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Adaptive Control for Hydronic Radiant Heating System Using Occupant Behaviors in Residential Building

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Featured Application: Developing occupant presence monitor and sensor station incorporated into heating and cooling system controllers in residential buildings.

Abstract: This study proposes an occupant-centric control strategy for residential heating systems, aiming to enhance thermal comfort and reduce energy consumption. A sensor station utilizing a frequency-modulated continuous wave radar sensor was developed to detect occupancy and infer activities within residential spaces. By analyzing field measurement data, schedules for occupancy and activities were established. These schedules were then used to implement a variable control strategy for the hydronic radiant heating system, adjusting its operating characteristics based on the identified activities. The proposed control strategy, which includes resetting the indoor set temperature during unoccupied periods and adjusting it during sleep to account for changes in metabolic rate and clothing insulation, resulted in significant energy savings. Compared to continuous operation, the hydronic radiant heating system's energy consumption was reduced by approximately 21% on peak load days and up to 34% over three winter months. This study demonstrates the potential of occupant-centric control for achieving substantial energy savings in residential buildings while maintaining occupant thermal comfort.

Keywords: occupant-centric operation; hydronic radiant heating system; thermal comfort; metabolism and clothing insulation; occupant behavior

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1. Introduction

Buildings consume a significant amount of energy globally, accounting for approximately 30% of total energy consumption and 25% of CO_2 emissions [1]. This highlights their critical role in climate change. Heating and cooling systems are the primary energy consumers in both residential (43%) and commercial buildings (30%) in developed countries [2]. Residential buildings account for nearly 70% of global building sector energy consumption, with thermal energy uses comprising a substantial and variable portion [3]. Over 68% of residential building energy is used for thermal purposes, including water heating (15.9%) and space heating (53.4%) [4].

The behavior of occupants, particularly in residential buildings, has attracted worldwide attention due to its potential to cause discrepancies between predicted and actual energy use and impact indoor thermal comfort [5]. Unlike other technical energy conservation measures, occupant behavior is uncertain and unpredictable, significantly affecting the development of strategic solutions for behavioral energy savings in residential buildings.

While many researchers have primarily focused on analyzing and predicting window opening behavior by occupants, which significantly impacts indoor environments in residential buildings [6–12], there is increasing interest in estimating occupancy schedules and patterns to understand the relationship between space occupancy conditions, such as

the number of occupants, duration and location of stay, random movements, and energy consumption in both residential and commercial buildings [13–19].

Kavousian et al. conducted an extensive survey of 1628 households to investigate the relationship between occupancy conditions and energy consumption in residential buildings [20]. They found that the number of occupants is a significant variable in predicting daily maximum energy consumption but not daily minimum energy consumption. Panchabikesan et al. presented a data-driven model that explored distinct occupant schedules and presence probabilities in a group of residential buildings. They identified lighting, plug load energy consumption, CO_2 levels, and relative humidity as indicators of occupant schedules and presence/absence [21]. Najeh et al. conducted experiments on human activity in residential buildings using real-time recognition of human activities (HAR) with an embedded algorithm for activity classification. They evaluated their developed algorithm with three different hardware architectures and found it to be a feasible solution for embedded systems [22].

The studies on occupancy models and interactions with heating and cooling systems have often focused primarily on the number of people in the space and their presence/absence, which may not be sufficient for deriving efficient control strategies for residential building heating and cooling devices. While these studies identified relationships between occupancy conditions and energy consumption, they did not fully explore the impact of individual occupant behavior and activities on energy use.

Recognizing the significant influence of occupant behavior on energy performance in both residential and commercial buildings, researchers have become interested in developing optimal control strategies for heating and cooling systems. L. Giusti and M. Almoosawi conducted an energy survey of 36 residential units in Abu Dhabi, UAE, finding that air conditioning and domestic water heating systems operated continuously throughout the day, even during unoccupied times, in most rooms. By conducting parametric analysis using building energy modeling, they determined that overriding the room setpoint to 24 °C was the most effective energy-saving measure without major building retrofitting [23].

H. Jang and J. Kang pointed out that energy use in residential buildings is more impacted by occupant behavior and exhibits more irregular fluctuations compared to commercial buildings. They developed an energy model considering the impact of occupant behavior on energy use in actual apartment buildings of different ages (pre-1980 and 1980–1988), finding a 10–30% deviation from average values and a range of 128% between minimum and maximum values [24]. J. Ahn and S. Cho developed a complex machine learning model based on artificial neural networks incorporated with design scenarios assuming unusual situations. This decision-making model determines the extent to which the cause of abnormal situations is associated with occupant behavior. The proposed model improved human thermal sensation by 10.2% and saved energy consumption by 25.7% for residential buildings [25]. However, previous studies often identified occupants' activities and clothing values as single variables for night and day. Sung and Hsiao presented a heating and cooling operation based on occupant thermal comfort, measured using an Internet of Things (IoT) sensor network. Even with fuzzy control algorithms evaluating thermal comfort for 10 occupants in the space, the activity and clothing levels were predefined due to the conventional office space [26].

Previous studies on occupancy models and interactions with heating and cooling systems have often neglected at least one of the following research problems: (1) generating timely occupancy patterns; (2) identifying individual behavior and activities in space; (3) managing heating and cooling systems through occupant-centric control; and (4) evaluating system performance with actual data.

This study proposes an intelligent control strategy for residential heating systems that prioritizes both thermal comfort and energy efficiency. By utilizing a sensor station capable of detecting not only the presence but also the location of occupants, comprehensive schedules for occupancy patterns and activity status within residential units were developed through field experiments. These schedules served as the foundation for formulating con-

trol strategies that dynamically adjust indoor air set temperatures to align with occupant activities. Through energy analysis modeling, the potential of these strategies to optimize heating system operation while maintaining occupant thermal comfort was evaluated. The findings of this study offer valuable insights for the development of an advanced control schema that can significantly enhance heating energy efficiency in residential buildings without compromising occupant thermal comfort.

2. Materials and Methods

2.1. Building Descriptions

Measurements were conducted in individual spaces within an actual residential building to determine occupancy status and location. Figures 1 and 2 illustrate the characteristics of the target building, a high-rise apartment located in Seoul, South Korea, with a typical floor plan and composition. The sole occupant was a 23-year-old male college student.

As depicted in Figure 2, the physical properties and composition of the building, including the thickness, length, and structure of exterior walls, windows, and floors, were generated based on architectural drawings and building equipment documentation to construct a suitable heating control simulator for the occupancy environment. The results are summarized in Table 1.

To determine occupancy status and location, the space was divided as shown in Figure 1. Zone 1, where the desk is located, was designated for general study and office work. Zone 2, housing the bed, was primarily used for sleep. Zone 3 encompassed areas for other movement and standing activities.

