

UNIVERSITÀ  
DEGLI STUDI  
DI PADOVA



DIPARTIMENTO  
DI INGEGNERIA  
DELL'INFORMAZIONE

MASTER THESIS IN CONTROL SYSTEM ENGINEERING

# Humans-In-The-Building, An Active Thermal Comfort Control And Validation Via Digital Twin

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ACADEMIC YEAR  
2024/2025







## **Abstract**

Ensuring thermal comfort in indoor environments while optimizing energy efficiency remains a significant challenge in building management. This thesis explores different control strategies for thermal regulation, integrating both conventional and innovative techniques. In particular, a novel control approach, Feedback Thermal Control, is introduced to dynamically adjust airflow based not only on room temperature but also on individual users' thermal preferences. This method enables a more personalized and adaptive climate control strategy, improving occupant satisfaction while maintaining energy efficiency.

To evaluate the effectiveness, the study first examines traditional control methodologies before introducing Feedback Thermal Control as an alternative approach. The performance of these control strategies is analyzed and compared through simulations in *Matlab/Simulink* and *IDA ICE*, a state-of-the-art building performance simulation tool.



## Sommario

Garantire il comfort termico negli ambienti interni ottimizzando al contempo l'efficienza energetica rappresenta una sfida significativa nella gestione degli edifici. Questa tesi esplora diverse strategie di controllo termico, integrando sia tecniche convenzionali che innovative. In particolare, viene introdotto un nuovo approccio di controllo, il Feedback Thermal Control per adattare dinamicamente il flusso d'aria non solo in base alla temperatura della stanza, ma anche alle preferenze termiche individuali degli utenti. Questo metodo consente una gestione del clima più personalizzata e adattiva, migliorando il comfort degli occupanti e mantenendo un'elevata efficienza energetica.

Per valutarne l'efficacia, lo studio analizza innanzitutto le metodologie di controllo tradizionali, per poi introdurre il Feedback Thermal Control come approccio alternativo. Le prestazioni di queste strategie di controllo vengono confrontate attraverso simulazioni in *Matlab/Simulink* e *IDA ICE*, un avanzato software di simulazione delle prestazioni energetiche degli edifici.



## **Acknowledgments**

This work was developed as part of a research project carried out under the supervision of Prof. Luca Schenato. I would like to take this opportunity to sincerely thank him for his guidance and support throughout this project. I am also grateful to him for giving me the opportunity to spend two months in Stockholm, an experience that has been both professionally and personally enriching.

I would also like to deeply thank Prof. Angela Fontan and Prof. Marco Molinari, who supervised my work during my time in Stockholm. The meetings I had with them were always extremely insightful and provided valuable guidance, allowing me to overcome challenges and make steady progress throughout the project.

I am deeply grateful to my family for their support and encouragement throughout my university years. Their constant presence has been a source of strength and motivation, helping me reach this important achievement in my life.

I wish to express my heartfelt gratitude to Marco and Michelle, two people who have played a very important role in my life and have always shown me their affection and care.



# Contents

|                                                      |             |
|------------------------------------------------------|-------------|
| <b>List of Figures</b>                               | <b>xi</b>   |
| <b>List of Tables</b>                                | <b>xiii</b> |
| <b>1 Introduction</b>                                | <b>1</b>    |
| 1.1 Motivation . . . . .                             | 1           |
| 1.2 Introduction to CPS . . . . .                    | 2           |
| 1.3 HVAC Systems and Thermal Comfort . . . . .       | 4           |
| 1.4 Other Critical Comfort Parameters . . . . .      | 5           |
| 1.5 A Formal Definition of Thermal Comfort . . . . . | 7           |
| 1.6 State of Art . . . . .                           | 8           |
| 1.7 The KTH Live-In Lab . . . . .                    | 9           |
| 1.8 Personal Contribution . . . . .                  | 11          |
| 1.9 Outline . . . . .                                | 11          |
| <b>2 Building Model</b>                              | <b>13</b>   |
| 2.1 An Introduction to Heat Transfer . . . . .       | 13          |
| 2.1.1 Energy balance . . . . .                       | 17          |
| 2.2 2RC1 Modeling Technique . . . . .                | 18          |
| 2.2.1 Elements of a Building . . . . .               | 18          |
| 2.2.2 Air Modeling . . . . .                         | 21          |
| 2.3 Disturbances modelling . . . . .                 | 21          |
| 2.3.1 People Impact . . . . .                        | 23          |
| 2.4 IDA-ICE Modeling Technique . . . . .             | 23          |
| <b>3 First Case Study: Single Room</b>               | <b>27</b>   |
| 3.1 One Room Implementation . . . . .                | 27          |
| 3.2 Control Implementation . . . . .                 | 31          |

## CONTENTS

|          |                                                          |           |
|----------|----------------------------------------------------------|-----------|
| 3.2.1    | PID Control . . . . .                                    | 31        |
| 3.2.2    | Bang-Bang Control . . . . .                              | 32        |
| 3.2.3    | LQR . . . . .                                            | 33        |
| 3.2.4    | LQR Weights Choice . . . . .                             | 34        |
| 3.3      | Thermal Feedback Control . . . . .                       | 35        |
| 3.3.1    | Human-in-the-Loop Concept . . . . .                      | 35        |
| 3.3.2    | A First Implementation: Binary Feedback . . . . .        | 35        |
| 3.3.3    | A Revised Implementation: Continuous Feedback . . . . .  | 38        |
| 3.3.4    | Creation of Synthetic Comfort Profiles . . . . .         | 39        |
| 3.4      | Simulation and Results . . . . .                         | 42        |
| 3.4.1    | Sensation Control with Feedback . . . . .                | 47        |
| <b>4</b> | <b>Second Case Study: Multi-Room Implementation</b>      | <b>51</b> |
| 4.1      | Multi-Room Implementation . . . . .                      | 51        |
| 4.1.1    | RGA Implementation . . . . .                             | 55        |
| 4.2      | Control Implementation and Results . . . . .             | 56        |
| 4.2.1    | Reference Profile . . . . .                              | 56        |
| 4.2.2    | PID Control with Anti-Windup and Output Limits . . . . . | 57        |
| 4.2.3    | Sensation Control with Feedback . . . . .                | 58        |
| 4.3      | User Discomfort Metric . . . . .                         | 62        |
| 4.3.1    | Interpretation . . . . .                                 | 65        |
| 4.4      | A Final Comment . . . . .                                | 65        |
| <b>5</b> | <b>IDA-ICE Study Case</b>                                | <b>71</b> |
| 5.1      | A Co-Simulation Between Matlab and IDA-ICE . . . . .     | 71        |
| 5.2      | A Comparison Between Simulink and IDA-ICE . . . . .      | 72        |
| 5.3      | An Overview of the Live-In-Lab Structure . . . . .       | 83        |
| 5.4      | Climate Data . . . . .                                   | 85        |
| 5.5      | Zones . . . . .                                          | 85        |
| 5.6      | Other Critical Parameters . . . . .                      | 88        |
| 5.7      | Simulation . . . . .                                     | 89        |
| <b>6</b> | <b>Conclusions and Future Works</b>                      | <b>97</b> |
| 6.1      | Conclusion . . . . .                                     | 97        |
| 6.2      | Future Work . . . . .                                    | 98        |
|          | <b>References</b>                                        | <b>99</b> |

# List of Figures

|      |                                                                                                                                                         |    |
|------|---------------------------------------------------------------------------------------------------------------------------------------------------------|----|
| 1.1  | Graphical representation of an all air conditioning system. . . . .                                                                                     | 4  |
| 1.2  | Minimal requirements given by surface temperatures, indoor air temperature, air velocity and thermal asymmetry . . . . .                                | 7  |
| 1.3  | KTH Live-In Lab data infrastructure . . . . .                                                                                                           | 10 |
| 2.1  | Heat transfer across different surfaces using the electrothermal analogy.                                                                               | 15 |
| 2.2  | Stratigraphy of an external wall: 1) gypsum plaster, 2) bricks, 3) air gap, 4) insulation, 5) bricks, 6) interior layer (gypsum plaster and paint). . . | 19 |
| 2.3  | Electrical model of heat transfer from layer $l_{-1}$ to layer $l_{+1}$ . . . . .                                                                       | 20 |
| 2.4  | External Temperature and Internal Load/Sunshine . . . . .                                                                                               | 23 |
| 3.1  | Floor plan of the room . . . . .                                                                                                                        | 28 |
| 3.2  | External Temperature Profile Used in the Simulation . . . . .                                                                                           | 29 |
| 3.3  | User Interface for Generating Feedback Signal . . . . .                                                                                                 | 38 |
| 3.4  | Binary Feedback Function for 4 Users . . . . .                                                                                                          | 40 |
| 3.5  | Aggregate Discomfort Function $h(T_r, \{\Delta_i\})$ . . . . .                                                                                          | 40 |
| 3.6  | Continuous Feedback Function for 4 User . . . . .                                                                                                       | 41 |
| 3.7  | Aggregate Discomfort Function $\ell(T_r, \{\sigma_i\})$ . . . . .                                                                                       | 41 |
| 3.8  | The reference signal used in tests. . . . .                                                                                                             | 43 |
| 3.9  | PID Temperature Control with Time-Varying Reference . . . . .                                                                                           | 43 |
| 3.10 | BANG-BANG Temperature Control with Time-Varying Reference                                                                                               | 44 |
| 3.11 | LQR Temperature Control with Time-Varying Reference . . . . .                                                                                           | 45 |
| 3.12 | Temperature Evolution via Different Controls . . . . .                                                                                                  | 46 |
| 3.13 | Temperature Evolution During a Workday . . . . .                                                                                                        | 47 |
| 3.14 | Input Control $u(t)$ During a Workday. . . . .                                                                                                          | 48 |
| 3.15 | Temperature Evolution During a Workday. . . . .                                                                                                         | 49 |
| 3.16 | Input Control $u(t)$ During a Workday. . . . .                                                                                                          | 49 |

## LIST OF FIGURES

|      |                                                                                      |    |
|------|--------------------------------------------------------------------------------------|----|
| 4.1  | Simplified office layout used for the multi-room thermal control simulation. . . . . | 52 |
| 4.2  | Reference Temperature Profiles for Each Room . . . . .                               | 57 |
| 4.5  | Heat Flow with PID Control . . . . .                                                 | 61 |
| 4.6  | Heat Flow with User's Feedback Control . . . . .                                     | 61 |
| 4.7  | Discomfort Evolution Over Time via Different Controls . . . . .                      | 64 |
| 4.8  | Results in percentages of comfort and energy consumption . . . .                     | 66 |
| 4.3  | Reference vs Actual Temperature under PID Control . . . . .                          | 67 |
| 4.4  | Temperature Evolution via Feedback Control . . . . .                                 | 68 |
| 5.1  | Floor plan of the three-room model implemented in IDA-ICE . . .                      | 73 |
| 5.2  | Temperature Evolution in Room 1 under PI Control . . . . .                           | 74 |
| 5.3  | Energy Flow Analysis in Room 1 under PI Control . . . . .                            | 74 |
| 5.4  | Temperature Evolution in Room 2 under PI Control . . . . .                           | 75 |
| 5.5  | Energy Flow Analysis in Room 2 under PI Control . . . . .                            | 75 |
| 5.6  | Temperature Evolution in Room 3 under PI Control . . . . .                           | 76 |
| 5.7  | Energy Flow Analysis in Room 3 under PI Control . . . . .                            | 76 |
| 5.8  | Temperature Evolution in Room 1 under Feedback Control . . . .                       | 78 |
| 5.9  | Energy Flow Analysis in Room 1 under Feedback Control . . . .                        | 79 |
| 5.10 | Temperature Evolution in Room 2 under Feedback Control . . . .                       | 79 |
| 5.11 | Energy Flow Analysis in Room 2 under Feedback Control . . . .                        | 80 |
| 5.12 | Temperature Evolution in Room 3 under Feedback Control . . . .                       | 80 |
| 5.13 | Energy Flow Analysis in Room 3 under Feedback Control . . . .                        | 81 |
| 5.14 | Discomfort Evolution Over Time via Different Controls . . . . .                      | 82 |
| 5.15 | Results in percentages of comfort and energy consumption . . . .                     | 83 |
| 5.16 | Floor plan of the KTH (LIL) building . . . . .                                       | 84 |
| 5.17 | 3D representation of the KTH (LIL) building . . . . .                                | 84 |
| 5.18 | Outdoor air temperature over a week . . . . .                                        | 85 |
| 5.19 | Location data for IDA ICE model . . . . .                                            | 86 |
| 5.20 | Geometrical values of the rooms . . . . .                                            | 87 |
| 5.21 | Discomfort Evolution Over Time in the Office . . . . .                               | 93 |
| 5.22 | Discomfort Evolution Over Time in the Bedrooms . . . . .                             | 94 |
| 5.23 | Energy consumption breakdown under different controls . . . .                        | 95 |
| 5.24 | HVAC system power demand over time under different controls .                        | 96 |

# List of Tables

|     |                                                                                                    |    |
|-----|----------------------------------------------------------------------------------------------------|----|
| 2.1 | Analogy between thermal and electrical quantities . . . . .                                        | 17 |
| 3.1 | Comparison of control strategies based on energy consumption<br>and tracking performance . . . . . | 45 |
| 3.2 | User Schedules for the Room . . . . .                                                              | 47 |
| 3.3 | Table of model parameters for one room . . . . .                                                   | 50 |
| 4.1 | User Schedules for Each Room . . . . .                                                             | 59 |
| 4.2 | User Preferences and Sensitivities . . . . .                                                       | 59 |
| 4.3 | Total Discomfort for Each Control Strategy Across Rooms . . . . .                                  | 63 |
| 4.4 | Table of model parameters for multi-room room . . . . .                                            | 69 |
| 5.1 | Total Discomfort for Each Control Strategy Across Rooms . . . . .                                  | 83 |
| 5.2 | Total Discomfort for Each Control Strategy Across Rooms . . . . .                                  | 94 |



# 1

## Introduction

### 1.1 MOTIVATION

Optimizing energy consumption for heating and cooling in buildings has always been a priority for energy engineers. However, in recent years, this field has gained increasing attention due to economic, environmental, and technological advancements. One of the primary reasons is economic savings: in Sweden, for instance, the built environment accounted for 34% of total annual energy use in 2022 [10], with the majority of this energy consumed by HVAC (Heating, Ventilation, and Air Conditioning) systems to maintain thermal comfort for occupants.

Beyond economic savings, optimizing HVAC energy consumption plays a crucial role in mitigating environmental impact. The building sector is a significant contributor to carbon emissions due to its energy consumption patterns. Implementing more efficient thermal management strategies can substantially reduce energy demand and associated emissions, aligning with global efforts to combat climate change. [14]

In addition to the environmental benefits, recent advancements in smart building technologies have opened up new possibilities for optimizing energy use. IoT-enabled sensors, machine learning-based predictive control, and advanced HVAC automation now enable more precise temperature regulation, demand forecasting, and adaptive control, further improving both efficiency and occupant comfort. These technological innovations are helping buildings become more responsive to real-time conditions, ensuring that energy is consumed only when and where it is needed.

## 1.2. INTRODUCTION TO CPS

While reducing energy consumption is crucial, maintaining thermal comfort for occupants remains a key challenge. People’s thermal preferences vary, and discomfort can negatively impact productivity, health, and overall well-being. Conventional HVAC systems, often designed to operate at fixed set points, are ill-suited to address individual comfort needs. Furthermore, these systems often run regardless of occupancy, leading to wasted energy. Thus, an optimal control strategy must balance energy savings with ensuring a comfortable indoor environment. In fact, studies have shown that improving thermal comfort can increase worker productivity and reduce absenteeism, making it an important aspect of any energy-efficient building strategy. [13]

Given these considerations, the optimization of HVAC systems, with a focus on energy efficiency, occupant comfort, and environmental sustainability, is a critical area of research. By integrating advanced technologies, regulatory frameworks, and a deeper understanding of human thermal preferences, this work aims to contribute to more sustainable, energy-efficient, and comfortable buildings in the future.

## **1.2** INTRODUCTION TO CPS

In recent years, the integration of physical systems with computational processes has spurred the development of Cyber-Physical Systems (CPS), a revolutionary concept that connects the physical world with real-time computing to optimize system behavior. As defined in [34], CPS are systems that tightly integrate computational resources with physical processes, allowing for continuous monitoring and adaptation of both the physical and computational components. The increasing capability of sensors, actuators, and communication technologies has led to the evolution of these systems across various fields, including manufacturing, healthcare, automotive, and building automation. This integration offers significant potential in enhancing performance, efficiency, and user comfort by enabling dynamic, context-aware decision-making.

In the domain of smart buildings, CPS technologies are poised to transform HVAC systems by enabling the adaptive regulation of indoor environments in response to both external weather conditions and user-specific preferences. A key advantage of this approach is its ability to use real-time feedback and predictive algorithms to optimize both thermal comfort and energy efficiency, a significant challenge in modern building management. In [37], the discussion

focuses on how CPS can enhance the energy performance of buildings by leveraging occupant feedback, predictive models, and energy management systems that adjust the indoor environment based on user needs while minimizing energy waste. These advancements align with the growing need for buildings to meet stringent sustainability goals while providing a comfortable environment for occupants.

The application of CPS in the thermal comfort domain involves continuously monitoring environmental parameters (such as temperature and humidity) and adjusting HVAC systems dynamically to respond to both individual preferences and external environmental factors. Unlike traditional systems that rely on fixed temperature setpoints, CPS-based approaches consider the real-time input of users, adjusting conditions to reflect their comfort while simultaneously optimizing for energy use. This creates a feedback loop where the user preferences are constantly updated, allowing for a more personalized and responsive system. One such approach to thermal comfort modeling is the use of systems like PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied) to quantify the comfort level of occupants, which can then be integrated into CPS-based feedback mechanisms. [15]

The predictive nature of CPS allows these models to be continuously updated, incorporating user behavior, environmental changes, and thermal responses over time to improve both comfort and efficiency. This dynamic system is a significant improvement over traditional methods where setpoints were static and did not take into account the complex interplay of personal comfort levels, energy consumption, and environmental changes.

Further enhancing the potential of CPS in buildings, smart sensors and actuators now enable real-time data collection, which, when analyzed through advanced algorithms, can be used to predict future thermal conditions and adjust controls proactively rather than re-actively. As discussed in [30], the use of embedded systems for real-time data processing allows CPS to handle the complex computations required to optimize comfort and energy use without overwhelming building occupants or requiring constant manual intervention. This not only improves the quality of life for users but also helps reduce energy costs by adjusting HVAC operations based on real-time demand rather than pre-programmed schedules.

In conclusion, the adoption of CPS frameworks in the management of indoor comfort and energy in buildings presents a holistic solution to modern chal-

### 1.3. HVAC SYSTEMS AND THERMAL COMFORT

lenges in building automation. By combining real-time feedback, user preferences, environmental conditions, and predictive algorithms, CPS enable more efficient, adaptive, and personalized thermal comfort systems. The ability to continuously adapt and optimize HVAC operations aligns with sustainability goals and provides a foundation for developing the next generation of smart, energy-efficient buildings. The integration of these technologies in building management systems offers significant potential for not only enhanced occupant satisfaction but also reduced environmental impact.

## 1.3 HVAC SYSTEMS AND THERMAL COMFORT

HVAC systems are typically managed according to industry standards such as ASHRAE Standard 55 (thermal environmental conditions for human occupancy) and ASHRAE Standard 62.1 (ventilation for acceptable indoor air quality). A typical HVAC system consists of one or more Air Handling Units (AHUs), which heat or cool air to a set temperature, and multiple Variable Air Volume (VAV) units that control the flow of conditioned air [3]. An example of this air-conditioning method is reported in Figure 1.1.

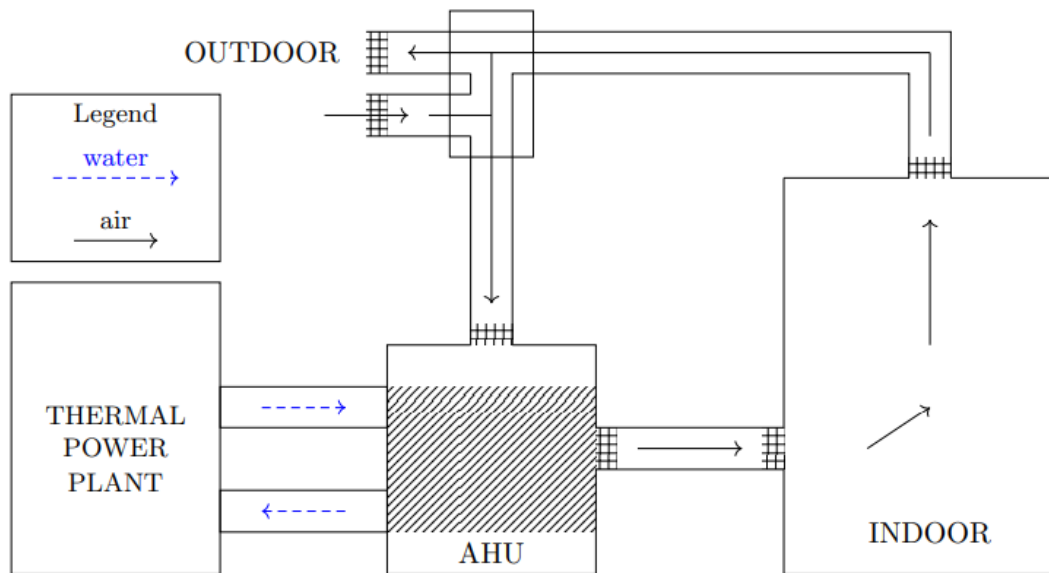


Figure 1.1: Graphical representation of an all air conditioning system.

Despite their widespread use, many HVAC systems fail to account for the dynamic nature of occupant comfort. Research has shown that current HVAC

operations often enforce uniform thermal conditions without considering individualized comfort preferences. However, thermal comfort is influenced by multiple factors, including gender, age, fitness level, clothing, and metabolic rate. Studies indicate that even within groups with similar characteristics, the standard deviation in preferred temperatures is around  $3^{\circ}\text{C}$ , and when considering additional factors such as clothing and metabolic rates, the variation can be even greater. [24]

Given these variations, maintaining thermal comfort in shared spaces with a single thermostat is nearly impossible. This issue becomes more pressing considering that urban dwellers in developed countries spend approximately 80% of their time indoors [26]. The quality of the indoor environment, including thermal, acoustic, and visual conditions, as well as indoor air quality, has a significant impact on human health and productivity [2]. As a result, ensuring high-quality indoor environments has become a central focus in architectural and building design. [17]

## 1.4 OTHER CRITICAL COMFORT PARAMETERS

While thermal comfort is the main focus of this work, a broader understanding of indoor comfort is essential for both current research and future developments, as also noted at the end of Section 1.3.

We begin this overview with noise comfort, which refers to the degree to which an environment is free from unwanted or disruptive sounds. The goal is to create an acoustic environment that supports concentration, relaxation, or communication depending on the context. This aspect is particularly important because poor noise conditions can lead to stress, reduced productivity, sleep disturbances, and even long-term health issues. [1]

In workspaces, excessive noise can also hinder communication and increase the likelihood of errors. Noise levels are typically measured in decibels (dB). For instance, libraries aim for approximately  $\sim 40$ , dB, while factories may tolerate much higher levels. To improve acoustic comfort, designers may implement sound-absorbing materials such as carpets, curtains, or acoustic panels. Additionally, enforcing noise policies in shared environments can help mitigate disruptive sound levels. [22]

Another key parameter is light comfort, which refers to the adequacy and quality of lighting in a space that supports human activities without causing discomfort

#### 1.4. OTHER CRITICAL COMFORT PARAMETERS

or fatigue. Factors include brightness, glare, color temperature, and the availability of natural light. Ensuring good lighting is essential, as poor lighting can cause eye strain, headaches, and negatively affect mood. Well-designed lighting can also enhance alertness and safety.

