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PECMS: modeling a personalized energy and comfort management system based on residents' behavior anticipation in smart home

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Abstract

Indoor electrical systems are aimed to provide comfort to the occupants. However, their operation is contingent on the presence or needs of the residents. Hence, to optimize energy consumption and guarantee the desired comfort level of residents, any indoor energy control system should consider the occupancy dynamism within houses and the occupants' behavior patterns. Moreover, there is a growing demand for localized and personalized comfort controls in residential buildings to improve the occupants' satisfaction. This paper presents a Personalized Energy and Comfort Management System (PECMS) that optimizes building energy consumption and meanwhile maintains residents' intended comfort levels by predicting their trajectories. Considering home thermal characterization, PECMS coordinates the building system devices and residents by anticipating residents' behavior using an activity mining and tracking method. With this capability, efficient scheduling of the electrical devices would be achieved. PECMS is simulated and tested on a dataset from a real-world smart home project, including the home's actual thermal zones, temperatures, and residents' preferences. Comparative analysis is conducted to evaluate PECMS against existing methods and systems, showcasing its effectiveness in achieving the desired trade-off between energy consumption and occupant comfort levels.

Keywords: Energy consumption · Simulating a Personalized Energy and Comfort Management System (PECMS) · Energy demand prediction · Resident comfort · Behavioral patterns

1 Introduction

Buildings are an integral part of everyday life. The built environment is a place where people spend 60-90% of their life [1]. It is argued that buildings are accounted for approximately one-third of total final energy consumption [2]. In order to deliver a safe, healthy, and comfortable atmosphere, buildings are equipped with a vast amount of resources, the majority of which rely on energy to operate. The most critical systems affecting human comfort in buildings are Heating, Ventilation, and Air Conditioning (HVAC) systems, lighting systems, and electrical appliances and devices, which respectively account for 36%, 18%, and 10% of building energy use [3]. Therefore, building energy consumption and occupant comfort are two critical parameters relying on which the indoor environment's performance can be assessed and improved.

Using the occupancy information - like occupants' presence, movement, etc. - the use of both centralized and decentralized facilities can be optimized to avoid energy waste [4]. Several studies have demonstrated that a building's energy use is influenced by its

occupants' behavior. In particular, in residential buildings, occupant behavior explains the determination of the large variability regarding comfort settings and energy use. This includes the interactions between occupants and energy control systems (i.e., thermostatic values and HVAC system set points), building components (i.e., windows, blinds, lights, and shades), and use of the appliance (i.e., artificial lighting system, computers, fridges, and plug loads) [5].

Most indoor facilities have fixed positions, and their operations are highly dependent on the occupants' presence. It is possible to extrapolate semantic meanings from locations, moving speeds, and times of occurrence. By analyzing occupants' trajectories, dynamic space occupancy would be revealed. Toward optimizing the building energy consumption as well as minimizing the occupants' discomfort hours, this paper presents a novel AI-based Personalized Energy and Comfort Management System (PECMS). PECMS monitors and stores the environmental and occupant data for the entire building system. By processing data gathered from sensors installed in the building, PECMS detects and predicts residents' behavior and movement and manages critical energy-consuming devices by considering the occupants' preferences.

PECMS is integrated with the proposed method of [6] that models and predicts smart home residents' activities through their trajectory information collected mainly from motion sensors. Using the predicted activity of the residents in conjunction with the environmental and building information, residents' desired comfort level, and considering the capacity and functionality of HVAC and lighting systems, PECMS schedules when each device should be turned on and for how long it should be operative to keep the desired lighting and thermal comfort. The goals behind the proposed PECMS can be counted as (1) personalizing the home environment for the resident, (2) providing a system that easily interfaces with building management systems (3) managing energy consumption while keeping the demanded residents' comfort level, (4) assessing and predicting how changes to the building, occupant behavior, and operational policies will affect energy consumption and occupant comfort, and (5) keeping PECMS modeling cost-effective by relying mainly on motion detector sensors. The contributions of this paper are highlighted as follows:

First, we utilize the proposed prediction model of [6] at the zone scale. Using the historical trajectory data, zones' occupancy would be predicted, which would be used as an input to PECMS. Second, light and thermal comfort-based device schedulers are integrated into PECMS. Third, PECMS is tested on a dataset collected in a real smart home project, accompanied by the actual thermal zones, temperatures, and residents' activities. The operations of the building are simulated according to different control strategies involving varying levels of intelligent coordination of devices and residents. The consumed energy and the achieved comfort level of these strategies are compared to the current state of the art. Obtained results depict that the proposed system is most effective in managing electricity consumption while increasing the residents' comfort compared to existing methods and systems. It should be noted that the prediction method and intelligent control strategies are not platform-specific and can be used with any PECMS platform.

The remainder of this paper is organized as follows: In Sect. 2, related works are reviewed. In Sect. 3, the proposed system is presented. Section 4 describes how to evaluate energy and comfort levels. Section 5 provides experimental analysis. Finally, Sect. 6 concludes the paper.

2 Related work

The need to understand how occupants' activities affect the amount of energy utilized in buildings is rising [7]. Human behavior and activities have a significant impact on building energy performance, and various studies have confirmed the human role in building operations [7]. Webber et al. [8] studied the after-hours power status of equipment in offices, schools, and medical buildings located in California, Pennsylvania, and Georgia. Results indicate that turn-off rates for most equipment are under 50%, demonstrating considerable energy savings potential from changes in occupants' behavioral patterns [8]. Similarly, [9] audited 16 buildings in various North American cities and observed low-turn-off rates for various office equipment categories [9]. Ioannou et al. [10] examined the impact of user behavior and building variables on energy consumption for heating, as well as the sensitivity analysis of energy consumption for heating.

Using EnergyPlus, [11] conducted parametric research to explore the effects of occupant behavior on the building's efficiency. The results showed that the occupancy loads affect the magnitude of the difference among the energy performances of various materials and thus can change the material selection strategy in the building life cycle. Another study conducted by [12] indicated that EnergyPlus has the ability to evaluate the energy performance of occupant behavior. In a real two-story office building, the energy performance of five behavior measures, including lighting, plug load, comfort criteria, HVAC control, and window control, was evaluated. Ahmadi-Karvigh et al. [13] proposed a framework for action detection, activity recognition, and associated energy waste estimation. According to two weeks of ground truth data, the performance for real-time activity detection was extremely accurate. Anastasiadi and Dounis [14] presented a fuzzy logic HVAC controller and used the Building Controls Virtual Testbed (BCVTB) to test the model with EnergyPlus. They demonstrated that their proposed technique decreases non-comfort hours by 50% while spending the same amount of energy when compared to a traditional on-off controller on the same structure.

In [15], behavioral Artificial Neural Network (ANN) models are used to simulate occupants' behavior. Indoor environmental parameters, clothing level, and metabolic rate were all elements addressed in behavioral ANN. EnergyPlus was also used to simulate the energy usage of HVAC systems in office buildings. An occupant behavior model in commercial buildings is created in [16]. The occupant behavior model is based on powerful agent-based modeling (ABM) tool that considers diverse occupant interactions with windows, doors, and window-blinds dependent on environmental circumstances.

Wei et al. [17] have proposed an approach to estimate the occupancy level based on blind system identification (BSI). Also, they have developed a neural network model to predict the electricity consumption of an Air Conditioner system utilizing the occupancy determined by BSI estimation. Jia et al. [18] presented a simulation experiment that combined an agent-based model of occupant behavior with an EnergyPlus-created building energy model. Five single-occupancy offices were chosen to verify the occupant behavior model, which was built based on an existing building. Occupant behavior was shown to be a major cause of the unpredictability of energy use. Dziedzic et al. [19] developed an algorithm utilizing Agent-Based Modeling and in situ observation of natural transitions of building occupants to emulate occupant mobility in buildings. Their method generates routes taken by occupants. It also allowed for a stronger emphasis on activity scheduling and scripting potential human behavior reactions.

Salimi et al. [20] have developed a methodology for determining the most effective occupancy-centered local control techniques. Based on the integration of a simulation model with a multi-objective optimization method, the work led to the discovery of optimum local control strategies. From a comfort standpoint, the basic HVAC plan with a 60-min resolution level is the ideal option for the implementation of local control techniques. In [21], by evaluating multiple occupant activity scenarios in a multifamily building model, the EnergyPlus simulation platform was used to evaluate the impact of weatherization, ventilation retrofits, and resident behavior on indoor air quality and energy consumption.