The heating system in the building is a hydronic radiant panel system, which utilizes hot water circulated through coils embedded in the floor to provide radiant heat. The district heating network supplied hot water to the entire building, and the amount of hot water supplied to individual panels was controlled by thermostats installed in each space.

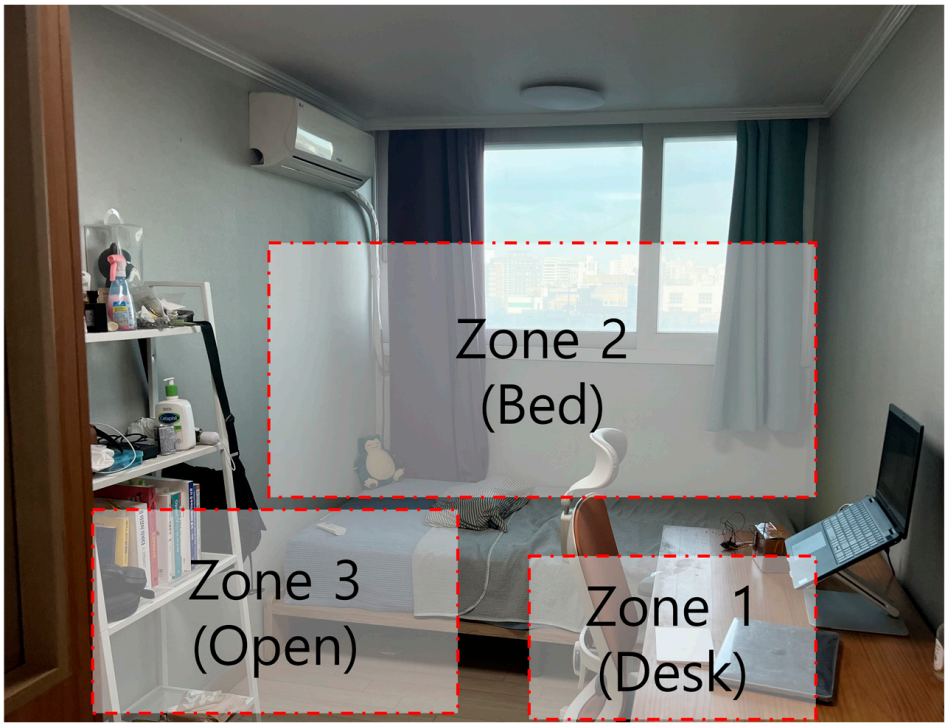


Figure 1. Target space condition and occupied zone condition.

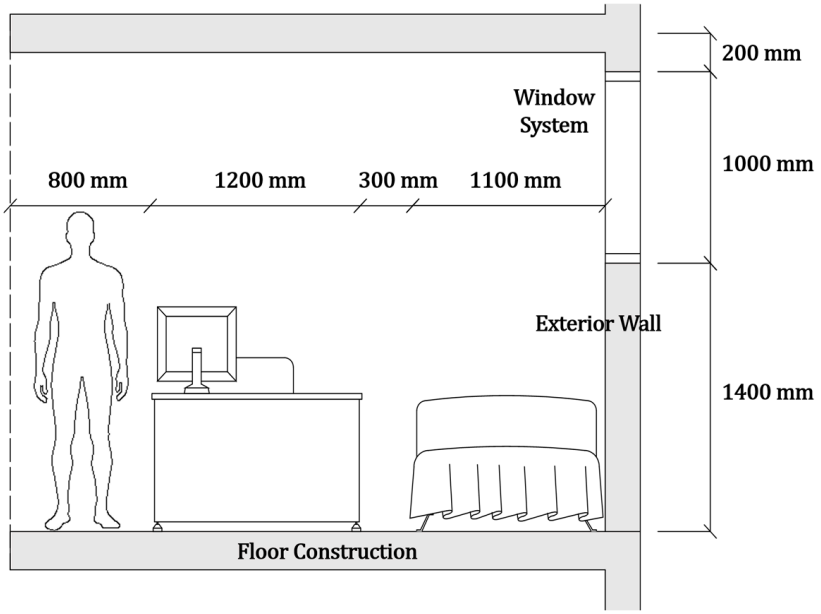


Figure 2. Sectional plan of target space.

Table 1. Residential building and target room specifications.

	Values or Description
Residential unit total area	108 m^2
Target room area	12.52 m^2
Exterior wall area	9.18 m^2
Exterior wall construction	Concrete (200 mm), k = 1.32 W/m-K Porous insulation (120 mm), k = 0.32 W/m-K Gypsum board (24 mm), k = 1.07 W/m-K Overall heat transfer coefficient = 0.20 W/m^2-K
Interior wall area	32 m^2
Interior wall construction	Porous insulation (120 mm), k = 0.32 W/m-K Gypsum board (24 mm), k = 1.07 W/m-K Glass wool insulation (50 mm), k = 0.32 W/m-K Gypsum board (24 mm), k = 1.07 W/m-K Overall heat transfer coefficient = 1.35 W/m^2-K
Window-Wall-Ratio	45%
Window System	Polyvinyl chloride (PVC) frame with double pane glass (12 mm clear glass + 24 mm air + 12 mm low emissivity glass) (U-value = 1.25 W/m^2-K, Solar heat gain coefficient = 0.43)
Infiltration	0.3 Air change per hour (ACH)
Floor construction	Concrete (250 mm), k = 1.32 W/m-K Sound isolation pad (20 mm), k = 1.02 W/m-K Autoclaved light concrete (40 mm), k = 0.13 W/m-K Cement mortar layer embedded hydronic radiant tubes (40 mm), k = 1.21 W/m-K Wood finishing (8 mm), k = 0.05 W/m-K
Heating system	Radiant heating system with hot water from district heating network
Cooling system	Packaged direct expansion (DX) coil air conditioner

k: thermal conductivity.

2.2. Occupant Identification Sensor Station

This study developed an occupancy detection sensor station based on frequency-modulated continuous wave (FMCW) radar to accurately detect the presence or absence of occupants in a specific space and infer their behavior based on their location. Figure 3 shows a schematic diagram of the developed sensor station. The FMCW radar transmits a continuous wave with a linearly varying frequency and receives reflected signals from targets to extract distance and velocity information. The frequency bandwidth of the chirp signal affects the range resolution, while the number of chirps affects the velocity resolution. High-velocity resolution is crucial for accurately distinguishing between stationary clutter and moving humans [27]. Table 2 presents the key specifications of the developed sensor station.

The sensor estimates the occupant's location by using measured distance and angle data. The system was adjusted and calibrated to determine the presence/absence and movement state, as well as distance and angle, by comparing the x–y coordinates of the predefined spatial data. Occupancy status and location data from the FMCW sensor were transmitted to an ESP32 microcontroller. Due to its cost-effectiveness and performance, the ESP32 has become a widely adopted platform for various IoT devices, aligning with previous studies [28,29]. Equipped with both Wi-Fi and Bluetooth capabilities, the ESP32 offers flexible connectivity options, simplifying system design and reducing the need for additional modules or components [30]. Data collected from the sensor was transmitted to a data analysis platform and stored at a rate of one data point per second.