The illumination is measured in lux (lx). For office work, typical lighting levels range from 300 to 500 (lx), while more detailed tasks may require even higher levels. Improving light comfort often begins with maximizing natural light through windows or skylights. Additionally, using adjustable lighting systems that adapt to specific tasks can greatly enhance visual comfort. [5]

A final and fundamental component is air quality comfort, which concerns how clean, fresh, and healthy the air is in indoor environments. It is determined by the presence of pollutants and the effectiveness of ventilation. Air quality directly impacts respiratory health, cognitive performance, and overall physical and mental well-being. [21]

Poor ventilation can allow pollutants including carbon dioxide (CO<sub>2</sub>) to accumulate, especially in densely occupied areas like classrooms or offices. Even moderate CO<sub>2</sub> levels can impair concentration, decision-making, and productivity. Indoor air quality is commonly assessed through the concentration of pollutants such as CO<sub>2</sub>, particulate matter (PM), volatile organic compounds (VOCs), and humidity levels. Among these, CO<sub>2</sub> is most commonly monitored, as it also serves as an indirect indicator of ventilation effectiveness and occupancy.

The concentration of CO<sub>2</sub> is measured in parts per million (ppm). Typical values in well-ventilated indoor environments range from 400 to 800 (ppm), and the recommended maximum is usually around 1,000 (ppm). Beyond this threshold, occupants may start to feel drowsy or cognitively impaired. Improving air quality can be as simple as ensuring proper ventilation whether mechanical or natural (e.g., opening windows). More advanced approaches involve the use of CO<sub>2</sub> sensors connected to automated ventilation systems that adjust airflow in real time based on sensor data. [40]

Following this overview of the main parameters contributing to indoor comfort, we now proceed to a detailed analysis and formal definition of thermal comfort, the central topic of this work.

## 1.5 A FORMAL DEFINITION OF THERMAL COMFORT

Thermal comfort plays a crucial role in indoor environmental quality, making it a widely studied topic. The ASHRAE Standard 55 defines it as "that condition of mind which expresses satisfaction with the thermal environment" (ASHRAE 55, 2004).

In particular, Figure 1.2 shows the minimal requirements for surface temperatures, indoor air temperature, air velocity and thermal asymmetry in order to achieve a satisfactory thermal comfort according to NS-EN ISO 7730. [33]

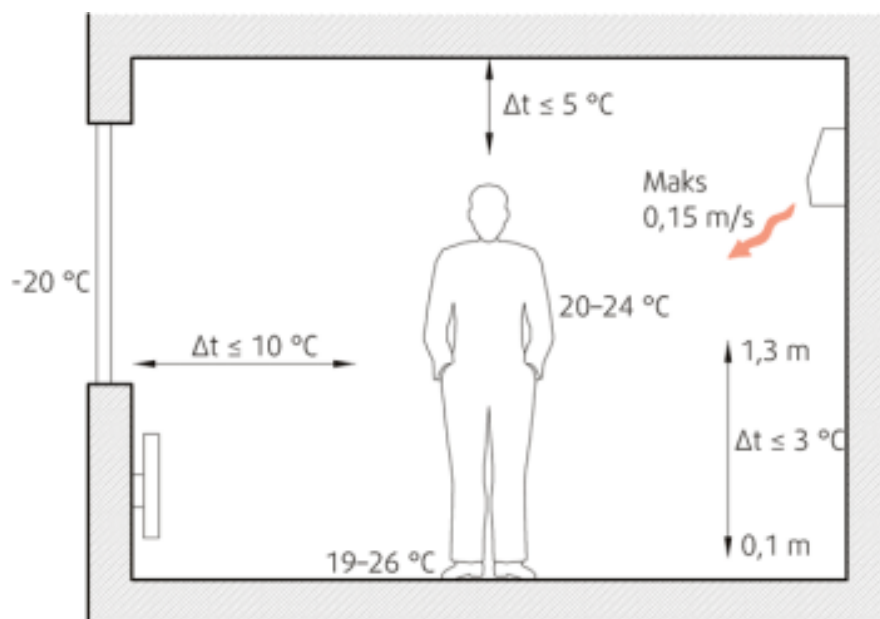


Figure 1.2: Minimal requirements given by surface temperatures, indoor air temperature, air velocity and thermal asymmetry

However, this definition has been criticized for its vagueness. Many studies, such as [20], argue that the term "condition of mind" lacks a precise definition, as it may refer to perception, emotional state, or subjective experience. Some researchers suggest that thermal comfort should be understood as an environmental property influenced by climate, surroundings, and the ability to regulate one's thermal conditions. By integrating various definitions, it becomes evident that thermal comfort is shaped by a combination of physical, psychological, cultural, and social factors. Rather than being an absolute state, it exists within a comfort zone that varies based on personal experience, expectations, and environmental conditions.

## 1.6. STATE OF ART

Among the many variables that influence thermal comfort, six parameters are widely recognized as the most important [16]. These are typically divided into two categories: environmental factors, which include air temperature, mean radiant temperature, humidity, and air speed; and personal factors, namely clothing insulation and metabolic rate.

### 1.6 STATE OF ART

In this study we investigate the intersection of building modeling and thermal control, two traditionally separate fields that have become increasingly integrated due to advancements in artificial intelligence and machine learning. The primary methodologies for building thermal modeling fall into three categories: black box, white box, and grey box models.

These classifications reflect the degree to which physical laws are incorporated into the modeling process. [6]

White box models rely on fundamental physical laws and require a comprehensive understanding of the system. They offer a high interpretability, making them ideal for scenario testing and parameter adjustments. Black box models, on the other hand, are purely data-driven, employing machine learning techniques without explicit reliance on physical principles. While they excel in predictive accuracy, their lack of transferability and adaptability limits their applicability in dynamic environments. Grey box models combine aspects of both, integrating physical laws with data-driven optimization to enhance performance.

Recent literature has shown a growing interest in black-box models for applications like energy consumption forecasting, HVAC control, and fault detection, as highlighted in [31]. Among these approaches, reinforcement learning (RL) has gained attention as a promising method for adaptive control. However, the effectiveness of black box models is constrained by their dependency on extensive historical data and their inability to test alternative control strategies before deployment. This limitation makes them less suitable for applications requiring interpretability and precise control, as is the case in our study.

White box models, in contrast, are built entirely on physical equations and do not require long-term data collection. This makes them highly reliable and flexible in terms of parameter modifications. Several widely used tools for white box modeling including IDA ICE. [9]

Among the most common methodologies in white box modeling are the Fi-

nite Element Method (FEM) and the Lumped-Parameter Method (LPM). FEM divides a system into discrete elements solved using mathematical approximations. While this method provides high accuracy, it is computationally intensive and often impractical for real-time control applications. Computational Fluid Dynamics (CFD) further extends FEM by simulating airflow dynamics but requires significant computational resources, limiting its feasibility for real-time implementation.

For practical control applications, LPM offers a more efficient alternative by assuming that thermal zones are homogeneous, meaning that temperature variations within a zone are negligible. This simplification allows for computationally efficient simulations while maintaining reasonable accuracy. The electro-thermal analogy used in LPM models buildings as RC circuits, where resistors correspond to thermal resistances and capacitors to heat storage capacities.

A fundamental representation in LPM is the 2R1C model, which characterizes a building component using two thermal resistances and one capacitance. This approach achieves a balance between computational efficiency and accuracy, making it widely used in thermal modeling. More advanced structures, such as the 3R2C model, refine accuracy while maintaining simplicity. Several studies have validated RC models against experimental data, demonstrating their reliability in predicting thermal behavior.

RC models offer several advantages, including ease of implementation, high interpretability, and computational efficiency. However, large-scale RC models can become complex, necessitating the development of model order reduction techniques that maintain accuracy while reducing computational demands.

Considering these factors, this study first employs an LPM-based approach, specifically using a 2R1C thermal model, followed by an FEM implementation with IDA-ICE software. Both models offer a physically meaningful representation of thermal dynamics while enabling real-time control optimizations, making them well-suited for this application.

## **1.7** THE KTH LIVE-IN LAB

The KTH Live-In Lab (LIL) is a cutting edge of research infrastructure located at the KTH Royal Institute of Technology in Stockholm, Sweden. It serves as a testbed platform aimed at accelerating the development and demonstration of innovative technologies for improving energy efficiency, indoor environmental

## 1.7. THE KTH LIVE-IN LAB

quality, and sustainability in the built environment. [28]

Unlike traditional monitoring facilities, which are often limited to office environments, the KTH LIL extends this capability to residential buildings, providing a unique opportunity to study and optimize building performance under real life conditions [35]. At the heart of the (LIL) is Testbed KTH, a highly flexible and reconfigurable residential space of approximately 305m<sup>2</sup>, which includes living areas, service areas, and project office space. The interior layout is modular, with lightweight interior walls that facilitate experimental reconfiguration to study the interaction between humans and the building.

Testbed KTH is supported by two additional buildings: Testbed Akademiska Hus and Testbed Einar Mattsson, which are residential buildings for students, all sited in the KTH main campus in Stockholm.

The building infrastructure integrates advanced Information and Communication Technologies (ICT), allowing researchers to monitor a wide range of environmental parameters, including temperature, relative humidity, CO<sub>2</sub>, occupancy through an extensive sensor network. These data are collected and managed via the KTH LIL Data Pool, enabling real time visualization and analysis. Beyond its physical infrastructure, the KTH Live-In Lab is envisioned as a cyber-physical- human system, where the interaction between occupants and technology is central to the research [4]. A simplified illustration of the KTH Live-In Lab data infrastructure is represented in Figure 1.3.

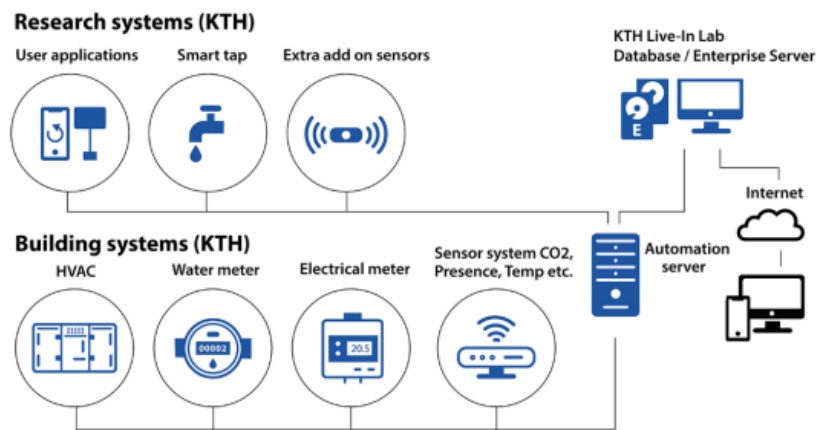


Figure 1.3: KTH Live-In Lab data infrastructure

In this thesis, we studied a specific configuration of the Testbed KTH, focusing on a particular experimental setup designed to analyze the interaction between building occupants and indoor environmental parameters. The setup allowed

us to collect real-time feedback from users and evaluate comfort levels in relation to temperature regulation and energy use.

## **1.8** PERSONAL CONTRIBUTION

This thesis represents a comprehensive effort to integrate theoretical foundations, control system design, and advanced simulation tools to address the challenge of optimizing thermal comfort in shared indoor environments. A key personal contribution lies in exploring how user feedback, enabled by recent advances in information technology, can be incorporated into the control strategy. By collecting real-time feedback from occupants about their thermal comfort while the building is in use, this work takes a step toward developing personalized thermal comfort models. This approach offers a novel perspective that complements traditional modeling techniques and enhances the adaptability and effectiveness of HVAC control systems.

## **1.9** OUTLINE

Following the introduction, Chapter 2 outlines the modeling approach adopted to develop the digital twin, starting with the building description and proceeding to the environmental modeling.

Chapter 3 and Chapter 4 presents the case study and the simulations carried out in MATLAB, providing an assessment of the model behavior and the performance of the implemented control strategies. Subsequently, Chapter 5 reports the results obtained using the IDA-ICE simulation environment.

Finally, Chapter 6 summarizes the main findings and proposes directions for future research.



# 2

## Building Model

This chapter introduces two modeling techniques for developing the building model, both based on the white-box approach. The first method is formulated using the Lumped-Parameter Method (LPM), specifically following the 2R1C model. Additionally, we provide an overview of the IDA-ICE software, explaining its functionality and how it computes building simulations

### 2.1 AN INTRODUCTION TO HEAT TRANSFER

To accurately model a buildings thermal behavior, it is essential to first understand how heat transfers through different materials and fluids. Heat is the energy exchanged between two systems or different parts of the same system, excluding thermodynamic work, energy conversion, or mass transfer. According to the second law of thermodynamics, heat naturally moves from a warmer body to a cooler one until thermal equilibrium is reached.

There are three primary mechanisms of heat transfer: conduction, convection, and radiation. Conduction occurs when heat flows through direct contact between materials, with energy moving from the hotter to the cooler region. Convection involves heat transfer through a fluid, where temperature differences create movement that transports thermal energy. Radiation, on the other hand, allows energy exchange between objects via electromagnetic waves, even without direct contact. Understanding these mechanisms is fundamental to developing accurate thermal models for buildings.

One of the earliest formulations of heat conduction is Fouriers postulate on thermal conduction. Consider a material where this process occurs, with an

## 2.1. AN INTRODUCTION TO HEAT TRANSFER

infinitesimal plane of area  $dA$ . If within the material there exist two points, denoted as  $P_1$  and  $P_2$ , positioned along a line and separated by a distance  $dn$ , and if these points have temperatures  $T_1$  K and  $T_2 = T_1 + dT$  K, where K represents the unit of measurement in Kelvin and this setup corresponds to a Dirichlet boundary condition, then the heat exchange between these two points is described as follows:

$$dQ = -\lambda_n dA \frac{dT}{dn} d\tau \quad (2.1)$$

where  $\lambda_n$  denotes the thermal conductivity of the material,  $d\tau$  represents the infinitesimal time interval, and  $\frac{dT}{dn}$  is known as the thermal gradient.

We now consider a material shaped as a parallelepiped with a thickness  $s$  and an area  $A$ , with heat propagation occurring along the thickness direction. By integrating over both space and time, the equation for the heat flux  $\dot{Q}$ , measured in watts (W), can be expressed as:

$$\dot{Q} = -\lambda_n A \frac{T_2 - T_1}{s} = \frac{\Delta T}{R} \quad (2.2)$$

where  $\Delta T = T_1 - T_2$  represents the temperature difference between two surfaces, and  $R$  the thermal resistance of the material, measured in  $\text{KW}^{-1}$ , defined as:

$$R = \frac{s}{\lambda_n A} \quad (2.3)$$

Thermal resistance establishes a mathematical analogy between heat transfer and electrical behavior. This is comparable to Ohm's law, which expresses the relationship between the voltage drop  $\Delta V$  across a resistor  $R$  and the current  $I$  flowing through it:

$$\Delta V = RI \quad (2.4)$$

By leveraging this analogy, the heat flux  $\dot{Q}$  corresponds to the electric current  $I$ , while the temperature difference  $\Delta T$  is analogous to the potential difference  $\Delta V$ . This concept greatly simplifies the analysis, particularly when multiple layers of material are in contact along the direction of heat flow. According to Fouriers law, the temperature gradient remains linear when considering materials with different thermal conductivities  $\lambda_1, \dots, \lambda_n$  for different materials. If each layer has a thickness  $s_i$ , its thermal resistance is given by:

$$R_i = \frac{s_i}{\lambda_i A} \quad (2.5)$$

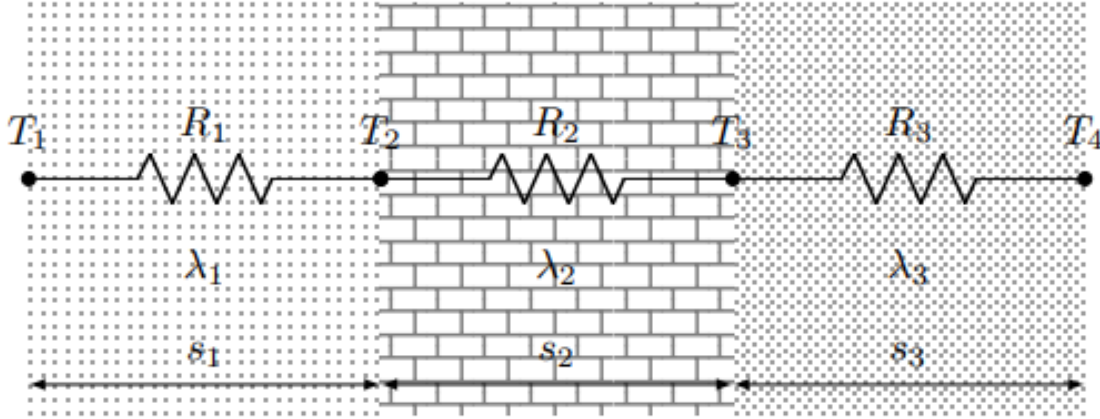


Figure 2.1: Heat transfer across different surfaces using the electrothermal analogy.

As shown in Figure 2.1, the total heat transfer between two points, one at temperature  $T_1$  and the other at  $T_4$ , follows the same principles as an electrical circuit with resistors in series. The equivalent thermal resistance is the sum of the individual resistances, leading to:

$$\dot{Q} = \frac{T_1 - T_4}{\sum_{i=1}^n R_i} \quad (2.6)$$

This approach is particularly useful for analyzing composite structures, such as building walls, which are composed of multiple layers designed optimize insulation and structural integrity.

The next mode of heat transfer we need to discuss is convection. In addition to energy transfer due to the random molecular motion (diffusion), energy is also transported by the macroscopic movement of the fluid. Thus, convection heat transfer can be defined as the transfer of energy within a fluid, driven by both conduction and the macroscopic motion of the fluid. Regardless of the particular characteristics of the convection process, the rate equation that governs this transfer generally takes the following form:

$$|\dot{Q}| = \alpha_c A |T_s - T_f| \quad (2.7)$$

where  $A$  is the area of surface in contact with the fluid and  $\alpha_c$  represent the convective heat transfer coefficient measured in  $\text{Wm}^{-2}\text{K}^{-1}$ .

Convective heat transfer can also be described through an analogy to Ohm's law.

## 2.1. AN INTRODUCTION TO HEAT TRANSFER

Specifically, we can define the thermal resistance for convection as follows:

$$R = \frac{1}{\alpha_c A} \quad (2.8)$$

In contrast to the conduction law, this represents an approximation of real-world behavior, and its suitability should be evaluated for each specific situation.

The last way of exchanging heat between bodies is by radiation. This behavior is described by Planck's law for black bodies, which is an extension of Stefan-Boltzmann's law. The simplest form of this law defines the heat flow  $\dot{Q}$  between two bodies, not necessarily in contact, one at temperature  $T_1$  K and the other at temperature  $T_2$  K is:

$$\dot{Q} = \epsilon \sigma F_{1 \rightarrow 2} (T_1^4 - T_2^4) \quad (2.9)$$

where  $\epsilon \in [0, 1]$  is the emissivity,  $\sigma \simeq 5.67 \times 10^{-8} \text{Wm}^{-2}\text{K}^{-4}$  is the Stefan-Boltzmann constant and  $F_{1 \rightarrow 2}$  is the view factor.

However, in buildings, this mode of heat transfer is generally negligible, except for solar radiation, which will be discussed in more detail in the following section.

To analyze the transient thermal behavior of the building model, it is essential to introduce the concept of thermal capacitance. During transient heat transfer, the internal energy and, consequently, the temperature of materials change over time. Thermal capacitance, or heat capacity, refers to a material's ability to store heat and is typically measured in units  $\text{J}/^\circ\text{C}$  or  $\text{J}/\text{K}$ .

For a homogeneous material with known physical properties, the thermal mass can be calculated by multiplying the material's mass by its specific heat capacity as:

$$C = mc_p \quad (2.10)$$

A summary about analogy between thermal and electrical quantities is reported in Table 2.1

Table 2.1: Analogy between thermal and electrical quantities

| Thermal           |            |         | Electric         |            |          |
|-------------------|------------|---------|------------------|------------|----------|
| Quantity          |            | m.u.    | Quantity         |            | m.u.     |
| Temperature       | $T$        | K       | Potential        | $V$        | V        |
| Temperature Diff. | $\Delta T$ | K       | Voltage          | $\Delta V$ | V        |
| Thermal Flux      | $\dot{Q}$  | J/s = W | Electric current | $I$        | A        |
| Resistance        | $R$        | K/W     | Resistance       | $R$        | $\Omega$ |
| Capacitance       | $C$        | J/K     | Capacitance      | $C$        | F        |

### 2.1.1 ENERGY BALANCE

Up to this point, the focus has been on determining the amount of heat transferred between bodies and exploring useful analogies between thermal and electrical systems. According to thermodynamic principles, heat flows from the hotter body to the cooler one until thermal equilibrium is achieved. The concept of internal thermal energy within a body governs and characterizes this heat transfer process:

$$U_T(T) = \rho V c_v T \quad (2.11)$$

where  $\rho$  is the density,  $V$  the body volume,  $c_v$  is the specific heat at constant volume and  $T$  the temperature.

Based on the principle of energy conservation, and excluding any work contributions ( $\Delta L = 0$ ) and phase changes in the material, the energy balance for complete heat transfer from a body at temperature  $T$  to another body at a higher temperature  $T_2$  with  $T_2 > T$  over a time interval  $\tau$  due to conduction can be expressed as follows:

$$\int_{t=0}^{\tau} \dot{Q} dt = U_T(\Delta T) + \int_{t=0}^{\tau} I \Delta V dt \quad (2.12)$$

where  $\Delta T = T_2 - T$  is the difference of temperature and  $I \Delta V$  indicates the Joule effect for the passage of the current  $I$  through the material with potential difference  $\Delta V$ .

Moving then to an infinitesimal form we have:

$$\dot{Q} = \frac{\Delta T}{R} = \frac{U_T(dT)}{dT} = \rho V c_v \frac{dT}{dt} \quad (2.13)$$

## 2.2. 2RC1 MODELING TECHNIQUE

where  $dT$  represents the change in the body's temperature over an infinitesimally small time interval  $dt$ . By rearranging the equation, we obtain:

$$\dot{Q} = \frac{T_2 - T}{R} = C \frac{dT}{dt} \quad (2.14)$$

where  $C = \rho V c_v$  is the heat capacity in  $\text{JK}^{-1}$ .

The equation is similar to a first-order differential equation governing the charge of an electric capacitor:

$$RC \frac{dT}{dt} + T = T_2 \rightarrow RC \frac{dV}{dt} + V = V_0 \quad (2.15)$$

and a solution for  $T = T(t)$  is:

$$T(t) = (T(t) - T_2) e^{-\frac{t}{RC}} + T_2 \quad (2.16)$$

where  $T(0)$  is the temperature of the body at the start of the heat transfer.

## 2.2 2RC1 MODELING TECHNIQUE

As discussed in the previous section, the thermal behavior of fluids and solids can be effectively represented using first-order differential equations, without significant loss of accuracy. This approach allows for the development of models that strike a balance between precision and simplicity, making them suitable for control applications. It is crucial to identify the buildings individual components and understand their characteristics to select the most appropriate model for each element.