Park [22] presented a human comfort-based control approach for energy management by monitoring the heating and lighting system. The system watched occupants' and environmental data as the knowledge of the whole building system. The system detected the presence of a resident in a location to take necessary action. In our proposed method in this paper, the movement of residents is taken into account, which results in a better thermal comfort level. Kwon et al. [23] introduced a system that includes prediction mechanisms and intelligent heating control algorithms to help maximize energy efficiency while taking resident satisfaction into consideration. They achieved this goal by developing an Artificial Neural Network (ANN)-based prediction approach. The system used environmental data to produce a prediction for comfort temperature, and then the system developed intelligent control strategies to automatically manage the temperature based on the predictions. Yuan et al. [24] proposed an ANN approach for the presence of occupancy forecasting utilizing occupant data from 16 different buildings. The proposed method in [6], in comparison with their work, showed promise in terms of prediction values and personalizing the home environment for the residents. In [25], the impact of demand-response on the thermal comfort of the occupants and energy consumption in small- to medium-sized leisure buildings is studied.

In summary, uncertainty about how occupants conduct their activities can cause significant differences in building energy performance. In light of this, this study describes a combined simulation of the occupant behavior model using EnergyPlus. The paper examines the influence of occupant behaviors on various elements of building performance, such as building energy use and thermal comfort, in order to provide a vision for building performance evaluation.

3 Personalized energy and comfort management system (PECMS)

This section demonstrates modeling PECMS. By recognizing occupants' normal behavior and activities, PECMS predicts their forthcoming movements and the duration of their stay in locations, thereby it can optimize the power consumption and can maximize occupants' comfort. For discovering human activities from sensor data, we have relied on the work in [6] in which a supervised method for discovering human activities from sensor data is presented. Since most indoor facilities are located in fixed positions, it is possible to extrapolate semantic meanings from locations, moving speeds, and times of occurrence.

3.1 Behavior prediction

The proposed method in [6] consists of two steps. First, detecting repeated patterns and generating the behavior model. Second, using the behavior model from the former step and relying on the sensor data, the resident's activities would be recognized and predicted. To discover activities that repeatedly happen in various ordering in an individual's home environment, Discovering Method for Varying Pattern (DMVP) is presented in [6].

DMVP combines frequent sequential pattern miner to find frequent patterns and Shortest Super Subsequences (SSS) method to find common patterns. DMVP identifies sensor event sequences that belong together and appear frequent enough to comprise an activity that can be tracked. The classification model is then used to recognize and predict the activities. The method is schematically depicted in Fig. 1.

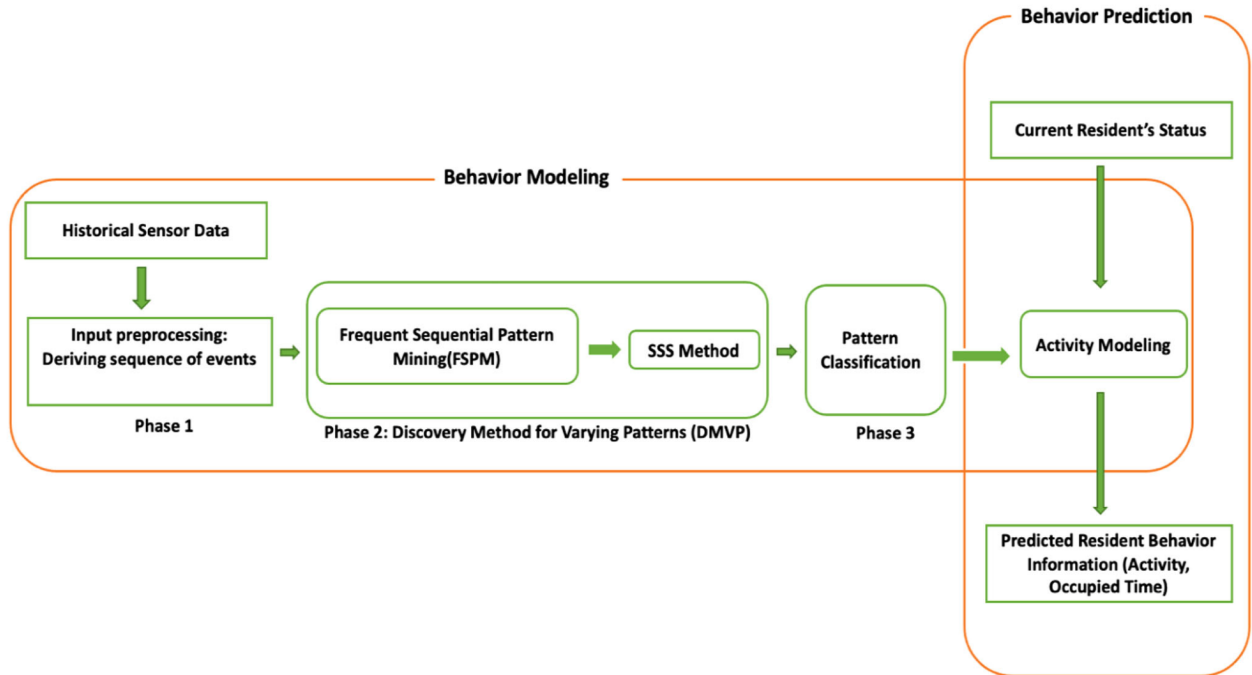


Figure 1. Representation of the proposed method in [6] for discovering and detecting activities

3.2 System architecture

The proposed PECMS consists of three main components, namely input module, planning module, and simulation module. Figure 2 depicts the architecture of the system. The sensor data from the outdoor and indoor environments and predicted activity are fed into the EnergyPlus. The EnergyPlus system then devises a schedule for electrical systems while addressing both energy consumption and the human thermal comfort level based on Predicted Mean Vote (PMV) developed by [26]. Each module is described in the following:

