Energy Saving Potentials of Integrating Personal Thermal Comfort Models for Control of Building Systems

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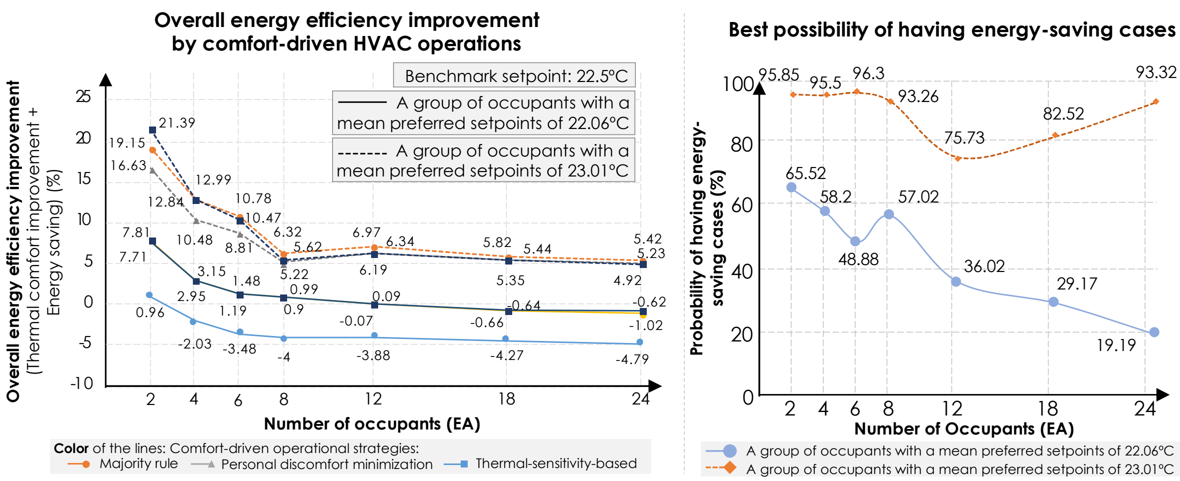
Graphical Abstract



Abstract

Research studies provided evidence on the energy efficiency of integrating personal thermal comfort profiles into the control loop of Heating, Ventilation, and Air-Conditioning (HVAC) systems (i.e., comfort-driven control). However, some conflicting cases with increased energy consumption were also reported. Addressing the limited and focused nature of those demonstrations, in this study, we have presented a comprehensive assessment of the *energy efficiency* implications of comfort-driven control to (i) understand the impact of a wide range of contextual factors and their combinatorial effect and (ii) identify the operational conditions that benefit from personal comfort integration. In doing so, we have proposed an agent-based modeling framework, coupled with EnergyPlus simulations. We considered five potentially influential parameters and their combinatorial arrangements including occupants' thermal comfort characteristics, diverse multioccupancy scenarios, number of occupants in thermal zones, control strategies, and climate. We identified the most influencing factor to be the variations across occupants' thermal comfort characteristics - reflected in probabilistic models of personal thermal comfort - followed by the number of occupants that share a thermal zone, and the control strategy in driving the collective setpoint in a zone. In thermal zones, shared by fewer than six occupants, we observed high potentials for energy efficiency gain (between 11% to 21% maximum gain) from comfort-driven control. Accounting for a wide range of personal comfort profiles, we have also demonstrated probabilistic bounds of energy saving potentials from comfort-driven control with a mean of 70-80% chance of energy saving in multioccupancy scenarios in a building with multiple thermal zones.

Keywords: HVAC; Personal Thermal Comfort; Thermal Comfort Models; Human-in-the-loop; Energy Efficiency; Thermal Comfort Sensitivity; Multioccupancy

1. Introduction

Comfort-driven control of Heating, Ventilation, and Air-Conditioning (HVAC) systems, which accounts for feedback from personal thermal comfort models or profiles in the control loop, has gained attention as one of the advanced control techniques for higher energy efficiency. Through our exhaustive literature synthesis study [1], we have observed that across the studies that demonstrated the effectiveness of comfort-driven HVAC control, a median value of 20% of energy saving potentials have been reported. Since such outcomes came along with, at least, maintaining the level of user comfort, energy efficiency of HVAC systems has been improved by providing comfort with minimum energy use. When it comes to energy use, shifting a temperature setpoint (hereinafter a setpoint) according to users' preferences does not guarantee energy saving, and the energy efficiency outcome could be affected by several contextual factors. We have further observed that in theses analyses, studies have investigated the impact of different potentially influential factors, such as individual thermal comfort characteristics, the number of occupants in a thermal zone, the configuration of thermal zones, the control strategy, and climate. Although previous studies have investigated energy efficiency, these studies have commonly focused on control framework development and looked at limited number of factors and contextual conditions. Therefore, a comprehensive understanding of the effect and potentials of comfort-driven control has not been presented in prior studies to provide an insight on its efficacy under different contextual circumstances.

Although studies have demonstrated energy use reduction, in certain cases, reported in the literature, the use of comfort-driven HVAC control have brought about increases in energy consumption. [2], through a field study of single-occupancy spaces, observed an increase in energy consumption for a subspace by using a comfort-driven control strategy. This was associated with the occupants' thermal preferences that required additional conditioning load, compared to the use of conventional setpoint. Another similar example can be found in the study by [3], which evaluated the energy implication of the comfort-driven HVAC operation in multiple climate zones at different building scales through simulation. They have shown different levels of energy savings – an average of 2.1% of energy reduction compared to a fixed building level setpoint of 22.5 °C and 6.1% of energy increase compared to the Department of Energy (DOE) reference setpoint of 24.0 °C. Furthermore, as observed in our literature assessment [1], majority of the studies on comfort-driven HVAC control have considered the warm Mediterranean climate, where cooling is the dominant conditioning mode for most of the year. In other words, due to the prevalence of overcooling in this climate, energy saving could potentially be seen when applying comfort-driven HVAC control. Therefore, understanding the impact of diversity in personal thermal comfort profiles is critical in identifying the energy efficiency bounds of comfort-driven control.

In addition, the selection of a specific comfort-driven HVAC control strategy (i.e., the method for integrating personal thermal comfort models into the control loop) can play a part in the observed performance of the HVAC systems. As noted, different studies have proposed different methods for combining the personal comfort feedbacks into a collective control signal. [4] showed that personal comfort deviation minimization could result in improved energy efficiency and [5] further demonstrated that additional energy saving could be achieved by also accounting for energy use aspect in a multi-objective optimization process. However, in the latter study, they have shown increased energy use by 7.3% in one the thermal zone (due to occupants' preferences), while the other zones had additional reduction in energy use by -18.8% and -32.3%. In other words, studies have shown that the implementation of different comfort-driven control strategies could lead to diverse results based on contextual conditions. Different studies have proposed a diverse set of comfort-driven control strategies including accounting for majority vote [6], discomfort minimization [4], multi-objective optimization of energy and comfort [5], and personal thermal comfort sensitivity [7, 8]. These strategies could result in different outcomes in terms of energy use and comfort satisfaction depending on the contextual conditions.

Moreover, the impact of thermal zone scale on comfort-driven HVAC control is a less explored factor. When it comes to occupancy-driven HVAC control, another major modality of Human-In-The-Loop (HITL) HVAC control [1], studies have demonstrated the usefulness of having multiple thermal zones, rather than a single thermal zone, to adapt to the sporadic dynamics of occupancy [9, 10]. However, according to our extensive literature analyses [1], the impact of occupancy density in thermal zones and the resolution of thermal zones (i.e., the number of thermal zones in a building) on the efficiency of comfort-driven control strategies has been rarely investigated.

Accordingly, in spite of the valuable demonstrations of potentials in comfort-driven HVAC control, understanding the energy use implications of comfort-driven HVAC control strategies calls for further investigations. Therefore, we have explored the impact of the aforementioned factors in driving the range of energy efficiency of comfort-driven HVAC control. As noted, energy efficiency refers to the effective (i.e., optimum) use of energy consumption for achieving thermal comfort satisfaction. In doing so, different combinations of these factors have been accounted for in this study to provide a comprehensive assessment on their impacts. Also, energy implications of an control strategy that we introduced in our previous studies [7, 8, 11] has not been explored. This approach enhances the collective thermal comfort in a multi-occupancy thermal zone by leveraging thermal comfort sensitivity (i.e., individual responses to temperature variations) compared to the strategies that focus only on occupants' preferred temperatures.

Therefore, through this study, the following research questions have been explored:

- What is the impact of occupant diversity, building, and climate features on the energy use of comfort-driven HVAC control?
- What is the impact of comfort-driven control strategies on energy efficiency?
- What is the probability of energy saving given the diversity in personal comfort preferences?
- Under what contextual conditions, the use of personal comfort profiles shows higher efficacy?

The first question aimed to investigate the impact of (1) occupants' thermal-comfort-related features, (2) number of occupants in thermal zones, (3) number of thermal zones in a building, (4) comfort-driven control strategy and (5) climate. The second question was investigated to provide insight into the pros and cons of each comfort-driven control strategy from different perspectives of energy efficiency. The third question seeks to identify the energy efficient circumstances given the uncertainty of diverse thermal comfort preferences. Lastly, through the investigations of the first three questions, the fourth question gets answered.

The rest of this paper is structured as follows. Section 2 discusses the research background on advances of comfort-driven HVAC control for energy efficiency enhancement. Section 3 explains the methodology of the study. Specifically, we have elaborated on the Agent-Based Model (ABM) that replicates the mechanism of comfort-driven HVAC control and its use, coupled with an EnergyPlus prototype of an office model developed by Pacific Northwest National Laboratory (PNNL). Section 4 explains the results and findings of the study. Section 5 presents the limitations of this study to provide the ground for further discussions and research. Lastly in Section 6, the conclusion and future directions of this study are provided.

2. Comfort-driven HVAC Operation Paradigm

In conventional control of HVAC systems, thermostats play a central role in acquiring occupants' feedback in the control logic of HVAC systems. However, their unsuitable locations and unclear authority over the devices often impede Human-Building Interaction (HBI) [12, 13]. These circumstances lead to underwhelming performance of indoor conditioning systems despite their significant role in the total energy consumption of building systems and occupants' thermal comfort [14]. Several studies have shown that the office occupants, who often face these limitations [12, 13], reported lower thermal satisfaction, compared to the residential occupants [13, 15]. Therefore, research efforts sought to enable the integration of contextual thermal comfort information into the control of HVAC systems. Starting from web-based surveys [16], which are highly accessible to users, studies have proposed different methods from using mobile devices [17, 18] to physiological sensing [19-21] in order to empower enhanced HBI. These methods have paved the way for collecting individual users' feedback on the environment in the form of thermal perceptions or preferences as opposed to desired temperature values in the legacy system (as thermostat settings). In this new paradigm, an indoor environment could be evaluated by using the personal thermal comfort models developed by using the thermal votes of individual users and other contextual environmental and human-related factors (i.e., personalized thermal comfort profiles or models) [22]. These models could provide information such as the probability distribution of thermal comfort associated with different contextual conditions.

The availability of users' thermal comfort feedback and their personalized profiles has enabled the comfort-driven HVAC control – that is, a system could adjust the indoor conditions based on actual and individual users' thermal preferences and sensitivities. Through simulation and field study evaluations, previous studies have shown the elevated performance of comfort-driven HVAC systems [2, 4, 5, 23, 24]. These studies have proposed specific strategies and frameworks for integrating the personal comfort models into the control loops and evaluated their performance. The findings show that such a control paradigm not only improves users' comfort, but also prevents over-conditioning beyond their thermal comfort zones.