### 2.2.1 ELEMENTS OF A BUILDING

A building is made up of several architectural components, each with its unique method of heat exchange with the environment. To simplify the analysis, these components can be categorized into two groups based on their thermal inertia. The first group includes elements with high thermal inertia, such as external walls, foundations, floors, and roofs, which are large and massive enough to retain heat over extended periods. The second group consists of elements with low thermal inertia, like windows, doors, and internal walls. Room air is not included in this classification due to its distinctive behavior,

which is addressed separately in Section 2.2.2.

The components of the first group, which have significant thermal inertia due to their high heat capacity, can be modeled using Equation 2.14. To enhance thermal performance, it is common to model an external wall as a multi-layered structure. Typically, an external wall consists, from the outer side inward, of a layer of gypsum plaster, followed by a layer of perforated bricks and an air gap. Next, there is an insulation layer, which is followed by another layer of perforated bricks. The final layer is made up of interior gypsum plaster and paint. An illustration of this structure is shown in Figure 2.2.

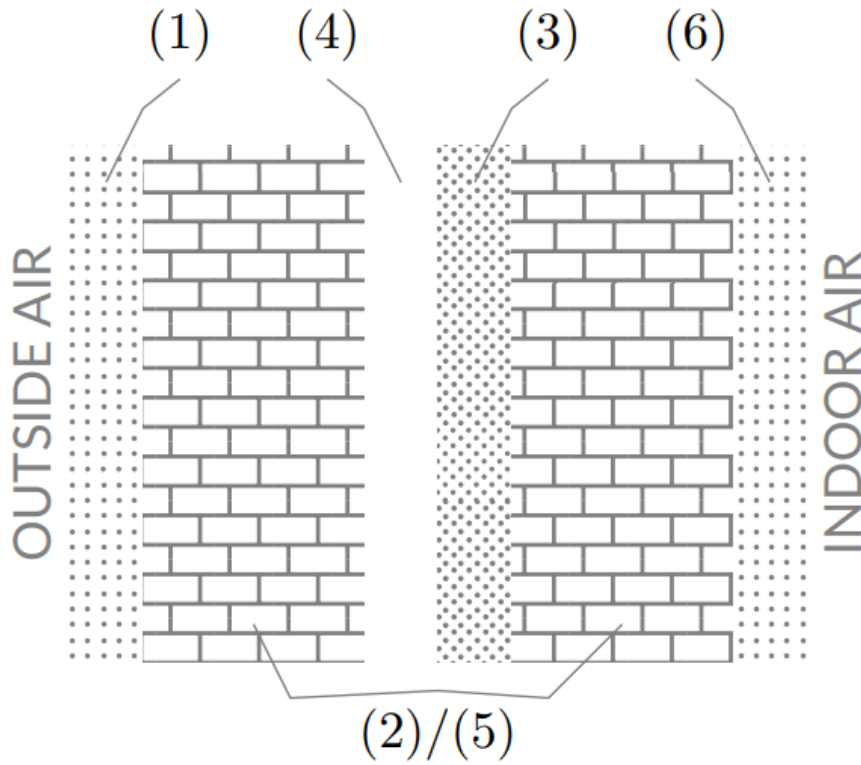


Figure 2.2: Stratigraphy of an external wall: 1) gypsum plaster, 2) bricks, 3) air gap, 4) insulation, 5) bricks, 6) interior layer (gypsum plaster and paint).

Each of these layers transfers heat horizontally to both the preceding and succeeding layers. To account for this, the Equation 2.14 must be adjusted accordingly. If we consider a layer  $l$  in contact with layers  $l_{-1}$  and  $l_{+1}$ , we can assume that the temperature is uniform across the layer. The temperature of the considered layer is  $T$ , while the temperatures of the two adjacent layers are  $T_{-1}$  and  $T_{+1}$ , respectively. Since heat transfer occurs by conduction, we can apply

## 2.2. 2RC1 MODELING TECHNIQUE

Equation 2.2. As a result, each layer transfers the following heat flow to layer  $l$ :

$$\dot{Q}_{-1} = \frac{T_{-1} - T}{R} \quad \text{and} \quad \dot{Q}_{+1} = \frac{T_{+1} - T}{R} \quad (2.17)$$

where  $R = \frac{R_l}{2}$  by assuming to measure the temperature in the middle of the layer, as suggested by [18].

By synthesizing all the previous results, we can conclude that the layer exhibits the following behavior, as described in [11]:

$$C_l \frac{dT}{dt} = \dot{Q}_{-1} + \dot{Q}_{+1} = \frac{T_{-1} - T}{R} + \frac{T_{+1} - T}{R} \quad (2.18)$$

The following equation is equivalent to the electrical circuit reported in Figure 2.3.

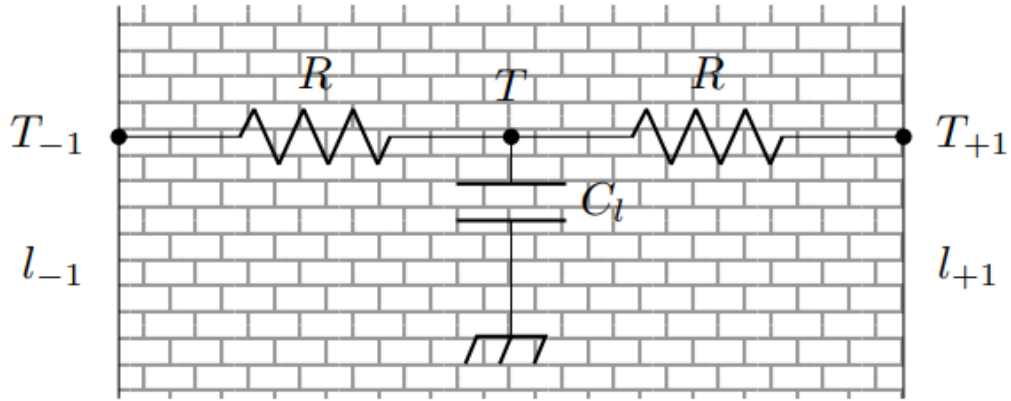


Figure 2.3: Electrical model of heat transfer from layer  $l_{-1}$  to layer  $l_{+1}$ .

By applying the same approach to all layers, a comprehensive model of the element's behavior can be constructed. The resulting circuit consists of a series of resistors interspersed with capacitors, which can become quite complex. To simplify the model, resistors and capacitors are grouped together, reducing their total number.

In contrast to the previously discussed elements, components such as windows, doors, and internal walls, which have minimal thermal inertia, can be directly modeled using Equation 2.2, as the heat transfer occurs by conduction and can be fully described by a single thermal resistance [32]. Consequently, for two rooms with temperatures  $T_0$  and  $T_1$ , separated by an internal wall, the heat flux

through the wall is given by:

$$\dot{Q} = \frac{T_0 - T_1}{R_w} \quad (2.19)$$

where  $R_w$  is the thermal resistance of the internal wall.

### 2.2.2 AIR MODELING

So far, the thermal behavior of a buildings primary solid elements has been described using differential equations. However, the role of air is one of the key factors influencing thermal comfort has yet to be examined.

To simplify the resolution of the thermal network, the air inside the room is modeled using a single capacitor while omitting resistors. This choice stems from the fact that the model provides temperature values only at capacitor nodes. If resistors were included, an additional fictitious capacitor would be required to determine the room temperature. Instead of introducing artificial values, we opted to use the standard heat capacity of air, calculated based on the volume of each room, along with an additional contribution for furniture  $c_f = 30 \text{ kJ K}^{-1}$  taking inspiration from [25]. Consequently, the interior of a room has been modeled as follows:

$$C_r = \rho_a c_{pa} V_r + c_f S_r \quad (2.20)$$

where  $C_r$  is the modeled thermal capacity of the room,  $V_r$  is the volume and  $S_r$  the floor surface. The last parameters are  $\rho_a = 1.204 \text{ kg/m}^3$  which represent the air density and  $c_{pa} = 1007 \text{ J/kg/K}$  is the air specific heat.

This values are obtained by supposing a temperature of  $20^\circ\text{C}$  and  $1 \text{ atm}$  pressure.

## 2.3 DISTURBANCES MODELLING

To accurately predict the thermal behavior of a building, it is essential to model both internal dynamics and the influence of the surrounding environment. A comprehensive digital twin must account for external factors that impact indoor temperature. The three primary drivers of temperature variation within a building are external temperature, solar radiation, and internal heat sources. External temperature influences the building's thermal state through

### 2.3. DISTURBANCES MODELLING

heat exchange by conduction. This process continues until thermal equilibrium is achieved, meaning that heat transfer stops when the internal and external temperatures match. The extent of this effect depends on the buildings insulation, wall materials, and fixture quality. Advances in insulation technology have significantly improved the ability of buildings to resist external temperature fluctuations, reducing unwanted heat loss or gain.

In contrast, solar radiation and internal heat sources actively contribute to temperature changes by supplying heat regardless of the current indoor temperature. Unlike external temperature, which seeks equilibrium, these sources function independently of thermal gradients and remain effective across various temperature conditions. Solar radiation transfers heat through radiation, and due to the immense temperature difference between the Sun and building surfaces, this energy exchange is primarily dependent on solar intensity rather than the temperature state of the receiving surfaces. Internal heat sources, such as occupants and electrical appliances, release heat into the indoor environment. Since most electrical devices do not perform mechanical work, their energy consumption is almost entirely converted into heat. For example, a computer dissipates heat equal to its power consumption, instantly affecting the surrounding temperature.

To effectively model these heat transfer mechanisms, an electrothermal analogy can be applied. Voltage sources represent fixed temperature influences, such as external air and ground temperature, which impact the system regardless of heat exchange requirements. Meanwhile, current sources symbolize heat flow, corresponding to solar radiation and internal loads, providing a continuous influx of energy irrespective of system temperature. A Resistor-Capacitor (RC) network representation is commonly used to model these thermal interactions as reported in Figure 2.4.

The impact of solar radiation requires additional consideration, as sunlight affects both external surfaces and interior spaces through windows. This dual influence necessitates an extended model to account for heat gains from direct sunlight exposure on walls and the transmission of radiation through glazing elements. By integrating these environmental factors into the thermal model, a more accurate simulation framework can be developed, enabling precise predictions of indoor temperature fluctuations and optimizing climate control strategies for improved energy efficiency.

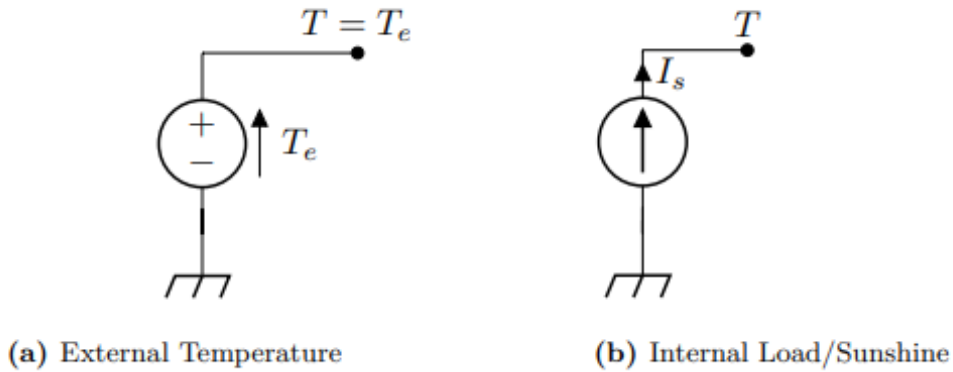


Figure 2.4: External Temperature and Internal Load/Sunshine

### 2.3.1 PEOPLE IMPACT

A human occupant in a building is not only the primary subject of thermal comfort but also a source of thermal variation within the control system. On average, an individual generates approximately 120W of heat [8] due to metabolic activity, though this value fluctuates based on factors such as physical activity and clothing insulation. [11]

Given the central role of occupants in this study, Chapter 5 will include simulations that account for the presence or absence of users. As a result, the heat gains associated with individuals will vary over time, depending on their activity and occupancy status. For this analysis, the office occupancy of a single user has been predefined based on an arbitrary assumption.

## 2.4 IDA-ICE MODELING TECHNIQUE

In this thesis, the building was modeled using *IDA Indoor Climate and Energy (IDA-ICE)*, a dynamic simulation tool developed by EQUA Simulation AB for analyzing building energy consumption, indoor air quality, and thermal comfort. First released in 1998, with version 3.0 available since 2001, IDA-ICE is a commercially available software platform that supports multiple languages, including English, Swedish, Finnish, and German.

IDA-ICE offers a physically detailed and comprehensive framework for multi-zone building modeling. It goes beyond simplified lumped-parameter approaches like the 2RC1 (two-resistance, one-capacitance) model, described in

## 2.4. IDA-ICE MODELING TECHNIQUE

Section 2.2, by employing advanced numerical techniques. Heat conduction through building components is solved using the Finite Element Method (FEM), while State-Space Modeling is employed for efficiently computing transient thermal responses. [38]

Heat flows between zones are determined through air heat balance equations that account for conduction, convection, and radiation [27]. Airflow between rooms, including those driven by wind and buoyancy through leaks and openings, are modeled via a fully integrated airflow network, ensuring accurate inter-zonal heat transfer calculations. [39]

Each zone, typically a room or section of the building, is modeled as a homogeneous volume with uniform temperature, pressure, and concentration. The software also supports vertical temperature gradients, air stratification in displacement ventilation systems, and dynamic occupant behavior models, which influence internal heat gains based on metabolic activity, equipment use, and lighting.

The model library of IDA-ICE is written in Neutral Model Format (NMF), a program-independent language for describing dynamic systems using differential-algebraic equations [36]. IDA, the underlying simulation platform, was developed by the Division of Building Services Engineering at the Royal Institute of Technology (KTH) in Stockholm and the Swedish Institute of Applied Mathematics (ITM). The mathematical models were validated against benchmark standards such as *Envelope BESTEST* (IEA Task 12) and *prEN 13791* test cases. IDA-ICE supports the simulation of numerous phenomena relevant to indoor climate and energy studies, including:

- Full zone heat and moisture balances, considering solar gains, internal loads, surface transmissions, and HVAC contributions;
- Detailed modeling of solar influx through windows, incorporating 3D shading from surrounding structures;
- Calculation of air and surface temperatures, operating temperatures, and comfort indices (PPD and PMV) at arbitrary occupant locations;
- CO<sub>2</sub> and moisture dynamics, useful for controlling VAV (Variable Air Volume) systems;
- Airflows, temperature, moisture, and pressure at various points in air-handling systems;
- Daylight levels, energy consumption, and primary / secondary system power levels;

- Total energy costs, potentially based on time-dependent tariffs.

Overall, IDA-ICE provides a highly sophisticated and validated platform for simulating building energy performance and indoor environmental conditions. Its multi-zone capabilities, advanced numerical modeling, and integration of HVAC systems and occupant behavior make it a powerful tool for achieving accurate, real-world predictions in building simulation contexts.



# 3

## First Case Study: Single Room

This section presents the single-room case study, which serves as an initial setup for testing and refining various control strategies. Control laws were designed, implemented, and analyzed using MATLAB Simulink. This environment provided a controlled context to evaluate the performance of each method and fine-tune parameters to achieve effective temperature regulation. The single-room case forms the foundation for understanding how different control systems respond to indoor thermal dynamics.

### 3.1 ONE ROOM IMPLEMENTATION

As a starting point, we consider a single room, illustrated in Figure 3.1, modeled with realistic structural parameters. The room dimensions are  $5\text{m} \times 5\text{m} \times 2.7\text{m}$ . The room thermal capacitance, already introduced in Equation 2.20, accounts for both the air volume and the contribution of the furniture, ensuring that the model accurately captures realistic indoor dynamics. Next, we define other key thermal parameters, namely the thermal resistance and capacitance of the walls and roof. From previous studies [23], thermal resistance can be computed as:

$$R_i = \frac{s_i}{\lambda_i A_i}$$

where  $s_i$  represents the thickness of material  $i$ ,  $\lambda_i$  its thermal conductivity, and  $A_i$  the area of the component. To capture the thermal evolution of the walls, the room, and the roof, we assign a heat capacity to each component using the

### 3.1. ONE ROOM IMPLEMENTATION

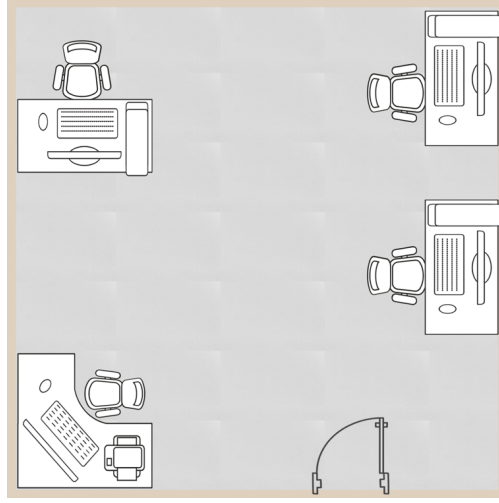


Figure 3.1: Floor plan of the room

relation:

$$C = mc_p$$

where  $m$  is the mass of the element and  $c_p$  its specific heat capacity. Another disturbance parameter that was taken into account is the ground temperature, which is generally modeled as a constant value (e.g.,  $T_g = 12^\circ\text{C}$ ). [19]

The final parameter to define in our simulation is the external temperature. For the sake of simplicity and to simulate natural daily fluctuations, we model it as a sinusoidal function. This approximation captures the typical variation between daytime and nighttime temperatures and provides a realistic disturbance input for the controller. The resulting temperature profile is shown in Figure 3.2.

Now that we have defined all the needed parameters it is possible to write the heat transfer equations about the four vertical walls and the roof. Since the vertical walls are equal in pairs, it is possible to eliminate the redundant equations by obtaining two distinct equations for the four walls.

Therefore, the following equations are obtained for the temperatures of the walls and the room. With reference to the first two walls:

$$C_{w1} \frac{dT_{w1}}{dt} = \frac{T_r - T_{w1}}{R_{w1}} + \frac{T_{\text{ext}} - T_{w1}}{R_{w1}} \quad (3.1)$$

This equation states that change of energy through north, south walls of the office space. A similar equation can be written for east and west walls with the

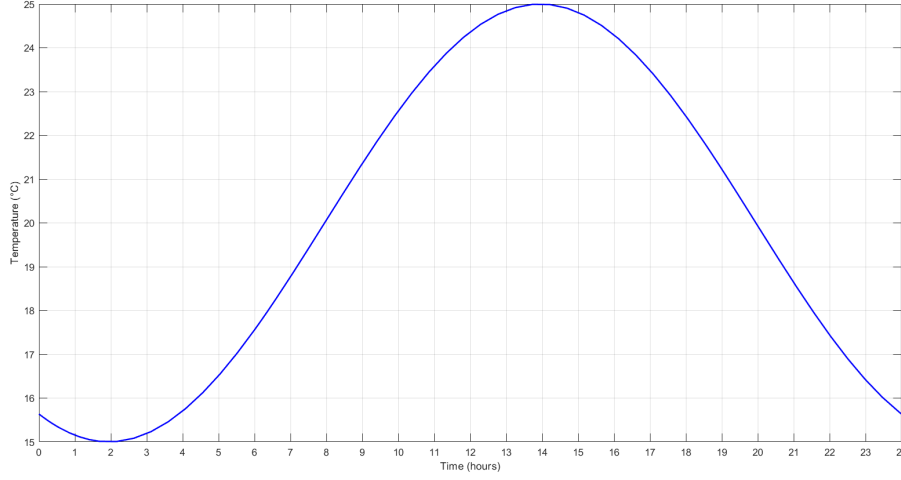


Figure 3.2: External Temperature Profile Used in the Simulation

same meanings of the first equation:

$$C_{w2} \frac{dT_{w2}}{dt} = \frac{T_r - T_{w2}}{R_{w2}} + \frac{T_{\text{ext}} - T_{w2}}{R_{w2}} \quad (3.2)$$

For the roof we get the following differential equation:

$$C_t \frac{dT_t}{dt} = \frac{T_r - T_t}{R_t} + \frac{T_{\text{ext}} - T_t}{R_t} \quad (3.3)$$

By combining all this results, we obtain the differential equation for the temperature of the room:

$$C_r \frac{dT_r}{dt} = 2 \frac{T_{w1} - T_r}{R_{w1}} + 2 \frac{T_{w2} - T_r}{R_{w2}} + \frac{T_t - T_r}{R_t} + \frac{T_g - T_r}{R_g} + q_{\text{int}} + \dot{Q}_r$$

where  $\dot{Q}_r$  is the heat flux introduced in the room and  $q_{\text{int}}$  represent the heat generation inside the room.

The control variable for temperature regulation is the heat flow supplied by the HVAC to the room. We denote this quantity as  $\dot{Q}_r$ , which, based on previous studies, is given by:

$$\dot{Q}_r = \dot{m} c_p (T_0 - T_r) \quad (3.4)$$

where  $\dot{m}$  represents the air mass flow rate,  $c_p$  is the specific heat capacity of air, and  $T_0$  is the temperature of the air entering the room through the HVAC.

From this point onward, for simplicity, we define the control input directly as

### 3.1. ONE ROOM IMPLEMENTATION

the heat flow rate  $\dot{Q}_r$ , which we denote by  $u$ , i.e.,

$$u = \dot{Q}_r.$$

Since we also aimed to implement a Linear Quadratic Regulator (LQR) controller, it was necessary to represent our thermal model in state-space form. State-space representation is essential in modern control theory, as it allows the application of optimal control techniques like LQR.

By having written the differential equations that describe heat transfer for each wall and room in the building and assembling them into a state-space model, we obtain the following dynamic system:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Gw(t) \\ y(t) = Cx(t) \end{cases}$$

Here,  $x(t)$  represents the system state,  $u(t)$  the control input, and  $y(t)$  the system output. Specifically, the state vector is defined as:

$$x(t) = \begin{bmatrix} T_r(t) & T_{w1}(t) & T_{w2}(t) & T_t(t) \end{bmatrix}^T$$

The system matrices for our thermal model are formulate as follows:

$$A = \begin{bmatrix} -\alpha & \frac{2}{C_r R_{w1}} & \frac{2}{C_r R_{w2}} & \frac{1}{C_r R_t} \\ \frac{1}{C_{w1} R_{w1}} & -\frac{2}{C_{w1} R_{w1}} & 0 & 0 \\ \frac{1}{C_{w2} R_{w2}} & 0 & -\frac{2}{C_{w2} R_{w2}} & 0 \\ \frac{1}{C_t R_t} & 0 & 0 & -\frac{2}{C_t R_t} \end{bmatrix} \quad (3.5)$$

$$B = \begin{bmatrix} \frac{1}{C_r} \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad G = \begin{bmatrix} 0 & \frac{1}{C_r R_g} & \frac{1}{C_r} \\ \frac{1}{C_{w1} R_{w1}} & 0 & 0 \\ \frac{1}{C_{w2} R_{w2}} & 0 & 0 \\ \frac{1}{C_t R_t} & 0 & 0 \end{bmatrix} \quad (3.6)$$

where the scalar coefficient  $\alpha$  is equal to:

$$\alpha = \frac{2}{C_r R_{w1}} + \frac{1}{C_r R_t} + \frac{1}{C_r R_g}$$

The disturbance vector  $w(t)$  is given by:

$$w(t) = \begin{bmatrix} T_{\text{ext}}(t) \\ T_g \\ q_{\text{int}} \end{bmatrix} \quad (3.7)$$

Finally, the measurement matrix  $C$ , which selects only the room temperature from the state vector, is defined as:

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \quad (3.8)$$

An overview of all the parameters used in the simulation is provided in Table 3.3.