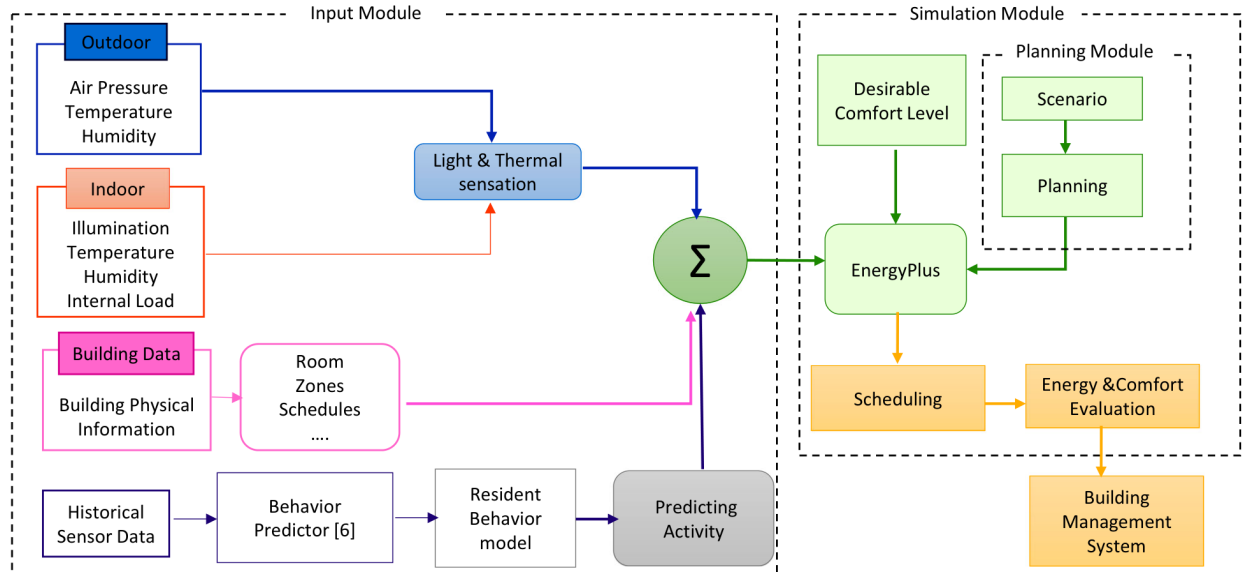


Figure 2. Representation of the input, planning, and simulation modules of PECMS

- **Input module** This module is responsible for gathering all contextual data that are to be used by the planning and simulation module. Required data are collected as outdoor, indoor, building, and behavioral data and are unified and sent to the simulation module. Outdoor data include weather and climate information about the building region. Indoor data contain all data that are gathered from temperature, humidity, illumination, and internal load sensors installed in the home. Building data include built material, geometric layouts of rooms, and thermal zones, as well as definitions of the connections between these defined spaces. Finally, resident behavioral information, which is the output of the residents' behavior prediction system.
- **Planning module** is responsible for directing EnergyPlus on how to operate and control the energy-consuming systems. Three main strategies can be assumed for using and controlling the devices in a home. In the first strategy that we refer to as the baseline strategy, all power-consuming systems are operated manually by residents based on their needs. To be more specific, residents turn on the lights when they enter a room and turn the lights off - 70% of the time - when they exit the room. Likewise, electronic appliances like HVAC are switched on or off according to the residents' needs. In the active strategy, to maximize the comfort level of the residents, HVAC systems are permanently switched on to always keep the indoor temperature at the residents' preferred degree. Likewise, other electronics and lighting systems are scheduled according to the needs of the residents. In the third strategy that we refer to as proactive strategy, based on the indoor and outdoor information, building material, residents' preferences, behaviors, and their predicted activities, power-consuming devices would be switched on or off. Based on the predicted activity and taking into account the characteristics of the zone where the activity would take place and as well as indoor and outdoor factors, specifications of the devices that should play a part in providing the required comfort level, the devices would be turned on or off in an appropriate time before and after the action actually takes place. This ensures that light and temperature would be at the preferred level while the resident gets into the zone, and the devices would be kept on only when they should be. This strategy keeps energy consumption optimized while guaranteeing the residents' comfort level. In effect, HVAC systems, like light switches, are turned on or off automatically according to the predicted presence or

absence of residents in the area. Due to the presence of natural light during the day, light systems work as dimmer and diminish their light intensity.

- **Simulation module** Based on the indoor and outdoor data and using the building and residents' behavior information, subject to the selected policy, in this module, the building's power consumption would be modeled. We use EnergyPlus in the simulation module. EnergyPlus is an open-source application that simulates heating, ventilation, cooling, lighting, water use, renewable energy generation, and other building energy flows and is a building simulation engine supported by the United States Department of Energy (DOE) [27]. It includes many innovative simulation capabilities, including sub-hourly time-steps, natural ventilation, thermal comfort, and co-simulation. EnergyPlus, as a part of PECMS, allows for a complete simulation of residents, devices, and consequential building conditions under different control strategies. These strategies include active and proactive control strategies in which HVAC and lighting systems are adjusted according to the presence and absence of residents and their preferences. In this study, the determination of the human comfort level is based on the PMV index that depends on the temperature, humidity, and metabolic rate of residents' activity. The output of this module is the scheduling of devices in the home that is passed to the building management system to take effect.

4 Energy consumption and thermal comfort level evaluation

4.1 Energy consumption

Throughout the simulation, building energy consumption is estimated for a 24-h period. Total building electricity consumption (KWh) in one day is calculated as

$$\begin{aligned} & \text{Building Electricity} \\ &= \sum_{i=\text{zone}1}^{\text{zone}n} (\text{HVAC}_i + \text{Light}_i + \text{Equipment}_i) . \end{aligned} \quad (1)$$

Building electricity is the aggregation of all the consumed energy in the building. Light meters contain the interior zone's light and exterior light. HVAC meters measure the energy consumed by the zones' HVAC systems. Equipment meters measure the energy consumed by the interior appliances.

4.2 Resident thermal comfort

Thermal comfort is a subjective evaluation that depends on metabolic rate, clothing insulation, air temperature, radiant temperature, airspeed, and humidity. Also, thermal comfort is the notion of a person's thermal sensation in a conditioned environment [28]. Many mathematical models regarding thermal comfort have been developed during the last forty years to evaluate people's comfort levels. The Fanger model proposed by [26] is one of the well-known thermal comfort prediction models. This model is related to the heat balance equations of the human body and a thermal sensation scale. To predict the thermal sensation, the model uses major environmental factors, such as MAT (mean air temperature), MRT (mean radiant temperature), RH (relative humidity), air velocity from [29], and a clothing insulation factor, which is usually considered as a fixed value of 1. The combination of these factors, as well as activity level and work efficiency, allows the calculation of thermal sensation prediction to be made [28].

In this model, all significant modes of energy losses from the human body are taken into account, and the person is assumed to be at a steady state in the interior environment. The model is correlated with experimental data and resulted in a “Predicted Mean Vote” (PMV) calculation that is based on the following equation:

$$PMV = \left(0.0303e^{-0.036M} + 0.028\right)(H - L), \quad (2)$$

where H, L, M, and W are defined in Table 1

Table 1. Nomenclature list for Fanger model

Symbol	Description	Units
H (= M - W)	Internal heat production rate of an occupant per unit area	W/m ²
M	Metabolic rate per unit area	W/m ²
W	Rate of heat loss due to the performance of work	W/m ²
L	All modes of energy loss from body	W/m ²

PMV index expresses the thermal sensation on a seven-point scale ranging from - 3 to + 3, where negative values denote cold sensation and positive values denote warm sensation. The value 0 denotes neutral sensation, which is the target value for indoor air conditioning. The PMV index - can be calculated in EnergyPlus - depicts the thermal comfort of the resident. If the PMV index falls between the interval of [- 0.5, + 0.5], it would be considered as a desirable thermal comfort level. Any time that the PMV index falls out of [- 0.5, + 0.5] that would be counted as thermal discomfort time in the house.

5 System simulation and evaluation

In order to show the effectiveness of the proposed method, we have simulated a home of the MIT smart home project with the three control strategies. We calculated the total consumed energy and achieved a comfort level with respect to the three control strategies, i.e., Baseline, Active, and Proactive.

As shown in Fig. 2, the simulation of the PECMS is centered around EnergyPlus. In effect, all required data, including outdoor (air pressure, temperature, humidity), indoor (illumination, temperature, humidity, internal loads), building physical information (layout, materials...), and predicted activities of the residents, should be fed to EnergyPlus. In conjunction with the desired comfort level and the selected strategy, EnergyPlus generates the scheduling of the devices.

Due to the fact that the resident of the MIT smart home is an employee woman who spent most of her time outside the home, and the bedroom thermal zone is the place in the home in which she spent most of the time sleeping or studying, for the sake of brevity, we elaborate on the bedroom zone to evaluate the result.

5.1 Data preparation

Figure 3a shows the layout of the smart home. The apartment is a common single-family house type in Massachusetts that is 133 m² with one bedroom, one bathroom, a kitchen, and a living/dining room. The resident who lived in the apartment was a 30-year-old professional woman who spent her free time at home. 77 sensors were installed in the apartment. The sensors were installed on doors, windows, cabinets, drawers, microwave oven, refrigerator, stove, sink, toilet, shower, light switches, lamps, some containers (e.g., water, sugar, and cereal), and electric/electronic appliances (e.g., DVD Player, TV, stereo, washing machine, dishwasher, coffee machine). Thus, the resident's activities inside the smart home are recorded using motion, door, temperature, and item sensors. Sensors are shown in Fig. 3a and described in Table 2. Historical sensory data are fed to the behavior prediction module to model the resident's behavior and predict her next activity.

