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Modelling An Occupancy-Based Hvac System Controller for Building Energy Efficiency

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Abstract

Heating, Ventilation, and Air Conditioning (HVAC) systems are major energy consumers in commercial buildings, often accounting for nearly half of total energy usage. A primary source of inefficiency is conventional operation that ignores occupancy patterns, leading to unnecessary conditioning of unoccupied spaces. This paper presents a simulation study of an occupancy-based HVAC control system using a simplified first-order thermal model of a building space. Three control strategies are compared: a baseline system without active control, a reactive On-Off controller, and a Proportional-Integral-Derivative (PID) controller tuned using the Ziegler-Nichols method. Both the On-Off and PID controllers are integrated with an occupancy model to enable adaptive operation. Simulation results show that the occupancy-based PID controller achieves the best performance in balancing energy efficiency and thermal comfort compared to the other strategies. In addition, this work highlights a planned extension toward intelligent control methods, such as Deep Reinforcement Learning (DQN), to provide more adaptive and robust HVAC operation in dynamic environments.

***Keywords**: HVAC, Energy Efficiency, Occupancy-Based Control, PID Controller, System Modelling*

1. INTRODUCTION

The thermal environment of a room is a critical factor influencing human productivity, comfort, and overall well- being (Ajala, 2012). Heating, Ventilation, and Air Conditioning (HVAC) systems are indispensable in modern infrastructure, tasked with maintaining a comfortable indoor temperature and ensuring high air quality. These systems are widely used in various commercial and residential buildings, including offices, schools, and homes. However, their operation comes at a significant cost. HVAC systems are one of the largest consumers of energy in the built environment, often accounting for up to 50 percent of a building's total energy consumption. Striking a balance between thermal comfort and energy efficiency has therefore become a central challenge in modern HVAC design (Yang et al, 2014).

This high energy demand presents a significant problem, primarily rooted in the operational model of conventional HVAC systems. Traditionally, these systems function on the basis of fixed schedules or constant operation, without considering the real-time presence or absence of people. This leads to considerable energy waste, as empty rooms are needlessly heated or cooled. The inefficiency of such conventional systems highlights a clear need for an adaptive HVAC control strategy that can intelligently adjust its operation based on the occupancy of the building, thus conditioning the spaces only when necessary (Esrafilian-Najafabadi & Haghighat, 2021).

This study investigates the effectiveness of occupancy-driven HVAC operation and specifically it aims to:
1. To develop a simplified thermal model of a building space that integrates occupancy information
2. To compare the performance of different control strategies that are baseline controller (no active control), On-off controller, and Proportional-Integral-Derivative (PID) in terms of thermal comfort and energy efficiency.
3. Establish PID as a strong baseline for future development of intelligent control methods that is Deep Reinforcement Learning such as DQN

The primary objective of this work divided by two: (i) to create an simulation-based validation of PID performance in occupancy based HVAC that operates dynamically based on whether a room is occupied, and (ii) an outlook toward adaptive reinforcement learning approaches for smarter building energy management.
Recently, more advanced control approaches have been explored to further improve HVAC efficiency, such as Fuzzy Logic, Model Predictive Control (MPC), and Reinforcement Learning (RL). Turley et al. (2020) highlighted the growing role of data-driven predictive control in HVAC research, demonstrating its capability to achieve superior comfort and energy savings compared to classical methods. Among these, Deep Q-Networks (DQN) have shown potential in building control applications by learning optimal policies directly from system interactions without requiring an explicit mathematical model. While this study focuses on modeling and validating PID as a strong baseline for occupancy-based HVAC control, the findings are also intended to establish a foundation for future integration of intelligent controllers like DQN.

2. RESEARCH METHOD

2.1 Type of Research
This study is categorized as a simulation based experimental research. The research will be focusing in modelling an analyzing the performance of different control strategies in HVAC based on room occupancy. There will be no physical hardware on this research and only

relies on simulation and computational modeling. The simulation will be executed using python software on standard personal computer.