For the data analysis platform, Home Assistant 2023, a highly extensible open-source home automation system, was selected. Home Assistant supports integration with over 1500 different devices and services and undergoes continuous development to incorporate new features and protocols [31]. Its flexible configuration is primarily based on YAML (Yet Another Markup Language) configuration files, while also providing an intuitive user interface. In this study, data collected from the ESP32 was integrated into Home Assistant for visualization and storage, laying the groundwork for a dynamic temperature control system through integration with heating control valves. Ultimately, the goal is to create a customized indoor environment based on occupancy and activity patterns.

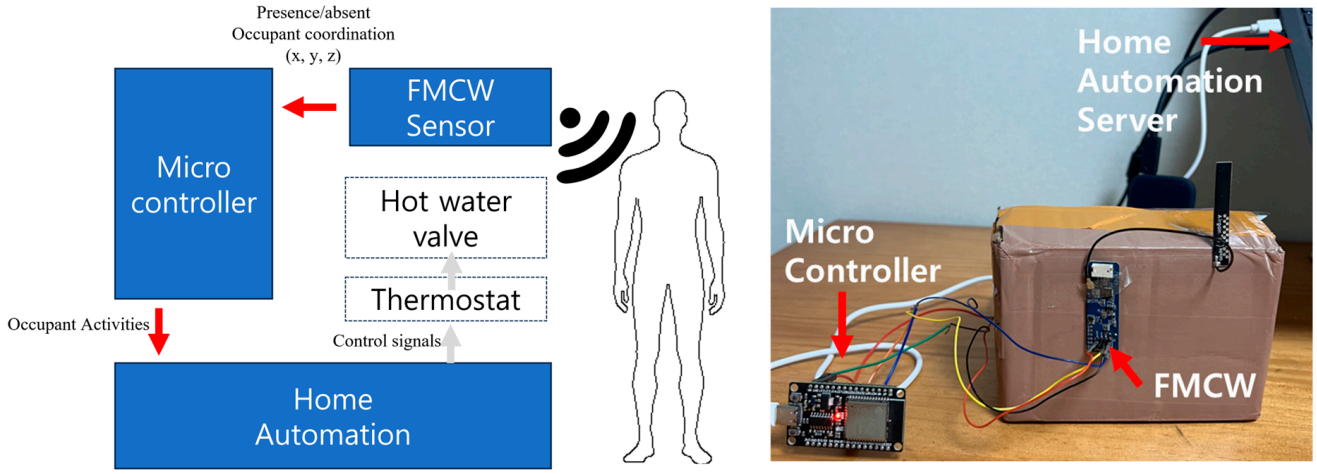


Figure 3. Configuration of sensor station: (**a**) Schematic diagram of data flow; (**b**) install condition of FCMW sensor, data acquisition device, and home automation platform.

Table 2. Occupant detection sensor specifications.

	Description
Type	24 G millimeter wave radar series
Operating frequency band	24–24.25 GHz
Power supply	DC 5 V, over 200 mA
Module method	Frequency Modulated Continuous Wave
Data interface	Universal asynchronous receiver/transmitter
Maximum sensing area	Three spatial zone detection and tracking
Distance	Maximum 6 m
Angle	±60°
Data rate	10 Hz
Operating temperature	−40–85 °C

2.3. Occupant Metabolic Rate (Met) and Clothing Insulation (Clo)

Thermal comfort in indoor environments is influenced by various factors. Zhai's study showed that environmental variables such as temperature, humidity, air velocity, and mean radiant temperature, as well as personal factors like activity level and clothing insulation, significantly impact thermal comfort [32]. Giedraityte et al. demonstrated that the amount of heat released from the human body (M) to the indoor environment varies depending on the body surface area and activity level, which can be calculated using Equation (1) [33].

$$M = EE \times \dot{VO}_2 \times 1/A_{Du} \quad (1)$$

Here, EE denotes the energetic equivalent, expressed in watt-hours per liter of oxygen ($W \cdot h/L\ O_2$), while $\dot{VO}_2$ represents the oxygen consumption rate ($L\ O_2/h$) and A_{Du} signifies the body surface area in square meters (m^2). The metabolic rate, typically expressed in metabolic equivalents (Met), serves as a measure of occupant activity level, with 1 Met defined as the heat production per unit area of a subject under resting conditions and in thermal equilibrium, equivalent to 58 W/m^2 [34]. Considering the specific characteristics of residential buildings, the activities of occupants within the measurement space and their corresponding MET values can be defined as delineated in Table 3 by reconfigured from [35,36].

Table 3. Heat production by occupant's potential activities in the target room.

Activity	Met	Heat Production (W/m^2)
Sleeping	0.7	40.6
Reclining	0.8	46.4
Standing	1.4	81.2
Sitting with Typing	1.2	69.6

Clothing serves a crucial role beyond simply covering the body; it acts as a barrier that regulates heat exchange between the human body and the external environment. The "Clo value," a measure of clothing's thermal insulation, significantly influences human thermal comfort [37]. The value varies depending on factors such as the type of clothing, its thickness, and the number of layers worn [38]. It can be determined through practical measurements or calculations. In thermal comfort assessments, the Clo value typically refers to the whole-body thermal resistance, indicating the overall thermal resistance of the human body. Relevant standards, such as those set by ISO [35] and ASHRAE [36], recommend a Clo value of 0.5 for summer clothing and 1.0 for winter clothing. However, these values are based on general activities, and during sleep, when individuals are covered by bedding, the Clo value can increase substantially.

Given that humans spend a significant portion of their day sleeping, the additional insulation provided by bedding during sleep can dramatically increase the overall Clo value. Previous studies have shown that the Clo value during sleep can range from 2.0 to

4.0 or more when using typical bedding conditions [39]. This indicates that individuals are in a much more thermally insulated state during sleep compared to when they are awake. Such elevated Clo values during sleep can influence indoor thermal environments and subsequently affect heating energy consumption.