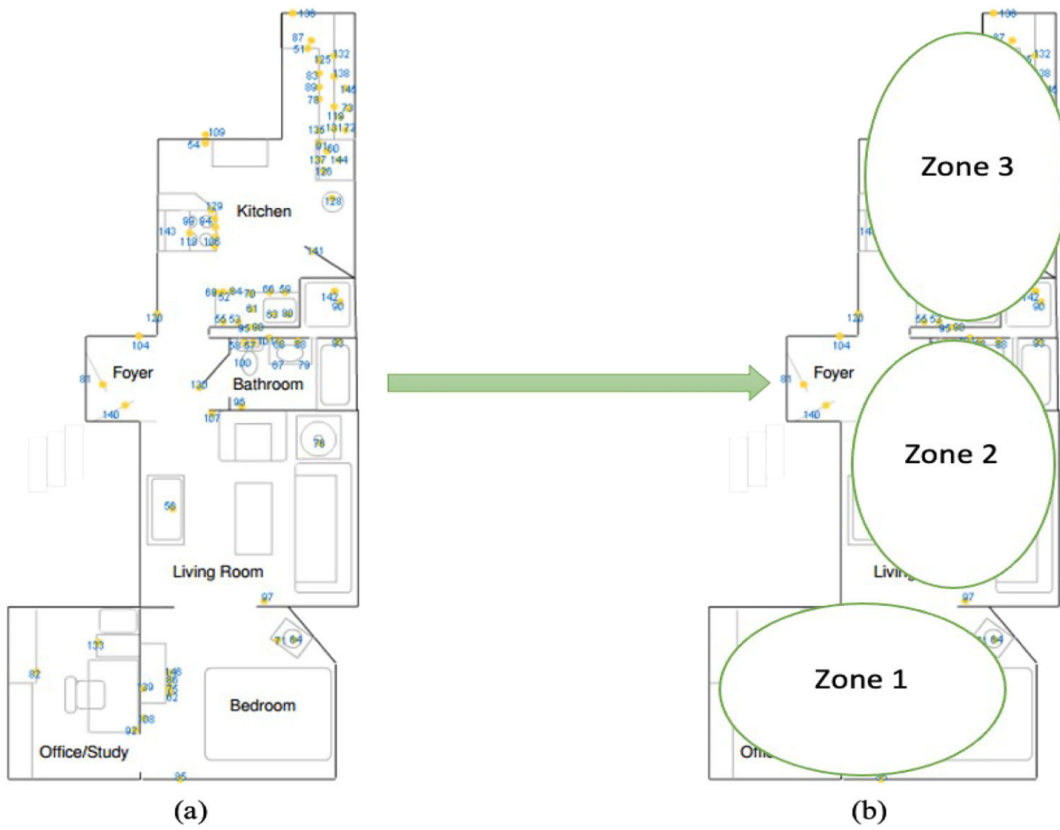


Figure 3. a Layout of MIT smart home used for data collection [31]. b three thermal zones identified in the smart home.

Table 2. The defined areas in the MIT smart house

Area	Object	Sensor IDs
Bathroom	Cabinet	67, 79
Bathroom	Door	130
Bathroom	Exhaust Fan	96
Bathroom	Light switch	101
Bathroom	Medicine cabinet	57, 58
Bathroom	Shower faucet	93
Bathroom	Sink faucet - cold	88
Bathroom	Sink faucet - hot	68
Bathroom	Toilet flush	100
Bedroom	Drawer	62, 71, 75, 86, 146
Bedroom	Jewelry box	139
Bedroom	Lamp	64
Bedroom	Light switch	108
Bedroom	Window	85
Foyer	Closet	81
Foyer	Door	140
Foyer	Light switch	104
Kitchen	Burner	94, 99, 106, 118
Kitchen	Cabinet	51, 53, 55, 59, 61, 63, 66, 72, 73, 80, 83, 89, 132, 133, 138
Kitchen	Cereal	145
Kitchen	Coffee machine	119
Kitchen	Containers	60
Kitchen	Dishwasher	70
Kitchen	Door	54, 141
Kitchen	Drawer	52, 69, 78, 84, 87, 125, 135
Kitchen	Freezer	137
Kitchen	Garbage disposal	98
Kitchen	Laundry Dryer	90
Kitchen	Light switch	95, 105, 120
Kitchen	Microwave	143
Kitchen	Oven	129
Kitchen	Refrigerator	91, 126, 144

Area	Object	Sensor IDs
Kitchen	Toaster	131
Kitchen	Washing Machine	142
Kitchen	Window	136
Living room	DVD	56
Living room	Lamp	76
Living room	Light switch	97, 107
Office/study	Drawer	82
Office/study	Light switch	92
Porch	Light switch	109

We have used Ecotect to draw the smart house in three-dimensional space - Fig. 4. Autodesk Ecotect Analysis is an environmental analysis tool that allows designers to simulate building performance from the earliest stages of conceptual design. The software helps to model the house, define spaces, and use materials in the building in the way that is required by EnergyPlus [30].

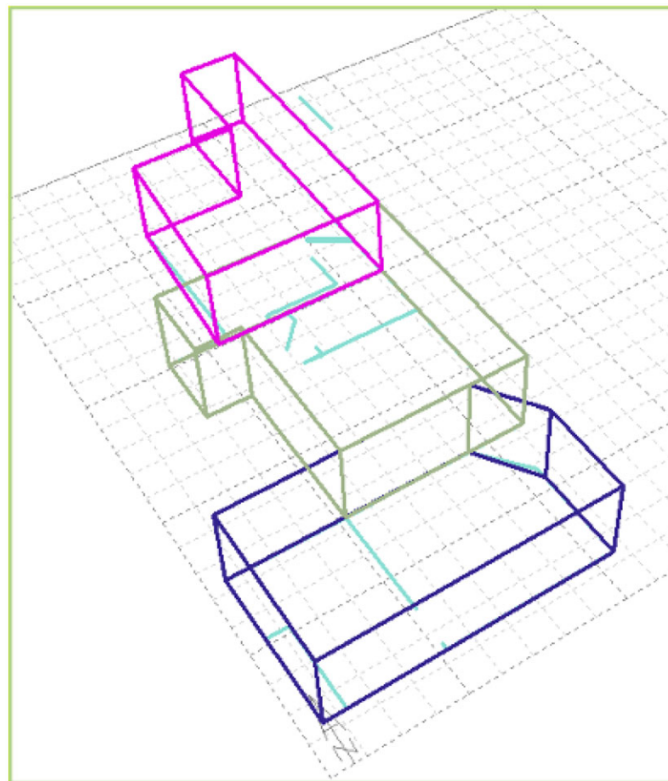


Figure 4. 3-Dimension smart home design in Ecotect software

Due to the fact that the outdoor weather data for this house was not provided within the dataset, the weather data of the region where the house is located to be used in this simulation is taken from Typical Meteorological Year3 (TMY3) at Cambridge, Massachusetts, USA [29].

The HVAC system of the house is a packaged terminal heat pump that supplies cool and hot air into thermal zones. The house is divided into different areas based on the

installed sensors [31] - Table 2. Based on this information and with respect to the location of devices in the house, we have divided the house into three thermal zones, namely the living room, kitchen, and bedroom, which are depicted in Fig. 3b. All the defined thermal zones are cooled down and heated up by the HVAC system. The internal loads of this house include one adult, lighting, and electrical equipment loads, such as a computer, TV, fridge, washing machine, and dishwasher. Materials that are used in the building are commonly used materials in construction, such as concrete, plaster, glass, roof insulation, and so on. Table 3 shows the architectural features of the single-family house model [32].

Table 3. One single house architectural features

Building component	Single-family house model
Type	Apartment
Floor area	133 m ²
Floor	Single story
Floor plan	One-bedroom
Orientation	North, 90°
Internal load	
Occupant	1 Resident
Lightening	3.875 W/m ²
Equipment	30.06 W/m ²
HVAC	Heated basement
Thermal zone	3 Zones
Weather and location	Cambridge, USA

5.2 Baseline strategy

In this experiment, we have studied the bedroom's thermal zone during the whole winter. However, in the following, first, we discuss the obtained results for a weekday in the winter (January 10th) since this case is usually one of the coldest days in winter and will demonstrate the admissible consumption of the HVAC system in the building. Figure 5 depicts a comparison of the outside temperature with the bedroom's temperature 24 h of the day. As mentioned, the resident uses her bedroom for sleeping and studying; therefore, from 12:00 am to 6:00 am, as she turns on the HVAC system in the bedroom, the inside temperature turns into a favorable one for her. Therefore, there has been a big difference between the inside and outside temperature during her presence in the bedroom. However, after 6:00 am, when she wakes up, she turns off the HVAC and leaves the room. Thus, the temperature has gradually reduced after 6:00 am.