2.2 Research Subjects and Objects

The subject of this study and research is an indoor thermal environment within a simplified single zone building space. This study will apply HVAC Control system in the environment that focusing on three strategies: (i) no control system (baseline), (ii) On-Off control system, and (iii) Proportional-Integral-Derivative (PID) controller. With these different control strategies, we will find the most energy efficient control system for building space.

2.3 Sampling Techniques

This research is simulation based, that means the sampling is represented by the design of occupancy schedules that serve as input to the thermal model. In this research, occupancy is modeled as a binary signal where 1 indicates that the room is occupied and 0 indicates that the room is empty or unoccupied. For the research, a 24-hour simulation was used to represent a typical working day. The building was considered occupied for 8 hours from 08:00 to 16:00 for working hours and unoccupied during the rest of time (16.00 - 08:00). This schedule provides a realistic yet tractable representation of building usage patterns, which enables the evaluation of control strategies under conditions that resemble the real word system.

2.4 System Thermal Modelling

The thermal dynamics of a single building zone or room is simplified and represented using a first-order Resistor Capacitor (RC) thermal model. This approach is widely adopted for its ability to capture the fundamental characteristics of heat transfer in buildings without requiring excessive computational complexity (Alghamdi et al., 2022), (Berouine et al., 2019). The model describes the rate of change in the temperature of the indoor air, T(t), as a function of the heat exchange with the external environment and the internal heat loads. The relationship is governed by the following ordinary differential equation (ODE), which follows classical control system modeling principles as described by Ogata (2010) as detailed in:

$$\frac{dT(t)}{dt} = \frac{1}{C}\left(\frac{T_{amb} - T(t)}{R} + Q_{HVAC} + Q_{occ}\right)$$

where $T(t)$ is the indoor temperature of the room at time t (°C), Tamb is the constant ambient temperature (outdoor) (° C), Q_{HVAC} is the heating or cooling power supplied by the HVAC system (W). This is the primary control variable, Q_{occ} is the internal heat gain generated by the occupants (W), R is the equivalent thermal resistance of the building envelope (°C/W), representing the resistance to heat flow through walls, windows, and ventilation, C is the equivalent thermal capacitance of the room (J/°C), representing the ability of the indoor air and mass to store thermal energy. This equation balances the heat flows into and out of the room, providing a dynamic model of how the indoor temperature responds to external conditions and internal control actions.

2.5 Controller Model

This research models and compares three distinct HVAC operational strategies to quantify the benefits of intelligent, occupancy-based control. The following table, Table I, summarizes the controllers.

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Tabel 1. Comparison of Controller Characteristics

Controller Type	Operating Principle	Characteristics
Without Controller	Operates On a fixed schedule, without feedback	Inefficient
On-Off Controller	Activates when occupancy is detected and temperature crosses a setpoint boundary.	Simple, Fast, prone to fluctuations
PID Controller	Continuously calculates the temperature error to determine the required output.	High Precision, stable, requires tuning

2.5.1 Baseline Controller

System without Active Control: The baseline case represents a conventional HVAC system that operates without any feedback control. In this mode, the HVAC system is activated based on a fixed timer or schedule, running continuously during operational hours without regard for the actual indoor temperature or occupant presence. This "always-on" approach is inherently inefficient and serves as the benchmark against which the energy savings of the other controllers are measured. The simple, open-loop nature of this system is depicted in the block diagram on Figure 1:

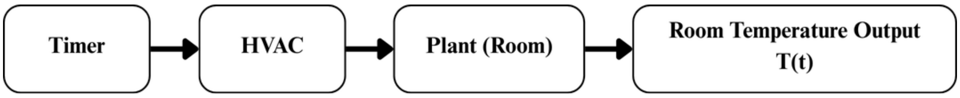

Figure 1. System without Active Control

2.5.2 On-Off Controller

The On-Off controller is a simple, reactive control strategy, the structure of which is illustrated in the closed-loop block diagram on Figure 2. Its operation is governed by two conditions:
Occupancy: The controller is only active when the room is occupied.
Temperature Threshold: When active, it turns the HVAC system on at full power if the indoor temperature T(t) moves outside a predefined threshold around the temperature setpoint Tset. It turns the system off once the temperature re-enters this threshold.