In the course of implementing this strategy, one of the inevitable questions is *which setpoint should be chosen in multi-occupancy spaces to achieve collectively comfortable environments*. The use of thermal zones (a number of rooms conditioned simultaneously by an HVAC unit) in current buildings reduces the occupancy density in multi-occupancy spaces. As the number of thermal zones decreases addressing the conflict between different occupants could be more challenging. As an example, most of residential buildings are designed as single thermal zones [25]. In these cases, diverse thermal preferences and responses to ambient temperatures from different occupants could complicate the choice of a setpoint [26]. Accordingly, studies have introduced several strategies to generate collectively comfortable conditions as follows:

- *Majority rule* – adjusting a setpoint based on the majority vote [6],
- *Error minimization* – identifying a setpoint where the total gap (i.e., errors) between setpoints and desired temperatures is minimized [4, 27],
- *Collective learning* – updating the PMV model based on collective thermal comfort feedback [23].
- *Thermal-comfort-sensitivity-based optimization* – benefiting from each user's thermal sensitivity in addition to thermal preferences to find an optimal setpoint [8, 11].

These control strategies were shown to have potentials for improving users' thermal comfort as well as energy efficiency. In an example study, the majority rule strategy was shown to consume 20% less energy while maintaining users' thermal comfort, compared to the conventional default setpoint setting [6]. The error minimization strategy was shown to result in 39% reduction in average daily air flow (i.e., energy saving) while keeping the temperature close to users' thermal preferences [4]. The collective learning strategy, proposed by [23], not only saved 10.1% of energy but also improved the overall thermal comfort.

However, despite the promising results in these studies, each study has used different benchmarks as well as different contexts in their studies. Such single demonstrations limit the comprehensive understanding of the viability of comfort-driven control strategy. Therefore, as noted, an in-depth understanding of the differences between these strategies calls for further assessment under the same context and circumstances. In a recent study, [28] have shown the energy implications of a comfort-driven strategy. In this study, the setpoint selection was carried out by summing all occupants' thermal comfort profiles in a thermal zone and selecting the setpoint with the maximum probability, similar to [5]. Nonetheless, the impact of having diverse number of occupants (with varied preferences) and thermal zones has not been addressed. Therefore, this study contributes to the understanding of the efficacy of comfort-driven control strategies by (i) investigating the energy efficiency implications derived from diverse comfort-driven HVAC control strategies under different contextual conditions as elaborated above, and (ii) quantifying the energy efficiency bounds given the uncertainty of occupants' thermal comfort preferences and contextual conditions.

3. Methodology

3.1. Overall framework

The overall framework of this study is presented in Figure 1. In general, the framework is a combination of (1) an Agent-Based Model (ABM) for interaction of users with the environment and (2) a building energy use simulation platform (i.e., EnergyPlus [29]). Even though EnergyPlus, developed by the U.S. DOE, is a powerful tool, it has limited capabilities in accounting for occupant behavioral dynamics and characteristics [30-33]. Hence, to incorporate individuals' thermal comfort features and implement comfort-driven HVAC control according to dynamic thermal comfort demands, we have developed the ABM module in the framework. This module enables us to reflect the dynamics of occupants and their interactions with the indoor environment as agents, which have their own objectives, behaviors, and properties. Accordingly, through the use of ABM, a diverse set of scenarios could be created and tested. The specific application of the proposed ABM model, in the context of this study, is the identification of setpoints according to personal thermal comfort models and different comfort-driven control strategies. Then, setpoint information is fed into the energy simulation environment to assess and quantify the energy implications of HVAC control. As noted, we have identified different parameters that could potentially affect the energy use of building systems. Accordingly, the framework, in Figure 1, depicts the components, the required data, and the flow of the information between different components. In the following subsections, we have described the specifics of each component and the required data.

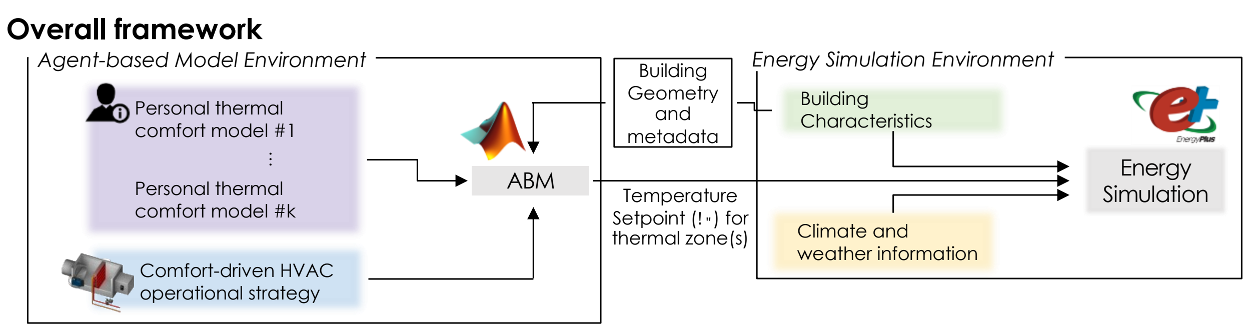


Figure 1. Overall simulation framework — coupled ABM and EnergyPlus Models

3.2. Agent-based modeling component

3.2.1. General mechanism

The developed ABM replicates the mechanism of comfort-driven HVAC control as reflected in Figure 2. This mechanism includes multiple agents, including human, Occupant Voting System (OVS), and HVAC agents that communicate with each other to seek an optimal setpoint that maximizes human agents' collective thermal comfort. Specifically, human agents report their perceptions about thermal environments as thermal votes to OVS agents, and OVS agents generate individual thermal comfort profiles. Then, the HVAC agent optimizes the setpoint by requesting feedback from OVS agents. The HVAC agent could use alternative control strategies for setpoint optimization. Each thermal zone has agents that interact to derive the operational setpoint of that specific zone independent of other zones. Given the simulation nature of our study, in the ABM simulations, we have assumed that the conditioned air is equally distributed in a space.

3.2.2. Human agents' thermal vote creation

To understand the impact of the diversity in individual preferences and the corresponding uncertainty in driving the energy use, we have created diverse sets of thermal comfort profiles (representing human agents) to be leveraged in various scenarios of multioccupancy. To this end, we have leveraged actual thermal comfort profiles reported by [34] and developed a data-driven process of thermal comfort profiling. This process is composed of three steps as reflected in Figure 3. [34], upon a comprehensive field measurement of personal thermal comfort feedback (collecting numerous thermal votes for several months), employed a multinomial logistic regression model to distinguish uncomfortably cool, comfortable, and uncomfortably warm states (blue, black, and red lines in Figure 3, respectively). Using this approach, they have provided six personal thermal comfort profiles as the outcome of their study. Given that these profiles were developed using a large number of votes and across different days of field measurements, we leveraged these profiles for creating simulated personal comfort profiles, representing a larger number of profiles [7]. To this end, we introduced two random variables to sample from the individual comfort profiles by picking (1) a random temperature within the range from 20 to 30°C (T_i) and (2) a thermal vote (V_i) by selecting a random probability in [0,1] that determines the thermal comfort perception state of the occupant from the distributions (reflected in the details of Figure 3). Through repeated sampling, we created datasets of (T_i, V_i) pairs for each occupant. In our study, we assumed that each human agent reports 50 thermal votes to the OVS agents (i.e., the OVS system sends the same number of requests to individuals), representing the average number employed for personalized comfort profiles in the previous studies (e.g., [4, 35, 36]). Depending on user dedication, the number of thermal votes for profile development could vary in reality, but we used the same number of thermal votes to minimize the impact of independent variables in our analyses. Although thermal comfort perception could vary depending on the context [37] (for example across different seasons), given the purpose of the study, we assumed that thermal comfort profiles remain constant. This is a realistic assumption given that we conducted our evaluations for a summer season and used a probabilistic representation for thermal comfort profile learning.

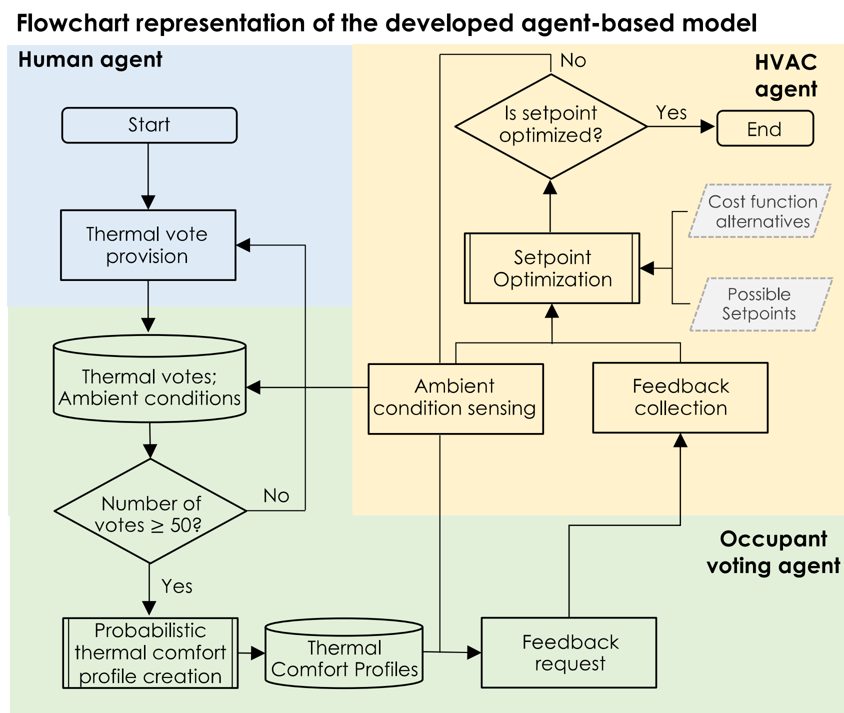


Figure 2. Mechanisms of interactions and optimization in the developed agent-based model

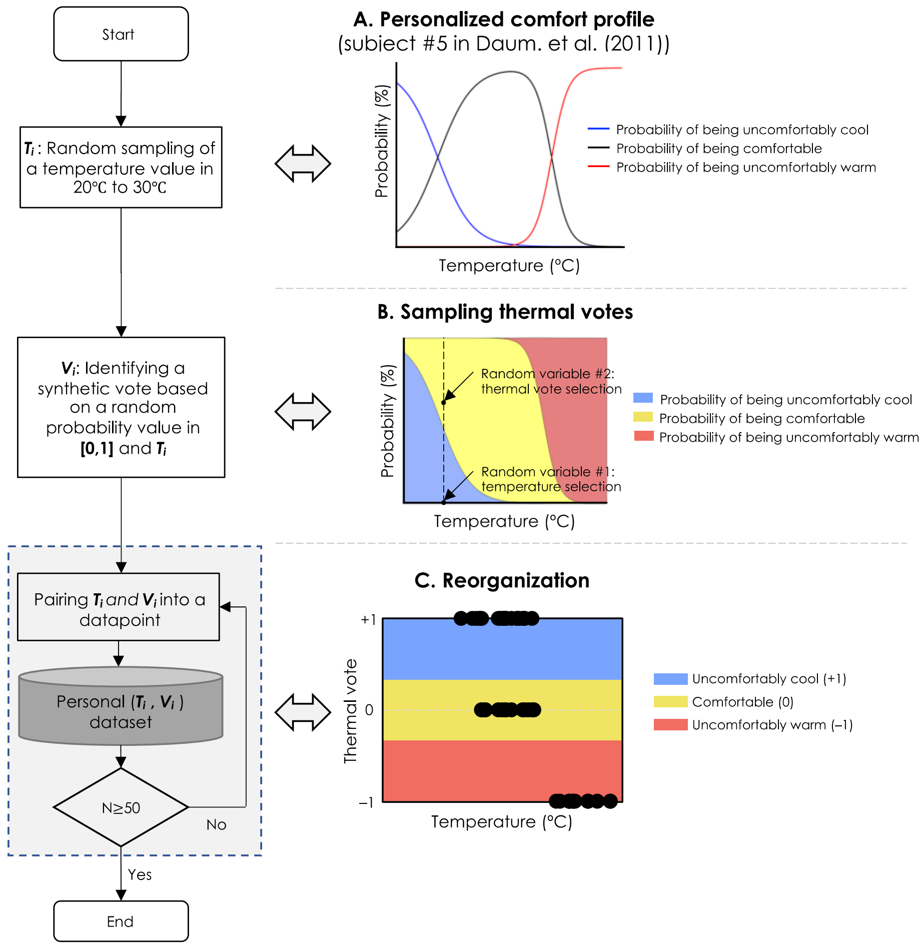


Figure 3. Process of synthesizing thermal comfort votes and creating (temperature, comfort vote) datasets to represent different human agents' comfort profiles