## 3.2 CONTROL IMPLEMENTATION

In this work, building control inputs, as already mentioned, are modeled as internal heat sources, allowing for precise temperature regulation. To achieve this, different control strategies are implemented and compared. The first approach is PID control, a classical method that adjusts heating power based on proportional, integral, and derivative error terms. Another strategy is Bang-Bang control, a simple on/off mechanism that activates or deactivates heating devices based on temperature thresholds. Additionally, a Linear-Quadratic Regulator (LQR) with integral action is employed to minimize a cost function while ensuring steady-state error correction. The final control strategy, referred to as the user feedback integral control method, incorporates occupant-reported thermal comfort into the control law. This approach refines temperature regulation based on subjective comfort perceptions.

### 3.2.1 PID CONTROL

The first controller we use is a continuous-time Proportional-Integral-Derivative (PID) controller. Although it is a fairly old technology, it has been included because it is the state of the art at industrial level for buildings. Its success mainly derives from its excellent performance with a low material cost: very often, it is implemented with analogue components, especially in older machines. However, this controller is not able to collect information about the environment and it controls each room independently of the others, thus failing to optimize

### 3.2. CONTROL IMPLEMENTATION

the whole. To identify the optimal PID parameters, we performed extensive simulations under various scenarios and selected the values that delivered the best overall performance. These are:

$$\begin{cases} k_p = 1420.22 \\ k_i = 9.59 \\ k_d = -682.16 \end{cases} \quad (3.9)$$

The possible configuration of our controller could be written as:

$$u(t) = \left( K_p + \frac{K_i}{s} + sK_d \right) (r(t) - T_r(t)) \quad (3.10)$$

where  $r(t)$  represent the reference temperature that we want to track.

#### 3.2.2 BANG-BANG CONTROL

One of the simplest control laws is the *ON-OFF* control law. This approach is widely used in thermostatic systems, where a heating source is either fully activated or completely turned off based on the deviation of the measured temperature from the desired setpoint.

In this method, the maximum heating power  $Q_{\max}$  must be chosen manually based on system characteristics and heating requirements. The control law is then defined as:

$$u(t) = \begin{cases} Q_{\max}, & \text{if } T_r(t) < r(t) \\ 0, & \text{if } T_r(t) \geq r(t) \end{cases} \quad (3.11)$$

To mitigate the frequent switching typically observed in such on/off control strategies, we also introduce a deadband around the reference temperature. Within this deadband range, the controller does not activate the heating system, allowing small fluctuations in temperature without triggering control action. This addition reduces unnecessary toggling, thereby improving energy efficiency and system stability.

This approach remains simple to implement and avoids complex computations, but even with the deadband, it may still lead to moderate oscillations around the setpoint due to its binary nature.

### 3.2.3 LQR

We introduce now the LQR controller, which is designed to minimize the error  $e(t) = r(t) - y(t)$ , where  $y(t)$  represents the temperature of the room. The goal is for  $y(t)$  to converge to  $r(t)$  robustly, with no steady-state error for any constant or piecewise-constant input or disturbance. We assume that temperature measurements are always available through a basic temperature sensors. However if this is not the case, the system's state can be estimated using a state observer.

To define the controller, we apply the Linear Quadratic Regulator (LQR) methodology to compute a constant feedback matrix  $K$ . The LQR framework optimizes the feedback matrix  $K$  to minimize the following performance index, given the initial state  $x(0)$ :

$$J(u, x(0)) = \int_0^\infty (x(t)^\top Q x(t) + u(t)^\top R u(t)) dt \quad (3.12)$$

where  $Q = Q^\top \geq 0$  is the state weighting matrix and  $R = R^\top > 0$  is the input weighting matrix. The cost function ensures a trade-off between the speed of convergence and the energy consumed by the control inputs.

To further enhance the controller's performance, an augmented state model can be introduced by incorporating an integral state,  $x_I(t)$ , defined as:

$$\dot{x}_I(t) = x_I(t) + e(t) \quad (3.13)$$

Hence, the new control target becomes  $x_I(t) \rightarrow 0$ , which implies that  $y(t) \rightarrow r(t)$ . The augmented state-space model is then given by:

$$\begin{bmatrix} \dot{x}(t) \\ \dot{x}_I(t) \end{bmatrix} = \begin{bmatrix} A & 0 \\ -C & 1 \end{bmatrix} \begin{bmatrix} x(t) \\ x_I(t) \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} r(t) + \begin{bmatrix} G & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} w(t) \\ 0 \end{bmatrix} \quad (3.14)$$

At this point, for simplicity, we will define as  $z(t)$  the following vector:

$$z(t) = [x(t) \quad x_I(t)]^\top$$

The quadratic cost function associated with this augmented model is:

$$J(u, z(0)) = \int_0^\infty (z(t)^\top Q_e z(t) + u(t)^\top R u(t)) dt \quad (3.15)$$

### 3.2. CONTROL IMPLEMENTATION

which can be expanded as:

$$J(u, z(0)) = \int_0^\infty (x_I(t)^\top Q_I x_I(t) + x(t)^\top Q_x x(t) + u(t)^\top R u(t)) dt \quad (3.16)$$

To find the optimal control law, we develop a linear state-feedback law  $u(t) = -K_e z(t)$ , where  $K_e$  is obtained by solving the Algebraic Riccati Equation (ARE) for the augmented system. The gain matrix  $K_e$  can be expressed as:

$$K_e = [K \quad K_I]$$

Here,  $K$  is the state-feedback gain and  $K_I$  is the integral gain. The matrices  $A_e$  and  $B_e$  denote the extended state-space representation that incorporates the integral state, as introduced in Equation 3.14, while  $Q_e$  is the corresponding extended weighting matrix.

Several numerical methods are available to solve the ARE, such as those based on the Schur decomposition or eigenvalue approaches [29]. In practice, software tools like *MATLAB* provide built-in functions to compute the optimal gain matrix efficiently.

#### 3.2.4 LQR WEIGHTS CHOICE

In an LQR controller, the selection of the  $Q$  and  $R$  matrices is essential for balancing system performance and control effort. The  $Q$  matrix determines the penalty assigned to deviations in each state variable, while the  $R$  matrix regulates the cost associated with the control input. Since the state vector  $x$  consists of both controllable and uncontrollable states, assigning higher weights in  $Q$  emphasizes minimizing deviations in the corresponding state variables.

As temperature regulation is the primary objective and directly controllable, its associated weight in  $Q$  should be relatively high to ensure that the controller prioritizes maintaining the desired setpoint. Other state variables, such as wall and roof temperatures, primarily represent internal system dynamics and therefore their weights should generally be lower. After conducting several simulations to fine-tune the performance, we decided to set  $Q_{11} = 10$ , corresponding to the room temperature, and  $Q_{ii} = 10^{-10}$  for  $i \in \{2, 3, 4\}$ , representing the other thermal states.

The weight  $R$ , associated with the control effort, is set to 1, as commonly done

in several studies and practical applications to balance performance and energy usage.

For a more detailed discussion on selecting these parameters, refer to [12].

### 3.3 THERMAL FEEDBACK CONTROL

In environments where multiple occupants share the same thermal space, setting a single temperature that satisfies everyone is inherently a non-cooperative problem. Each user has their own comfort preferences, which may conflict with others. Instead of relying solely on a centralized thermostat, this section introduces a new approach where users provide feedback through a structured interface. The system then optimizes the temperature based on aggregated inputs, ensuring fairness while promoting energy savings.

#### 3.3.1 HUMAN-IN-THE-LOOP CONCEPT

Conventional HVAC systems treat occupants as unpredictable disturbances. A more effective strategy, however, is to incorporate them into the control process through *Human-in-the-Loop* (HITL) control. This approach uses direct user feedback to create a more responsive and personalized thermal environment. Advances in information and communication technologies have made HITL systems increasingly practical. By integrating real-time occupant feedback, these systems continuously refine temperature regulation, moving beyond static set-points. This not only enhances comfort but also optimizes energy use. A major benefit is the creation of personalized comfort profiles. Historical feedback helps identify individual temperature preferences, enabling smarter future adjustments. Additionally, emerging methods like real-time surveys and physiological sensors are expanding the possibilities for user feedback, making HITL systems more adaptive and user-centric.

#### 3.3.2 A FIRST IMPLEMENTATION: BINARY FEEDBACK

In this new implementation, we suppose that each user  $i$  provides feedback on their thermal sensation via a simple control interface with three options: cold ( $\eta_i(t) = +1$ ), neutral ( $\eta_i(t) = 0$ ), and hot ( $\eta_i(t) = -1$ ). To quantify discomfort, we define the *signed discomfort function*  $\tilde{f}_i(T_r)$ , which maps room temperature

### 3.3. THERMAL FEEDBACK CONTROL

to a discomfort level within the range  $(-1, 1)$ , describing the users thermal perception. This function is continuous, strictly decreasing, and satisfies the boundary conditions:

$$\tilde{f}_i(-\infty) = 1, \quad \tilde{f}_i(+\infty) = -1$$

The ideal comfort temperature  $T_i^*$  is defined as the point where  $\tilde{f}_i(T_i^*) = 0$ , representing the users preferred thermal state.

In recent years, several discomfort functions have been developed, including the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD), which are widely used to assess thermal comfort. Additionally, other approaches, such as Gaussian Mixture Models based on experimental data [7], have also been implemented to better capture and predict thermal discomfort.

In this work, the discomfort function is modeled as:

$$\tilde{f}_i(T_r) = -\tanh\left(\frac{T_r - T_i^*}{\sigma_i}\right) \quad (3.17)$$

where  $\sigma_i$  represents the users sensitivity to temperature variations.

It is considered that an occupant perceives the indoor temperature as comfortable as long as their level of thermal discomfort remains below a personal threshold  $\epsilon_i$ .

When this threshold is exceeded, the occupant provides feedback, indicating whether they feel too warm or too cold, through the remote interface. Given that the discomfort function  $\tilde{f}_i$  is assumed to be invertible, we can therefore identify the negative and positive thermal comfort tolerance of each occupant as:

$$\Delta_i^- := T_i^* - \tilde{f}_i^{-1}(\epsilon_i), \quad \Delta_i^+ := \tilde{f}_i^{-1}(-\epsilon_i) - T_i^*$$

The users feedback signal can be finally expressed as:

$$\eta_i(T_r, \Delta_i^\pm) = \begin{cases} +1, & \text{if } T_r < T_i^* - \Delta_i^-, \\ 0, & \text{if } T_i^* - \Delta_i^- \leq T_r \leq T_i^* + \Delta_i^+, \\ -1, & \text{if } T_r > T_i^* + \Delta_i^+. \end{cases} \quad (3.18)$$

From this point onward, we assume that each individual's positive and negative discomfort tolerance are equal, i.e.,  $\Delta_i^- = \Delta_i^+ = \Delta_i$ .

We can now extend the concept to a group of  $N$  users. To quantify the total

discomfort across all users, we introduce the discomfort count, which sums the number of users in discomfort:

$$d(T_r, \{\Delta_i\}) = \sum_i^N |\eta_i(T_r, \Delta_i)|$$

Here, it is clear that  $0 \leq d(T_r, \{\Delta_i\}) \leq N$ .

To optimize the indoor temperature the objective is to minimize this discomfort count:

$$\Upsilon^* := \arg \min d(T_r, \{\Delta_i\})$$

However,  $d(T_r, \{\Delta_i\})$  may not be quasi-convex, meaning  $\Upsilon^*$  may not always lead to a compact temperature set. To address this, we define an aggregate discomfort function, which accounts for both individuals in positive and negative discomfort, as follows:

$$h(T_r, \{\Delta_i\}) = \sum_i^N \eta_i(T_r, \Delta_i) \quad (3.19)$$

This function measures the imbalance between cold and hot discomfort.

We can identify several key properties of this function:

- $h(-\infty, \{\Delta_i\}) = -N$
- $h(+\infty, \{\Delta_i\}) = +N$
- $h(T_r, \{\Delta_i\})$  is a monotonically decreasing function

The last property arises because  $h(T_r, \{\Delta_i\})$  is the sum of non-increasing functions.

Consequently, we know that there exists a value  $T_r$  such that  $h(T_r, \{\Delta_i\}) = 0$ , which indicates balanced discomfort levels and can be interpreted as fairness.

We then define the optimal temperature range  $\Upsilon$  as:

$$\Upsilon := [T_{\min}, T_{\max}] = \{T_r \mid h(T_r, \{\Delta_i\}) = 0\} \quad (3.20)$$

where  $T_{\min}$  and  $T_{\max}$  are the lower and upper bounds of this range.

After this brief overview, we can now define the control law. This control strategy incorporates user feedback directly into the temperature regulation process. The

### 3.3. THERMAL FEEDBACK CONTROL

resulting control input is expressed as:

$$u(t) = k \sum_{i=1}^N \eta_i(T_r(t), \Delta_i) \quad (3.21)$$

where  $k = C_r$  is the room thermal capacity.

#### 3.3.3 A REVISED IMPLEMENTATION: CONTINUOUS FEEDBACK

While predefined feedback values effectively balance  $h(T_r, \{\Delta_i\}) = 0$ , they may result in noticeable temperature fluctuations. To improve responsiveness and user comfort, we implemented a refined approach that allows users to provide continuous feedback within the interval  $[-1, 1]$ .

Each user can select any value in this range via a slider-based control interface, enabling more precise and intuitive expression of thermal (dis)comfort. A very simple interface representation is shown in Figure 3.3.

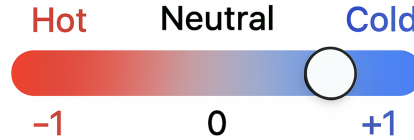


Figure 3.3: User Interface for Generating Feedback Signal

User sensitivity  $\sigma_i$  is fundamental, as larger values indicate gradual transitions, while smaller values reflect high sensitivity.

The feedback values are obtained directly by using the discomfort function introduced in Equation 3.17, which allows the definition of a new aggregate discomfort function as:

$$\ell(T_r, \{\sigma_i\}) = \sum_{i=1}^N \tilde{f}(T_r, \sigma_i) \quad (3.22)$$

The final control input is then given by:

$$u(t) = k \sum_{i=1}^N \tilde{f}(T_r(t), \sigma_i). \quad (3.23)$$

where  $k$  is still the room's thermal capacitance.

This continuous and user-adaptive approach establishes a new control law still grounded in individual comfort preferences.

### 3.3.4 CREATION OF SYNTHETIC COMFORT PROFILES

Thermal comfort is an inherently subjective experience, influenced by a variety of personal and environmental factors such as metabolic rate, clothing insulation, activity level, and individual psychological or cultural preferences. Accurately capturing this variability is essential for designing systems that can adapt to the needs of different occupants.

To support the development of individualized comfort profiles, we leverage two well-established datasets provided by ASHRAE. The first, RP884 (1998), comprises over 21,000 data points collected from 160 buildings worldwide, capturing both subjective thermal sensation votes and objective environmental conditions. The second dataset, known as the *ASHRAE Global Thermal Comfort Database II* (2018), significantly expands this resource with approximately 82,000 data points gathered from 52 field studies conducted across 28 countries. Together, these datasets offer comprehensive insights into the relationship between perceived comfort and measurable indoor environmental variables, such as air temperature, humidity, and air speed.

These empirical data form the foundation for our generation of synthetic user profiles, which aim to realistically reflect individual variability in thermal preferences. In our model, we consider a shared indoor environment occupied by four individuals, each with a distinct ideal temperature. Specifically, we define their preferred temperatures as  $T_i^* = [22, 23, 20, 21]^\circ\text{C}$ , where each occupant is also associated with a tolerance range for acceptable deviation, given by  $\Delta_i = [3, 2, 2, 3]^\circ\text{C}$ .

These values represent the range within which each person still perceives thermal comfort, and they serve as critical parameters for evaluating comfort levels and optimizing the control strategy within the shared space.

We can now visualize the *feedback functions*  $\eta_i(T_{\text{room}}, \Delta_i)$ , which capture each

### 3.3. THERMAL FEEDBACK CONTROL

user's response based on their perceived thermal comfort along with the corresponding *aggregate discomfort function*, denoted as  $h(T_r, \{\Delta_i\})$ , respectively in Figure 3.4 and Figure 3.5.

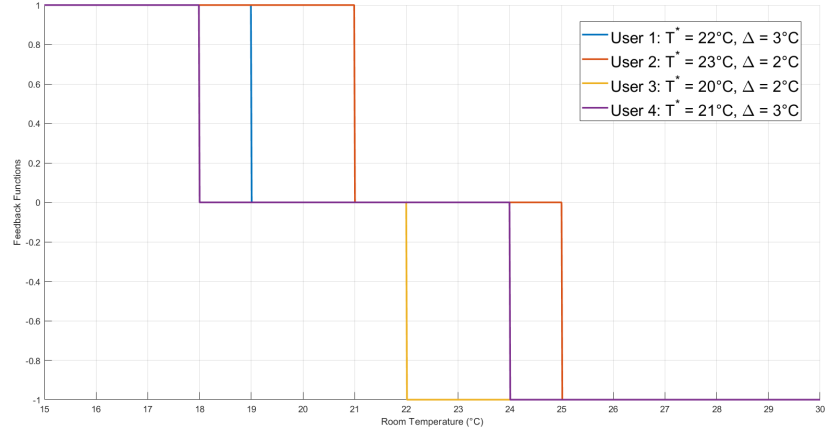


Figure 3.4: Binary Feedback Function for 4 Users

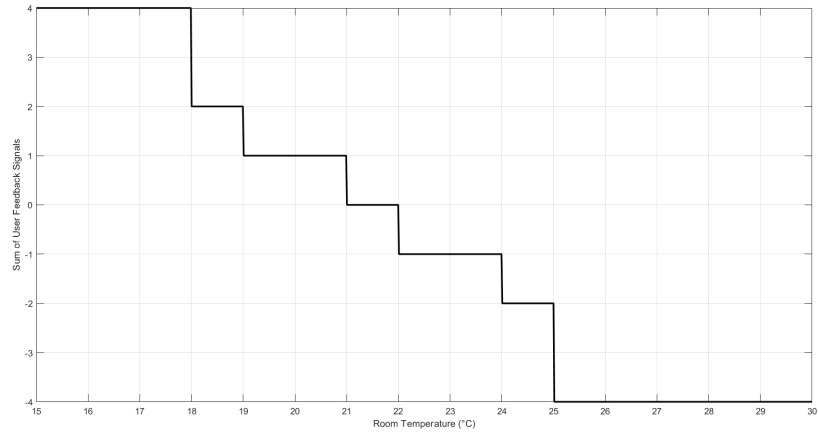


Figure 3.5: Aggregate Discomfort Function  $h(T_r, \{\Delta_i\})$

As shown in Figure 3.5, we can define the optimal temperature range  $\Upsilon := [21, 22]^\circ\text{C}$ , which corresponds to the set where the sum of the discomfort signals is equal to zero. Ideally, we would like our simulation to show that the temperature converges within this range. We can now display also the theoretical results for the new feedback signal introduced in Section 3.3.3. To evaluate temperature sensitivity, we assign the same thermal comfort tolerances as before, selecting  $\sigma_i = [3, 2, 2, 3]^\circ\text{C}$  for the four users. The ideal temperatures  $T_i^*$  remain

unchanged.

We can observe some key difference. First, the feedback functions are no longer modeled as discrete step functions but as continuous ones, as illustrated in Figure 3.6, which shows the comfort feedback curves for each user.

Additionally, in this framework, the optimal temperature range, previously denoted by  $\Upsilon$  and defined in Equation 3.20, has effectively collapsed into a single equilibrium temperature. This is visually represented in Figure 3.7, where the sum of the continuous feedback functions crosses zero.

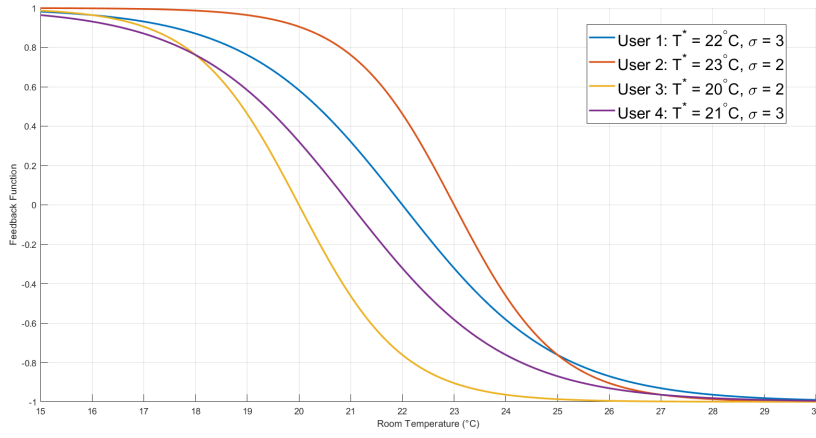


Figure 3.6: Continuous Feedback Function for 4 User

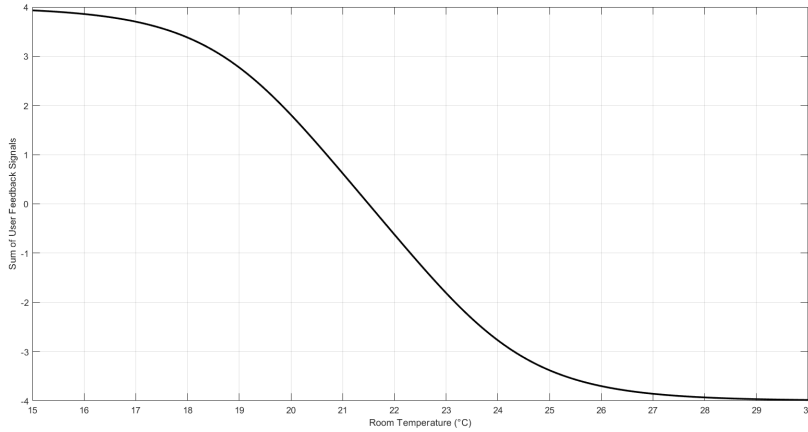


Figure 3.7: Aggregate Discomfort Function  $\ell(T_r, \{\sigma_i\})$

### 3.4 SIMULATION AND RESULTS

To evaluate and compare the performance of different controllers, we selected two key performance indicators: the tracking error and the total energy consumption. Both are *lower-is-better* metrics, meaning that effective controllers should aim to minimize them.

These indicators capture the core objectives of a control strategy, accuracy and efficiency, but must be interpreted together. Excelling in one while performing poorly in the other can signal an unbalanced or ineffective controller. For instance, keeping the system turned off would result in zero energy consumption, the theoretical optimum in terms of energy, but would fail entirely at maintaining thermal comfort, making it an impractical control strategy. Energy consumption is obtained by placing an integrator at the plant input within the simulation environment to measure the total energy delivered over time. To ensure a physically meaningful estimate, we consider the absolute value of the control input, accounting for both positive values (heating) and negative values (cooling). The tracking error is computed using a custom Root-Mean-Square Error (RMSE) formula. This dual analysis allows us to assess not only how well the system maintains the desired temperature but also how efficiently it does so in terms of energy usage.

Inspired by typical residential heating patterns, we test the controllers by having them track a reference temperature profile shaped as a square wave with a 24-hour period. In most households, it is common to differentiate between daytime and nighttime temperature settings, with lower temperatures during the night. In our scenario, the reference temperature is set to 23°C from 6:00 a.m. to 7:00 p.m., and reduced to 18°C for the remaining hours. The resulting reference profile is shown in Figure 3.8.

To better understand the trade-offs between tracking accuracy and energy consumption, we now present the simulation results. The following plots illustrate the temperature evolution over time, alongside the reference temperature for each controller. For every simulation, we set the initial room temperature to 15°C. While this is admittedly lower than typical indoor comfort levels, our goal in this first simulation is just to observe how the control system responds and adjusts the temperature over time, rather than to replicate realistic starting conditions.