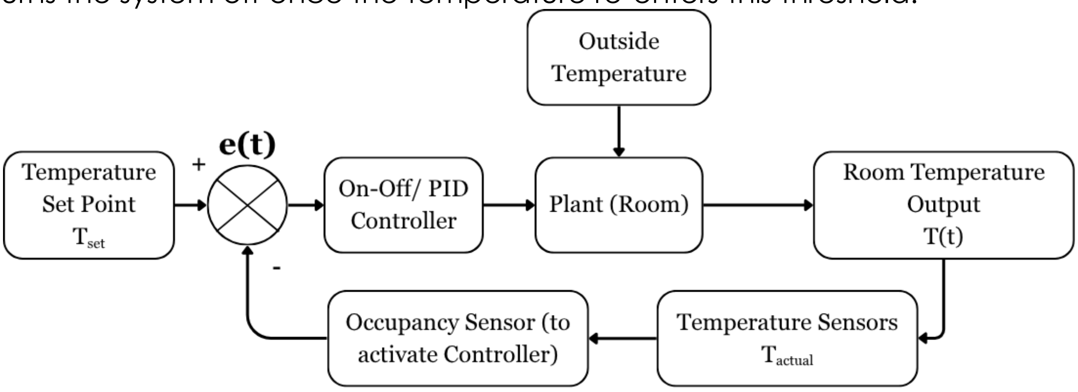

Figure 2. On-Off/PID Controller Block Diagram

While simple and responsive, this method often leads to temperature fluctuations around the setpoint and can cause Kp =300, Ki =0.2, Kd =50 increased mechanical wear on the HVAC equipment due to frequent cycling.

2.5.3 PID Controller

The PID controller offers a more sophisticated and stable control method. Its general structure follows the same closed-loop, occupancy-gated system shown in the block diagram. It also operates only when occupancy is detected. It continuously calculates the error e(t) between the temperature setpoint and the actual measured temperature:

$$e(t) = T\_set - T(t)$$

The controller then modulates the HVAC output QHVAC based on a weighted sum of the error's proportional, integral, and derivative terms. The governing equation for the PID controller is:

$$Q_{HVAC(t)} = K_p e(t) + K_i \int_0^t e(\tau) d\tau + \frac{K_d\big(de(t)\big)}{dt}$$

The design and tuning of the PID controller parameters follow the classical PID control theory as described by Åström & Hägglund (1995).

Here, Kp, Ki, and Kd are the proportional, integral, and derivative gains, respectively. These parameters must be carefully tuned to achieve a fast response with high precision and stability, minimizing both temperature overshoot and steady state error. PID-based setpoint control strategies such as this have also been shown to provide flexibility for energy-efficient demand response in residential and commercial buildings (Yin et al, 2016).

For the second controller configuration, The Proportional-Integral-Derivative (PID) controller was tuned using the Ziegler-Nichols method, a widely used heuristic tuning approach in control engineering (Allu & Toding, 2020). This method involves determining the ultimate gain Ku and the oscillation period Tu of the system by observing the onset of sustained oscillations under proportional-only control. Based on the thermal response of the simulated RC model, the values were estimated as:

$$K_u = 500, T_u = 8$$

Using the standard Ziegler–Nichols tuning rules for PID control:

$$K_p = 0.6K_u = 300, K_i = \frac{2K_p}{T_u} = 75, K_d = \frac{K_p T_u}{8} = 300$$

These values were initially applied for the second PID configuration. While the performance was generally effective, further analysis revealed that the relatively high integral and derivative gains introduced oscillations and slight instability due to the slow-response nature of the thermal system.