3.2.3. Comfort profiling process by Occupant Voting System (OVS) agents

After compiling thermal votes from human agents (i.e., (T_i, V_i) pairs), the OVS agents proceed with the profiling process using the Bayesian network modeling method in [36]. This method generates a joint probability distribution that identifies the probabilities of being comfortable leveraging reported uncomfortably cool, uncomfortably warm, and comfortable votes. With the normality assumption, the normal distributions of data points for each one of the triple thermal perception vote types, are jointly represented as in Equation (1):

$$P(oc|t) = \frac{P(c|t)}{P(uc|t) + P(c|t) + P(uw|t)} \tag{1}$$

where $P(oc|t)$ indicates the probability distribution of the overall comfort for a given temperature, $P(uc|t)$ refers to the probability distribution of uncomfortably cool votes, $P(c|t)$ is the probability distribution of comfortable votes, and $P(uw|t)$ is the probability distribution of uncomfortably warm votes. Each individual probability distributions uses a Gaussian distribution defined by the average and the standard deviation of corresponding temperatures for the votes. Figure 4 presents an example illustration for creating a personal thermal comfort profile accounting for different classes of thermal comfort perceptions. In other words, this profile shows how this human agent changes its thermal satisfaction with respect to variations in air temperature. In addition to identifying the ideal temperature for each human agent, these profiles show the rate of change in thermal satisfaction with respect to cooler or warmer conditions – thermal comfort sensitivity. More details of this Bayesian network modeling method has been provided in our previous study [7].

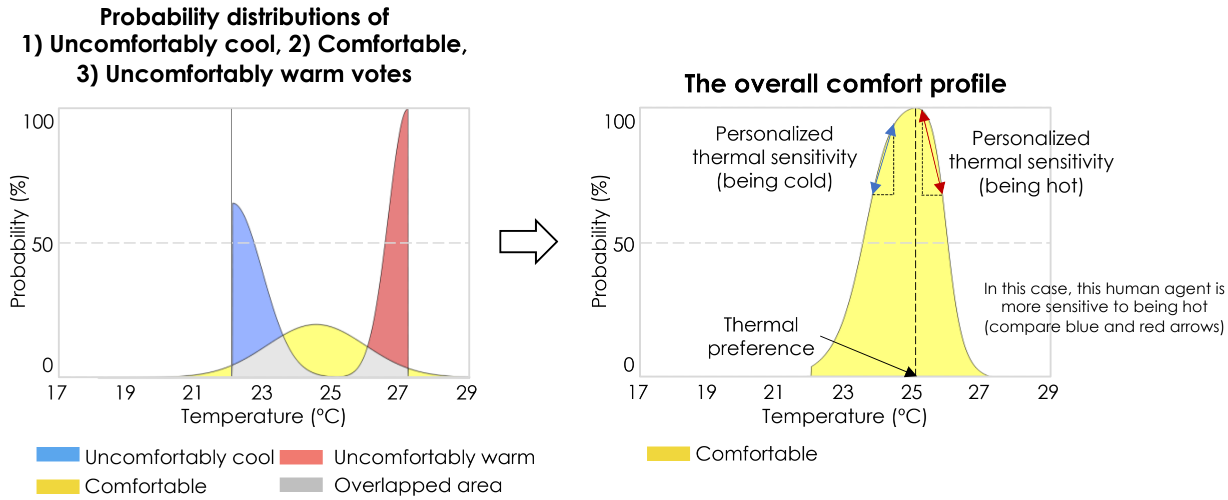


Figure 4. Process of creating a personalized comfort profile and its properties

After identifying each human agent's thermal comfort characteristics, such as preferred temperatures (personal comfort zone) or thermal comfort sensitivity, the OVS agent communicates this information to the HVAC agent. In each multioccupancy thermal zone, OVS agent receives a temperature setpoint from HVAC agent and queries the comfort profiles of human agents to send their reaction back to the HVAC agent for optimization. The reaction will be in the form of comfort satisfaction probability and the rate of change in satisfaction probability (for one control strategy).

3.2.4. HVAC agent's control strategy

The HVAC agent utilizes an control strategy to seek an optimal setpoint by communicating with OVS agents with the aim of maximizing human agents' comfort. Figure 5 presents the details of this process and its associated steps. Starting from the temperature setback (i.e., a setpoint during vacancy to curtail the conditioning load; hereinafter a setback), the HVAC agent evaluates each operable setpoint utilizing a cost function to determine the setpoint. The cost functions vary depending on the HVAC control strategies – i.e., the approaches that are used to integrate individual personal comfort models for collective conditioning of a thermal zone. The cost functions are as presented in Table 1.

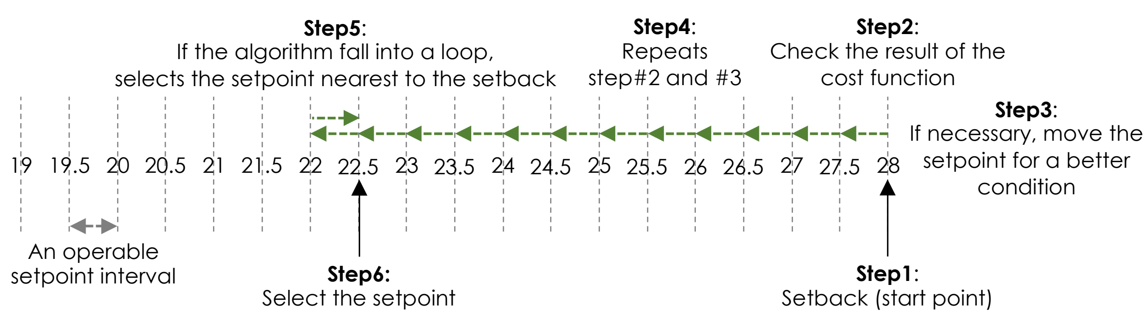


Figure 5. The setpoint selection process using different control strategies

In this study, the following control strategies were evaluated:

(1) using majority thermal votes (majority rule),
(2) minimizing collective thermal comfort deviation for a thermal zone (error minimization)

(3) thermal-comfort-sensitivity-based optimization

The collective learning, presented in Section 2, has been excluded as this approach does not account for individuals' characteristics. Each strategy requires a different type of feedback from OVS agents as shown in Figure 6. In the first approach, each OVS agent submits a vote among warmer (+1), no change (0) and cooler (-1) options for a given temperature setpoint. For each potential setpoint, the HVAC agent sums all the thermal votes and proceeds to change the setpoint if the sum has either a positive or negative value. In the second approach, the HVAC agent calculates the sum of the deviations between thermal preferences (i.e., the temperature that offers 100% of satisfaction to a human agent) and each potential setpoint. Then, it selects the setpoint that has the minimum collective error. In the third strategy, the HVAC agent aims to maximize the collective probability of being comfortable for all human agents by comparing each human agent's thermal comfort sensitivity. Thermal sensitivity measures the probability of thermal satisfaction change by moving from one setpoint to an adjacent one as shown in Figure 6. This strategy accounts for thermal votes in the first step to check the range of setpoints that results in a neutral feedback from occupants as a group (i.e., sum of votes from all occupants is zero) - where thermal comfort sensitivity comes to play in optimization. Then, it evaluates each human agent's thermal comfort sensitivity in the range of collective neutral votes to prioritize the human agents with higher sensitivities - i.e., to avoid higher drops in individual comfort due to change in the setpoint.

Table 1. Feedback type and cost function for different Each comfort-driven control strategies

#	Control strategy	Feedback type	Cost function
1	Using majority thermal vote	Thermal vote: warmer (+1), no change (0), cooler (–1).	$\sum Thermal\ votes$
2	Optimizing collective thermal comfort deviation (error)	Error: deviation between desired and operable setpoints (e.g., 2.4°C).	$argmin(\sum Error)$
3	Using thermal comfort sensitivity	Thermal vote and rate of change in probability of being comfortable (PC)	$argmax\left(\sum PC\right)$ $if\ sum\ of\ thermal\ vote\ is\ zero$

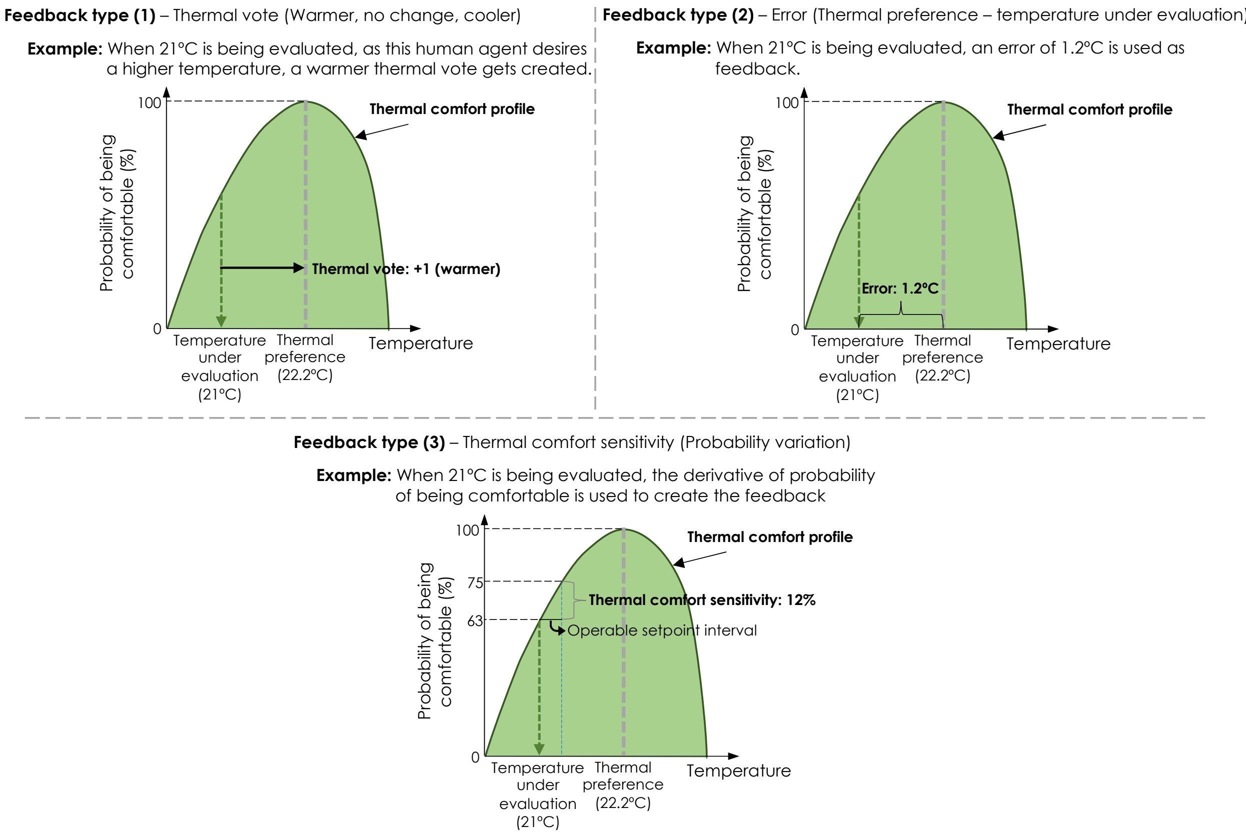


Figure 6. Calculation of feedback type in each control strategy

More details and the pseudo code of each control strategy could be found in our previous study [7]. In addition, as shown in [7], having a high resolution operational setpoint interval (e.g., 0.1°C) could aid in creating a slightly better collectively acceptable environment, but the impact is marginal. Therefore, we chose 0.5°C as the operable setpoint interval, which is practical and flexible for users. This ABM for HBI has been used in cooperation with a building energy simulation model, which has been elaborated in the following subsection.