The first controller implemented is the PID controller, and its results are shown

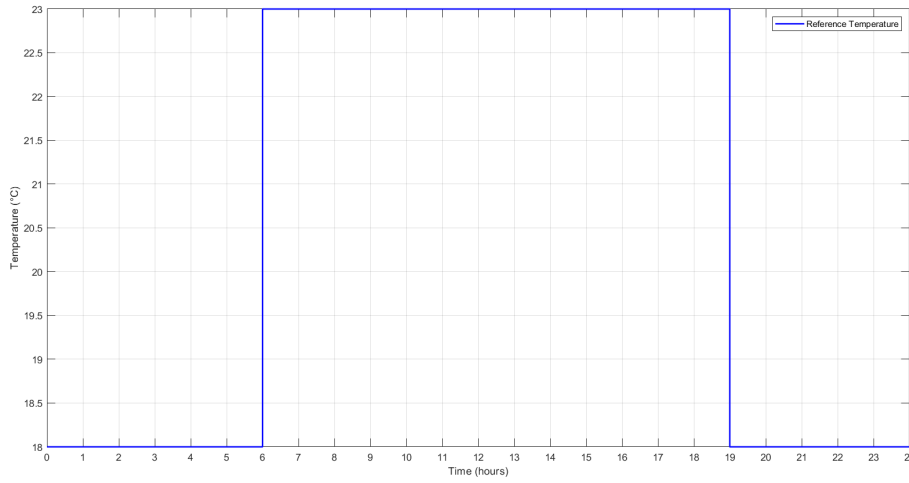


Figure 3.8: The reference signal used in tests.

in Figure 3.9.

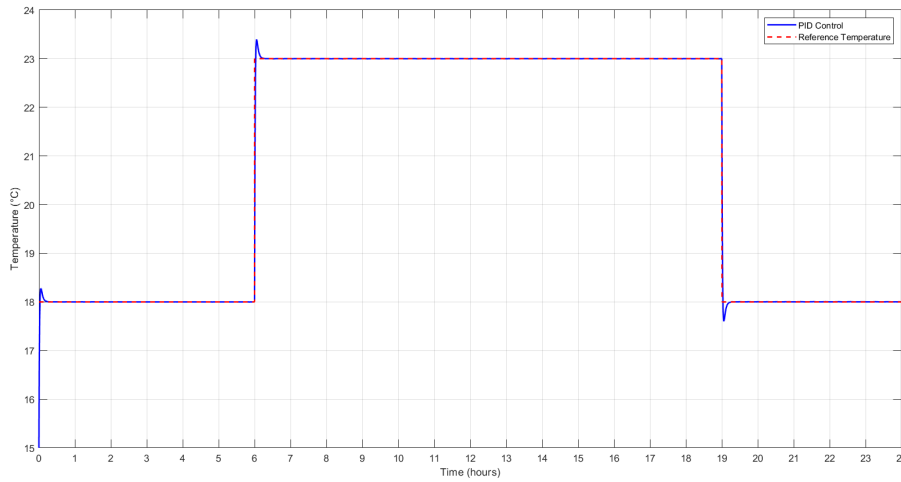


Figure 3.9: PID Temperature Control with Time-Varying Reference

Upon examining the plot, it is evident that the controller exhibits an initial overshoot of  $0.3^{\circ}\text{C}$  when first reaching the reference temperature set point at  $18^{\circ}\text{C}$ . For the next two reference changes, the first results in an overshoot of  $0.4^{\circ}\text{C}$ , while the second exhibits an undershoot of equal magnitude, as shown in Figure 3.12a. However, these values remain within an acceptable range and demonstrate the controller's ability to closely follow the setpoint with minimal deviation. The next controller we analyze is the BANG-BANG controller. Based on pre-

### 3.4. SIMULATION AND RESULTS

liminary simulations, we decided to set the maximum heating power to  $Q_{\max} = 2000 \text{ J/s}$  for the implemented setup. The deadband was set to  $\pm 1^\circ\text{C}$ . The corresponding simulation results are shown in Figure 3.10.

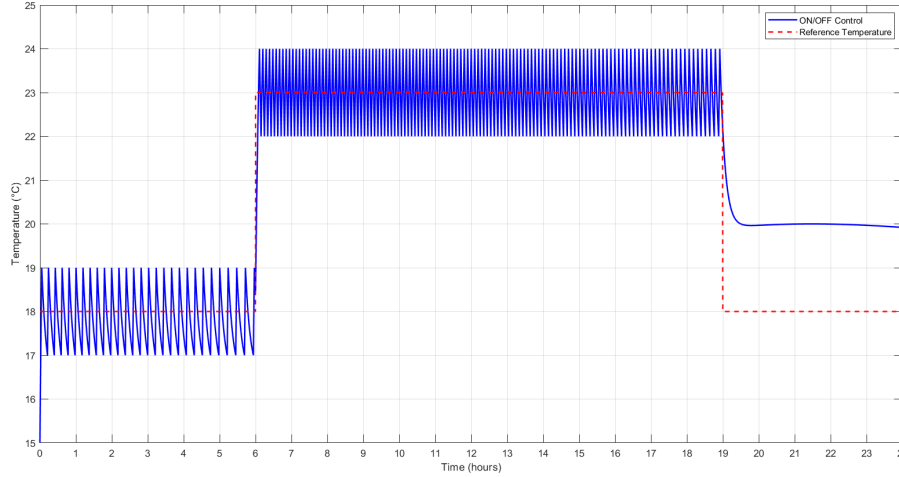


Figure 3.10: BANG-BANG Temperature Control with Time-Varying Reference

As anticipated, this controller demonstrates the poorest performance among the tested strategies. The temperature trajectory exhibits significant oscillations and lacks the precision necessary to reliably track the reference, underscoring the limitations of this simplistic control logic in our application. In particular, the system completely loses track of the reference when it switches to  $18^\circ\text{C}$ , as it is inherently unable to cool the environment by design.

The frequent switching between the 'ON' and 'OFF' states leads to rapid fluctuations in temperature, which are especially problematic in systems where maintaining stable conditions is fundamental. In addition, the controller's inability to adjust smoothly to gradual temperature changes results in inefficient energy usage, further limiting its suitability for precise thermal regulation.

The final controller implemented in this study is the LQR controller. The simulation results obtained with the LQR controller are shown in Figure 3.11.

Among all the tested controllers, the LQR demonstrates the best overall performance. At the beginning of the simulation, the controller exhibits a minimal overshoot of only  $0.1^\circ\text{C}$  when first reaching the reference temperature. For the subsequent two reference changes, the overshoot and the undershoot remains low, reaching a maximum of  $0.2^\circ\text{C}$ , as illustrated in Figure 3.12c. Another notable improvement is the settling time, which is significantly faster compared

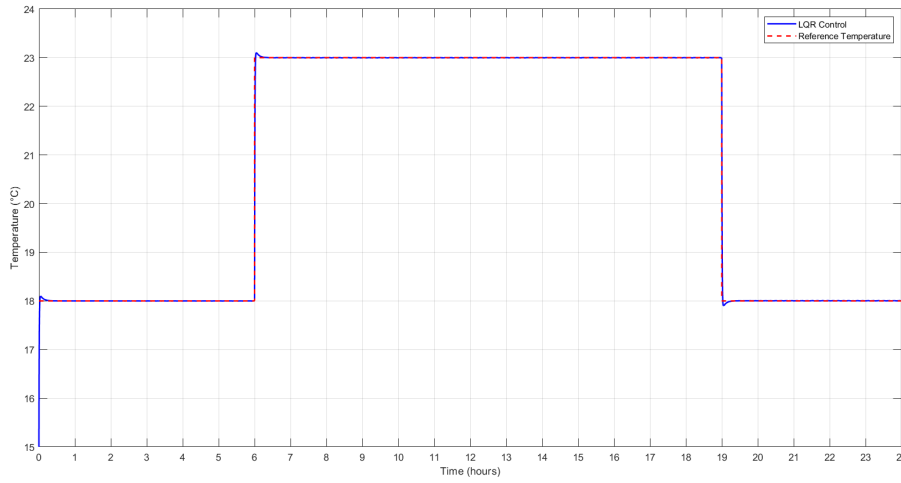


Figure 3.11: LQR Temperature Control with Time-Varying Reference

to the PID controller, allowing the system to reach and maintain the desired temperature more efficiently. As previously mentioned, to provide a comprehensive overview of the controllers performance, we report two key metrics: the Root Mean Square Error (RMSE) and the total energy consumption, measured in kWh. These results are illustrated in the following table:

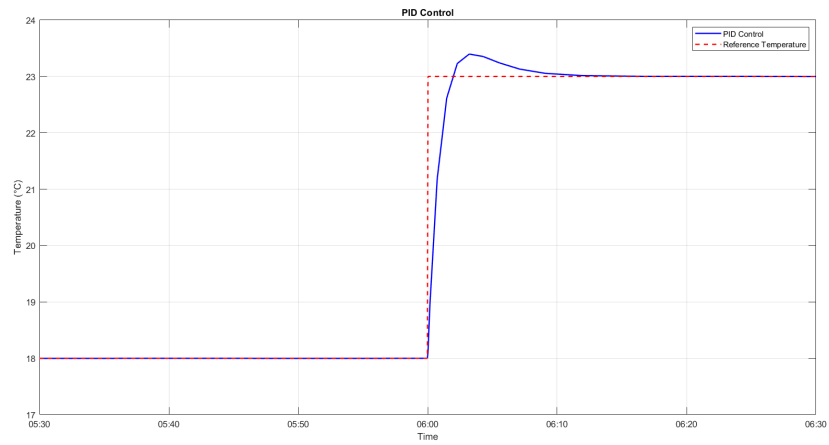
Table 3.1: Comparison of control strategies based on energy consumption and tracking performance

| Controller | Energy Use (kWh) | RMSE (°C) |
|------------|------------------|-----------|
| PID        | 18.11 (kWh)      | 0.256 °C  |
| ON/OFF     | 19.95 (kWh)      | 2.851 °C  |
| LQR        | 17.32 (kWh)      | 0.103 °C  |

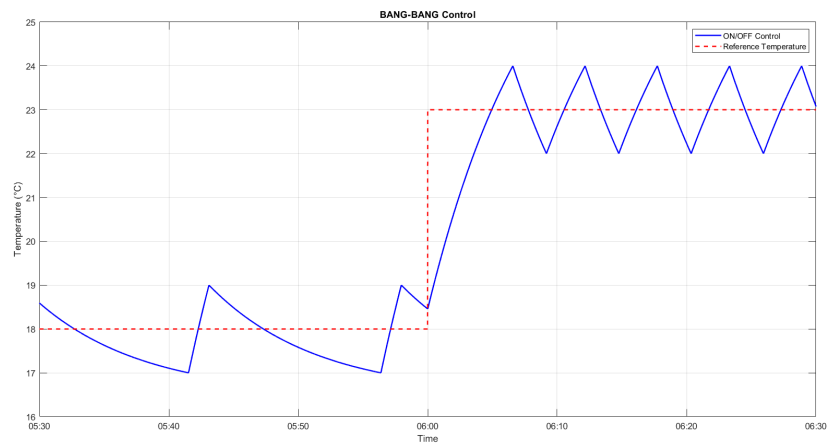
From the presented data, it is evident that the controllers implemented in this study exhibit distinct performance profiles. In terms of tracking error, the BANG-BANG controller performs the worst, as expected due to its on-off nature and lack of precision. On the other hand, the LQR controller achieves the lowest RMSE, confirming its superior ability to maintain temperatures close to the desired setpoints.

While the differences in energy consumption among the controllers are less pronounced, the LQR still demonstrates the best overall performance, managing to combine accuracy and energy efficiency more effectively than the others.

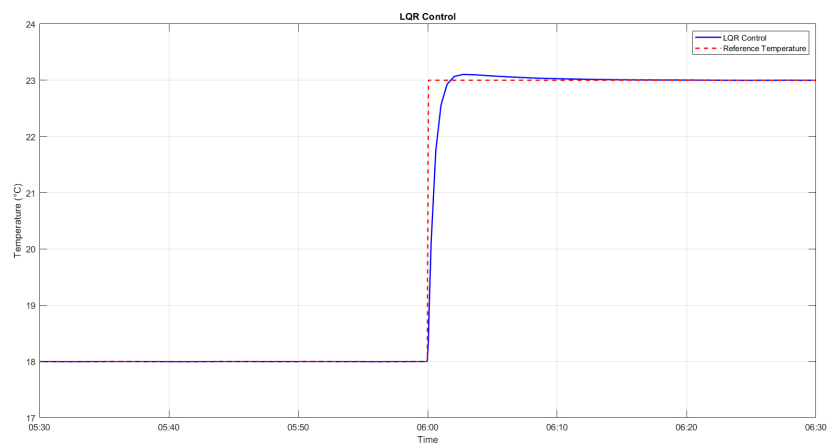
### 3.4. SIMULATION AND RESULTS



(a) Temperature Evolution via PID Control from 5:30 to 6:30



(b) Temperature Evolution via ON/OFF Control from 5:30 to 6:30



(c) Temperature Evolution via LQR Control from 5:30 to 6:30

Figure 3.12: Temperature Evolution via Different Controls

### 3.4.1 SENSATION CONTROL WITH FEEDBACK

To simulate a more realistic and heterogeneous working environment, we consider four users with different work schedules. This variation introduces diverse thermal comfort demands over time, allowing us to better evaluate the controller's adaptability. The assumed working hours for each user are defined in Table 3.2.

Table 3.2: User Schedules for the Room

| Room   | User   | Schedule              |
|--------|--------|-----------------------|
| Room 1 | User 1 | 8:00 a.m. – 1:00 p.m. |
|        | User 2 | 8:00 a.m. – 1:00 p.m. |
|        | User 3 | 8:00 a.m. – 7:00 p.m. |
|        | User 4 | 8:00 a.m. – 7:00 p.m. |

This configuration introduces both short-term and long-term occupancy patterns, allowing us to assess the system's response to time-varying thermal demands.

From this point forward, the initial room temperature will be set to 18°C. The resulting plots illustrate the evolution of the room temperature and the corresponding input control signals throughout the simulated workday respectively in Figure 3.13 and Figure 3.14.

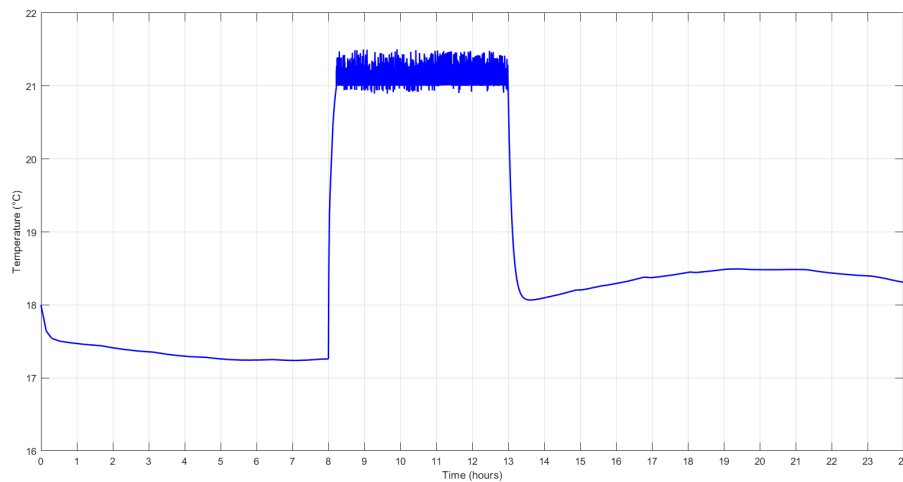


Figure 3.13: Temperature Evolution During a Workday

### 3.4. SIMULATION AND RESULTS

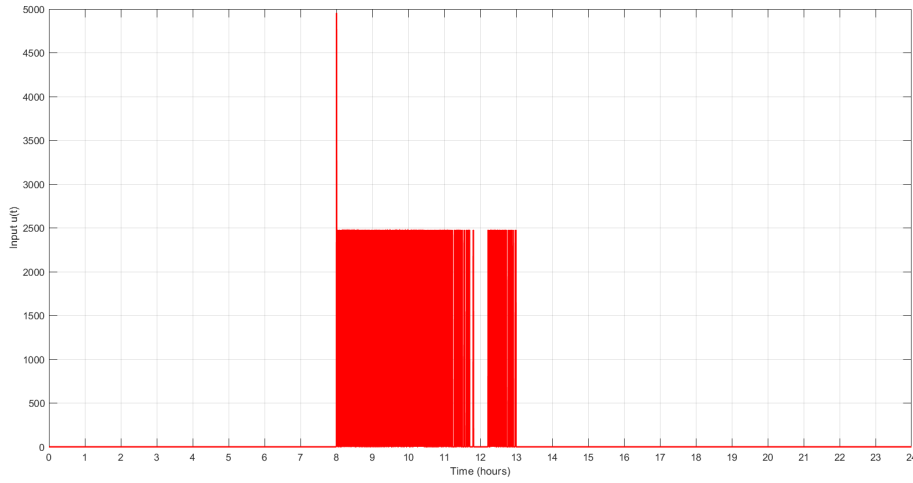


Figure 3.14: Input Control  $u(t)$  During a Workday.

At the beginning, before any users are present, the system evolves under free dynamics with no control input applied. The loss of nearly  $1^{\circ}\text{C}$  during the night is mainly due to the initial conditions assigned to the external walls and the roof, which were set to  $15^{\circ}\text{C}$  and to the external temperature.

Then, as expected, when all four users are present in the room, the temperature fluctuates within the tolerated range  $\Upsilon$ . Once the first two users leave, the input signal drops to zero, indicating that the remaining users are satisfied with the natural evolution of the room temperature and do not require further adjustments.

We conclude this section by analyzing the results obtained with the newly implemented feedback function. Specifically, we examine the evolution of the room temperature and the corresponding control input over the course of a typical working day. The results are presented in Figure 3.15 and Figure 3.16.

With this new implementation, we observe a significantly improved outcome: the room temperature no longer exhibits oscillatory behavior and instead converges smoothly to a stable value. This enhanced performance is a direct result of integrating user feedback through a continuous slider, rather than relying on predefined discrete values such as  $\{-1, 0, 1\}$ .

In this configuration, the feedback signals remain consistently close to zero, when the users are in the room, indicating that users are generally thermally satisfied. As expected, the system continues to apply non-zero heating or cooling inputs even when users are near their preferred temperatures. This continuous

adjustment smooths out the temperature trajectory, resulting in a more linear evolution over time and minimizing oscillations. These results confirm not only the effectiveness of the control strategy in maintaining thermal comfort, but also its responsiveness to individual user preferences.

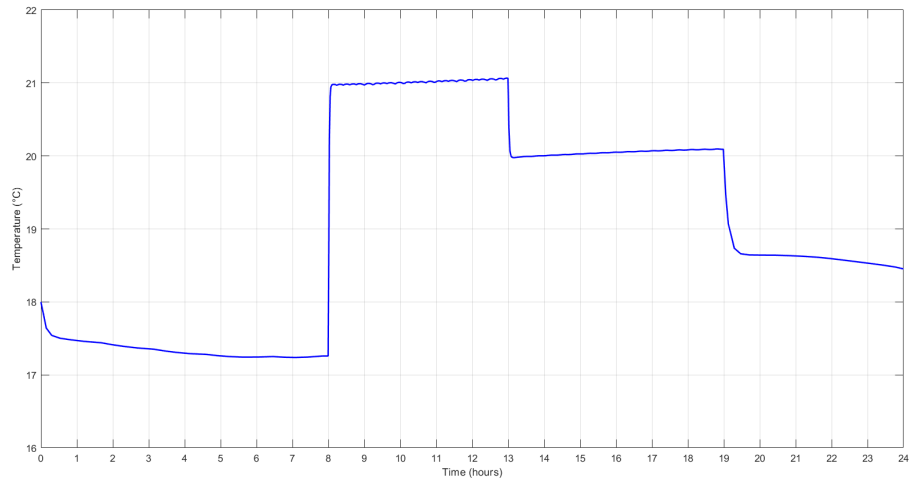


Figure 3.15: Temperature Evolution During a Workday.

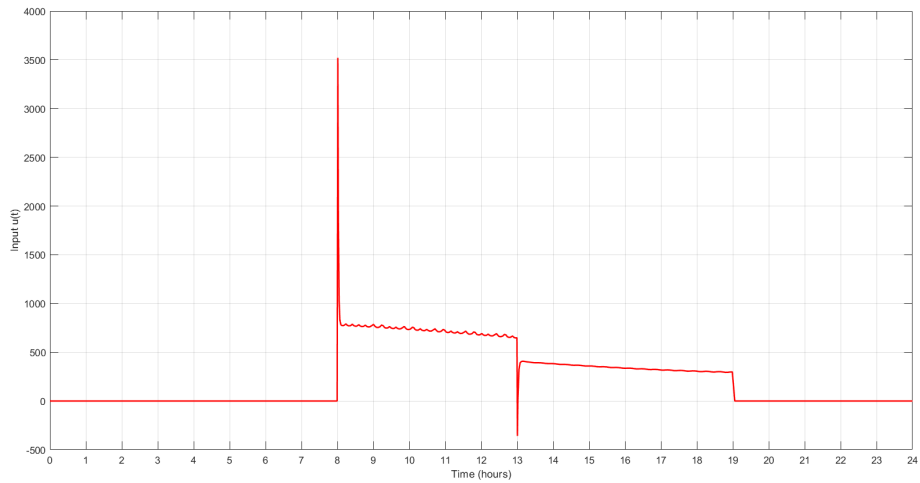


Figure 3.16: Input Control  $u(t)$  During a Workday.