To address this, a fine-tuning process was carried out to reduce the aggressiveness of the control response. The integral and derivative gains were scaled down while maintaining the same proportional gain. The final gains used in the simulation were:

$$K_p = 300, K_i = 0.2, K_d = 50$$

This fine-tuned configuration, shown in Figure 6, demonstrated excellent performance in temperature regulation with high precision and low energy usage, validating the effectiveness of the Ziegler–Nichols method when combined with empirical refinement.

2.6 Simulation Setup

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To quantitatively assess the performance of the different control strategies, a simulation was designed and executed. The simulation framework leverages the thermal and controller models described in the previous section to create a dynamic environment for testing. The primary goal is to compare the performance of the baseline (no controller), On-Off, and PID control systems in terms of their ability to maintain thermal comfort while minimizing energy consumption.

2.6.1 Simulation Scenario and Environment

The simulation scenario is designed to reflect the typical operational conditions of a commercial office building during a standard 8-hour workday (480 minutes). This approach allows for a focused evaluation of the controller's performance without the added complexities and uncertainties of real-world field data, a common and effective method for initial controller validation (Esrafilian-Najafabadi & Haghighat, 2021), (Nguyen et al., 2024). The environment and system parameters are detailed in Table II.

Tabel 2. Comparison of Controller Characteristics

Parameter	Value	Description
Thermal Capacitance (C)	20,000 J/∘C	Represents the room's capacity to store heat. A larger value implies a slower temperature change.
Thermal Resistance (R)	6 ∘C/W	Represents the resistance of the building envelope to heat transfer
Ambient Temperature (T_{amb})	30 ∘C	A constant outdoor temperature is assumed for the simulation period.
Temperature Setpoint (T_{set})	24 ∘C	The target indoor temperature for occupant comfort
Max HVAC Cooling Power	-1500 W	The maximum cooling power the HVAC unit can provide.
Simulation Duration	480 minutes	Corresponds to an 8-hour operational period

The simulation was implemented in Python, using the first order ODE model to calculate the room's temperature at each time step in response to the active control strategy and environmental conditions.

2.6.2 Performance Evaluation Metrics

To provide a comprehensive comparison, the performance of each controller was evaluated using two key metrics: control accuracy and energy efficiency.

Control Accuracy: The accuracy of the system in main training the desired temperature is measured using the Mean Absolute Error (MAE). The performance of each controller was quantified using Mean Absolute Error (MAE), which provides a straightforward measure of average deviation from the setpoint (Xu & Wang, 2023). The MAE calculates the average absolute difference between the actual indoor temperature T(t) and the target setpoint Tset over the simulation period N.

$$MAE = \frac{1}{N}\sum |T(t) - T_{set}|$$

A lower MAE value indicates better control performance and more stable indoor thermal conditions.

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Energy Efficiency: The energy efficiency is determined by calculating the total energy consumed by the HVAC system over the simulation duration. The energy E (in Joules) is the integral of the absolute power output QHVAC(t) over time. For the discrete simulation, this is calculated as a summation.

$$E = \sum_{t} |Q_{HVAC}(t)|\Delta t$$

The final value is converted to kilowatt-hours (kWh) for a more intuitive comparison of energy consumption. A lower energy value signifies a more efficient control strategy.

3. RESULTS AND DISCUSSION

This section presents the simulation results for each of the three control strategies: the baseline system without a controller, the occupancy-based On-Off controller, and the occupancy-based PID controller. The performance of each is evaluated based on its ability to maintain the temperature setpoint and its overall energy consumption.

3.1 Simulation Results

The performance of each controller was simulated over a 480-minute (8-hour) period. The results are summarized below.

3.1.1 Baseline Controller

The performance of the baseline system is visualized in the Fig. 3. It exhibits poor temperature regulation, fluctuating significantly and rarely meeting the comfort setpoint of 24°C, resulting in a very high Mean Absolute Error (MAE) of 5.79°C. The total energy consumed was 0.10 kWh. This performance is characteristic of conventional HVAC systems that operate on fixed schedules without feedback, leading to both thermal discomfort and energy inefficiency (Esrafilian-Najafabadi & Haghighat, 2021), (Nguyen et al., 2024).