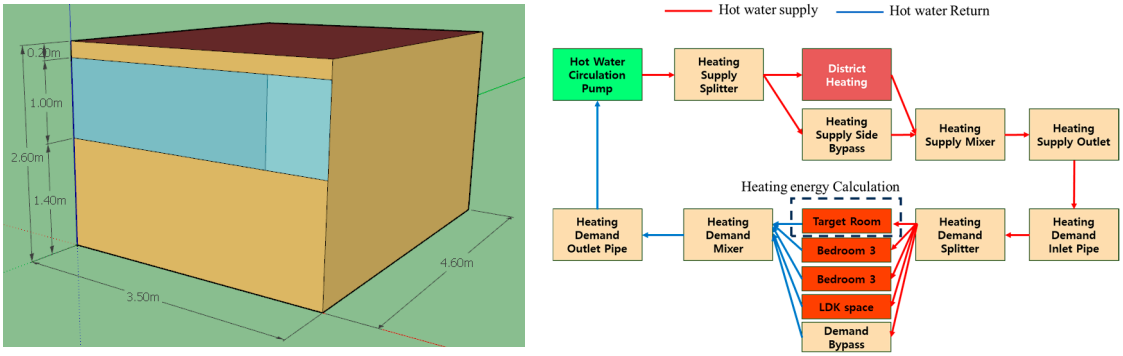
In this study, we adopted differentiated Clo values during conventional activities and during sleep (refer to Table 3) to account for the varying thermal conditions. Table 4, which is reconfigured from [39], presents the categorization of Clo values based on these distinctions.

Table 4. Occupant clothing insulation levels in the target room.

Activity	Clo	Thermal Resistance
Sleeping Reclining	3.0–4.0	0.465–0.620 m^2-K/W
Standing Sitting with Typing	1.0	0.155 m^2-K/W

2.4. Heating System Control Simulator

This study quantitatively examined the impact of varying occupancy patterns on heating energy consumption in a building, aiming to inform the design of energy-efficient indoor climate control systems. A three-dimensional energy simulator model representing the target building's geometry, heating system, and internal layout was developed using EnergyPlus 23.1.0, a validated software by several standards [40–42]. Figure 4 presents a schematic diagram of the EnergyPlus 23.1.0 model, detailing the building envelope properties with Table 1. The target room has one exterior wall with a window facing outdoor air. The remaining three walls are adjacent to conditioned spaces, such as other bedrooms, the living room, and the dining room, where heat transfer is assumed to be negligible. Additionally, heat transfer through the floor and ceiling is considered adiabatic due to the unit's location between identical units above and below. The heating system is configured as a radiant floor heating system utilizing district heating, where the supply water temperature is adjusted based on outdoor conditions. To simulate diverse occupancy patterns, various scenarios were established, including time-varying indoor temperature setpoints, supply water temperature, and heating system operation modes [43]. From the building operational conditions for the reference building model of the multifamily residential building sector [43], Table 5 provides detailed information on the base case scenario, particularly emphasizing the varying indoor temperature setpoints to reflect the changes in heating load associated with different occupancy patterns.



(**a**) (**b**)

Figure 4. Space energy simulator: (**a**) geometrical condition; (**b**) system node configurations.

Table 5. Indoor environmental condition and heating system operation in base case scenario.

Type	Values
Occupant density	0.2 m^2
Occupant schedule	00:00–24:00
Heating setpoint mean air temperature	21.1 °C
Heating system operation	00:00–24:00
Supply water temperature	60 °C
Supply water variable flow control	0–0.08 kg/s

2.5. Evaluation of Thermal Comfort and Energy Consumption

The primary objective of a heating system is to provide occupants with an adequate level of thermal comfort while simultaneously minimizing energy consumption to ensure efficient building energy management. Individual thermal sensations can vary depending on personal characteristics and environmental conditions. However, the Predicted Mean Vote (PMV) index is commonly used to assess thermal comfort. PMV quantifies the average thermal sensation of occupants, and it is calculated using Equation (2) [44]:

$$\text{PMV} = f(Met, Clo, T_a, RH, MRT, V_a) \quad (2)$$

where Met and Clo, which have been previously defined, represent personal factors. The remaining variables, RH, MRT, T_a, and V_a, denote the relative humidity (%), mean radiant temperature (°C), indoor air temperature (°C), and air velocity (m/s), respectively.

The PMV model is a widely adopted design tool in the field of thermal comfort standards. ASHRAE Standard 55 recommends a PMV range of −0.5 to 0.5, indicating a zone of thermal neutrality [36]. ISO 7730 offers a more nuanced approach, specifying different PMV ranges for various building types [35]. For example, existing buildings are often associated with a PMV range of −0.7 to +0.7, while new buildings are typically designed to achieve a PMV range of −0.5 to +0.5.

Under conditions where heat loss through an exterior wall and heat gain from internal heat sources and solar irradiance occur continuously, the heating energy supplied to the interior space to satisfy the indoor temperature set by occupants or to ensure thermal comfort can be calculated using Equation (3).

$$Q = \dot{m} C_p (T_{in} - T_{out}) \quad (3)$$

where Q is heating power (W), and $\dot{m}$, C_p, T_{in}, and T_{out} denote the water mass flow rate (kg/s), specific heat (J/kg-°C), supply water temperature (°C), and return water temperature (°C), respectively.

2.6. Conditions of Implementation

Figure 5 illustrates the overall structure of this study. An FMCW-based human presence sensor was installed in a single room of an actual residential building, and occupancy was monitored for five consecutive weekdays and two weekends. By utilizing the geometric distance provided upon occupancy detection, not only the occupancy status but also the relative position of the occupant within the occupied space was determined to infer the activities performed during occupancy. The measured data were analyzed in a time-series manner to determine occupancy and non-occupancy durations. Using the analyzed data, the occupant's schedule, Met value during occupancy, and Clo value were inferred to generate occupancy environment data for the residents (Part A). A building thermal response model was developed, reflecting the thermal properties of the building's walls, floor, and ceiling based on their shapes and structures. A building energy analysis model was constructed by combining this thermal response model with a system model identical to the heating system used in the actual building (Part B). The constructed building energy analysis model was used to analyze the heating energy consumption of the model during

the winter season, utilizing real weather data from the region where the building is located. By comparing the indoor thermal comfort and energy consumption when operating the hydronic heating system using the derived actual occupancy and activity schedule with the case of operating the heating system with a typical residential building operating schedule and set conditions, an operating strategy to reduce the heating energy required while maintaining indoor thermal comfort was developed (Part C).

