around us. Similar to the simulated occupants mentioned above, we have observed that some individuals never turn off their personal devices until they leave the office.

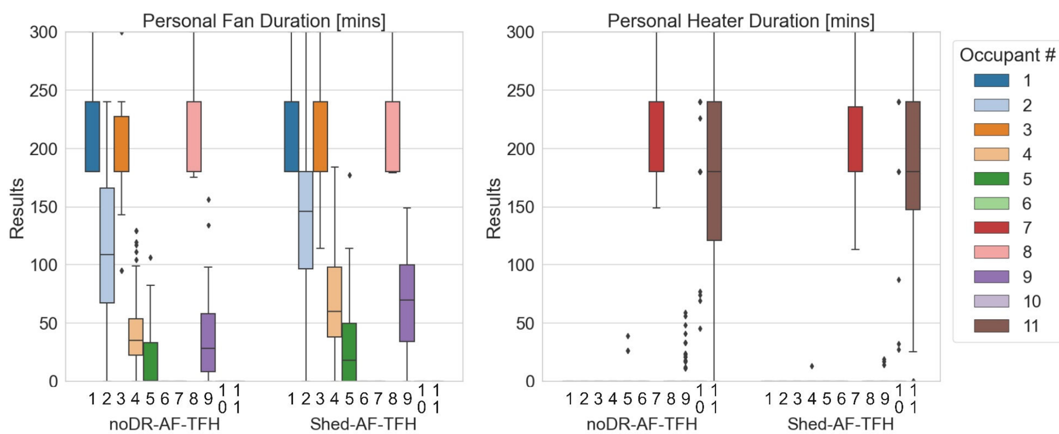

Figure 18 Occupant Personal Equipment Runtime during the Peak Period

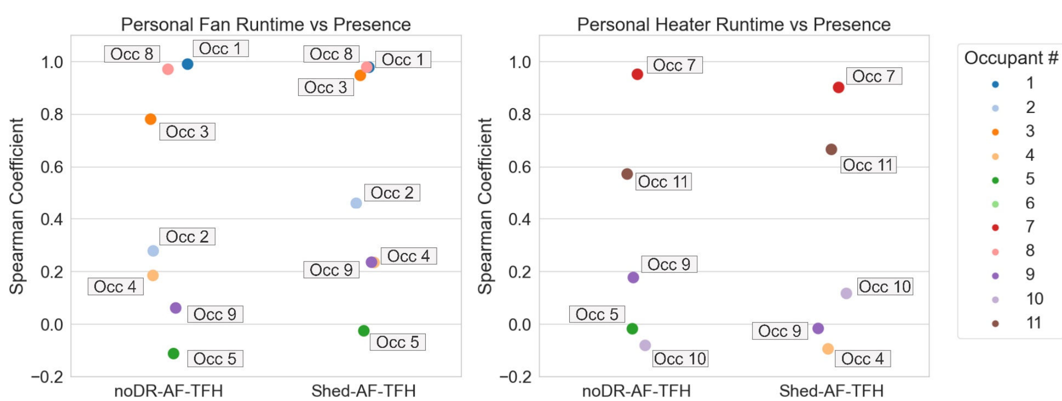

Figure 19 Spearman Correlation Coefficient between the Personal Equipment Runtime and Occupant Presence during the Peak Period

Additionally, as indicated in Figure 18, behavioral constraints play a notable role in behavior simulation. For example, Occupants #5 and #9 share an identical thermal acceptability range of [-1,2]. Their warm discomfort durations are comparable as depicted in Figure 17. However, Occupant #5, who has a *care energy use* constraint, exhibits a shorter duration of personal fan use compared to Occupant #9.

Conclusion

This paper has presented an advanced co-simulation framework designed to evaluate the interplay between occupant behaviors and demand flexibility in commercial buildings. Through the integration of a comprehensive suite of models, including HVAC system, building zone load, indoor airflow, supervisory control, and occupant comfort and behavior, this research provides a new lens through which to view the complexities of energy use and occupant dynamics within typical commercial buildings.

In our case study using a typical small office building model, we have identified pivotal insights regarding the framework's components. The findings indicate that the direct impact of detailed indoor airflow modeling on energy consumption is marginal. This revelation suggests that for expansive studies where the primary focus is on energy efficiency and demand flexibility across building stocks, the benefits of excluding the airflow model may outweigh its detailed contributions, given the high computational and temporal demands of its implementation. Therefore, strategic deliberations are necessary when deciding whether to integrate airflow modeling in large-scale energy assessments.

The study has also highlighted the significant influence occupant behavior has on demand flexibility. It was demonstrated that a 1.11 °C (2 °F) increase in cooling setpoint could yield median relative energy savings between 14 % and 32 %, but the uncertainty associated with these savings, due to the stochastic nature of occupant behaviors, ranged widely from 1 % to 57.9 %. Put simply, this means the actual reduction in demand could be significantly lower than anticipated, or in some cases, it might even lead to increased energy usage instead of savings. This variability underscores the importance of considering occupant behavior in demand flexibility studies to ensure that energy savings are both substantial and predictable.

Limitations of this research should be noted. The simulation settings were premised on typical occupant behaviors within office buildings, potentially not mirroring those actively engaged in DR programs who may modify their behaviors in response to incentives. Additionally, the OBM presupposes an instantaneous response to thermal discomfort. A model that accounts for the accumulation of discomfort over time might better reflect actual human behavior, especially given the observed discrepancy between short-term discomfort and long personal equipment runtimes in our case study. However, integrating such a temporal dimension into discomfort response models would present a challenge in determining accurate parameters.

In conclusion, the simulation framework developed through this study serves as a valuable tool for evaluating demand flexibility in commercial buildings, with a focus on occupant comfort and behaviors. Future research could build upon this work by conducting broader and more comprehensive simulations that incorporate a diverse array of buildings, climate conditions, control strategies, and occupant characteristics in demand flexibility assessments. Furthermore, the framework has the potential to facilitate the creation of data sets for developing data-driven, occupant-centric control strategies, advancing the field toward more personalized energy management.

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Declaration of competing interests

The authors report there are no competing interests to declare.

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