### 3.4. SIMULATION AND RESULTS

| Parameter                   | Symbol                    | Value                                                                 |
|-----------------------------|---------------------------|-----------------------------------------------------------------------|
| Air density                 | $\rho_a$                  | 1.204 kg/m <sup>3</sup>                                               |
| Air specific heat           | $c_{pa}$                  | 1007 J/kg/K                                                           |
| Furniture contribution      | $c_f$                     | 30 kJ/K/m <sup>2</sup>                                                |
| Room length                 | $l_1, l_2$                | 5 m                                                                   |
| Room height                 | $h$                       | 2.7 m                                                                 |
| Room volume                 | $V_r$                     | $l_1 \times l_2 \times h = 67.5 \text{ m}^3$                          |
| Room surface                | $S_r$                     | $l_1 \times l_2 = 25 \text{ m}^2$                                     |
| <b>Wall Parameters</b>      |                           |                                                                       |
| Thickness                   | $s_{\text{wall}}$         | 0.3 m                                                                 |
| Density                     | $\rho_{\text{wall}}$      | 1150 kg/m <sup>3</sup>                                                |
| Heat capacity               | $c_{\text{wall}}$         | 840 J/kg/K                                                            |
| Thermal conductivity        | $\lambda_{\text{wall}}$   | 0.6 W/mK                                                              |
| Area                        | $A_{\text{wall}}$         | $2.7 \times l_1 = 13.5 \text{ m}^2$                                   |
| Volume                      | $V_{\text{wall}}$         | $s_{\text{wall}} \times A_{\text{wall}} = 4.05 \text{ m}^3$           |
| <b>Roof Parameters</b>      |                           |                                                                       |
| Thickness                   | $s_{\text{roof}}$         | 0.3 m                                                                 |
| Density                     | $\rho_{\text{roof}}$      | 1150 kg/m <sup>3</sup>                                                |
| Heat capacity               | $c_{\text{roof}}$         | 840 J/kg/K                                                            |
| Thermal conductivity        | $\lambda_{\text{roof}}$   | 0.6 W/mK                                                              |
| Area                        | $A_{\text{roof}}$         | $l_1 \times l_2 = 25 \text{ m}^2$                                     |
| Volume                      | $V_{\text{roof}}$         | $s_{\text{roof}} \times A_{\text{roof}} = 7.5 \text{ m}^3$            |
| <b>Ground Parameters</b>    |                           |                                                                       |
| Thickness                   | $s_{\text{ground}}$       | 2 m                                                                   |
| Thermal conductivity        | $\lambda_{\text{ground}}$ | 0.6 W/mK                                                              |
| Area                        | $A_{\text{ground}}$       | $l_1 \times l_2 = 25 \text{ m}^2$                                     |
| <b>Thermal Capacitances</b> |                           |                                                                       |
| Room capacitance            | $C_r$                     | $\rho_a c_{pa} V_r + c_f S_r$                                         |
| Wall capacitance            | $C_{w1}, C_{w2}$          | $c_{\text{wall}} \times \rho_{\text{wall}} \times V_{\text{wall}}$    |
| Roof capacitance            | $C_t$                     | $c_{\text{roof}} \times \rho_{\text{roof}} \times V_{\text{roof}}$    |
| <b>Thermal Resistances</b>  |                           |                                                                       |
| Wall resistance             | $R_{w1}, R_{w2}$          | $\frac{s_{\text{wall}}}{\lambda_{\text{wall}} A_{\text{wall}}}$       |
| Roof resistance             | $R_t$                     | $\frac{s_{\text{roof}}}{\lambda_{\text{roof}} A_{\text{roof}}}$       |
| Ground resistance           | $R_g$                     | $\frac{s_{\text{ground}}}{\lambda_{\text{ground}} A_{\text{ground}}}$ |
| <b>External Conditions</b>  |                           |                                                                       |
| Outside temperature         | $T_{\text{ext}}$          | Figure 3.2                                                            |
| Ground temperature          | $T_g$                     | 12°C                                                                  |
| Internal heat gain          | $q_{\text{int}}$          | 200 W                                                                 |

Table 3.3: Table of model parameters for one room

# 4

## Second Case Study: Multi-Room Implementation

This section focuses on the multi-room environment, which extends the analysis to a more complex and interconnected setting. Here, the goal is to assess the systems performance across multiple zones without reapplying the full set of control methods previously tested in the single-room setup. The study highlights how the implemented control laws adapt to interactions between spaces, offering insights into scalability and the robustness of the control strategies in achieving consistent thermal comfort throughout the building.

### **4.1** MULTI-ROOM IMPLEMENTATION

In real-world office environments, multiple rooms often share structural elements such as walls, floors, or ceilings, which leads to significant thermal interactions between adjacent spaces. Moreover, shared zones like open-plan workspaces or meeting rooms add complexity due to variable occupancy and mixed thermal loads. The number of occupants in each room can also vary throughout the day, influencing internal heat gains and the rooms thermal behavior.

To better capture these dynamics, we developed a multi-room thermal model where each room is influenced not only by its own heater and occupancy, but also by neighboring rooms through shared walls. The control strategy is implemented on a simplified office layout, as shown in Figure 4.1, where each room is assumed to host a maximum of four workers.

#### 4.1. MULTI-ROOM IMPLEMENTATION

The thermal and structural parameters associated with each room are summarized in Table 4.4.

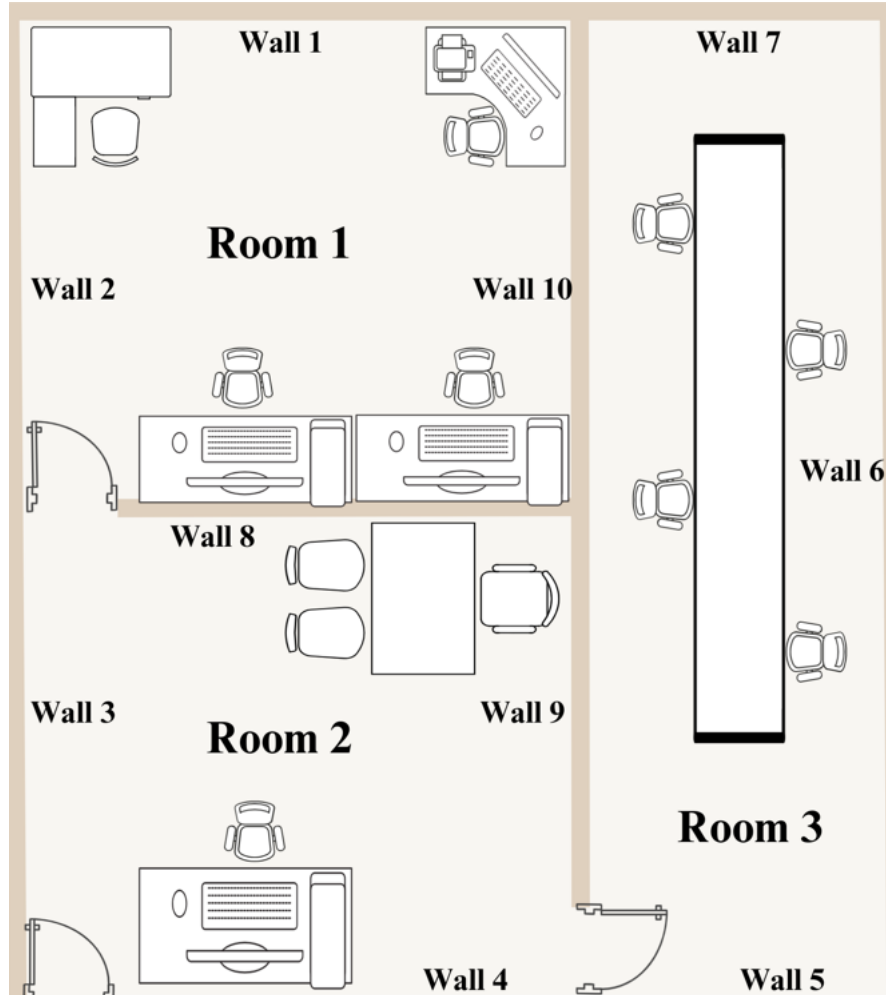


Figure 4.1: Simplified office layout used for the multi-room thermal control simulation.

As done for the single-room case, we can begin by implementing the differential equations for the three-room setup.

For the external walls, we derive specific equations for each room. Room 1 has two external walls, each exchanging heat with both the internal environment and the outside. Similarly, Room 2 has two external walls with the same heat exchange behavior.

Room 3, instead, is characterized by three external walls, each transferring heat between the room and the exterior.

For the walls of Room 1 we obtain the following equations:

$$C_{w,i} \frac{dT_{w,i}}{dt} = \frac{T_{r,1} - T_{w,i}}{R_{w,i}} + \frac{T_{\text{ext}} - T_{w,i}}{R_{w,i}} \quad \text{for } i \in \{1, 2\} \quad (4.1)$$

For the walls of Room 2:

$$C_{w,i} \frac{dT_{w,i}}{dt} = \frac{T_{r,2} - T_{w,i}}{R_{w,i}} + \frac{T_{\text{ext}} - T_{w,i}}{R_{w,i}} \quad \text{for } i \in \{3, 4\} \quad (4.2)$$

For the walls of Room 3:

$$C_{w,i} \frac{dT_{w,i}}{dt} = \frac{T_{r,3} - T_{w,i}}{R_{w,i}} + \frac{T_{\text{ext}} - T_{w,i}}{R_{w,i}} \quad \text{for } i \in \{5, 6, 7\} \quad (4.3)$$

Regarding the internal walls, we obtain three differential equations, each describing the thermal interaction between adjacent rooms. One internal wall connects Room 1 and Room 2, another connects Room 2 and Room 3, and the third wall connects Room 3 and Room 1. In each case, the wall exchanges heat with both rooms it separates. The corresponding equations are:

$$\begin{cases} C_{w,8} \frac{dT_{w,8}}{dt} = \frac{T_{r,1} - T_{w,8}}{R_{w,8}} + \frac{T_{r,2} - T_{w,8}}{R_{w,8}} \\ C_{w,9} \frac{dT_{w,9}}{dt} = \frac{T_{r,2} - T_{w,9}}{R_{w,9}} + \frac{T_{r,3} - T_{w,9}}{R_{w,9}} \\ C_{w,10} \frac{dT_{w,10}}{dt} = \frac{T_{r,3} - T_{w,10}}{R_{w,10}} + \frac{T_{r,1} - T_{w,10}}{R_{w,10}} \end{cases} \quad (4.4)$$

In the single-room model, the roof was represented by a single differential equation. However, for a multi-room setup, a more suitable approach might be to divide the roof into  $n$  zones, one for each room, and define a corresponding dynamic equation for each zone.

We obtain the following 3 differential equations:

$$\begin{cases} C_{t,1} \frac{dT_{t,1}}{dt} = \frac{T_{r,1} - T_{t,1}}{R_{t,1}} + \frac{T_{\text{ext}} - T_{t,1}}{R_{t,1}} \\ C_{t,2} \frac{dT_{t,2}}{dt} = \frac{T_{r,2} - T_{t,2}}{R_{t,2}} + \frac{T_{\text{ext}} - T_{t,2}}{R_{t,2}} \\ C_{t,3} \frac{dT_{t,3}}{dt} = \frac{T_{r,3} - T_{t,3}}{R_{t,3}} + \frac{T_{\text{ext}} - T_{t,3}}{R_{t,3}} \end{cases} \quad (4.5)$$

#### 4.1. MULTI-ROOM IMPLEMENTATION

At this stage, we can formulate the differential equations for the air temperature in each room. These equations account for thermal exchanges with all connected walls, the respective roof zones, the ground, and any internal heat gains. The resulting system describes the complete dynamic behavior of the thermal environment across the three interconnected rooms.

The corresponding equations are presented below:

$$\begin{cases} C_{r,1} \frac{dT_{r,1}}{dt} = \frac{T_{w,1}-T_{r,1}}{R_{w,1}} + \frac{T_{w,2}-T_{r,1}}{R_{w,2}} + \frac{T_{w,8}-T_{r,1}}{R_{w,8}} + \frac{T_{w,10}-T_{r,1}}{R_{w,10}} + \frac{T_{t,1}-T_{r,1}}{R_{t,1}} + \frac{T_g-T_{r,1}}{R_{g,1}} + q_{\text{int},1} + \dot{Q}_{r,1} \\ C_{r,2} \frac{dT_{r,2}}{dt} = \frac{T_{w,3}-T_{r,2}}{R_{w,3}} + \frac{T_{w,4}-T_{r,2}}{R_{w,4}} + \frac{T_{w,8}-T_{r,2}}{R_{w,8}} + \frac{T_{w,9}-T_{r,2}}{R_{w,9}} + \frac{T_{t,2}-T_{room,2}}{R_{t,2}} + \frac{T_g-T_{r,2}}{R_{g,2}} + q_{\text{int},2} + \dot{Q}_{r,2} \\ C_{r,3} \frac{dT_{r,3}}{dt} = \frac{T_{w,5}-T_{r,3}}{R_{w,5}} + \frac{T_{w,6}-T_{r,3}}{R_{w,6}} + \frac{T_{w,7}-T_{r,3}}{R_{w,7}} + \frac{T_{w,9}-T_{r,3}}{R_{w,9}} + \frac{T_{w,10}-T_{r,3}}{R_{w,10}} + \frac{T_{t,3}-T_{r,3}}{R_{t,3}} + \frac{T_g-T_{r,3}}{R_{g,3}} + q_{\text{int},3} + \dot{Q}_{r,3} \end{cases}$$

In this implementation, we define three separate heat flow inputs, one for each room. The rationale behind this choice will be discussed in Section 4.1.1.

Following the approach used for the single-room model, we can now derive the corresponding state-space representation.

The resulting system has the following dimensions:  $A \in \mathbb{R}^{16 \times 16}$ ,  $B \in \mathbb{R}^{16 \times 3}$ ,  $G \in \mathbb{R}^{16 \times 5}$ , and  $C \in \mathbb{R}^{3 \times 16}$ .

The dynamic behavior of the system can be described using the following state-space representation:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + Gw(t) \\ y(t) = Cx(t) \end{cases} \quad (4.6)$$

The state vector  $x(t) \in \mathbb{R}^{16 \times 1}$  contains all the relevant temperatures of the system:

$$x(t) = \begin{bmatrix} T_{r,1}(t) & T_{r,2}(t) & T_{r,3}(t) & T_{w,1}(t) & T_{w,2}(t) & \cdots & T_{w,10}(t) & T_{t,1}(t) & T_{t,2}(t) & T_{t,3}(t) \end{bmatrix}^T$$

The disturbance vector  $w(t) \in \mathbb{R}^{5 \times 1}$  includes external temperature, ground temperature and internal heat gains:

$$w(t) = \begin{bmatrix} T_{\text{ext}}(t) & T_g & q_{\text{int},1} & q_{\text{int},2} & q_{\text{int},3} \end{bmatrix}^T$$

Finally, the control input vector  $u(t) \in \mathbb{R}^{3 \times 1}$  represents the heating power sup-

plied to each room:

$$u(t) = \begin{bmatrix} \dot{Q}_{r,1}(t) & \dot{Q}_{r,2}(t) & \dot{Q}_{r,3}(t) \end{bmatrix}^T$$

#### 4.1.1 RGA IMPLEMENTATION

The system under study has three control inputs and a corresponding output vector  $y(t) \in \mathbb{R}^{3 \times 1}$ , representing the temperatures of the three separate rooms. To determine whether a decentralized control approach is appropriate, the Relative Gain Array (RGA) was computed at steady state. The RGA matrix can be computed using the following formula:

$$\Lambda = G(0) \circ (G(0)^{-1})^T$$

where  $G(0)$  is the steady-state gain matrix and  $\circ$  denotes the element wise Hadamard product.

To compute the steady-state gain matrix  $G(s)$ , we use the following relationship:

$$G(s) = -C (sI - A)^{-1} B$$

For the current system, the computed RGA matrix is:

$$\text{RGA} = \begin{bmatrix} 1.0401 & -0.0201 & -0.0200 \\ -0.0201 & 1.0401 & -0.0200 \\ -0.0200 & -0.0200 & 1.0400 \end{bmatrix} \quad (4.7)$$

The matrix exhibits strong diagonal dominance, with values close to 1 along the diagonal and small off-diagonal elements. This indicates that each output is primarily influenced by a single corresponding input, with minimal interaction between different input-output pairs.

Therefore, it is justified to design and implement three independent control strategies, one for each room. This decentralized approach simplifies both controller design and implementation, while still ensuring effective temperature regulation in each space.

### 4.2 CONTROL IMPLEMENTATION AND RESULTS

Given the poor performance and challenges encountered with the BANG-BANG controller and the user feedback controller based on predefined values in the initial single-room setup, we have decided not to pursue their computation in this more complex multi-room scenario.

Although we have seen that the LQR is the best-performing controller implemented so far, we will not explore LQR control for this case, as it does not reflect real-world practices. In commercial HVAC systems, LQR is rarely used due to its reliance on accurate linear models, complex tuning, and limited integration with existing control platforms.

Instead, we will implement three independent PID controllers, each dedicated to controlling the temperature of one room. The final part of this section will focus on the implementation of the user feedback control strategy based on a slider interface.

In this phase, we will simulate a complete working day and assess the system's performance under real-world conditions, considering various practical scenarios and user interactions.

#### 4.2.1 REFERENCE PROFILE

Rather than relying on a simple step reference and a basic setup, we now address a more realistic and complex scenario. Based on a brief investigation, we assume that the minimum allowable temperature during night hours in office workspaces is  $18^{\circ}\text{C}$ . Therefore, we set this value as the initial room temperature and as the baseline reference during unoccupied periods.

In addition, we revise the daytime reference temperature to  $21^{\circ}\text{C}$ , instead of the  $23^{\circ}\text{C}$  used in the previous simulation, as  $21^{\circ}\text{C}$  is generally considered a more realistic and energy-efficient indoor temperature for office environments.

During the day, we also account for intermittent room occupancy: whenever a room is unoccupied, the reference temperature is reset to  $18^{\circ}\text{C}$ .

The temperature reference profiles for each room are shown in the following Figure 4.2 .

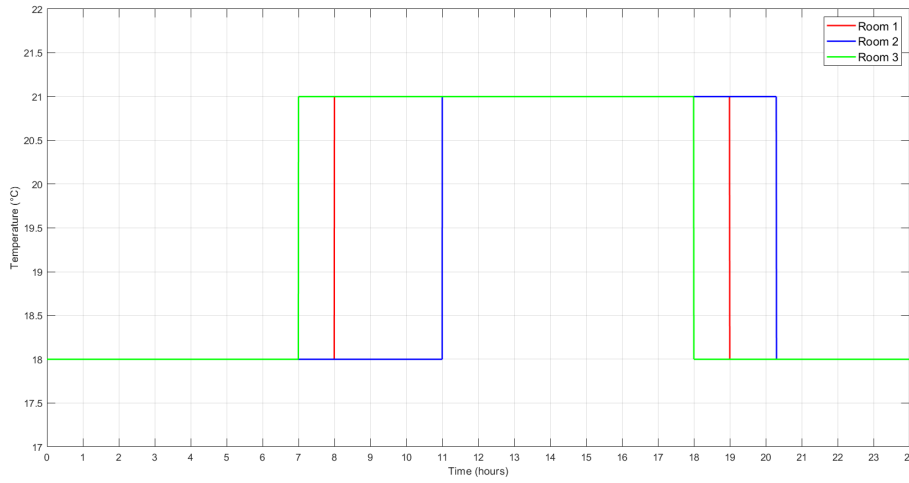


Figure 4.2: Reference Temperature Profiles for Each Room

#### 4.2.2 PID CONTROL WITH ANTI-WINDUP AND OUTPUT LIMITS

For the PID parameters we used the same as for the single room, represented in Equation 3.9, since after running some simulations, they are still quite good in terms of overshoot and settling time.

To regulate the temperature in a more energy-efficient and physically realistic manner, we implemented a continuous PID controller with output saturation and an anti-windup strategy.

The output of the controller was constrained between  $-3500$  W and  $3500$  W during the day, reflecting the physical capabilities of a standard HVAC system in both heating and cooling modes. However, during nighttime hours, when rapid cooling is not necessary, the lower bound was raised to  $0$  W.

This effectively disables active cooling at night, allowing only heating or passive temperature stabilization, in line with energy-saving policies and the absence of immediate comfort requirements. This also ensures that when the reference temperature drops during the night period, the system responds gradually, allowing a smoother and more realistic transition driven by the natural thermal dynamics of the room.

To address the integrator windup issue, especially when the controller output saturates, we employed the clamping anti-windup method. This technique limits the integrator's operation when the controller output reaches its saturation bounds, effectively clamping the integrator to prevent further accumulation.

## 4.2. CONTROL IMPLEMENTATION AND RESULTS

This ensures that the integral term does not continue growing when it would lead to an output that exceeds the actuator limits.

This configuration allowed the system to respond smoothly to changes in the reference temperature, avoiding large overshoots or undershoots, while also ensuring that the controller behaved properly even under actuator constraints.

It is worth noting that, in the single room implementation, no saturation limits were applied to the control input. There, the goal was primarily to track the reference temperature as closely as possible, without considering the physical bounds of the system.

Figure 4.3 illustrates the temperature response in the three rooms.

The results obtained from the plots highlight the effectiveness of the new PID configuration. The temperature response in all rooms exhibits minimal overshoot, with a maximum deviation of just  $0.2^{\circ}\text{C}$  observed in all rooms. As expected, when the reference temperature is lowered to  $18^{\circ}\text{C}$  during the night period, the system does not enforce active control, allowing the room temperatures to evolve freely. This results in a smooth and gradual drift toward the new reference, driven primarily by the system's inherent thermal dynamics.

### 4.2.3 SENSATION CONTROL WITH FEEDBACK

As already mentioned in the previous section, user comfort parameters, such as the ideal temperature and thermal comfort tolerance, play a key role in this implementation. We assume that each room can accommodate a maximum of four people, resulting in a total of 12 working users across the offices. Before presenting the results, it is important to consider a realistic challenge. With the proposed control law, heating input is applied whenever at least one worker is present in a room. However, during nighttime, the offices are empty, and no control action is taken. This can cause a significant drop in indoor temperature, potentially falling below the lower comfort threshold, which we consider to be  $18^{\circ}\text{C}$ . To address this issue, we implemented a simple smooth on-off controller that activates heating when the rooms are unoccupied and deactivates it otherwise. With this addition, the overall system performance improves, as shown in the following results. To maintain a more consistent and paradigmatic simulation approach, the occupancy schedule is defined to reflect the reference profiles previously used in the PID control setup and illustrated in Figure 4.2.

In particular, we ensure that at least one worker is present in each room when-

ever the reference temperature is set to the daytime value of 21°C.

We start by defining the users' working schedules. Rooms 1 and 3 follow typical office hours, while Room 2, functioning as a shared conference room, is reserved for two meetings between from 11:00 a.m. to 3:00 p.m. and from 3:00 p.m. to 8:15 p.m. The schedule is summarized in Table 4.1.

Table 4.1: User Schedules for Each Room

| Room   | User    | Schedule               |
|--------|---------|------------------------|
| Room 1 | User 1  | 8:00 a.m. – 5:00 p.m.  |
|        | User 2  | 8:00 a.m. – 5:00 p.m.  |
|        | User 3  | 9:00 a.m. – 7:00 p.m.  |
|        | User 4  | 9:00 a.m. – 7:00 p.m.  |
| Room 2 | User 5  | 11:00 a.m. – 3:00 p.m. |
|        | User 6  | 11:00 a.m. – 3:00 p.m. |
|        | User 7  | 3:00 p.m. – 8:15 p.m.  |
|        | User 8  | 3:00 p.m. – 8:15 p.m.  |
| Room 3 | User 9  | 7:00 a.m. – 4:00 p.m.  |
|        | User 10 | 7:00 a.m. – 4:00 p.m.  |
|        | User 11 | 9:00 a.m. – 6:00 p.m.  |
|        | User 12 | 9:00 a.m. – 6:00 p.m.  |

To proceed with our simulation, we must define the thermal comfort parameters for each individual. One possible set of values is reported in Table 4.2.

Table 4.2: User Preferences and Sensitivities

| Room   | User    | $T^*$ [°C] | $\sigma$ [°C] |
|--------|---------|------------|---------------|
| Room 1 | User 1  | 21         | 2.8           |
|        | User 2  | 20.5       | 2.2           |
|        | User 3  | 22         | 2.1           |
|        | User 4  | 21.5       | 2             |
| Room 2 | User 5  | 21         | 2             |
|        | User 6  | 22         | 1.5           |
|        | User 7  | 20.5       | 1.8           |
|        | User 8  | 21         | 2.2           |
| Room 3 | User 9  | 21.5       | 2             |
|        | User 10 | 21         | 1.8           |
|        | User 11 | 20.5       | 1             |
|        | User 12 | 20         | 2             |

## 4.2. CONTROL IMPLEMENTATION AND RESULTS

Before presenting the temperature evolution for each room under feedback control, it is important to mention that to prevent unrealistic heat flow input values in an HVAC system, we introduce a simple saturation block. The saturation limits are set to match the values used in the PID control for simplicity.

Now, we can proceed to show the temperature evolution for each room under the new feedback control setup, illustrated in Figure 4.4 .

We can first observe that when a user enters or leaves a room, the temperature dynamics respond immediately, exhibiting a distinct *step up* or *step down* depending on the thermal preference of the individual.

This behavior highlights the real-time adaptability of the feedback control system to occupancy changes and user-specific comfort needs.

We now turn to the corresponding heating/cooling power  $\dot{Q}$ , comparing the two control strategies. The results are shown in Figure 4.5 and Figure 4.6.