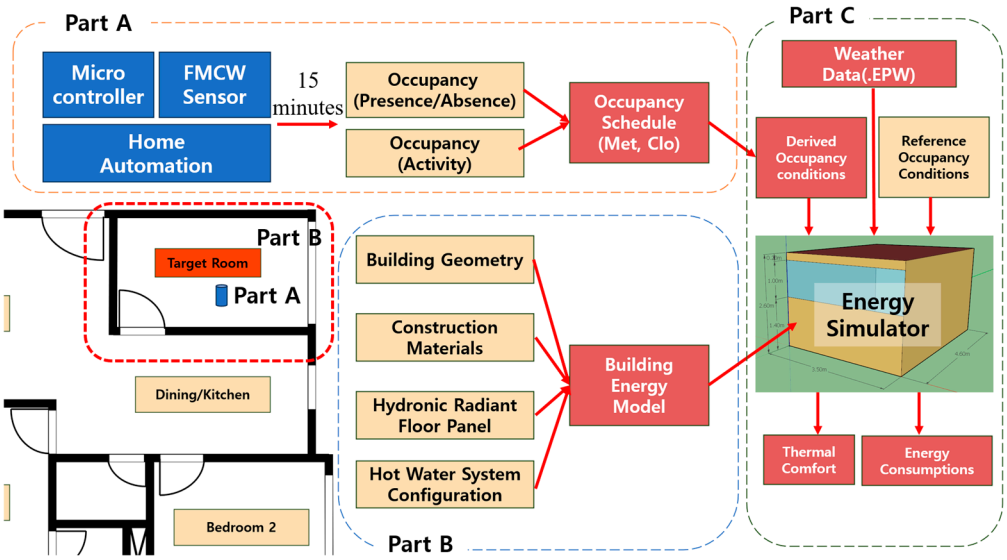


Figure 5. Schematic structure of study condition.

3. Results

3.1. Occupant Behaviors

3.1.1. Spatial Patterns

Occupancy sensors were installed in the measurement space to analyze occupancy patterns in each zone over five weekdays in the winter season. The FMCW sensor generates data using a coordinate system when occupancy occurs, calculating the distance and angle of the occupant relative to the sensor's center point at a rate of one data point per second. The measured data are converted back into coordinate values (x-y distance) using a microprocessor and can be displayed on a planar representation of the space through location mapping. Missed and lost signals are represented as null values to prevent confusion with unoccupied conditions (Zone 0). For cases where the position changes at each measurement, the most frequent position for 15 min is determined as the occupancy location at that measurement time. Figure 6 illustrates the spatial distribution of occupants within the target space during five weekdays (4–8 December 2023). By employing the plane of the space and predefined zones, the measured data, including the sensor's measurable angle (60 degrees) and distance, were converted into location coordinates and visualized. Zone 1, characterized by the presence of a desk, is primarily designated for sedentary activities such as work and study. Zone 2, where the bed is situated, is predominantly utilized for sleep. Zone 3, comprising bookshelves and closets, represents activities beyond those in zones 1 and 2, primarily standing. Over the five-day period, the occupancy pattern was predominantly centered in Zone 2, reflecting the prevalence of sleep-related activities. Zones 1 and 3, associated with study and work activities and standing activities, respectively, exhibited lower occupancy frequencies.

Table 6 presents the frequency of each activity over a week, including weekends. Out of a total of 672 measurements, approximately 65% of the time was occupied, while the remaining 35% was unoccupied. Analysis of occupancy-related activities revealed that sleep accounted for about 70%, study and office work for approximately 20%, and other

activities for around 10%. These findings suggest that the primary use of this space is for sleep.

These occupancy patterns indicate the need for energy conservation measures such as heating cessation or the resetting of the set temperature during unoccupied periods, and the implementation of optimal heating operations during sleep, the primary activity while occupied, to ensure comfort and reduce heating energy consumption.

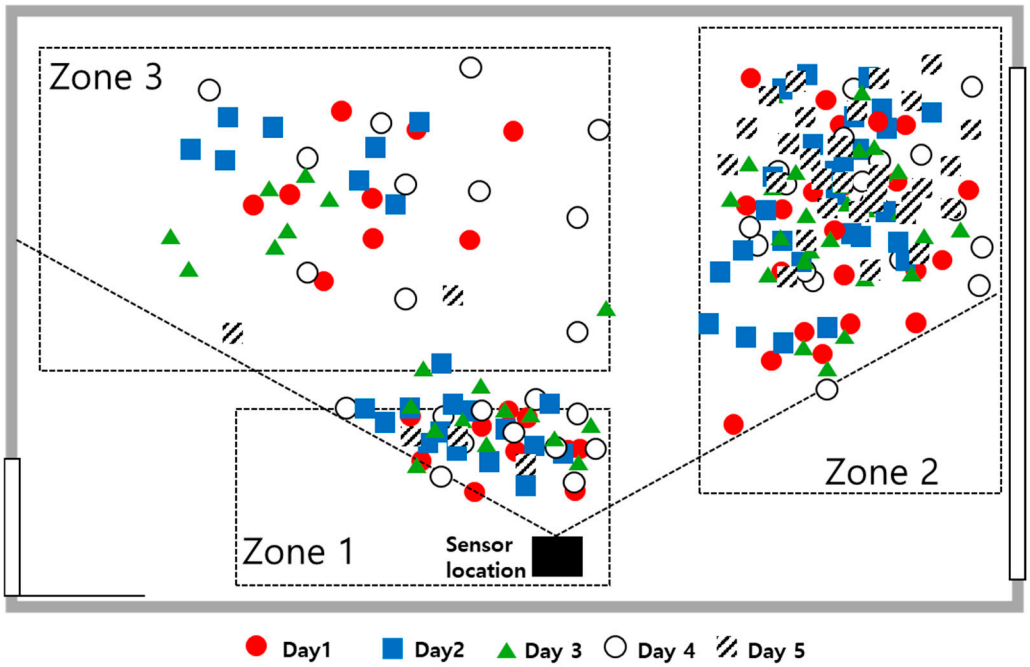


Figure 6. Spatial occupant presence for five weekdays.

Table 6. Presence occurrence in each zone.

Type	Occurrence	Rate
Non-occupied	238	35.41%
Zone 1	90	13.39%
Zone 2	303	45.08%
Zone 3	41	6.1%
Total	672	100%

3.1.2. Timeseries Occupancy Patterns

To formulate an indoor environmental control strategy that is commensurate with occupants' activities, time-series data pertaining to the activities of individual occupants are imperative. By augmenting the location data from the preceding chapter with temporal data, we conducted a time-series analysis of occupant activities within each zone. Figure 7 presents the occupancy status of each zone at 15 min intervals during the measurement period. On weekdays, occupants were consistently detected in Zone 2 (bedroom) from 00:00 to 07:00, indicating sleep. They typically initiated their activities around 7:00 and left the space by 8:30. From 08:00 to 18:00, the occupants were categorized as being in Zone 0 (unoccupied). Occupancy resumed between 17:00 and 18:00, with individuals returning to Zone 2 around 22:00. On the weekends, occupancy frequency increased, particularly in Zones 1 and 3. However, Zone 2 still exhibited a relatively high occupancy rate compared to weekdays. The time-based occupancy frequency provides insights into the occupant's schedule. A representative schedule can be constructed as follows: sleep from 00:00 to 07:00, preparation and activities from 07:00 to 08:00, unoccupied from 08:00 to 18:00, study and activities from 18:00 to 22:00, and sleep again from 22:00 to 24:00. It is evident that the occupancy status and activity levels vary significantly different by time during weekdays

compared to the constant occupancy conditions provided in the benchmark operation model for the multi-family residential building sector [43]. Operating the heating system in an occupant-centric manner is expected to yield significantly different energy consumption characteristics. Furthermore, the energy model can be adapted by resetting the schedules for occupancy status and occupancy environments (activity levels and clothing levels) each time.