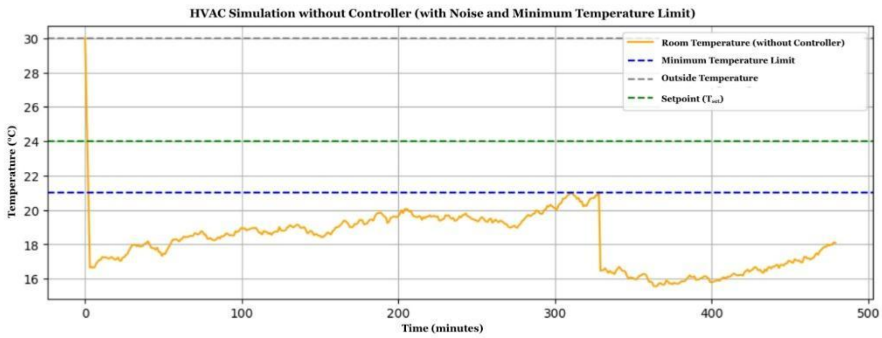

Figure 3. HVAC Simulation Without Active Control

3.1.2 On – Off Controller

The introduction of the occupancy based On-Off controller, shown in the graph in Fig. 4, yields a substantial improvement. The system actively works to keep the temperature within a deadband around the setpoint, but only when the room is occupied. This strategy reduces the MAE during occupied periods to 1.47°C and lowers energy consumption to 0.07 kWh. However, the temperature still shows noticeable oscillations, which is a known characteristic of simple reactive controllers (Esrafilian-Najafabadi & Haghighat, 2021), (Berouine et al., 2019)

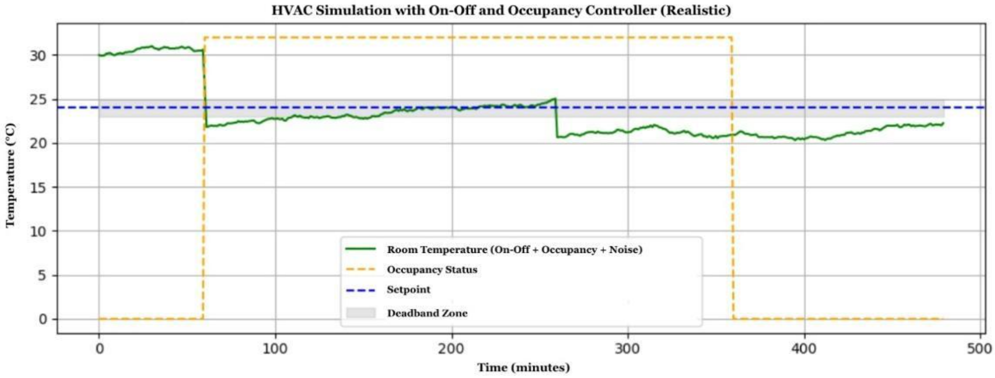

Figure 4. HVAC Simulation with On-Off and Occupancy Controller

3.1.3 PID Controller

The PID controller demonstrates the most effective performance, as shown in the simulation graphs from Fig. 5, Fig. 6, and Fig. 7. The results from three different PID tuning configurations show its ability to maintain the indoor temperature very close to the setpoint with minimal fluctuation. The optimally tuned PID controller (Fig. 6) achieves an exceptionally low MAE of 0.39°C and the lowest energy consumption at 0.04 kWh. This highlights the PID controller's strength in providing precise and stable control, which is crucial for balancing comfort and energy efficiency (Alghamdi et al., 2022).