The plots of the heating/cooling power  $\dot{Q}$  for both the PID and the user feedback control strategies reveal significant differences in their behavior. In the PID-controlled scenario, we observe that in some cases, the heat flow exhibits a strong oscillatory pattern. In contrast, the user feedback-based strategy results in a much smoother and more linear input, which is consistent with the system's continuous adjustment to occupant feedback signals.

Furthermore, during unoccupied periods, the feedback control strategies effectively stabilize the room temperatures around a baseline of 18°C. This is accomplished with a minimal and continuous heat flow input, typically ranging between  $\dot{Q} = [400, 700]$  J/s across all three rooms, showcasing the efficiency of the smooth on/off control mechanism. Finally, at night, the PID controller also performs reliably, maintaining a low heating output in response to the reduced thermal demand.

## CHAPTER 4. SECOND CASE STUDY: MULTI-ROOM IMPLEMENTATION

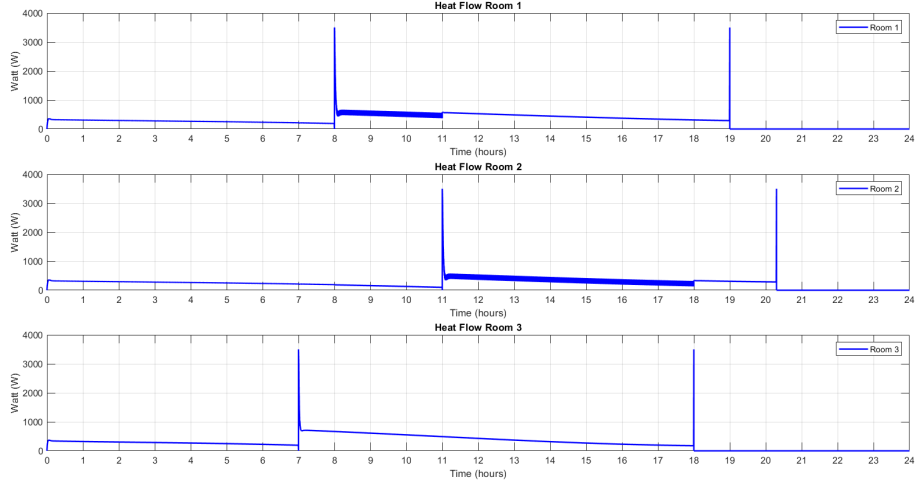


Figure 4.5: Heat Flow with PID Control

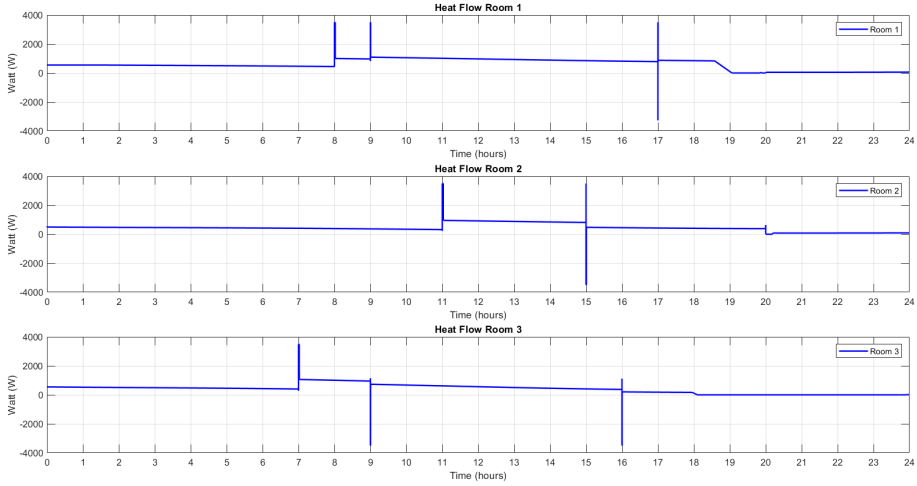


Figure 4.6: Heat Flow with User's Feedback Control

To conclude the comparison between the two control methods, we evaluate the total energy consumption required to heat the three rooms, as previously done for the single-room case. However, in this scenario, a direct RMSE comparison is not applicable, since the user feedback strategy does not rely on a predefined reference temperature. Instead, we introduce a discomfort-based metric, as described in Section 4.3, which considers each occupant's individual temperature preference and presence schedule. This approach allows for a more meaningful comparison between the traditional PID controller and the

### 4.3. USER DISCOMFORT METRIC

user-driven feedback controller, especially in terms of user satisfaction.

For the PID controller, the energy consumption values are as follows: Room 1 requires 13.77 kWh, Room 2 consumes 11.22 kWh, and Room 3 uses 12.35 kWh, resulting in a total energy consumption of 37.34 kWh. For the feedback-based approach, the energy usage is 14.55 kWh for Room 1, 8.69 kWh for Room 2, and 10.91 kWh for Room 3, leading to a total energy consumption of 34.15kWh.

These results are consistent with expectations: Room 1 and Room 3 are the most frequently occupied during the working day. In the feedback-controlled case, Room 1 also consumes more energy than Room 3, as it is used by individuals with higher ideal temperatures, keeping the room temperature above 21°C for most of the time. In contrast, Room 2 consistently shows the lowest energy usage under both control strategies, as its HVAC system is active for fewer hours compared to the other rooms.

An important observation is that the feedback-based control strategy overall results in lower energy consumption compared to the PID approach. This difference stems from the way users interact with the system: in the feedback case, occupants actively influence temperature dynamics based on their comfort, whereas the PID controller rigidly tracks a fixed reference temperature.

## 4.3 USER DISCOMFORT METRIC

To evaluate the thermal comfort experienced by occupants across the three rooms, we introduce a quantitative metric of discomfort. While various approaches exist to quantify user discomfort, in this section we propose a new and more refined method for computing overall discomfort, improving upon the simpler approach presented in Chapter 3.

As previously discussed, each occupant is characterized by three key parameters:

- A preferred temperature  $T_i^*$  [°C];
- A temperature sensitivity  $\sigma_i$  [°C];
- A schedule specifying the time intervals during which the user is present in the room.

This formulation allows discomfort to be personalized and weighted more realistically: higher sensitivity results in a larger penalty for the same deviation. For each user, discomfort is accumulated over time only when they are present in the room. To evaluate user discomfort over time, we consider the following integral for each user  $i$ :

$$D_i = \int_0^T \chi_i(t) \cdot \left( \frac{|T_r(t) - T_i^*|}{\sigma_i} \right)^2 dt$$

where  $\chi_i(t)$  is an indicator function equal to 1 when user  $i$  is present, and 0 otherwise.

In practice, this integral is approximated numerically using the simulation data as:

$$D_i \approx \sum_{k=1}^N \chi_i(t_k) \cdot \left( \frac{|T_r(t_k) - T_i^*|}{\sigma_i} \right)^2 \cdot \Delta t$$

where  $\Delta t$  is the sampling time step, and the sum is carried out over all time steps  $t_k$  during the simulation.

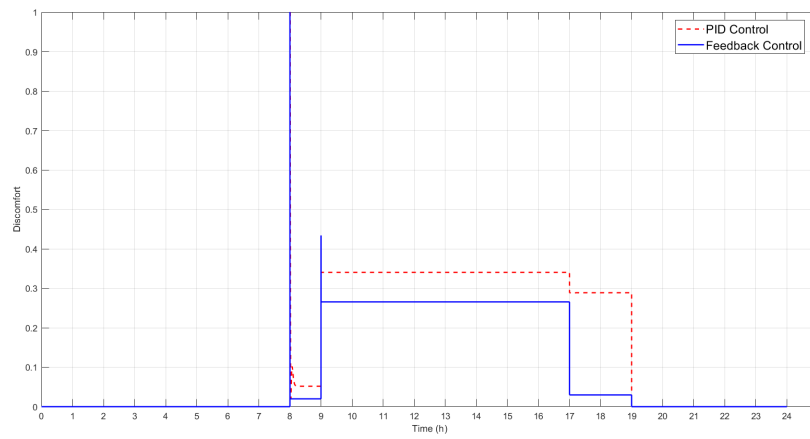
The total discomfort for each room is obtained by summing the discomfort of all users assigned to that room. This method enables a more accurate and fair evaluation of thermal comfort, especially in shared environments where user needs may differ significantly.

A summary of total discomfort values for all rooms and control strategies is shown in Table 4.3, while the evolution of discomfort over time for each room is illustrated in Figures 4.7.

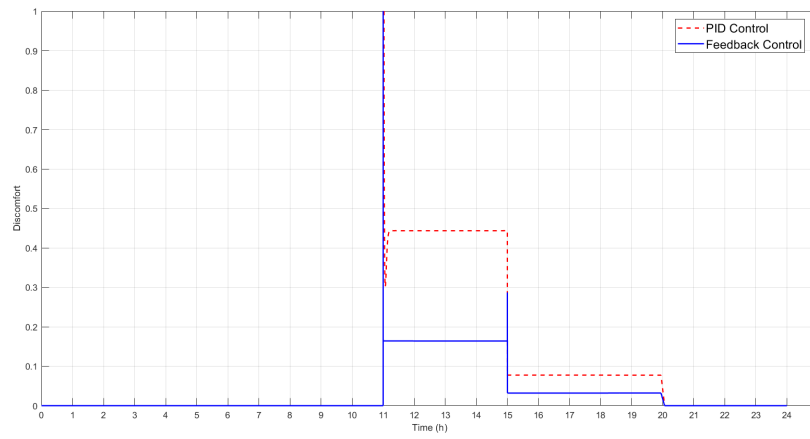
Table 4.3: Total Discomfort for Each Control Strategy Across Rooms

| Control Strategy      | Room 1      | Room 2      | Room 3      |
|-----------------------|-------------|-------------|-------------|
| PID Control           | 0.3324 °C·s | 0.4673 °C·s | 0.4919 °C·s |
| User Feedback Control | 0.0986 °C·s | 0.1743 °C·s | 0.2701 °C·s |

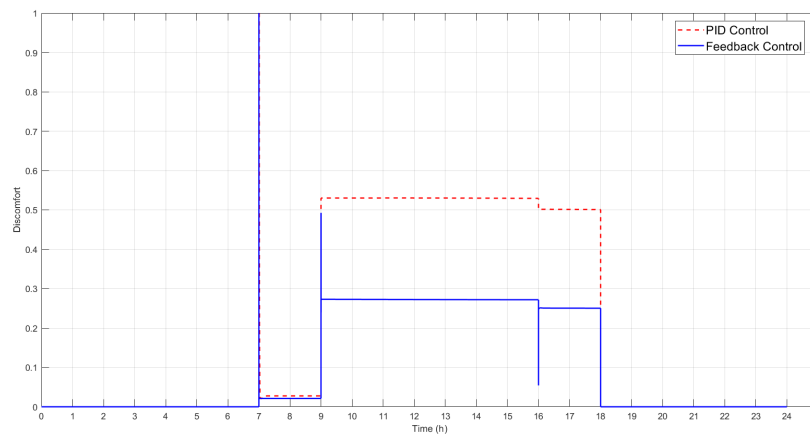
### 4.3. USER DISCOMFORT METRIC



(a) Discomfort Evolution Over Time in Room 1



(b) Discomfort Evolution Over Time in Room 2



(c) Discomfort Evolution Over Time in Room 3

Figure 4.7: Discomfort Evolution Over Time via Different Controls

### 4.3.1 INTERPRETATION

The proposed metric enables a fair comparison between different control strategies, PID control and user feedback control, by capturing the frequency and magnitude of thermal discomfort experienced by occupants.

As expected, the feedback control approach results in a lower total discomfort across all three rooms when compared to PID control. Notably, Room 3 exhibits relatively high discomfort in both scenarios, which can be attributed to the narrower comfort thresholds of its occupants compared to those in the other rooms. This highlights how user-specific parameters, such as tight tolerance bands, can significantly affect the overall room discomfort even under optimal control. It also suggests that room-specific strategies or differentiated weighting of user comfort might be necessary in shared spaces with heterogeneous preferences.

## 4.4 A FINAL COMMENT

Following the presentation of this initial implementation, a few closing remarks can be made. The first observation concerns the *step up* and *step down* temperature adjustments that characterize the feedback-based approach. While such abrupt changes are not fully realistic in a practical setting, they offer valuable insight into the potential responsiveness and adaptability of the proposed control law.

A second important consideration lies in the differing roles of users across the last two control strategies implemented. In the PID-controlled system, occupants play a passive role, as temperature adjustments occur without accounting for their real-time feedback. Conversely, the feedback-based strategy positions users as active participants whose comfort signals directly influence the system's behavior. This perspective introduces a compelling interpretation of the system as a dynamic interaction among agents as each user acts as a player who influences the temperature evolution. From this viewpoint, the control problem can be framed as a trade-off, or even a non-cooperative game, between thermal comfort and energy consumption. Reaching equilibrium in this setting is inherently challenging, as it requires balancing competing objectives. On one hand, maximizing comfort may increase energy usage; on the other, limiting consumption could compromise user satisfaction. Further exploration of this interaction may offer valuable insights for the development of more intelligent

#### 4.4. A FINAL COMMENT

and adaptive climate control strategies.

Lastly, in order to analyze the trade-off between thermal comfort and energy consumption for different control strategies, we plotted the results in a two-dimensional space. On the x-axis, we represent the comfort level of each room, while on the y-axis, we display the corresponding energy consumption. Since the raw comfort data was provided in terms of normalized discomfort (values ranging between 0 and 1), we computed the comfort as the complement of discomfort. The comfort percentage was then calculated as:

$$\text{Comfort [\%]} = (1 - \text{Discomfort}) \times 100 \quad (4.8)$$

Similarly, the energy consumption values were normalized with respect to the maximum observed energy consumption to express them as percentages:

$$\text{Energy Consumption [\%]} = \frac{\text{Energy Consumption (kWh)}}{\max(\text{Energy Consumption})} \times 100 \quad (4.9)$$

Each room and control strategy combination (PID control and feedback-based control) is represented as a distinct point on the graph, using different markers and colors to facilitate comparison.

This visualization allows us to easily compare the effectiveness of the control strategies in achieving a desirable balance between comfort and energy consumption.

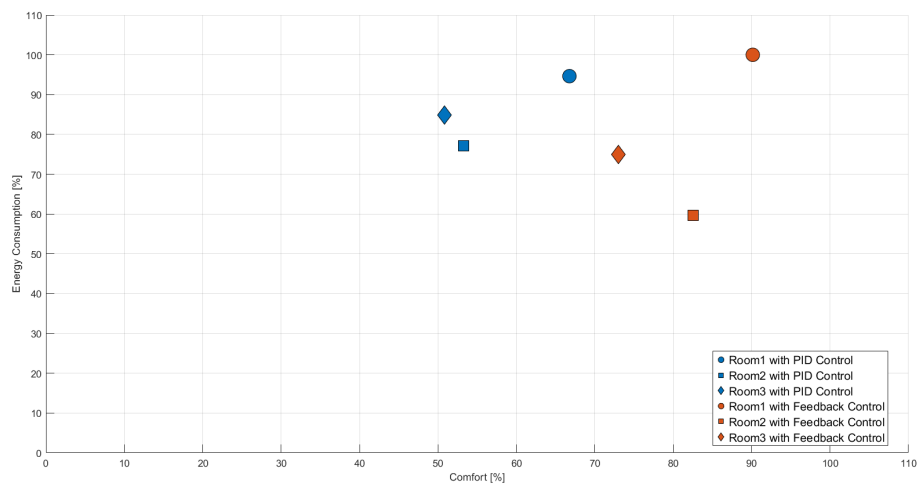
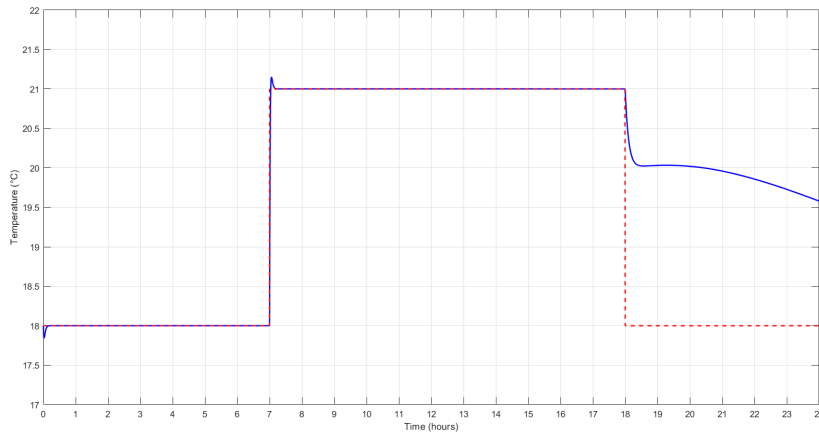
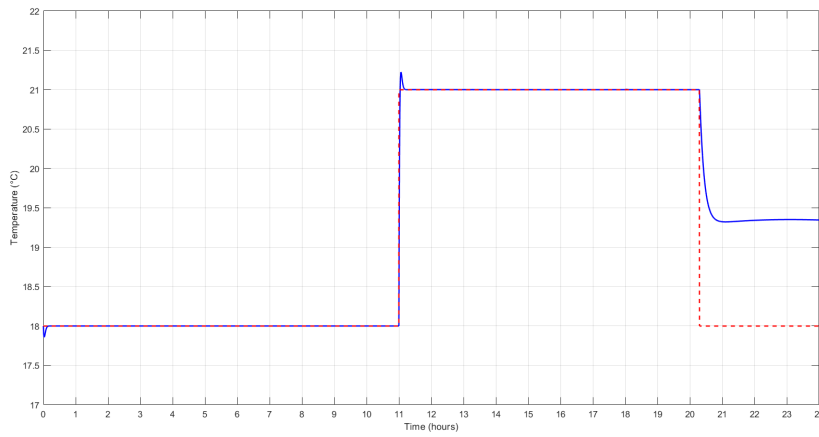


Figure 4.8: Results in percentages of comfort and energy consumption

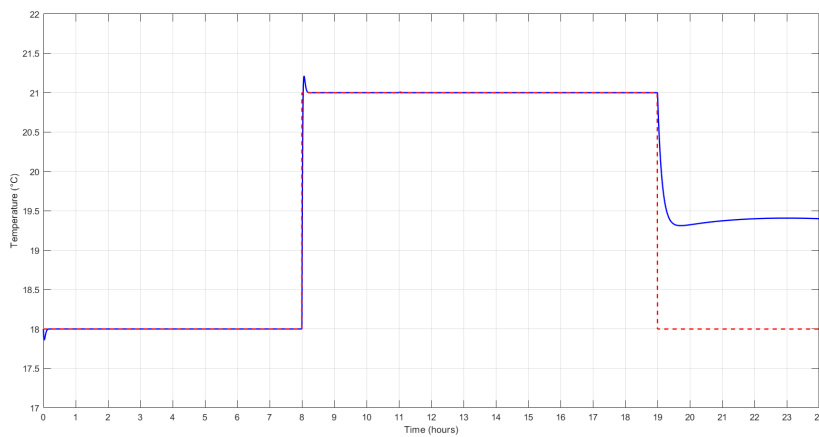
## CHAPTER 4. SECOND CASE STUDY: MULTI-ROOM IMPLEMENTATION



(a) Reference vs Actual Temperature under PID Control in Room 1



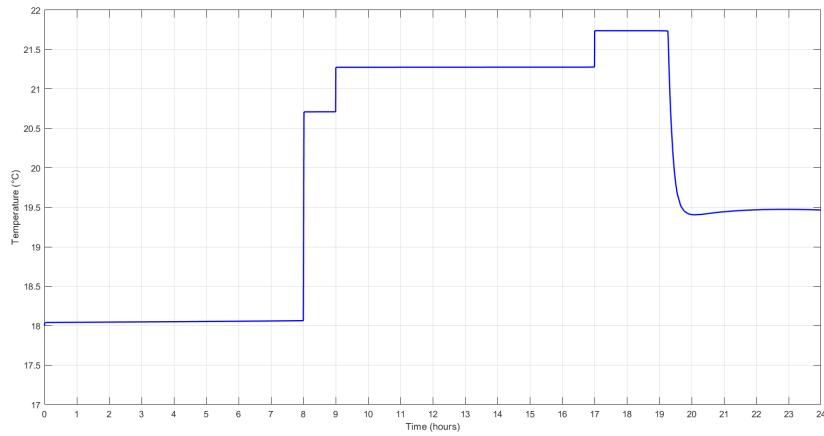
(b) Reference vs Actual Temperature under PID Control in Room 2



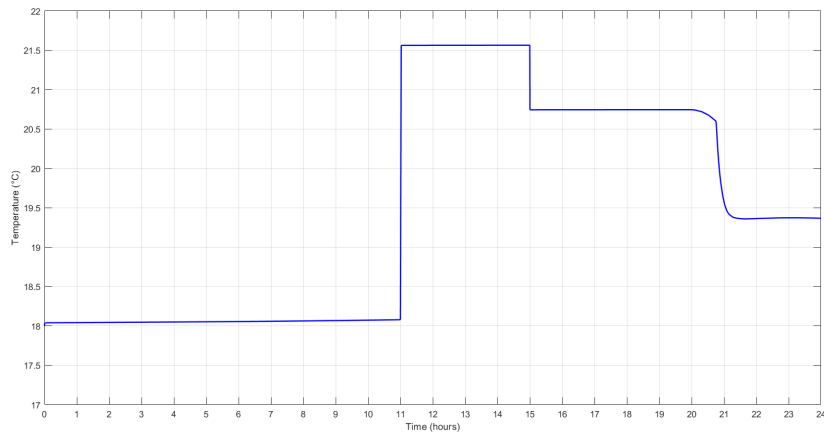
(c) Reference vs Actual Temperature under PID Control in Room 3