3.3. Energy simulation component

3.3.1. Prototype building model

In order to evaluate the energy implications of comfort-driven control for different parameter combinations, the ABM simulates the HBIs and passes the information to energy simulation model. To do so, we have chosen to use the prototype of a small office building developed by Pacific Northwest National Lab (PNNL). This model has the total floor area of 511 m^2 in one floor with windows fractions of 24.4% for south and 19.8% for the other three orientations evenly distributed around the building. The heating type of this model is air-source heat pump with gas furnace as back up and the cooling type is air-source heat pump with maximum, and minimum supply air temperature of 40ºC and 13.8ºC, respectively. The major energy source is electricity. Further details of the model are provided in [38]. This model suits our objectives considering that this model (1) covers all 8 U.S. climate zones and (2) has five thermal zones with different sizes and occupancy capacities (as shown and described in Figure 7 and Table 2, respectively) and facilitates our analyses for diverse set of scenarios. Specifically, we could simulate different conditions by changing the number of occupants, the number of thermal zones, and setting the climate conditions.

Table 2. Details of thermal zones in the office building model for our study taken from [38]

Thermal zone name	Area (m^2)	Volume (m^3)	Occupancy capacity
Core	150	457	9
Perimeter top	113	346	7
Perimeter bottom	113	346	7
Perimeter left	67	205	4
Perimeter right	67	205	4
Total	510	1559	31

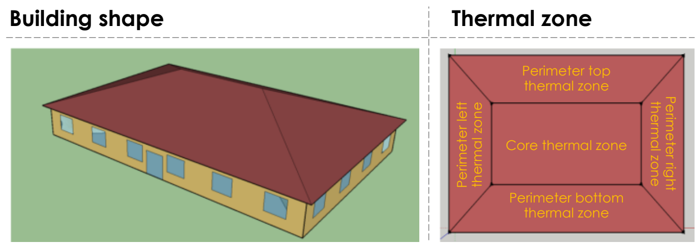


Figure 7. Schematics of prototype small office building, developed by PNNL for EnergyPlus simulation [38]

3.3.2. Control and experimental scenarios

We considered different values for each one of the aforementioned parameters. Furthermore, a number of parameters in the analyses were set to be the same (i.e., default parameters) across all the scenarios to facilitate the interpretation of the results and focus on the parameters of the study. The adopted parameters for different scenarios and the method for their calculations are as elaborated below.

Default parameters: Table 3 shows the default parameters used in this study. For the period of analyses, the summer season has been chosen. Although the data used for creating the personal thermal comfort models were collected through a longitudinal survey over three years [34], with the assumption that thermal comfort profiles might not vary significantly in a season, we chose the summer season. The setback was set to be at 29.44°C (i.e., 85°F), which was the initial temperature in the EnergyPlus model by PNNL. Moreover, a uniform occupancy profile was considered for the environment – full occupancy from 9:00 am to 6:00 pm during weekdays and vacancy during weekends.

Table 3. Default constant parameters and their values in energy simulation

Parameter	Value
Period of simulation	Summer (June to August)
Occupancy profile	100% from 9:00 am to 6:00 pm during weekdays
Temperature setback	29.44°C (85°F)

Thermal comfort profiles: As indicated in Table 2, given the full capacity of the prototype building, we generated sets of 31 human agents with different thermal behaviors using our proposed ABM simulation OVS agent component. With the aim of addressing the impact of having diverse groups of occupants with different thermal comfort characteristics in a building, we have chosen two sets of 31 human agents with distinguishable patterns for our analyses. These two sets represent cases in which most of the occupants in a building prefer a warmer environment or a cooler environment. These representative occupant profiles help us consider the impact of a wide range of occupant diversity in assessing the uncertainty of energy efficiency potentials. More details on this process is presented in Section 4.

Climate conditions: In order to account for the impact of varied climate conditions, three locations, with moderate climates, were selected given their different temperature characteristics as shown in Table 4. We excluded locations with extreme climates.

Table 4. Climate zone type, location, and characteristics used for simulations

Zone type	Location	Characteristics
2B	Tucson, Arizona	Hot and dry
4B	Albuquerque, New Mexico	Mixed and dry
6B	Great Falls, Montana	Cold and dry

Number of thermal zones: In our simulations, the following (one single zone, as well as three thermal zones) configurations were adopted from the five thermal zones, defined in the PNNL prototype model, as shown in Figure 8. By diversifying the number of thermal zones, we have intended to gauge the impact of the thermal zones' resolution in a building. Using the original five thermal zones results in unnecessarily complicated combinations of human-agents and increased computational time. To this end, we considered thermal zones to be combined by applying the same setpoint for the zones. In case #1, all the zones were considered to act as one unified thermal zone. In case #2, we combined (1) the perimeter left and top zones and (2) the perimeter bottom and right zones to have three zones in total.

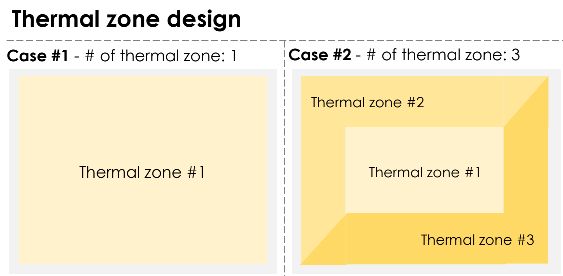


Figure 8. Thermal zone resolution adjustment and associated compositions

Number of occupants (i.e., human agents) in case #1: In this case, we have explored how the number of occupants in a single thermal zone (the whole building as one thermal zone) for a wide range of multioccupancy scenarios will affect the performance of comfort-driven strategies. To explore the impact of having varied number of human agents (k) with diverse thermal comfort preferences, we considered different combinations of 6, 12, 18, and 24 human agents at a time out. However, as reflected in Table 5, we constrained the total number of human agents (n_t) to be less tan 31 for each k to avoid the utilization of all possible combinations. Increasing the total number of human agents (n_t) substantially increases the number of combinations (N_c). For example, selecting groups of 12 human agents among 31 will result in 141,120,525 cases as calculated by using Equation (2). To this end, the n_t, for each k, was manually chosen so that N_c is sufficiently low and more than 1,000 combinations. However, for statistical analysis, we repeated the selection of combinations for 100 times per each k value to create a wide range of variability.

$$N_c = \frac{n_t!}{k!\,(n_t - k)!} \tag{2}$$

Table 5. Occupants' (i.e., human agents) sub-group selection and their associated combinations for simulations in a single thermal zone

Total number of human agents	Number of human agents in a single thermal zone	Number of combinations	Number of repetitions	Total number of combinations
13	6	1,716	100	171,600
16	12	1,820	100	182,200
21	18	1,330	100	133,000
27	24	2,925	100	292,500

Number of occupants (i.e., human agents) in case #2: For case #2 in Figure 8, we used the same total number of human agents in the building but distributed them in three thermal zones. Accordingly, different combinations of human agents were created in each thermal zone, compared to the case #1. This change created much larger number of combinations. Considering all possible combinations of arranging different thermal comfort profiles in adjacent thermal zones would have been computationally expensive while not necessary in answering the questions in this study. Hence, to simplify the approach, the following steps were taken:

1. We randomly sampled the number of human agents (6, 12, 18, and 24) out of total 31 data sets.
2. The selected human agents were considered to be equally distributed in three thermal zones. Hence, the possible combinations in each thermal zone ($C(k, \frac{k}{3}$); e.g., $C(6,2)$ or $C(12,4)$) were calculated.
3. The previous steps were repeated several times to create sufficiently diverse cases for our analyses (Table 6 has shown the detailed information). The outcome could represent different sets of thermal comfort profiles in shared thermal zones.
4. Then, for each set of human agents, through the developed ABM, we acquired optimized setpoints for different comfort-driven control strategies. The outcome of this step was sets of the possible combination of setpoints for different combinations of the human agents. In other words, for a group of diverse human agents and for different combinations of multioccupancy scenarios in each zone, the ranges of possible setpoints were identified. Given three thermal zones and different possible sets of setpoints in each zone, we created different combinations of setpoints in adjacent thermal zones.
5. Through the EnergyPlus simulation, the energy use for different combinations of setpoints in adjacent thermal zones were calculated. As one example combination, 9,100 kWh is consumed by having 20.5°C in thermal zone #1 and #2 and 21.0°C in thermal zone #3).
6. Since the probability distribution of the selected setpoints in step #4 is calculated for different combinations of human agents (e.g., 20.0°C – 10%, 21.0°C – 20%, and 22.0°C – 30%), we could compute the possibility of a setpoint combination. For example, when all three thermal zones have 20.0°C as the setpoint, the probability of such a case is $10\% \times 10\% \times 10\% = 0.1\%$. By using these probabilities, the distribution of energy use for all combinations were calculated.

Table 6. Number of human agents in thermal zones and the numbers of combinations for simulation analyses for simulations in multiple zones

Number of thermal zones	Total number of human agents	Number of human agents			Number of repetitions	Total number of combinations
		Thermal zone #1	Thermal zone #2	Thermal zone #3		
3	6	2	2	2	1,000	15,000
	12	4	4	4	100	49,500
	18	6	6	6	100	1,856,400
	24	8	8	8	2	1,470,942

3.4. Comparison with a benchmark:

In the evaluations, we set up the benchmark setpoint to be 22.5°C as it is the commonly used temperature setpoint in the previous studies [3, 39] and the conventions in practice. Therefore, the energy consumption difference (E_{diff}) is calculated using Equation (3).

$$E_{diff} = \frac{(E_{comf} - E_{ben})}{E_{ben}} \times 100 \qquad (3)$$

in which E_{ben} is the energy consumption for the benchmark setpoint and E_{comf} is the energy consumption for the comfort-driven control. In calculating the energy saving potentials, the mean value of energy savings for each control strategy was used as E_{comf}.

As discussed, comfort-driven control could result in either less or more energy consumption depending on the occupant thermal comfort characteristics, the combinations of occupants in thermal zones, and the outside temperature, compared to the conventional benchmark operation. Given that we are interested in assessing the energy saving potentials and their combinatorial bounds for the comfort-driven control, in presenting the results, we specified the percentages of the cases that result in energy savings compared to the benchmark setpoint (specified by a darker shade in the background as shown in Figure 9). In other words, we are presenting a rough estimate of the cumulative distribution function (CDF) value for energy consumption cases that are less than the benchmark energy consumption – i.e., $P(E_{comf} \leq E_{ben})$. In this figure, the bars that are overlapping with the shaded background, represent the possibility of energy saving.