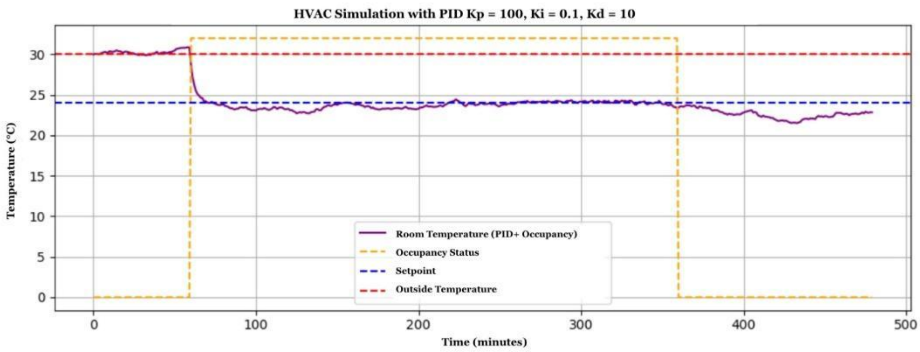

Figure 5. HVAC Simulation with PID1 (Kp = 100, Ki = 0.1, Kd = 10)

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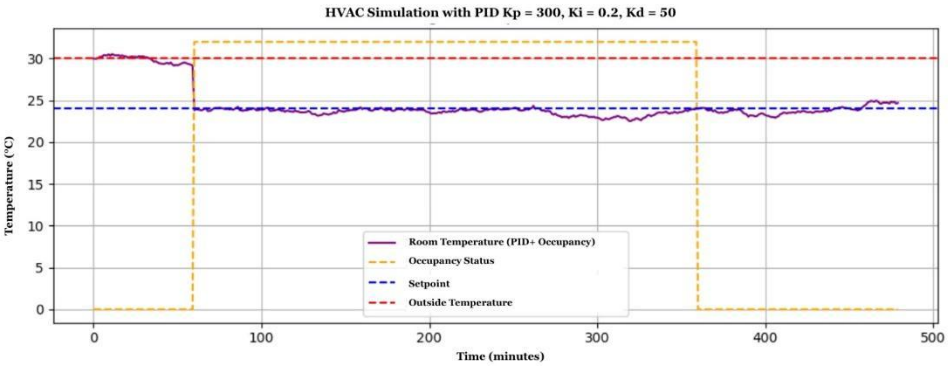

Figure 6. HVAC Simulation with PID2 (Kp = 300, Ki = 0.2, Kd = 50)

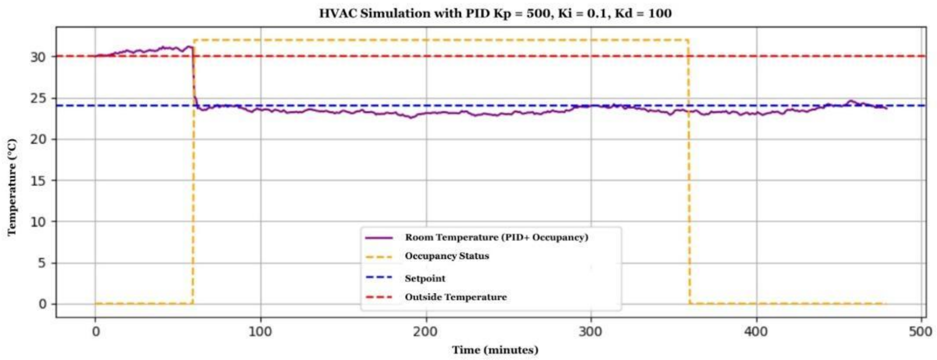

Figure 7. HVAC Simulation with PID3 (Kp = 500, Ki = 0.1, Kd = 100)

3.2 Comparative Analysis
The performance of each controller was simulated over a 480-minute (8-hour) period. The results are summarized below.