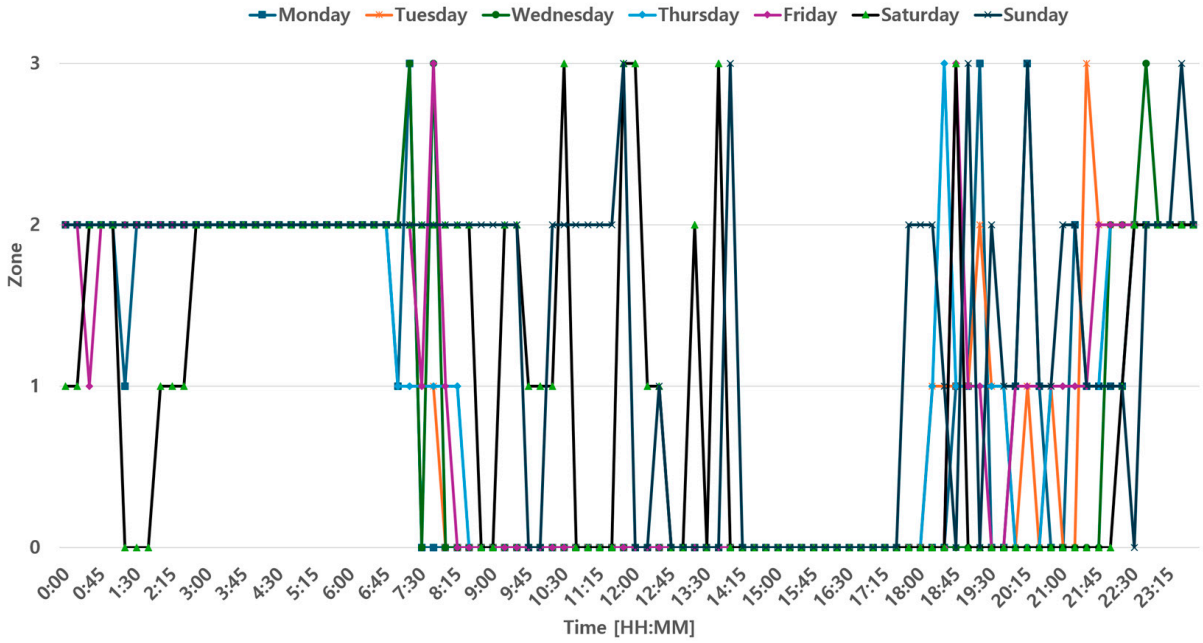


Figure 7. Time-based occupancy conditions in each zone.

3.2. Thermal Sensation

3.2.1. Case Descriptions

To investigate the impact of occupancy patterns on heating system performance, this study developed occupancy schedules based on comprehensive data regarding occupancy status and location within the residential unit. These schedules were subsequently classified according to distinct activity patterns, providing a nuanced understanding of occupant behavior.

To establish various heating system operation scenarios, three distinct cases were defined, as outlined in Table 7. The baseline case (Base), a reference multifamily residential building model [43], assumed a constant set temperature and disregarded uncertainties in occupancy. Additionally, Met and Clo were maintained at consistent levels.

Case 1 deviated from the baseline by incorporating a variable set temperature, resetting the mean air setpoint temperature during unoccupied periods while maintaining constant Met and Clo values. Case 2 further refined the analysis by distinguishing between occupied and unoccupied periods, and within occupied periods, between general activity zones and sleep zones with the actual measured data. For sleep zones, a moderate Clo value (3.0) was assumed, reflecting the use of standard bedding, while the metabolic rate was adjusted to align with the characteristics of sleep.

Case 3, similar to Case 2, considered the impact of heavy bedding in cold and dry climates by applying a Clo value of 4.0, representing a higher level of clothing insulation.

Table 7. Case descriptions for occupant's thermal sensation.

Case	OCC.	OCC Schedule	Met	Clo	Mean Air Setpoint Temperature (°C)
Base	1 person	00:00–24:00	1.0	1.0	21.1
Case 1		08:00–18:00	1.0	1.0	17
		00:00–08:00 18:00–00:00			21.1
Case 2		08:00–18:00	1.0	1.0	17
		07:00–08:00 18:00–22:00	1.0	1.0	21
		22:00–07:00	0.7	3.0	21
Case 3		08:00–18:00	1.0	1.0	17
		07:00–08:00 18:00–22:00	1.0	1.0	21
		22:00–07:00	0.7	4.0	21

3.2.2. Thermal Comfort with Different Cases

Figure 8 presents the calculated thermal comfort levels for each case at hourly intervals on a day with a minimum outdoor temperature of −15 °C. In the base case, with a constant metabolic rate (Met) and clothing insulation (Clo), the PMV values ranged from −0.7 to 0.3, indicating thermal comfort. During the afternoon, the PMV value reached a maximum of 0.3 due to the operation of the heating system and solar heat gain, resulting in an increase in indoor temperature.

In contrast, Case 1, which separated occupied and unoccupied periods, showed similar results to the base case during occupied periods (00:00–08:00, 18:00–24:00). However, during unoccupied periods (08:00–18:00), especially in the morning (08:00–13:00), the lower set temperature resulted in PMV values outside the comfort zone (−1.3). Nevertheless, solar heat gain in the afternoon brought the PMV back within the comfort range.

Case 2 exhibited similar patterns to Case 1 during unoccupied periods. However, during sleep periods, the maximum PMV value was 0.33, closer to thermal neutrality (PMV = 0) compared to the base case. In Case 3, where a higher Clo value was applied to account for thicker bedding, the PMV value increased to 0.7 during nighttime sleep, indicating the need for appropriate measures to ensure thermal comfort.