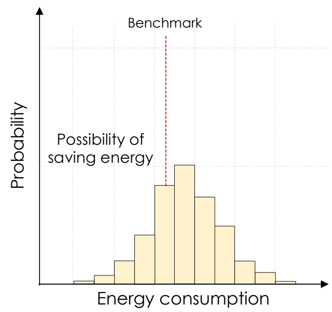


Figure 9. The quantification of energy saving potentials compared to the control based on benchmark setpoint

3.5. Energy efficiency of comfort-driven control

As energy use in context of HVAC control is for occupant thermal comfort, energy efficiency should account for the amount of energy use and the level of occupant thermal comfort. Therefore, in addition to the energy consumption assessments, for each control strategy, we have quantified the thermal comfort improvement. Similar to the calculation of energy consumption difference (Equation (3)), the improvement of thermal comfort (TC_{imp}) is calculated as below.

$$TC_{imp} = \frac{(TC_{comf} - TC_{ben})}{TC_{ben}} \times 100 \tag{4}$$

in which TC_{ben} is the probability of being comfortable using the benchmark setpoint (22.5°C). Similarly, the TC_{comf} represents the average probability of comfort for each control strategy.

Lastly, to demonstrate the overall performance (O_p) in terms of energy efficiency, we have used the following indicator:

$$O_p = TC_{imp} - E_{diff} \tag{5}$$

Given that both metrics are in [0,1], the subtraction of energy difference from comfort improvements will boost the thermal comfort efficiency for reduced energy consumption (i.e., $E_{diff} < 0$). That is, less energy use by the comfort-driven control leads to a negative value and we count such cases as positive. To the contrary, an increase in the energy use penalizes the improvement in thermal comfort gain.

4. Results and Findings

In running the analyses, as noted, we selected two sets of 31 diverse thermal comfort profiles to represent a wide range of human agents. The rationale behind selecting two sets of profiles was to assure that we account for a wide range of preferred temperatures across a spectrum of possible occupancy scenarios. In doing so, a data-driven approach was adopted to ensure the maximum difference between the thermal comfort profile sets in terms of preferred temperatures. To this end, we created 1000 sets of 31 thermal comfort profiles and the histogram of the mean preferred temperatures setoff the sets is as presented in Figure 10. As this graph shows, the range for mean preferred temperatures varied and we selected two sets that has the maximum difference in their mean preferred temperatures (the first set had 22.06°C and the second set had 23.01°C). The contextual meaning of having these two sets is that there are two groups of occupants with different temperature preferences (and thus preferred setpoints) overall. Using these two data sets will help us quantify the bounds of energy saving potentials in for using comfort-driven control.

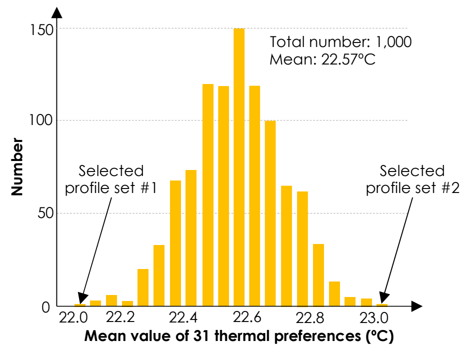


Figure 10. Histogram of mean preferred temperatures across 1000 sets of 31 thermal comfort profiles

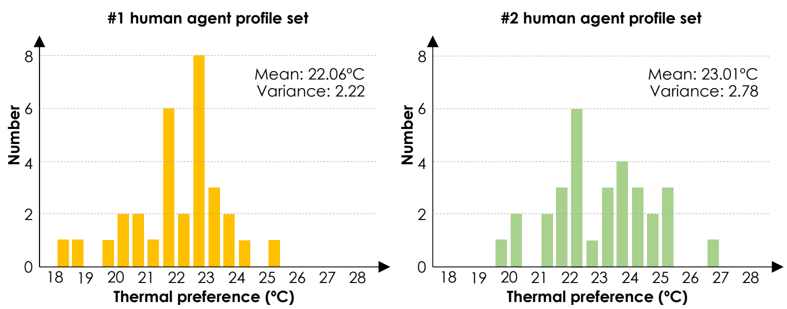


Figure 11. Thermal preferences' distributions for two selected sets of 31 human agents

Figure 11 shows the temperature preferences for each set of profiles. We tested the normality of each human agent's set of thermal votes by using the Kolmogorov-Smirnov test, one of the widely used normality tests [40]. To ensure the normality of each data set, sampling thermal votes was conducted until a p-value less than 0.05 was obtained. The first set had a lower variance, indicative of more similarity between the preferred setpoints of human agents, compared to the second set.

In the following subsections, we have divided the presentation of findings according to the impact of individual parameters in our study in the following order: (1) number of occupants in a single zone, (2) increase in the number of thermal zones, and (3) varied climate conditions. Except for climate, parameters have been evaluated for three control strategies as described in the methodology section.

4.1. The impact of number of occupants (individual comfort profiles)

Figure 12 presents how energy consumption has varied depending on (1) the number of human agents in one single thermal zone and (2) the control strategy. To focus on the impact caused by these two factors, Albuquerque was solely used as the location on the account of its mixed climate nature. Different columns of this figure represent the results of the analyses for different number of occupants in thermal zones and different rows show the control strategy for integration of personal thermal comfort profiles. The bars in Figure 12 represent the histograms of energy consumption across different combinatorial realizations. The darker shades differentiate the results for the second set with higher average preferred temperatures from the results for the first set (lighter shades). It is worth noting that the benchmark energy consumptions across the columns in Figure 12 are different due to the differences in the number of occupants, which in turn, affect the required thermal conditioning load.

The realizations for these two sets help us differentiate the impact of personal thermal comfort profiles on energy consumption and efficiency expectations from comfort-driven control. Figure 13 summarizes the observations in Figure 12. Figure 13.A presents the percentage of energy use difference on average for different number of human agents and different control strategies and Figure 13.B presents variations in percentage of energy saving cases (an estimate for the cumulative probability of achieving energy saving by using comfort-driven control) under different circumstances. The realizations for the second set showed more energy savings on average, compared to the benchmark regardless of the control strategy (Figure 13.A). Having the mean value of thermal preferences (23.01°C) above the benchmark setpoint (22.5°C) resulted in such outcome. On the other hand, the use of the first set with a relatively low average thermal preference (22.06°C), compared to the benchmark setpoint, resulted in an increased overall energy consumption (Figure 13.A). Furthermore, Figure 13.B presents the energy saving potential bounds under a wide range of realizations and quantifies the energy saving potentials under the uncertainty of diverse occupancy scenarios. As this figure shows, under different operational configurations, an upper-bound of energy saving probability between 70-93% is observed. On the other hand, for the best performance, a lower-bound of energy saving probability between 19-36% is observed. Given that we have selected two sets of human-agents with maximum distance between average preferred temperatures, this observation shows that on average, there is a possibility that in almost 50-65% of occupancy scenarios, the use of comfort-driven control could lead to energy savings.

Throughout the evaluations for all the scenarios (i.e., combinations of thermal comfort profiles), regardless of the control strategy, it was observed that a denser population in a thermal zone limits the selection of setpoints because many conflicts (i.e., desiring the opposite side of setpoints) exist between human agents. In other words, the setpoint selection converges to the mean value of the preferred temperatures from different profiles. Hence, the distributions for different realizations in energy consumption analyses have narrowed. This trend demonstrates that, for multioccupancy spaces with relatively dense occupancy, the conventional operational models such as the PMV model characterizing the satisfaction of a large group of people is a reasonable approach. This is an important finding that integration of personal comfort models is more effective in thermal zones with low occupancy density. However, occupancy in buildings is dynamic and the density of occupants could vary across time. Therefore, in a responsive and adaptive building system, the diversity of personal models in thermal zones in reality provides opportunities for dynamic setpoint adjustment and lead to saving energy. Thus, the employment of personal thermal comfort profiles is crucial given the variety of mean preferred temperatures. These observations further accentuate the necessity of facilitating and enhancing HBI, rather than applying the most-likely desired setpoint.

When it comes to the impact of the control strategies, the approach that seeks to minimize the deviation (error) between thermal preference and the temperature in the zone (the second approach) showed the most energy consumption followed by the approach that uses the thermal comfort sensitivity as shown in Figure 13. For the first (majority rule) and third (thermal comfort sensitivity) strategies, the HVAC agent finds the optimal setpoint by starting from the setback (i.e., a low conditioning load) and moves the setpoint until reaching a point of no conflict. With an odd number of human agents in a thermal zone, the majority vote approach could give higher weight to the majority. However, with even number of occupants and evenly distributed thermal votes, this approach stops the setpoint selection process closer to the setback once the sum of the thermal votes is zero, which could be interpreted as the outcome of a drifting strategy [41]. In drifting, with the objective of reducing energy consumption, the HVAC agent seeks to shift the setpoint closer to a setback or outdoor temperature until a thermal dissatisfaction vote is reported. However, the approach based on thermal comfort sensitivity can move further away from the setback given its evaluation process of accounting for thermal comfort sensitivities in addition to preferences. Lastly, the error minimization approach selects a setpoint somewhere in between all the preferred temperatures, which often results in more conditioning loads than the other approaches.

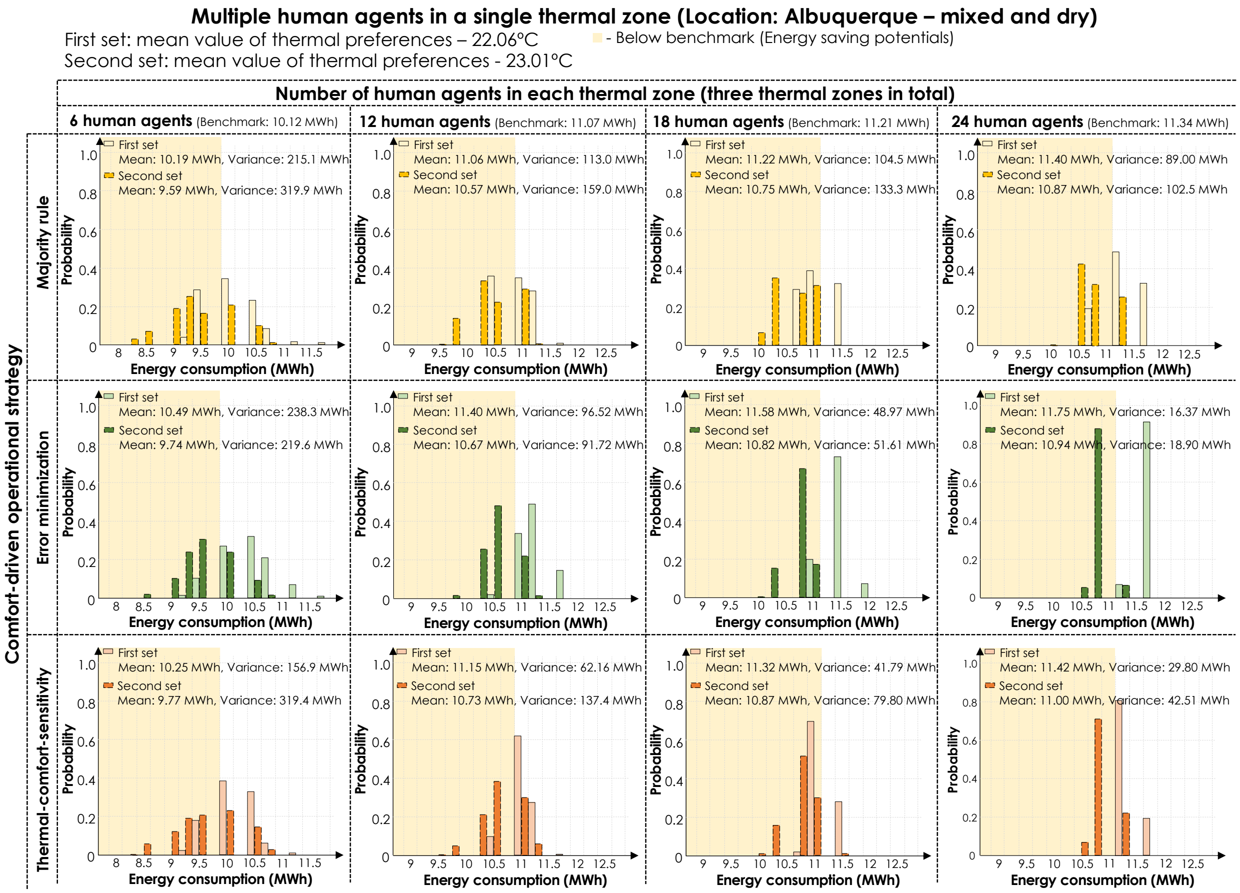


Figure 12. Energy consumption distributions in a single thermal zone for different number of occupants (i.e., human agents) and different comfort-driven control strategies in a mixed and dry climate.