Table 3. Comparative Performance of Control Strategies

Controller Type	Energy (kWh)	MAE (◦C)	Min Temp (◦C)	Max Temp (◦C)
Without Controller	0.10	5.79	15.56	30.0
On-Off Controller	0.07	1.47	20.32	31.02
PID Controller 1	0.06	0.42	21.52	30.89
PID Controller 2 (Optimal)	0.04	0.39	22.52	30.54
PID Controller 3	0.05	0.64	22.52	31.20

From this comparison, it is evident that the optimally tuned PID controller outperforms the other methods on both key metrics. It not only uses the least amount of energy but also maintains the most stable and accurate temperature, providing the highest level of thermal

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comfort. The On-Off controller serves as a significant improvement over the baseline but cannot match the precision of the PID controller.

3.3 Energy Efficient Gains
The primary objective of implementing an intelligent con troller is to improve energy efficiency. Based on the calculations:

$$Energy\ Efficiency\ (\%) = \left(\frac{E_{no\ control} - E_{method}}{E_{no\ control}}\right) x\ 100\%$$

the energy savings relative to the baseline "no control" scenario significant.
• The On-Off controller achieves an energy efficiency gain of 30 percent.
• The optimally tuned PID controller achieves an energy efficiency gain of 60 percent.
These results clearly demonstrate that an occupancy-based control strategy can drastically reduce HVAC energy consumption. Furthermore, the choice of control algorithm has a major impact on the potential savings, with the more advanced PID controller nearly doubling the efficiency gains of the simpler On-Off controller.
3.4 Discussion
The simulation results confirm that integrating real-time occupancy data into HVAC control is a highly effective strategy for reducing energy consumption in buildings. The baseline scenario, representing a system without feedback, performed poorly, validating the premise that conventional HVAC systems are a major source of energy waste.
The On-Off controller, while simple, demonstrated the core benefit of occupancy-based control by preventing the conditioning of an empty room. This led to a 30 percent reduction in energy use. However, its reactive nature resulted in noticeable temperature swings, which can impact occupant comfort.
The PID controller provided the best of both worlds: superior thermal comfort and maximum energy efficiency. By modulating its power output based on the proportional, integral, and derivative of the temperature error, it achieved a stable indoor environment with an MAE of only 0.39°C. This stability also translates to greater efficiency, as the controller avoids the energy-intensive cycles of overcooling and correction inherent in On-Off systems. The 60 percent energy saving highlights the value of advanced, well-tuned control logic in building automation.
In conclusion, while any form of occupancy-based control is beneficial, the sophistication of the control algorithm plays a critical role in maximizing performance. The PID controller, by effectively balancing responsiveness and stability, proves to be a superior solution for achieving both energy efficiency and occupant comfort in HVAC systems.

4. CONCLUSION

The primary contribution of this work is the quantitative comparison of different occupancy-based control strategies against a conventional baseline system. Based on the simulation results, the following conclusions can be drawn. Occupancy-based control is highly effective: Integrating a simple occupancy sensor to activate the HVAC system only when a room is occupied results in substantial energy savings. Even a basic On-Off controller achieved a 30 percent reduction in energy consumption compared to a system without any active control. This validates the core premise that conditioning empty spaces is a

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primary driver of energy waste in buildings. Advanced control logic yields superior performance: While the On-Off controller proved beneficial, the Proportional-Integral-Derivative (PID) controller demonstrated far superior performance. By providing modulated and stable control, the optimally tuned PID controller not only achieved a much higher energy efficiency gain of 60 percent but also delivered significantly better thermal comfort, as indicated by its low Mean Absolute Error (MAE) of 0.39°C. The first-order thermal model is a valid tool for analysis: The simple first-order ODE model proved sufficient for capturing the fundamental thermal dynamics of the room and effectively differentiating the performance of the various control strategies. This confirms its utility as an accessible tool for controller design and evaluation in early-stage research. In summary, this study reinforces that the method of control is as important as the concept of occupancy-based operation itself. The advanced, stable control provided by a well-tuned PID controller proves to be an excellent solution for simultaneously enhancing occupant comfort and achieving deep energy savings.

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