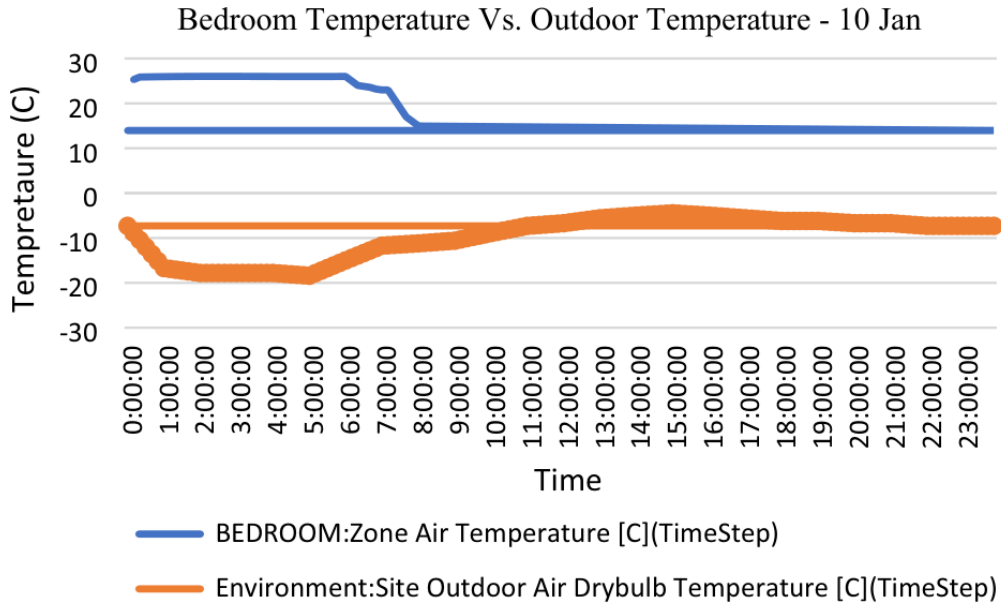


Figure 5. Bedroom inside/outside temperature on Jan. 10th

Figure 6 shows the bedroom HVAC energy consumption and the resident thermal comfort. After entering the bedroom, she turns on the HVAC system and sets the HVAC temperature to the desirable one. So, after about 10 min, the PMV index reaches the optimal range between - 0.5 and + 0.5, which is depicted in the Thermal Comfort axis on the chart. However, when the HVAC system is turned off, the optimal thermal comfort drastically drops.

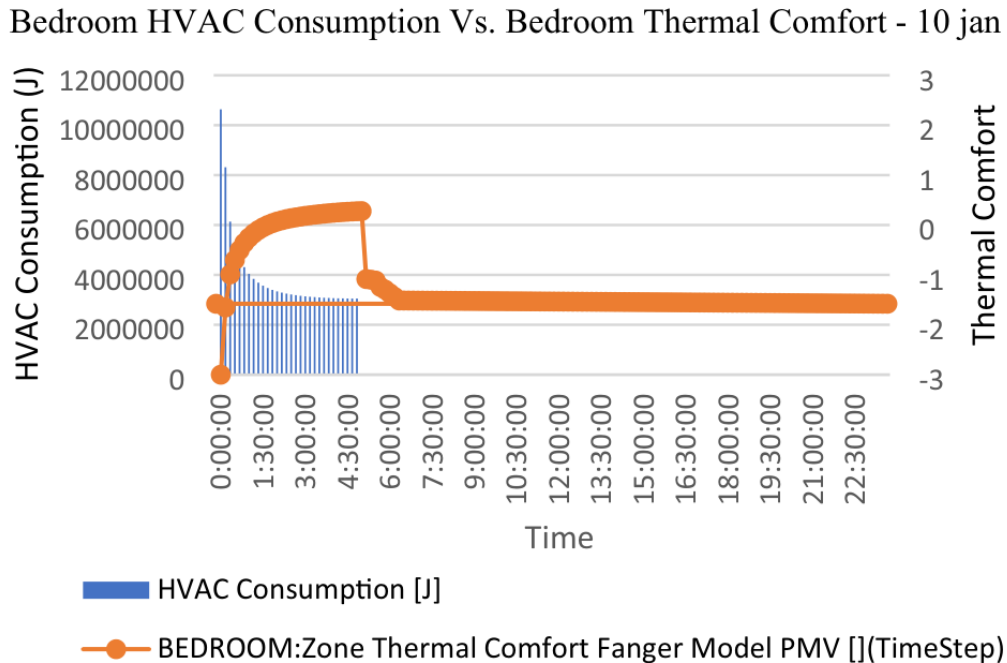


Figure 6. Energy consumption of the HVAC system (baseline strategy)

Figure 7 shows the room temperature during the presence and the absence of the resident in the room. With the user's presence in the bedroom area, the HVAC system is turned on, the temperature is set to the optimum level, and the comfort level reaches

the standard level. Afterward, when the resident leaves the room, the appliance is switched off, and after a while, the thermal comfort has drastically decreased.

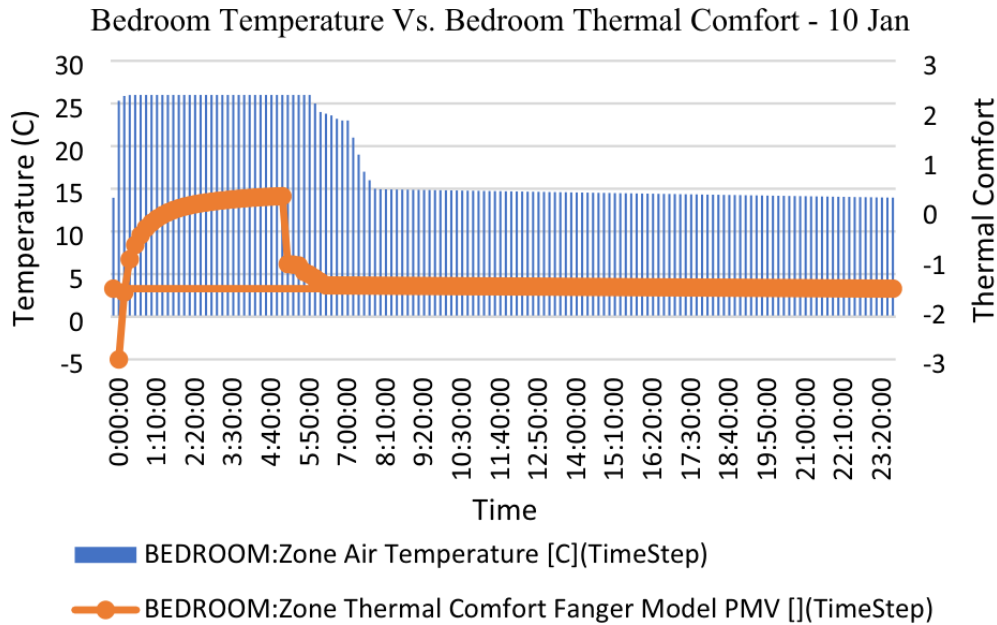


Figure 7. Bedroom temperature and thermal comfort of the resident on Jan. 10th (baseline strategy)

Finally, Fig. 8 depicts the HVAC system's energy consumption in the whole house and the time (in minutes) in which the resident has been in a state of discomfort. The figure indicates that when the HVAC system is switched on, at first, the resident has had a few minutes of discomfort. After passing a few minutes, thermal comfort has reached the desired level. In this case, even though the resident herself has turned the system on and off according to her interests, she had spent some time in an uncomfortable state.

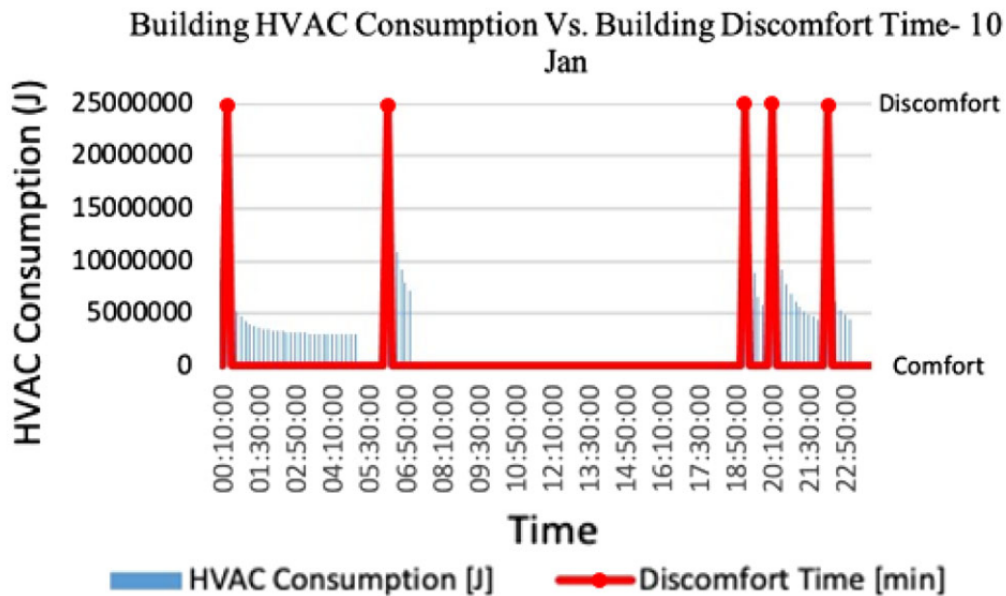


Figure 8. HVAC energy consumption of the whole house and the discomfort time on Jan. 10 (baseline strategy)

5.3 Active strategy

Based on this strategy, HVAC systems are always kept on to permanently maintain the desired internal temperature and, consequently, the resident's comfort level. Figure 9 shows the temperature of the bedroom during the day with thermal comfort. Although the temperature has been kept constant in the room, the thermal comfort has fluctuated. This is because thermal comfort depends on the resident's presence in the room, the activity that the resident is performing in the room, and the amount of energy she has lost. However, with this strategy, the resident is entirely in her comfort zone.