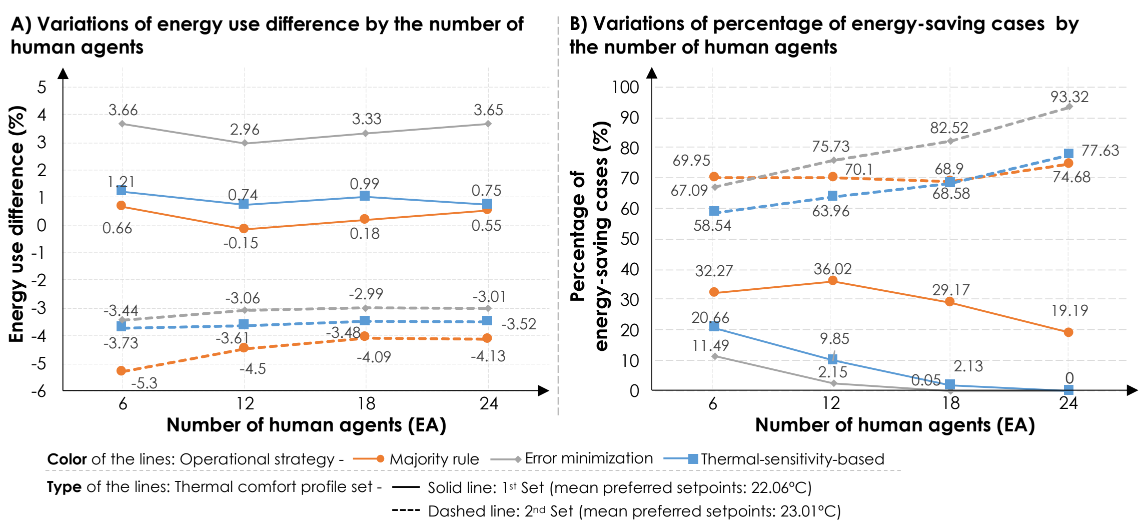


Figure 13. Variation of energy use difference and percentage of energy-saving cases depending on the number of human agents and control strategies

4.2. The impact of increased number of thermal zones

Figure 14 presents how energy consumption has varied according to (1) the number of human agents distributed across multiple zones and (2) different control strategies. Similarly, Albuquerque was selected as the location for the representative climate. In these analyses, the number of the occupants per zone will reduce but more complex combinations of profiles were tested across multiple zones. As Figure 14 shows in the reported values on the graphs, with the increase in the number of thermal zones, similar general trends in terms of average energy consumption could be observed across different control strategies and as the number of occupants increases. The higher the number of human agents in each thermal zone, the narrower the energy use distributions. Moreover, the first set of comfort profiles showed higher energy consumption, compared to the second set. Lastly, as discussed, the error minimization strategy consumed the most energy and the thermal-comfort-sensitivity-based approach followed.

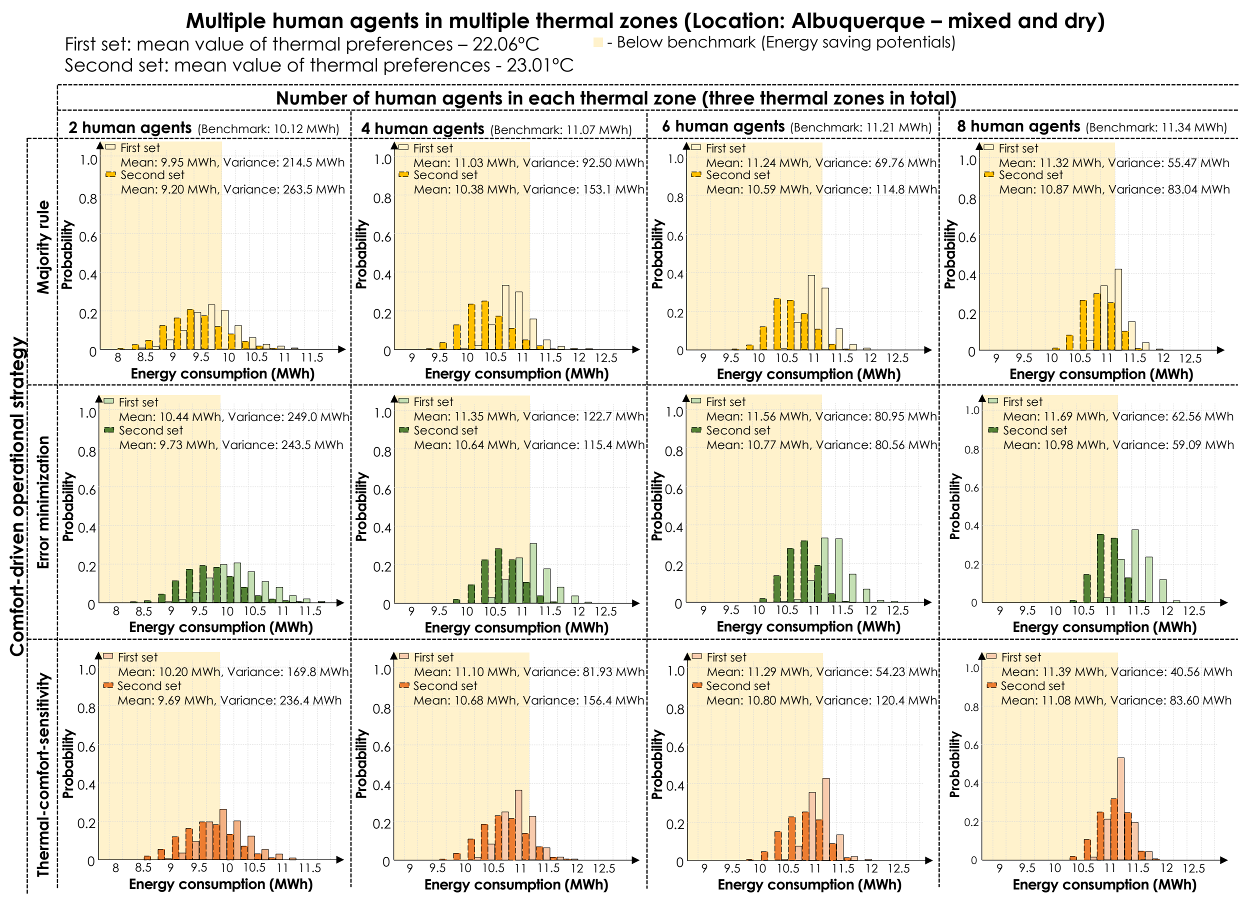


Figure 14. Energy consumption distributions for different number of occupants (i.e., human agents) and different comfort-driven control strategies in a mixed and dry climate across multiple thermal zones.

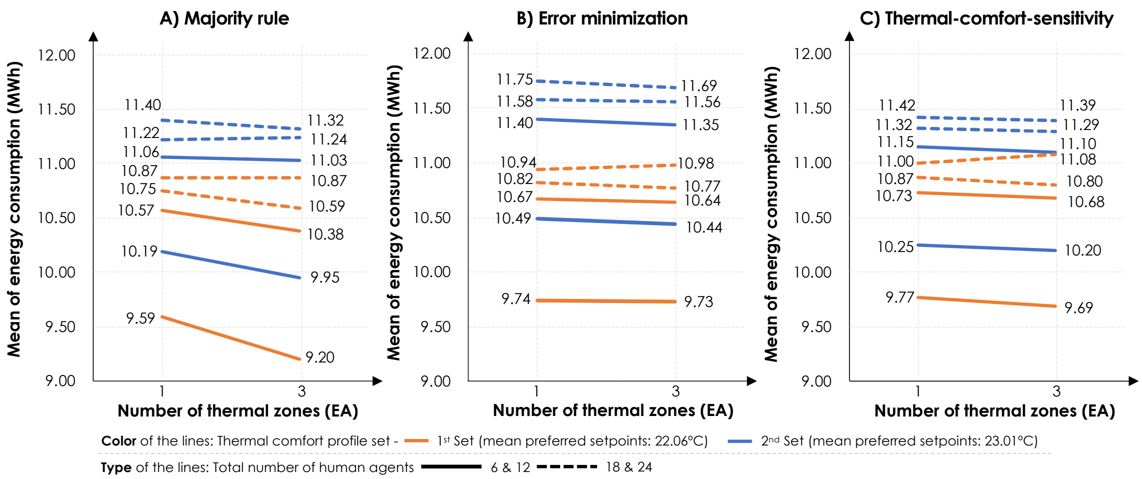


Figure 15. Variation of the mean values in Figure 12 and Figure 14.

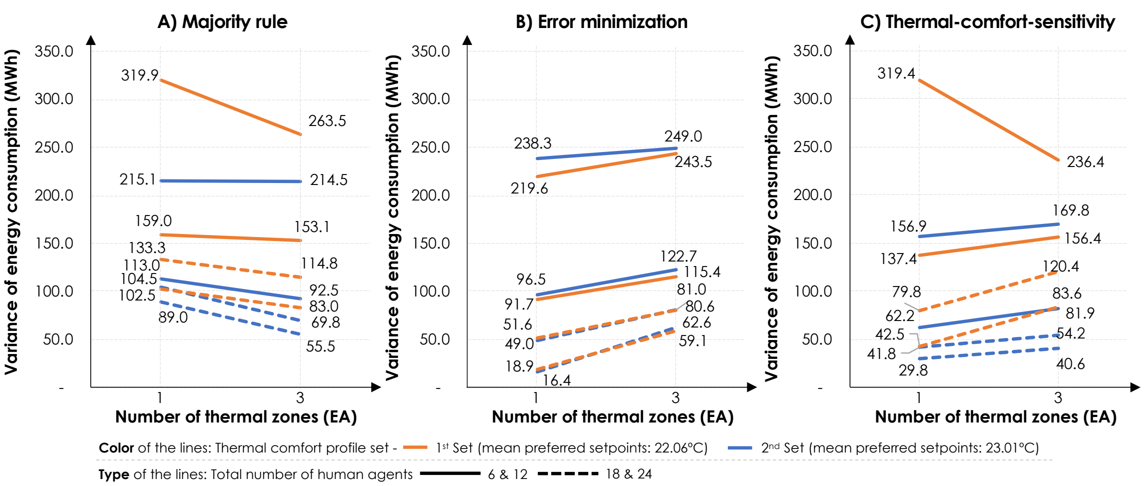


Figure 16. Variation of the variance values in Figure 12 and Figure 14.