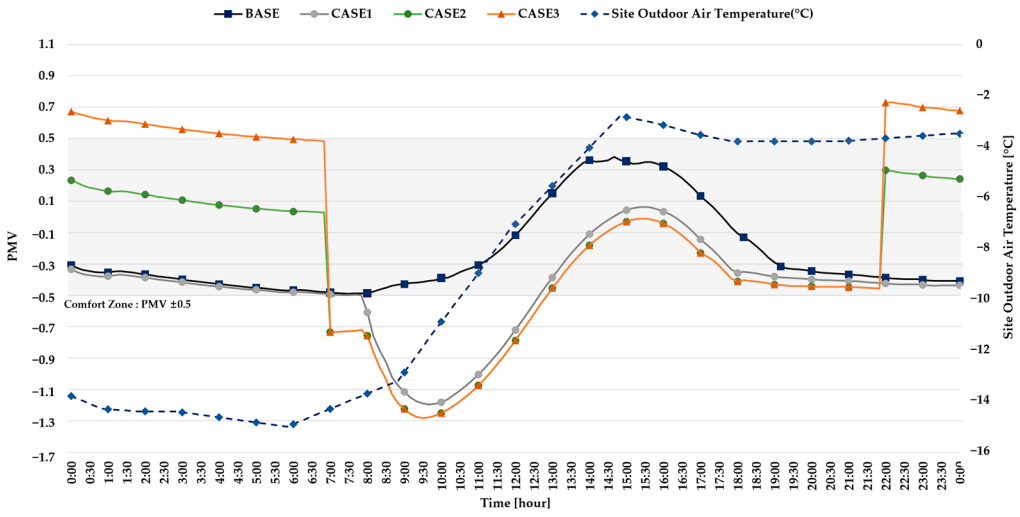


Figure 8. PMV variations with different cases.

3.2.3. Thermal Comfort with Adoptive Set Point Overriding

When considering the effects of metabolic rate during sleep and the type of bedding, higher PMV values were obtained compared to using the standard indoor set temperature. This indicates the need for differentiated indoor environments during sleep and general activities.

Figure 9 shows the hourly changes in PMV values for Cases 2 and 3, which account for metabolic rates during sleep and different clothing conditions when the indoor set temperature decreased by 1 °C at a time. In Case 2, where moderate bedding was used, setting the indoor temperature to 18 °C maintained PMV values within the comfort range (−0.4 to −0.27) during sleep hours (00:00–07:00, 22:00–24:00). Thermal neutrality was the closest when the set temperature was 19 °C. In contrast, for Case 3, where heavy bedding was used, maintaining a set temperature below 19 °C was necessary to ensure thermal comfort throughout the sleep period. The closest thermal neutrality was achieved at the adjusted set temperature of 17 °C. These findings suggest that lowering the temperature during sleep not only enhances thermal comfort but also offers the potential for energy savings.

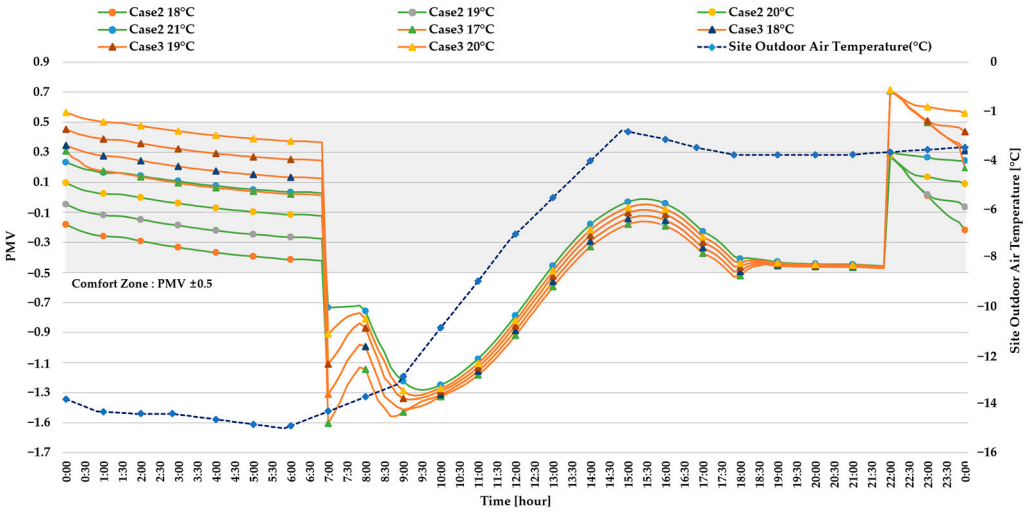


Figure 9. PMV variations with different setpoint temperature conditions in Case 2 and Case 3.

3.3. Heating Energy Consumptions

3.3.1. Energy Consumption on the Peak Day

Adjusting the indoor set temperature can reduce the thermal load on the heating system and the operation of its components. As illustrated in Figure 10, adjusting the indoor set temperature during sleep can decrease the required circulation flow rate of the hydronic radiant panel heating system. The base case, operating at a constant set temperature throughout the day, required a maximum instantaneous flow rate of 0.06 kg/s, and a range of 0.027 kg/s to 0.053 kg/s during both sleep and occupied periods. In contrast, resetting the set temperature based on occupied and unoccupied periods eliminated the need for daytime heating and significantly reduced the required circulation flow rate during sleep and occupied periods. For Case 2, with a target setpoint air temperature of 18 °C during sleep hours, the flow rate ranged from 0.021 to 0.045 kg/s. For Case 3, with the setpoint override temperature of 18 °C, the flow rate ranged from 0.018 to 0.043 kg/s. When comparing the daily heating energy consumption on a day with the lowest outdoor temperature of the year, as shown in Figure 11, Case 2 achieved up to an 18% reduction and Case 3 up to a 21% reduction in energy consumption compared to the base case.

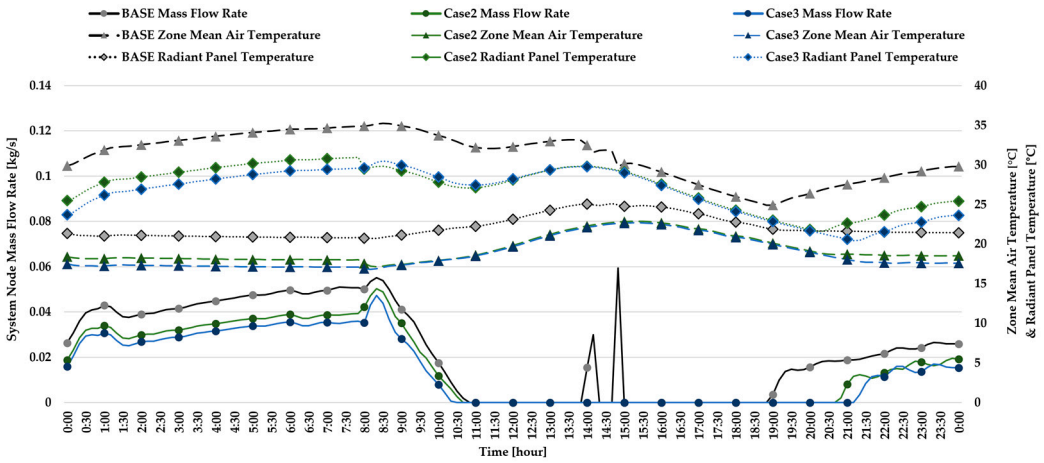


Figure 10. Water supply rate by the adjusted setpoint temperature in Case 2 and Case 3.