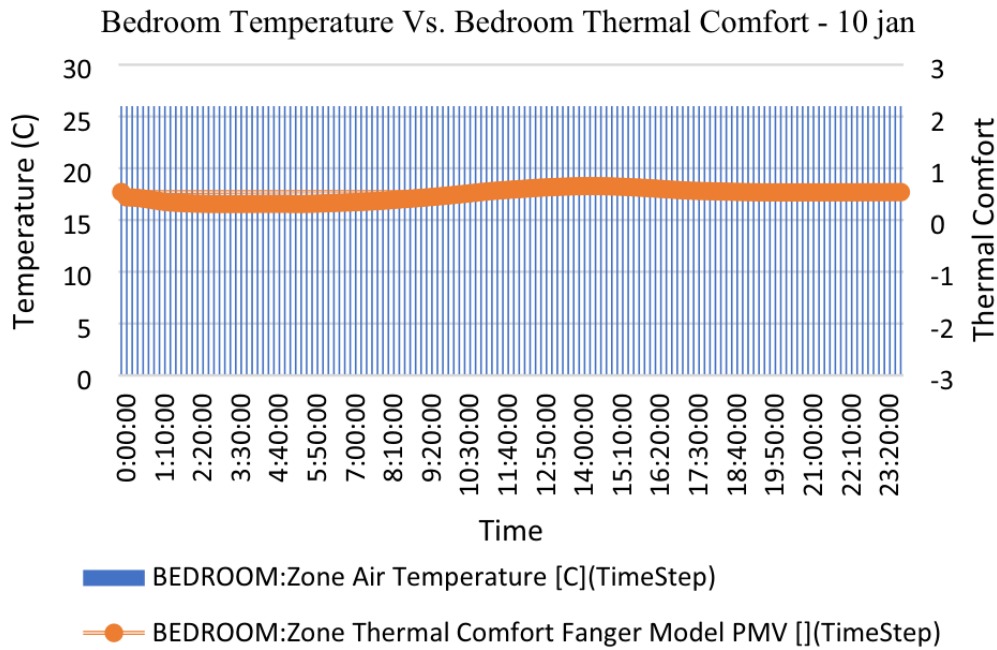


Figure 9. Temperature and thermal comfort in the bedroom on Jan. 10 (active strategy)

Figure 10 shows the amount of energy consumed by the whole house HVAC system during the day. As expected, there has not been any time of discomfort. This is due to the fact that the HVAC systems have always been active, and the temperature has been kept at the optimal level, so the total amount of discomfort time was zero.

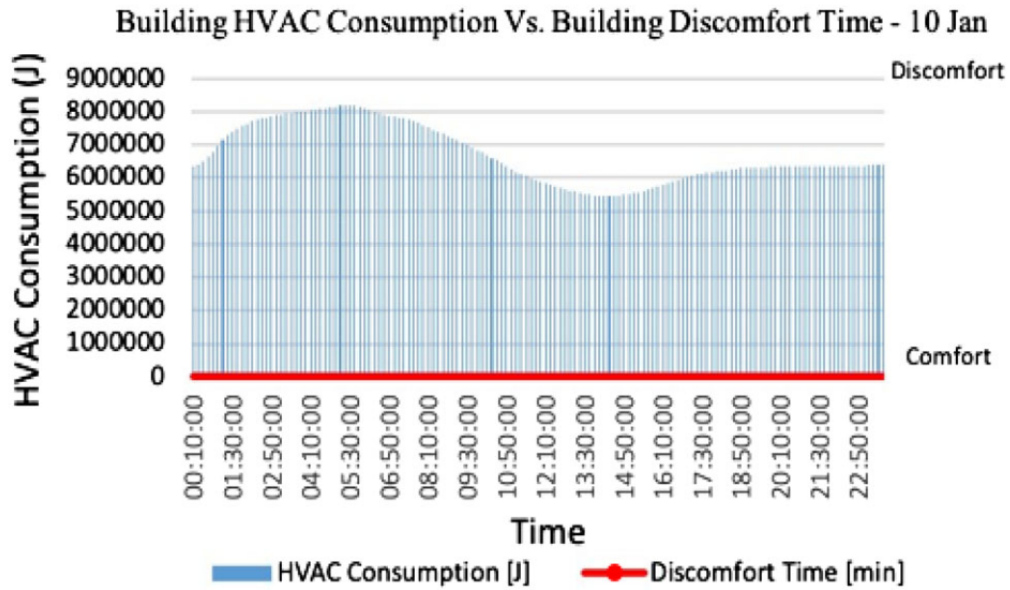


Figure 10. HVAC energy consumption of the whole house and the discomfort time on Jan. 10 (active strategy)

5.4 Proactive strategy

In this strategy, considering the predicted activities, the schedule for electronic devices is set based on the presence and absence of residents in the area and the activity the resident is doing. Figure 11 shows room temperature and thermal comfort simultaneously. Based on the predicted behavior of the resident, before the presence of the person in the room, i.e., 12:00 am, the HVAC system is turned on, and the temperature is set to the desired level before she arrives in the room. However, a while before the resident leaves the room at 6:00 am, the HAVAC system is turned off. The thermal comfort decreases gradually, but until the resident is present, it does not fall out of the comfort bounds.

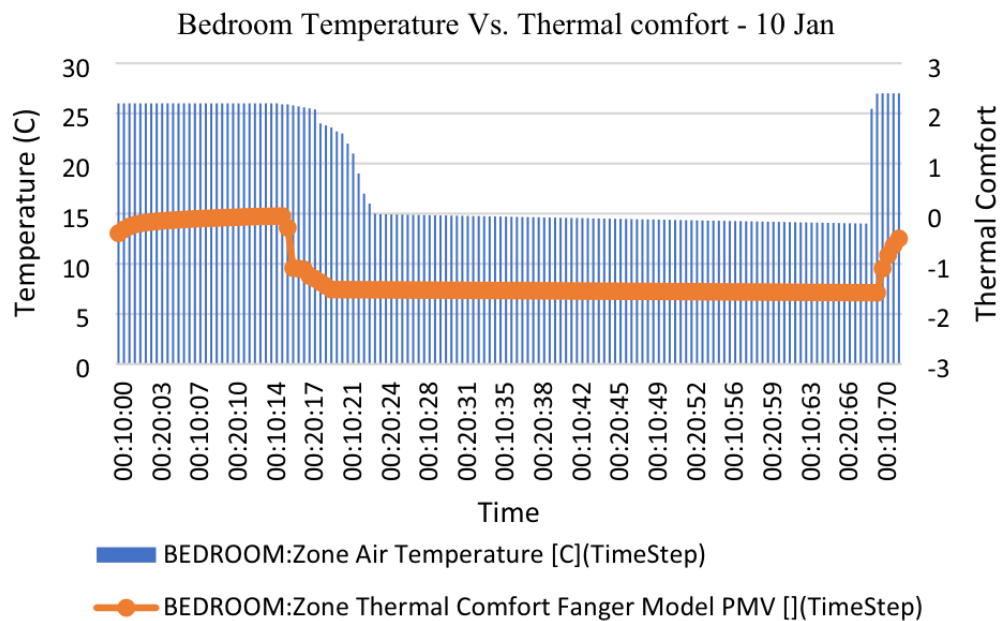


Figure 11. Temperature and the thermal comfort inside the bedroom on Jan. 10 (proactive strategy)

Figure 12 illustrates the time interval in which the HVAC system has been active in the bedroom and the energy consumed by HVAC. By turning on the HVAC system before the resident's presence in the room, the resident's thermal comfort during her presence in the room is satisfied. According to the figure, the thermal comfort is at the optimal level as soon as the person arrives in the room at 12:00 am.