In these analyses, the most noticeable difference, as reflected in Figure 16, is that the variance of the energy use distributions increased, which could be associated with increased combinations of setpoints in the building due to the increase in the number of thermal zones. This observation does not hold true for the majority rule approach (i.e. higher variances were observed in the single zone results of Figure 12), which could be associated with the nature of this control strategy as it often chooses setpoints away from the mean preferred temperatures even with a large number of human agents. The increased variance is important as it increases the possibility of energy saving, compared to the benchmark control strategy of using predetermined setpoint as reflect in Figure 17, which summarizes the observations in Figure 14. Figure 17.A presents the percentage of energy saving on average for different contextual factors and different control strategies and Figure 17.B presents an estimate for the cumulative probability of achieving energy saving by using comfort-driven control under different circumstances.

Furthermore, quantitative assessments showed that having more thermal zones and a small number of human agents per thermal zone in the building resulted in an overall lower energy consumption as mean values in Figure 15 show. Figure 17 demonstrates that even with the use of the first set of comfort profiles, the approach based on majority rule showed energy saving potential when having two or four occupants (human agents) in each thermal zone (Figure 17.A). With the second set of profiles and two human agents in each thermal zone, the majority rule approach showed an average energy saving of 9.10% (Figure 17.A) with 95.85% of different combinations showing energy saving (Figure 17.B). By comparing Figure 13 and

Figure 17, it could be seen that increase in the number of thermal zones (and reducing the occupancy density) highly increased the probability of having energy-saving cases. With similar level of uncertainty in the diversity of human agents, we could observe improvements in both lower and upper bounds of energy saving probability. That is, there is a possibility that in almost 70-80% of occupancy scenarios, the use of comfort-driven control could lead to energy savings.

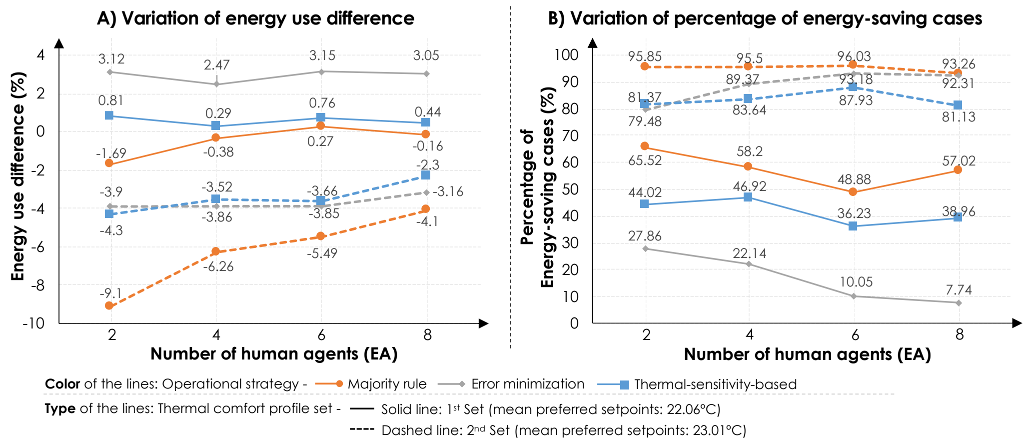


Figure 17. Variation of energy use difference and percentage of energy-saving cases depending on the number of thermal zones (human agents) and control strategy

4.3. The impact of climate

In Figure 18, we have presented the energy use patterns, caused by different number of human agents and varied thermal comfort profiles in three different climates. These analyses were conducted by using the third control strategy to limit the independent variables. Figure 19 summarizes the observations in Figure 18 to show the percentage of energy use differences and an estimate of the cumulative probability of energy saving cases for each configuration. Figure 19.A summarizes the observations in the single thermal zone on the left two columns of Figure 18 and Figure 19.B summarizes the observations across multiple thermal zones on the right two columns of Figure 18. The results of using diverse comfort profiles in different climate zones have shown similar trends as observed in Figure 12 and Figure 14. Similar effects from number of occupants and number of thermal zones when using personal comfort profile integration into control loop (i.e., comfort-aware control) could be observed across different climates. By increasing the number of zones, the variance of the energy use distributions increases that in turn results in increased cumulative probability of energy saving cases. This observation demonstrates the dominant role of thermal comfort profiles in comfort-aware control.

Furthermore, the impact of different climate conditions is manifested in the change of average energy consumption – i.e., the cooler climates call for reduced energy consumption for cooling. Compared to the average energy consumption in the representative mixed climate (Albuquerque – the first row in Figure 18), we observed an almost 1.0 MWh increase in the representative hot climate (Tucson - the second row in Figure 18) and an almost 4.0 MWh decrease in the representative cold climate (Great Falls – the third row in Figure 18). These results provide an estimate of the energy saving magnitudes and are compatible with the fact that the difference between indoor and outdoor temperatures is a key factor in driving the energy consumption differences.

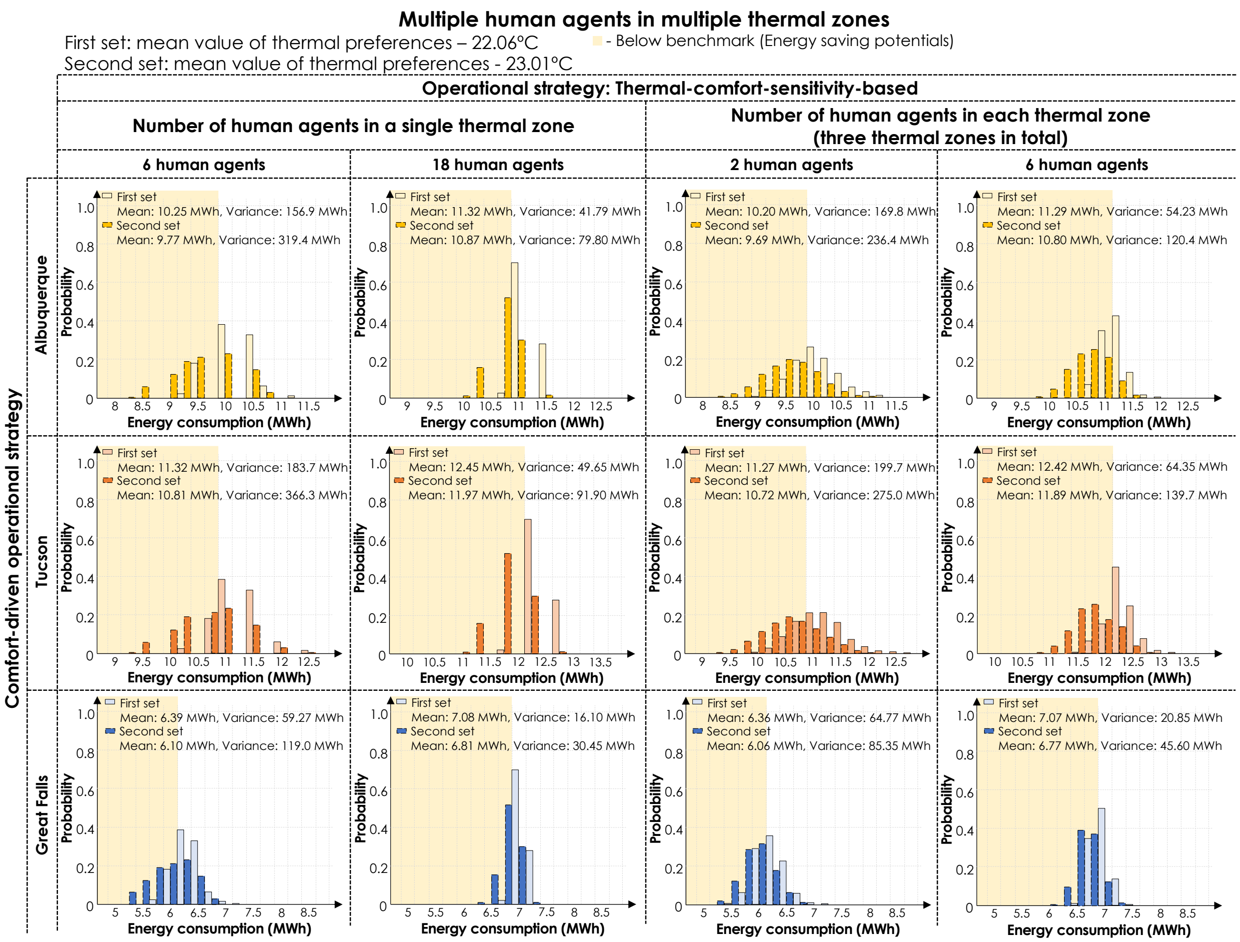


Figure 18. Energy consumption distributions for different combinations of occupancy density and varied thermal comfort profiles for three different climates

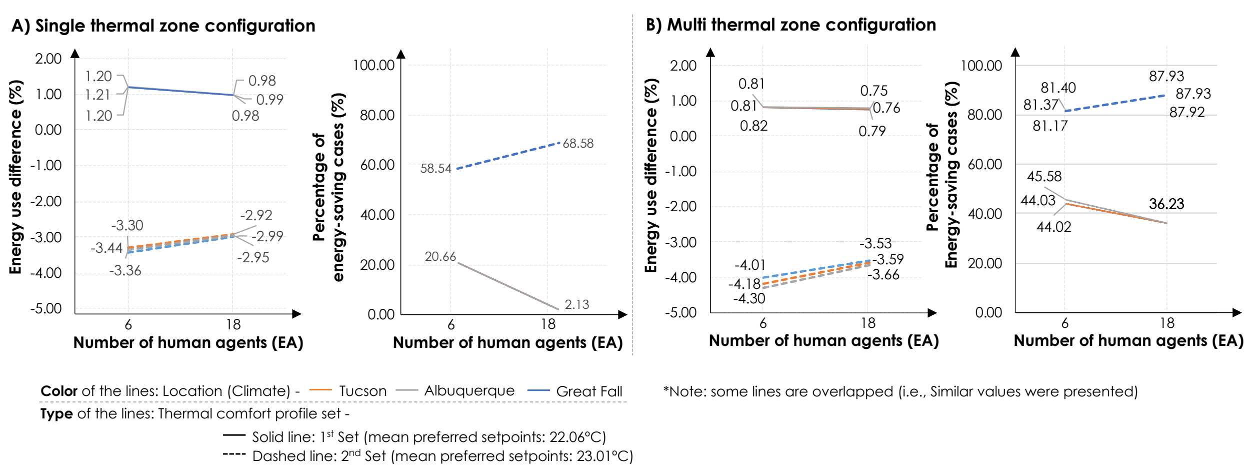


Figure 19. Energy use difference and percentage of energy-saving cases for different climates and thermal comfort characteristics in the single thermal zone (A) and multi thermal zones (B) configurations

Figure 20 presents an illustration that summarizes the observed impact of different studied parameters on the energy use distributions by using comfort-driven control:

- The mean of energy use distributions is dominantly determined by thermal comfort characteristics of occupants as a group (i.e., mean value of the preferred temperatures) followed by the control strategy.
- The variance of energy use distributions is also highly influenced by thermal comfort characteristics of occupants, followed by the number of occupants in a thermal zone and the number of thermal zones (the number of thermal zones plays a part in reducing occupancy density in a thermal zone).
- An increase in the variance of energy use distributions results in an increase in the cumulative probability of energy saving circumstances under the uncertainty of multioccupancy scenarios.
- The control strategies have shown to affect the performance. The approach based on thermal comfort sensitivity has shown to be the second most effective approach after the approach based on majority thermal vote.