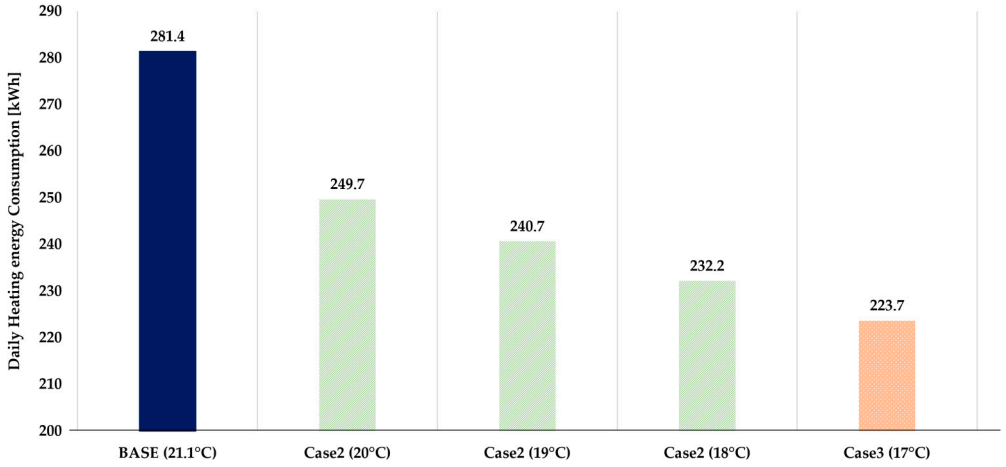


Figure 11. Daily total heating energy consumption.

3.3.2. Comparison of Monthly Energy Consumption

The scenario proposed above can be validated through analysis of both the peak load conditions that occur during the coldest outdoor temperatures and long-term trends in energy consumption. Therefore, it compares the required heating energy consumption based on indoor occupancy status and changes in the set temperature according to the occupants' activities. Table 8 compares the energy consumption over 78 weekdays for Case 2 and Case 3, which reset the indoor set temperature, adjusting indoor air temperature by occupant activity, considering clothing insulation, using actual weather data for Seoul from January to March 2024. Compared to the base case with a single set temperature of 21.1 °C for the entire daily period, resetting the set temperature to 17 °C during non-occupancy hours (Case 1) and applying moderate Clo (3.0) and heavy Clo (4.0) during sleep time, which utilizes the occupant's thermal sensation to change the indoor set temperature from 17 to 18 °C, resulted in a minimum of 31% to a maximum of 34% of heating energy savings. These findings suggest that flexibly changing the indoor set temperature according to occupants' activities can not only ensure occupant comfort but also achieve energy savings.

Table 8. Monthly heating energy consumption of each case in kWh.

Month	Base	Case 1	Case 2 [1]	Case 3 [2]
January	7534.9	6853.7	5938.1	5668.6
February	5766.7	4522.7	3693.9	3400.3
March	3863.6	3443.6	2328.0	2189.2
Total	17,165.2	14,820.0	11,960.0	11,258.1

[1]: setpoint temperature at 18 °C during sleep. [2]: setpoint temperature at 17 °C during sleep.

4. Discussion

This study conducted a parametric study based on an energy model along with an experimental analysis of occupancy status and activities in predefined spatial zones. By defining activities in residential buildings considering furniture placement and utilizing the characteristics of FMCW radar sensors for pre-zoning, this study developed and evaluated operation scenarios for a hydronic radiant panel heating system based on occupancy patterns. Microcontrollers and home automation systems were used to automatically acquire data on occupied spaces, and schedules for sleep, daily activities, and unoccupied states were created based on the stored sensor data. The potential for varying set temperatures according to these schedules was evaluated in terms of thermal comfort and energy consumption using an energy simulation model.

The results of this study can be linked to those of previous research. Compared to previous studies on occupancy presence sensors [16,18] and tracking individual occupant movements [14], our approach offers several advantages: cost-effective wireless sensor stations, enhanced privacy through non-terminal occupancy detection, and the ability to infer activities within occupied zones based on spatial characteristics. While our method requires additional effort to cluster indoor space dimensions and furniture locations, it may also necessitate system integration with conventional thermostats for controlling heating systems based on occupant activity. Additionally, our approach may require multiple sensors to cover large spaces due to the limited detection range of 6 m.

Additionally, compared to office buildings where occupant indoor activities are relatively simple and the number of occupants is a primary concern, this study can be linked to systems like [26] to implement occupant-based optimal control for residential buildings where various activities such as sleep, daily work, study, and others take place. By linking it to methods for evaluating the correlation between the age of a residential building and its energy consumption [24], a comprehensive analysis model can be developed that considers occupant activities and performance degradation due to the building's age.

From a policy perspective, when developing reference energy models for specific regions and building stocks, providing time-based occupancy status and activity information along with single activity level and clothing level indicators [44] can minimize the gap between actual building energy consumption and the results of energy analysis models, reflecting real-world data in building energy standards.

To enhance the generalizability and practicality of the research findings, the following additional studies will be conducted: First, research will be conducted to improve the reliability of the sensor system. The current single occupancy sensor and software-based space division may lead to erroneous judgments when there is no movement for a certain period. Therefore, it is necessary to use various sensors or improve the occupancy detection algorithm to obtain more accurate occupancy information. Second, the integration with home automation systems will be strengthened. The system developed in this study has shown the potential to effectively control indoor temperature and ensure comfort. Based on this, the performance of the system will be verified in a real environment through direct connection with heating water control valves, and optimal control strategies will be developed by applying various scenarios. Third, verification in various spaces and building types is necessary. Performance verification has thus far focused on individual spaces like bedrooms. To gain a more comprehensive understanding, it should evaluate the energy model and system operation in various settings, including total residential units

with multiple spaces and heating controllers and commercial buildings. Furthermore, it is necessary to study how heating and cooling controls adapt to the different activities of multiple occupants.

5. Conclusions

This study analyzes the correlation between occupant behavior, indoor set temperature variations based on occupant behavior characteristics, indoor comfort, and energy consumption in residential buildings with floor heating. The results show that an affordable FMCW radar-based sensor network can effectively detect occupant entry, occupancy duration, and spatial occupancy within predefined zones. This system can distinguish between general activities and sleep activities based on furniture and characteristics within the zone and can also track the duration of each activity. By estimating the insulation value of clothing during sleep, considering factors like beds and blankets in winter, and controlling the floor heating system accordingly, thermal comfort can be maintained while reducing the indoor set temperature. Resetting the indoor target temperature during sleep and resetting the indoor temperature during unoccupied periods can reduce peak load energy consumption by over 21% and total heating energy consumption over a three-month heating period by up to 34%. Future research aims to develop a versatile system applicable to various spaces and building types. This will involve enhancing the reliability and resolution of the sensor systems, integrating them with home automation systems, and conducting comprehensive performance evaluations in diverse environments. It may be possible to provide personalized comfortable environments and promote energy conservation.

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