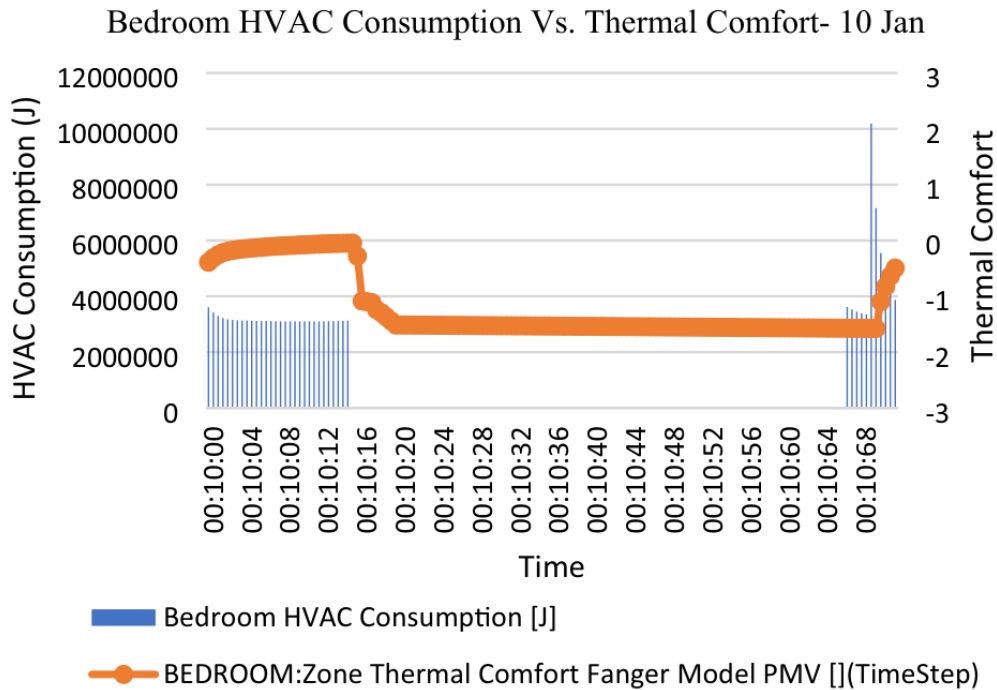


Figure 12. The energy consumed by the bedroom HVAC system based on the resident presence (proactive strategy)

In Fig. 13, the horizontal axis shows all the time when the HVAC system is turned on during the presence of the resident and before the resident's presence in the area. According to the predicted action, the HVAC system is turned on a few minutes before the presence of a person in that area in order to provide favorable thermal comfort. As shown in the figure, when the resident enters the home's specific area, the thermal comfort is already set at her desirable level; the discomfort time has been zero minutes. Figure 14 compares the total electricity consumption in the house with respect to the three control strategies on January 10th.

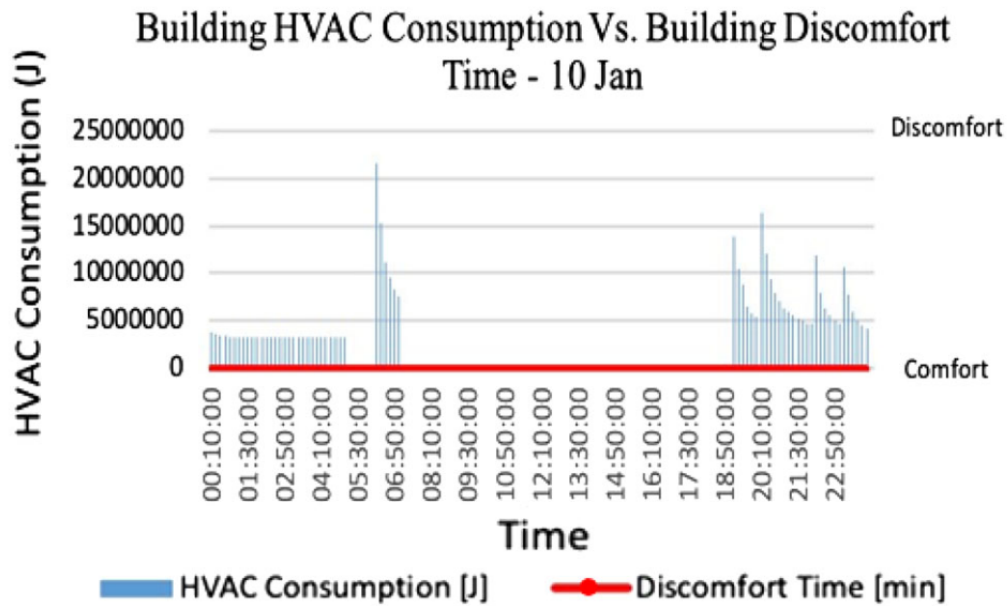


Figure 13. HVAC Energy consumption and discomfort times on Jan 10 (proactive strategy)

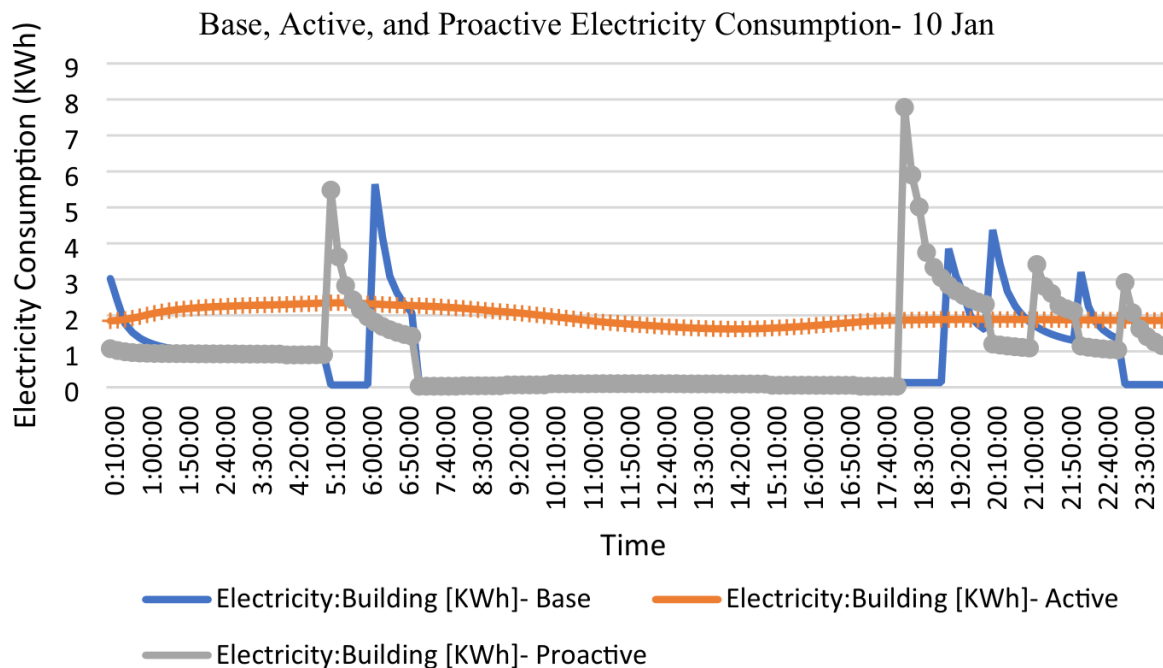


Figure 14. Energy consumption for three control strategies simulated for Jan. 10

Table 4 depicts the house energy consumption and the duration of discomfort time on a 24-h day on the winter day for the three control strategies. As shown in the table, the active strategy compared to the baseline strategy has no discomfort time since the HVAC systems are always kept on to satisfy resident thermal comfort. However, energy consumption has increased significantly. In the proactive strategy, as discussed before, the HVAC systems are turned on before the arrival of the resident and turned off a short while before the resident's departure in order to provide acceptable thermal comfort for the resident. Thus, there is no sign of discomfort time, and clearly, the amount of energy consumption has increased in comparison with the baseline strategy but is much lower than the active strategy.

Table 4. Comparison of the energy consumption and the duration of discomfort in all three control strategies on the 10th of January

Strategy	Building energy consumption (KWh)	Discomfort time (min)
Baseline	115.03107	30
Active	283.08420	0
Proactive	117.8658	0

Table 5 shows the results obtained for the entire winter season. The amount of energy consumed for lighting and HVAC systems is estimated along with the building's total energy consumption and the duration of discomfort time in all the zones of the house.

In proactive strategy, by predicting the resident's activities, energy consumption by the lighting system is lower than the baseline. The lighting system in daylight operates like a dimmer, which in the presence of natural light, reduces the intensity of artificial light. However, in contrast to the lighting systems, HVAC systems are activated before the presence of a person in the area to achieve the desired thermal comfort, so the HVAC systems consume more energy than in the baseline strategy.