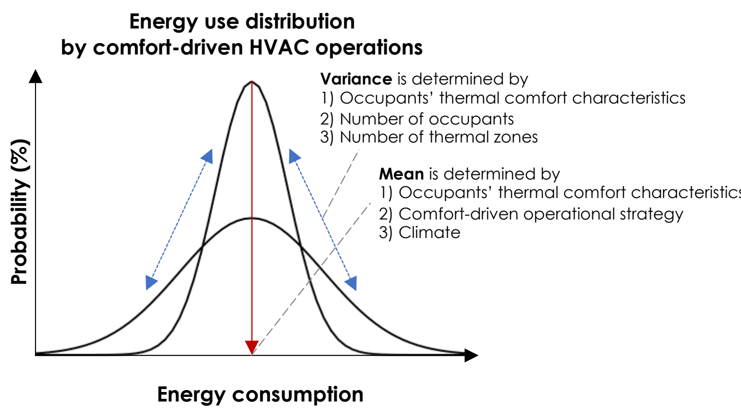


Figure 20. Graphical summary of the impact of parameters on the energy use distributions by comfort-driven control

4.4. Energy efficiency evaluation

As noted, energy efficiency in the context of this study looks at the intersection of energy use and thermal comfort satisfaction. When it comes to the improvement in thermal comfort (as calculated by Equation 4), the thermal-comfort-sensitivity-based approach had the best and the majority rule approach was the next as shown in Figure 21. In general, the increase in the number of human agents reduces the benefits of comfort-driven control – that is, it is desirable to have low occupancy density in a thermal zone for increased gain from adaptive HBI.

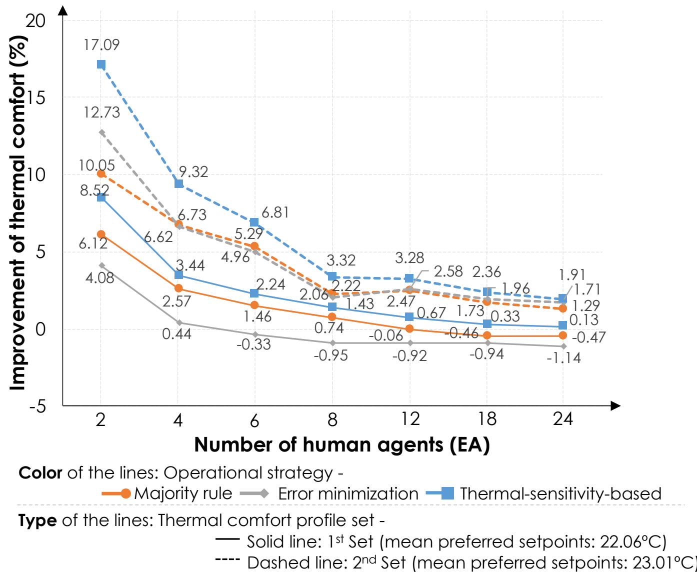


Figure 21 Improvement of thermal comfort (TC_{imp}) for each control strategy depending on the number of human agents in a thermal zone

To account for energy efficiency (i.e., energy use for thermal satisfaction), the overall performance improvement by each control strategy were calculated by using Equation 5 as presented in Figure 22. For the occupants in the first set, the thermal-comfort-sensitivity-based approach revealed the best overall performance despite its relatively higher energy use. Compared to the majority rule approach, the thermal comfort improvement from thermal-sensitivity-based approach has contributed the most in this observation. The error minimization approach showed an underwhelming performance primarily due to its higher energy demand. On the other hand, with the second set, the majority rule approach was the best except for the case with two occupants. These observations demonstrate that having thermal zones with a small number of occupants brings about higher energy efficiency when using a comfort-driven control strategy. As before, the overall benefits of comfort-driven control were curtailed with larger number of human agents.

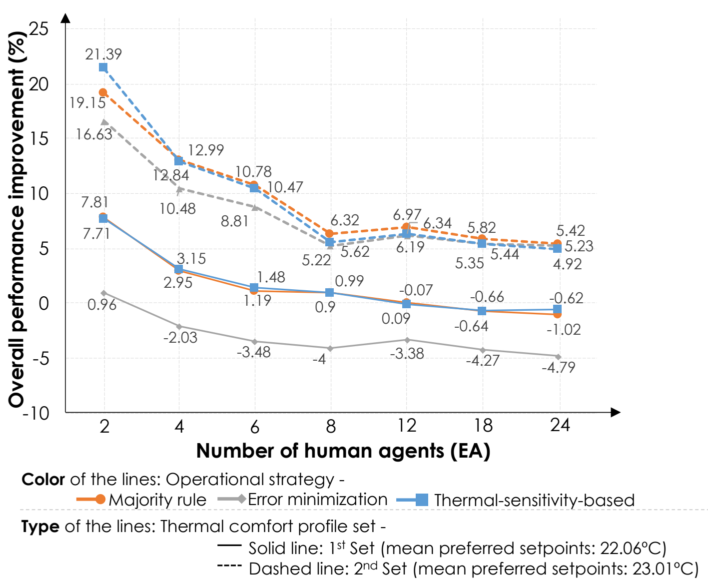


Figure 22. Overall performance improvement by comfort-driven control strategies

5. Limitation and Discussion

In this section, we elaborated the limitations of this study to open the discussion to the research community. We intentionally have chosen two sets of thermal comfort profiles at tail ends of the distribution (as depicted in Figure 10) on the account of their potential for demonstrating a wide-range of difference in occupants' diversity and difference in energy use. Given that these profiles were developed using realistic datasets, both datasets represent real-world scenarios. Moreover, complaints of over-conditioning from occupants in buildings shows that the application of comfort-driven HVAC control could potentially result in energy saving and improved thermal comfort. For the future research, as the public datasets on thermal comfort become available in the community and get expanded (through efforts like [42]), more insight into the diversity of personal thermal comfort profiles could be provided.

One of the core assumptions in our developed ABM framework is that each human agent seeks to maximize thermal comfort. However, in reality, other human behavior attributes can come to play in determining the energy use of HVAC control. For instance, the energy saving objectives might affect the desire of maximizing thermal comfort. Given the differences in occupant behavior (as they might perceive comfort differently and react to variations of temperature differently), the personal differences in decision-making process with regard to the tradeoff between energy use and comfort (i.e., adaptive behavior) could also be influential in energy efficiency of HVAC systems. In other words, the use of personal thermal comfort models is one of the drivers in HITL HVAC control.

Another limitation is the static nature of thermal comfort profiles across different simulations. Although this was part of the design for this study, long-term acclimation to the climate has been demonstrated in the literature [43] that could affect the change in thermal comfort profiles. A potential solution to this limitation could be the use of long-term field studies to ensure diversity in observations as is the objective of data-sharing. Moreover, despite the capability of implementing dynamic occupancy profiles and updating thermal comfort profiles in our proposed ABM framework, we restricted the occupancy level and the possibility of changing thermal comfort profiles of human agents for the ease of interpretation in answering the research questions. Another factor that could be further studied is the probability of user engagement in comfort-driven control. An interesting question is whether the advances in technologies such as wearables help with a higher rate of engagement. Also, further analyses on scenarios of partial engagement could be explored.

Lastly, as pointed out by [26], applying a single setpoint derived from a comfort-driven control strategy throughout the entire operation might violate the *fairness*. As an example, when two occupants have conflicting thermal preferences and an control strategy is biased towards one, the other occupant might be dissatisfied all the time. Therefore, alternating between different occupants' preferred temperatures could increase the fairness. However, the energy implication of such strategy needs further assessment given that a quick transitioning between different setpoints could result in excessive energy consumption [44].

The findings of this study could be characterized as (i) an in-depth understanding of the impact of different contextual factors that affect the energy performance of context-aware control strategies in buildings, and (ii) providing probabilistic bounds of energy use variation under different contextual conditions, which could be used in probabilistic simulation of energy performance. Therefore, these findings could contribute to studies with the goal of energy performance improvement at building level (e.g.,[45, 46]), as well as studies that look at demand-response (e.g., [47, 48]) and integration of Distributed Energy Resources (DERs) (e.g.,[46]) at both building and community levels. Contextual conditions and the sensitivity of the control algorithms to these conditions are critical in understanding the potentials for adaptive operation of thermal conditioning systems in buildings that bring about improved energy performance. Adaptive operations, could also contribute to quantification (specifically probabilistic quantification) of load flexibility that determines the capacity of the loads for demand-response and peak load shaving, as well as compatibility with different DERs such as renewable energy resources and storage systems.

6. Conclusion

In this study, we have investigated the energy efficiency implications of comfort-driven HVAC control strategies in multi-occupancy cases – i.e., integrating personal thermal comfort profiles of occupants into the control loop of HVAC systems – to better understand their potentials under a diverse set of contextual conditions. Prior research studies have evaluated the performance of comfort-driven control for specific contextual conditions and reported both positive and negative energy saving outcomes. These observations have called for a comprehensive understanding of the efficacy of comfort-driven HVAC control in terms of energy efficiency. By reviewing the literature and the reported energy efficiency trends, we identified the potential parameters that could affect the energy efficiency of these strategies: (1) the diversity in occupants' thermal comfort characteristics and uncertainty in multioccupancy scenarios, (2) the thermal zone configuration, (3) climate, and (4) the control strategy. To this end, by developing diverse sets of thermal comfort profiles from real-world field data, we employed a coupled agent-based modeling scheme and EnergyPlus simulation to evaluate the impact of the aforementioned parameters for different combinations. Then, we have provided quantified bounds of energy saving potentials given the uncertainty in multioccupancy scenarios. The thermal comfort profiles were selected to be distributed across a range of preferred indoor temperatures to show the impact of diversity in individual differences. In these evaluations, we looked at the histogram of energy use across different combinatorial realizations.

The results showed that the occupants' thermal comfort characteristics and the number of occupants per thermal zone are the most impactful parameters in shaping the energy use distributions and determining the energy saving potentials of comfort-driven control. In other words, if the average of preferred temperatures by occupants in a building lies above the standard setpoints, the probability of energy saving increases and vice versa. However, the impact of comfort-driven control comes into play regardless of the average preferred temperature by groups of occupants in a building. Our analyses over a wide spectrum of occupants' characteristics show an average estimate for cumulative probability of energy saving cases of 50-65% in a single thermal zone and 70-80% in multiple thermal zones.

Analyses on energy efficiency in this study (i.e., the use of energy for improving thermal comfort) showed that as the number of occupants per multioccupancy zones increases, the opportunities for energy efficiency improvement by using personal comfort profiles decreases. The use of comfort-driven control showed to have a maximum of 21% to 11% improvement in energy efficiency when a thermal zone is shared by 2 to 6 occupants, respectively. By having more than six occupants per zone, the benefits of using personal comfort diminishes although there are still potential for improved energy performance. In those cases, the integration of personal comfort models converges to more conventional models such as the PMV model. In addition, control strategies were proven to be effective in driving energy efficiency of control. Specifically, the thermal-comfort-sensitivity-based approach showed to result in the best performance in generating collectively comfortable conditions and thermal-vote-based approach was shown to be more energy efficient than the other strategies. Among the future directions of this study are the investigation of energy efficiency potentials at the intersection of occupancy and comfort modalities, as well as investigating the impact of temperature distributions through more advanced simulations or field studies, where the temperature distributions across a thermal zone could be affected by different contextual variables and result in varied occupant experiences.

7. Acknowledgment

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