Consequently, in the proactive strategy, the amount of energy consumed by the entire house is approximately 1000 kWh more than the baseline strategy. Finally, the duration of discomfort time, which is one of this study's purposes, has diminished from 3840 min in the baseline strategy to zero minutes in the proactive strategy. As discussed in Sect. 4.2, the PMV index depends on a great number of variables, such as air velocity, humidity, and people's activity. PMV index in the range [- 0.5, + 0.5] offers high levels of thermal comfort and, thus, the highest level of user acceptability. Also, all major modes of energy loss from the human body are considered, and the person is assumed to be in a steady state of activity level in the interior environment. Therefore, discomfort time goes to zero minutes during the presence of a resident in the designated area. In the active strategy, we have the highest energy consumption with minimal discomfort time, but the total energy consumption in the house is approximately 1.9 times more than the energy consumption with the proactive strategy.

Table 5. Comparison of energy consumption of lighting systems, HVACs, and total energy at home and duration of discomfort in winter

Strategy	Lightning energy consumption (kWh)	HVAC energy consumption (kWh)	Building energy consumption (kWh)	Discomfort Time (min)
Baseline	60.66	9609.58	10,869.63	3840
Active	165.24	20,661.87	22,026.5	0
Proactive	55.27	10,634.63	11,454.84	0

5.5 Discussion

We have compared the performance of the proposed method with [3, 12, 14, 20, 23]. Comparisons are based on two criteria, namely, changes in power consumption with respect to the baseline strategy and discomfort time.

Klein et al. [3] presented a multi-agent comfort and energy system (MACES) to model alternative management and control of building systems and occupants. MACES is

implemented and tested with input from a real-world building. The operations of the building are then simulated. 12% reduction in energy consumption and 5% improvement in occupant comfort are realized by this system.

The study of [12] introduced a simulation approach to estimate energy savings based on occupant behavior. First, it defined five typical occupant behavior measures in office buildings, then simulated and analyzed their individual and integrated impact on energy use in buildings. The energy performance of the five behavior measures was evaluated using EnergyPlus simulation for a real office. The Occupancy Simulator was used to simulate the occupant movement in each zone with inputs from the site survey of the case building. The five behavior measured in this study includes lighting, plug load, comfort criteria, HVAC control, and window control. Based on the simulation results, the occupant behavior measures achieved overall site energy savings as high as 22.9%. However, this paper is a case study with limited scope to a certain type of buildings and is not designed to estimate the energy-saving potential in a larger-scale environment.

In [14], the author has investigated the use of fuzzy logic in HVAC control as means of enhancing thermal comfort provision for the building occupants while maintaining or improving the resulting energy consumption of the building's HVAC system. In order to assess the application of fuzzy logic on HVAC control, a single zone building model along with an HVAC model was created using EnergyPlus software and Transient System Simulation Tool, respectively. In addition, an HVAC fuzzy logic controller along with a conventional on-off controller, both thermal comfort-based, was developed using Simulink. In terms of the provided thermal comfort to the building occupants, the fuzzy HVAC controller managed to reduce the non-comfort hours by more than 50%.

In [20], full-year dynamic occupancy profiles were developed using real occupancy data capturing the stochastic behavior of occupants. Having the dynamic occupancy profiles along with the indoor environmental conditions, this study contributed to the exploration of optimal local control strategies based on the integration of a simulation model with a multi-objective optimization process. Based on two applications of occupancy prediction, HVAC, and lighting control, different prediction horizons were used in this study. HVAC control utilized a 30-min prediction horizon due to the lag associated with preheating, and lighting used a short-term prediction, i.e., 5 min. The application of HVAC and lighting local control strategies results in improving the thermal condition by 50%, along with 2% savings in energy consumption. In this paper, only one lag time is used, i.e., 30 min, for the prediction horizon. When evaluating an occupancy model, wider preconditioning horizons are more valuable when considering lag times that range from 30 min to 3 h. An intelligent system with a prediction mechanism and intelligent control strategies was proposed by [23]. They did a realistic measurement on 100 different houses for the evaluation phase. According to the findings, the system was able to reduce energy use by 14% while maintaining resident satisfaction by 91%. However, comfort satisfaction represents the feature of each room owner, and it could not be generalized to the residents in the living room.

Table 6 compares the performance of our proposed system in energy consumption and thermal comfort to other studies with respect to the baseline strategy in which the control is manual. Compared to the baseline strategy, the proactive strategy has caused a 5% increase in energy consumption. However, the duration of discomfort time was cut down by 100%. The active strategy that does not use any indoor, outdoor, or built behavioral information demands all devices be always operative, which naturally eliminates the discomfort time; however, with over 102% increase in energy

consumption. Kwon et al.'s method [23] saves energy consumption by about 14%, but it comes with the expense of not full satisfaction. Our proposed proactive method provides full satisfaction; however, it increases power consumption by about 5%. It is not easy to judge which method is better than the other. From the perspective of saving energy, Kwon et al.'s method [23] but from the viewpoint of comfort, our method is preferred. However, calculating the pricing associated with both methods that demand determining when the decrease or increase in power consumption happens in both methods would provide another clue for comparison that can be the subject of future studies. Sun et al.'s [12] method saves energy by about 22.9%. Their simulation has been on office space. Moreover, the comfort level they have reported in the paper (80%) is based on the perceived thermal comfort level by all occupants and is not comparable by what is discussed in this paper. The reduction of discomfort time achieved with other methods is much lower than our method. Hence, their power savings cannot be sufficing.

Table 6. PECMS comparison with other methods

System	Verification	Method	Strategy	Energy consumption (with respect to the baseline strategy)	Discomfort time
PECMS	Simulation	Intelligent Control	Proactive	+5%	-100%
PECMS	Simulation	Intelligent Control	Active	+102.6%	-100%
Kwon et al. [23]	Experiment	Intelligent Control		-14%	-91%
Salimi et al. [20]	Simulation	Intelligent Control		-2%	-50%
Anastasiadi et al. [14]	Simulation	fuzzy logic-based control		0%	-50%
Sun et al. [12]	Simulation	Intelligent Control		-22.9%	
Klein et al. [3]	simulation	Intelligent Control		-12%	-5%

6 Conclusion

Occupancy-related information is recognized as an influential factor affecting the energy operation in buildings. In order to enhance the energy management of buildings, the need for localized and customizable comfort controls is increasing in residential buildings to improve the occupants' satisfaction. Compared to more traditional control systems, such as those that include both occupancy and occupant preferences, the simulation of building control revealed substantial comfort satisfaction. In this paper, we propose a novel AI-based Personalized Energy and Comfort Management System (PECMS) that monitors and stores environmental and occupant data as knowledge and information. Based on the data collected from sensors mounted in the building, the PECMS analyzes occupants' movements and manages critical energy-consuming devices, considering the occupants' preferences. The evaluation results indicate that compared to the baseline strategy, the proactive strategy support by PECMS increases energy consumption by 5%, however, reduces the duration of discomfort time by 100%. The active strategy that does not use any indoor or outdoor behavioral data requires all devices to be continuously operational, which, although it eliminates discomfort time, increases energy consumption by over 102%.

The main contribution of this paper is providing value in using resident, building, and environmental information. In the proposed system, using low-cost motion sensors, resident behavior is modeled and predicted. Anticipating when and for how long the resident would be in any zones of the home, integrating with the indoor, outdoor, and built information, enables eliminating discomfort time without a significant increase in energy consumption. Modeling the proposed method on MIT smart home dataset has shown a considerable improvement in reducing discomfort time without a considerable increase in energy consumption. Comparing the simulated results of the proposed method with other existing methods demonstrates its efficiency in terms of resident satisfaction. Using the simulated method in open-plan building results in (1) developing local control strategies for building energy-consuming systems; (2) determining the best settings for operating HVAC systems, such as the type of HVAC schedule; and (3) determining the trade-off between buildings' energy consumption and occupant comfort levels by keeping the PMV index within the comfortable range. The proposed method's practical application intends to aid decision-makers in determining the most efficient occupancy-centered building operations. The given PECMS provide motivation for further research into multi-occupancy systems for better building energy management and occupant comfort. For future work, we will investigate the performance of our framework in multi-occupancy residential testbeds with more population and on other building types like commercial and retail.

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Declarations

Conflict of interest. Authors declare that they have no conflict of interests.

Ethical approval. This article does not contain any studies with human participants or animals performed by any of the authors.

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