Figure 4.3: Reference vs Actual Temperature under PID Control

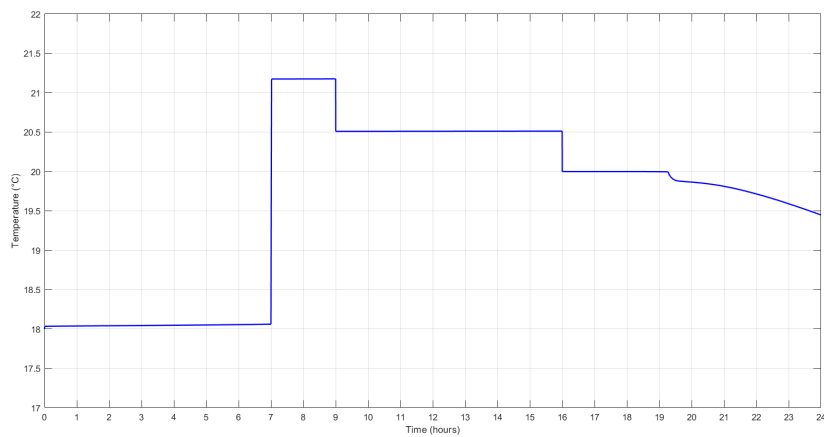
#### 4.4. A FINAL COMMENT



(a) Temperature Evolution via Feedback Control in Room 1



(b) Temperature Evolution via Feedback Control in Room 2



(c) Temperature Evolution via Feedback Control in Room 3

Figure 4.4: Temperature Evolution via Feedback Control

| Parameter                   | Symbol                    | Value                                                                   |
|-----------------------------|---------------------------|-------------------------------------------------------------------------|
| Air density                 | $\rho_a$                  | 1.204 kg/m <sup>3</sup>                                                 |
| Air specific heat           | $c_{pa}$                  | 1007 J/kg/K                                                             |
| Furniture contribution      | $c_f$                     | 30 kJ/K/m <sup>2</sup>                                                  |
| Room height                 | $h$                       | 2.7 m                                                                   |
| <b>Wall Parameters</b>      |                           |                                                                         |
| Thickness                   | $s_{\text{wall}}$         | 0.3 m                                                                   |
| Density                     | $\rho_{\text{wall}}$      | 1150 kg/m <sup>3</sup>                                                  |
| Heat capacity               | $c_{\text{wall}}$         | 840 J/kg/K                                                              |
| Thermal conductivity        | $\lambda_{\text{wall}}$   | 0.6 W/mK                                                                |
| <b>Roof Parameters</b>      |                           |                                                                         |
| Thickness                   | $s_{\text{roof}}$         | 0.3 m                                                                   |
| Density                     | $\rho_{\text{roof}}$      | 1150 kg/m <sup>3</sup>                                                  |
| Heat capacity               | $c_{\text{roof}}$         | 840 J/kg/K                                                              |
| Thermal conductivity        | $\lambda_{\text{roof}}$   | 0.6 W/mK                                                                |
| <b>Ground Parameters</b>    |                           |                                                                         |
| Thickness                   | $s_{\text{ground}}$       | 2m                                                                      |
| Thermal conductivity        | $\lambda_{\text{ground}}$ | 0.6 W/mK                                                                |
| <b>Room 1 and 2</b>         |                           |                                                                         |
| Room length                 | $l_1, l_2$                | 5 m                                                                     |
| Room volume                 | $V_{r,i}$                 | $l_1 \times l_2 \times h = 67.5 \text{ m}^3$                            |
| Room surface                | $S_{r,i}$                 | $l_1 \times l_2 = 25 \text{ m}^2$                                       |
| <b>Room 3</b>               |                           |                                                                         |
| Room length                 | $l_3, l_4$                | $l_3 = 10\text{m}, l_4 = 2\text{m}$                                     |
| Room volume                 | $V_{r,i}$                 | $l_3 \times l_4 \times h = 54 \text{ m}^3$                              |
| Room surface                | $S_{r,i}$                 | $l_3 \times l_4 = 20 \text{ m}^2$                                       |
| <b>Thermal Capacitances</b> |                           |                                                                         |
| Room capacitance            | $C_{r,i}$                 | $\rho_a c_{pa} V_{r,i} + c_f S_{r,i}$                                   |
| Wall capacitance            | $C_{w,i}$                 | $c_{\text{wall}} \times \rho_{\text{wall}} \times V_{\text{wall},i}$    |
| Roof capacitance            | $C_{t,i}$                 | $c_{\text{roof}} \times \rho_{\text{roof}} \times V_{\text{roof},i}$    |
| <b>Thermal Resistances</b>  |                           |                                                                         |
| Wall resistance             | $R_{w,i}$                 | $\frac{s_{\text{wall}}}{\lambda_{\text{wall}} A_{\text{wall},i}}$       |
| Roof resistance             | $R_{t,i}$                 | $\frac{s_{\text{roof}}}{\lambda_{\text{roof}} A_{\text{roof},i}}$       |
| Ground resistance           | $R_{g,i}$                 | $\frac{s_{\text{ground}}}{\lambda_{\text{ground}} A_{\text{ground},i}}$ |
| <b>External Conditions</b>  |                           |                                                                         |
| Outside temperature         | $T_{\text{ext}}$          | Figure 3.2                                                              |
| Ground temperature          | $T_g$                     | 12°C                                                                    |
| Internal heat gain room 1   | $q_{\text{int-1}}$        | 200 W                                                                   |
| Internal heat gain room 2   | $q_{\text{int-2}}$        | 200 W                                                                   |
| Internal heat gain room 3   | $q_{\text{int-3}}$        | 200 W                                                                   |

Table 4.4: Table of model parameters for multi-room room



# 5

## IDA-ICE Study Case

The aim of this chapter is to present and analyze the results obtained using the IDA-ICE software. The simulations were carried out to evaluate the thermal behavior of the building under different control strategies and occupancy scenarios. Key metrics such as indoor temperature evolution, user thermal comfort, and energy input are discussed. The outcomes offer insights into the effectiveness of the implemented strategies and support the assessment of user satisfaction and system performance.

### 5.1 A CO-SIMULATION BETWEEN MATLAB AND IDA-ICE

To perform building simulations using IDA ICE, we implemented a co-simulation environment that connects MATLAB R2015b and IDA ICE. In contrast to the continuous-time simulation described in Chapter 3, this configuration operates in discrete time, with data exchanged between the two platforms at fixed intervals. This approach enables the control algorithm to respond dynamically to the evolving thermal conditions of the simulated environment.

A central component of this setup is the establishment of bidirectional communication channels between MATLAB and IDA ICE, allowing real-time interaction between the controller and the building model:

- **IDA ICE to MATLAB:** Room temperature values are sent to MATLAB at each simulation step.
- **MATLAB to IDA ICE:** Heating/Cooling control signals are computed and transmitted back to influence the room's thermal state in the following step.

## 5.2. A COMPARISON BETWEEN SIMULINK AND IDA-ICE

MATLAB is used to model synthetic user profiles, each characterized by specific temperature preferences, occupancy schedules, and sensitivity to thermal discomfort. Based on the temperature values received from IDA ICE, MATLAB calculates the appropriate heating signal and transmits it back, thus closing the control loop.

The communication between the two environments is implemented using the *CreateStorage* and *OpenStorage* functions from the *IdalibN* library. Each communication channel is uniquely identified and configured to manage a defined number of variables. For each variable, the settings specify whether values are held constant or linearly interpolated between time steps, and whether the simulation should wait for new data or extrapolate from previous values. The IDA ICE model itself is launched and managed directly from MATLAB scripts, ensuring synchronized execution and data exchange.

This architecture supports scalability to multiple rooms by replicating the channel setup, making it suitable for more complex building models with multiple thermal zones.

### **5.2** A COMPARISON BETWEEN SIMULINK AND IDA-ICE

The first results obtained with IDA-ICE concern the implementation of the three-room model introduced in Chapter 3. For this initial setup, we aimed to match the parameters as closely as possible to those used in the Simulink model. In particular, the geometrical properties of the building structure were kept identical. A schematic of the floor layout for the three room model is presented in Figure 5.1. The user occupancy schedule was applied consistently, as detailed in Table 4.1. Furthermore, user preferences and sensitivity parameters remained the same as in the previous simulations, with corresponding values reported in Table 4.2. The reference temperatures used in this implementation are the same as those shown in Figure 4.2.

Instead of using a PID controller as in the Simulink implementation, we opted for a PI controller directly available within IDA-ICE. This choice simplified the simulation process while still allowing effective temperature regulation.

Subsequently, we implemented the feedback-based control strategy using the co-simulation setup with MATLAB, as described in Section 5.1.

As for the heating and cooling sources, IDA-ICE provides several room unit options. In this implementation, we selected an ideal heater unit to supply ther-

mal energy to the rooms. As in the previous case, a maximum power limit was imposed, which for this simulation was set to 2000 W.

Finally, the simulation was carried out over a typical workday, specifically on January 8<sup>th</sup>, 2018. To ensure more accurate initial conditions, IDA-ICE provides a *custom startup* feature, which we utilized by simulating the building's behavior for one week prior to the target day. This warm-up period allows the model to reach a realistic dynamic state, aligning the internal temperatures and system parameters more closely with real-world conditions before the main simulation begins.

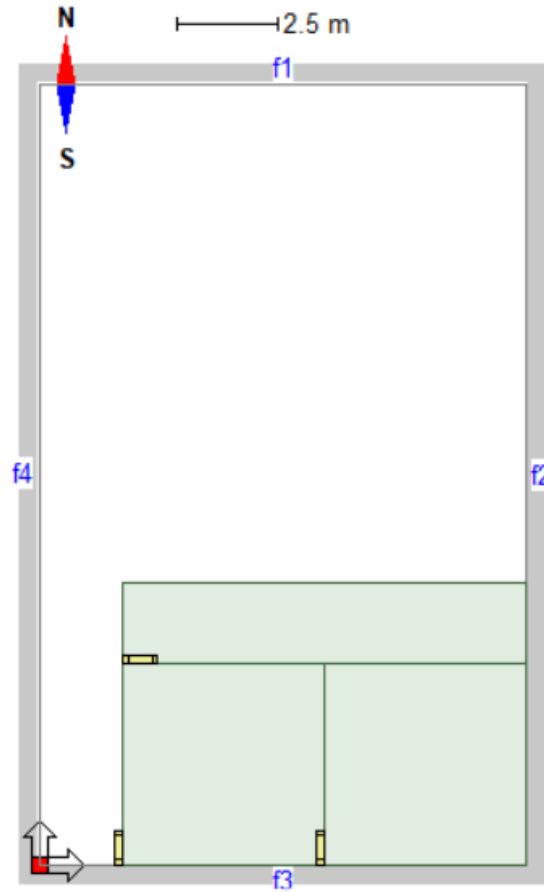


Figure 5.1: Floor plan of the three-room model implemented in IDA-ICE

We first start by showing the results obtained with the PI controller. The temperature evolution for the three rooms is shown in Figures 5.2, 5.4, and 5.6, while the corresponding energy balances are presented in Figures 5.3, 5.5, and 5.7.

## 5.2. A COMPARISON BETWEEN SIMULINK AND IDA-ICE

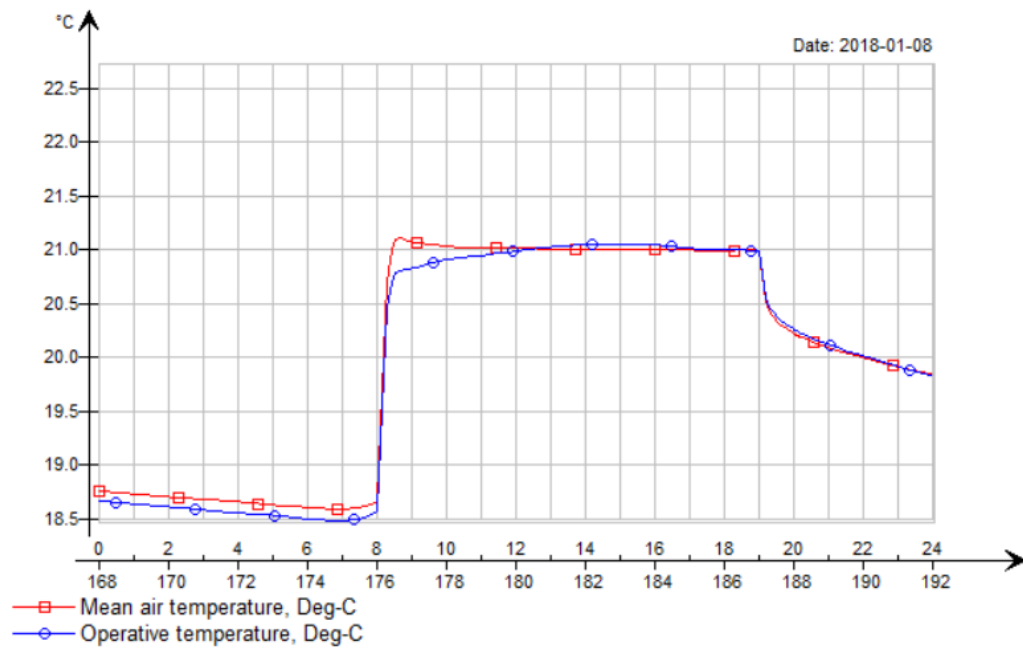


Figure 5.2: Temperature Evolution in Room 1 under PI Control

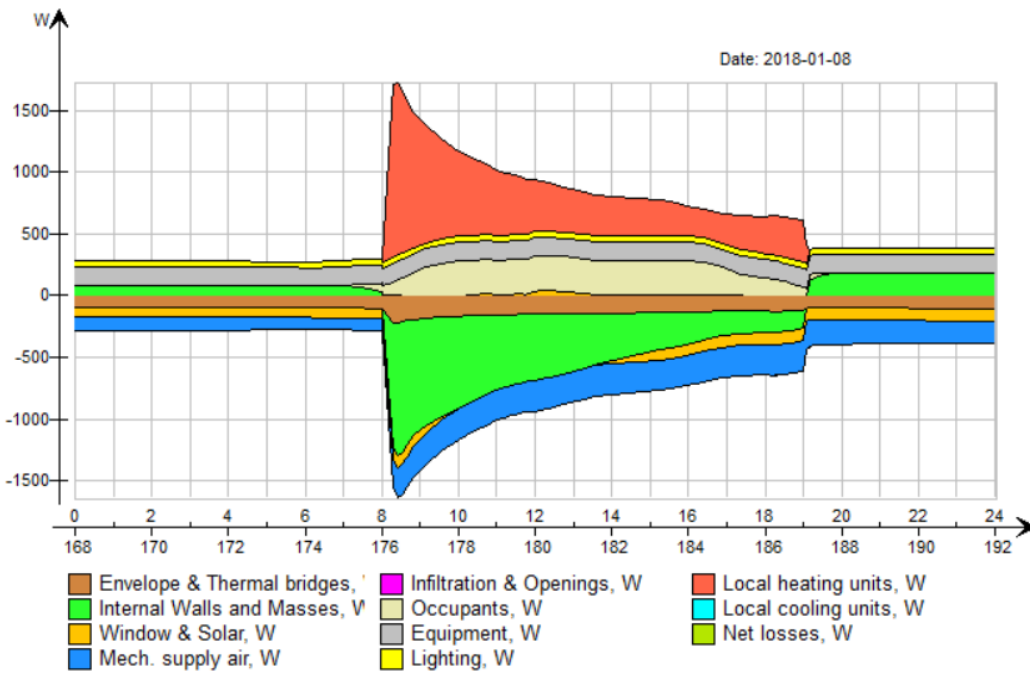


Figure 5.3: Energy Flow Analysis in Room 1 under PI Control

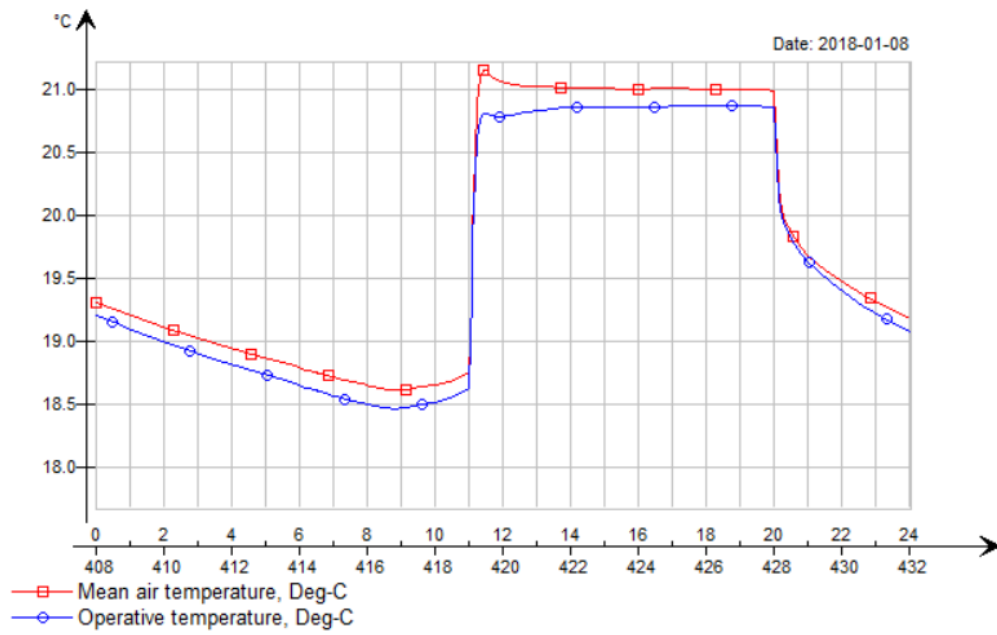


Figure 5.4: Temperature Evolution in Room 2 under PI Control

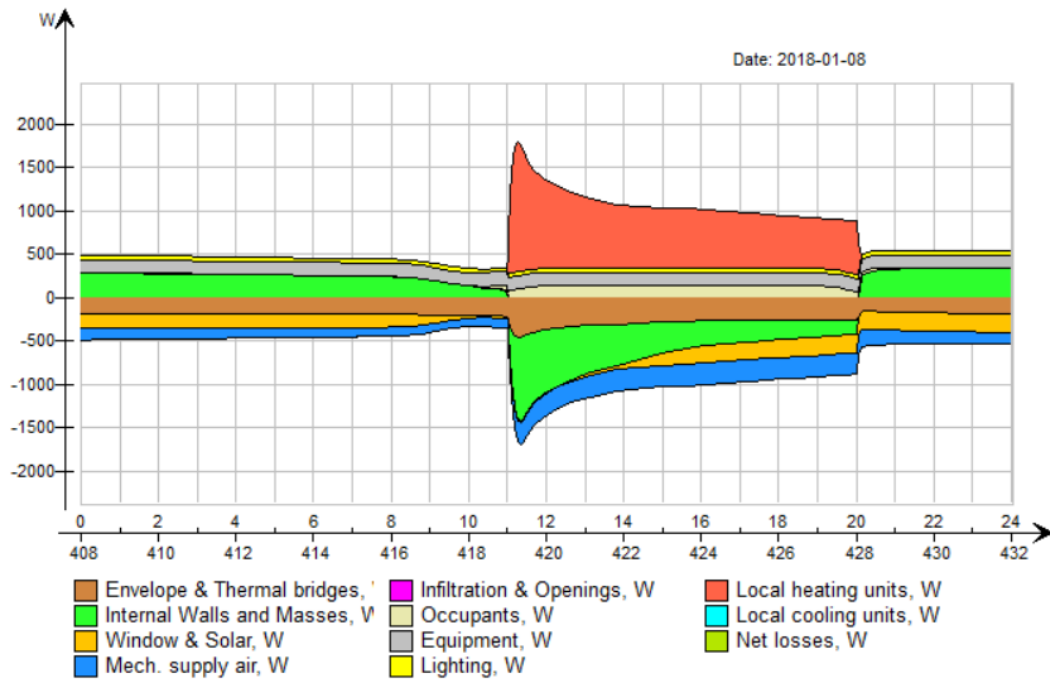


Figure 5.5: Energy Flow Analysis in Room 2 under PI Control

## 5.2. A COMPARISON BETWEEN SIMULINK AND IDA-ICE

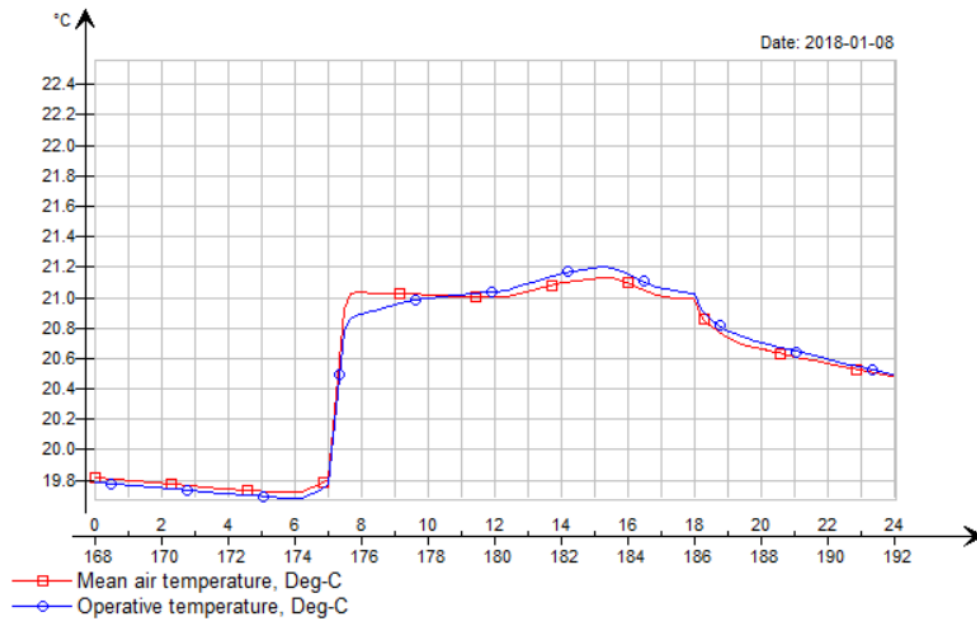


Figure 5.6: Temperature Evolution in Room 3 under PI Control

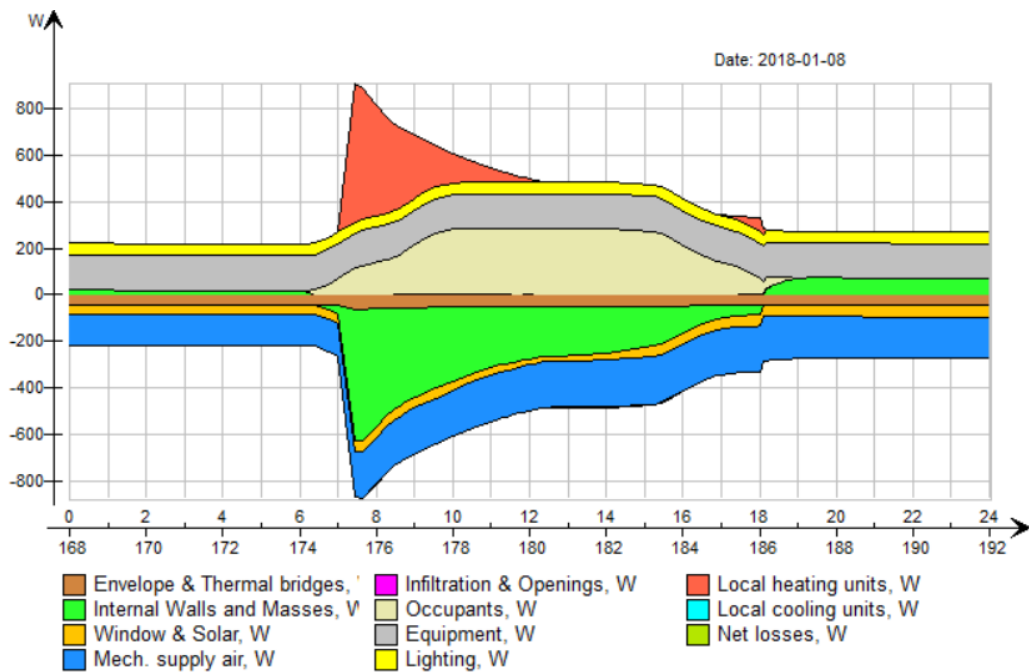


Figure 5.7: Energy Flow Analysis in Room 3 under PI Control

In the room temperature plots, two temperature profiles are displayed: the

mean air temperature and the operative temperature. The mean air temperature refers to the average temperature of the air within the room and is influenced primarily by the HVAC system and air circulation. In this analysis, the PI controller is designed to regulate the mean air temperature in each room.

The operative temperature, on the other hand, provides a more comprehensive measure of thermal comfort by combining the effects of air temperature and the mean radiant temperature of surrounding surfaces. It accounts for both convective and radiative heat exchange and is therefore considered a better indicator of perceived comfort for occupants.

Each of the three rooms exhibits distinct thermal behavior due to differences in geometry, surface exposure, and heating dynamics. It is important to recall that during nighttime hours, a passive heating strategy is implemented: heating units are activated only if the room temperature drops below 18°C; otherwise, the temperature is allowed to evolve freely without any control intervention.

However, in this simulation, the passive heating was never activated, as the temperature in all three rooms remained above the 18°C threshold throughout the night.

When the reference temperature steps up to 21°C in the morning, Rooms 1 and 2 start from lower initial temperatures and must recover a larger gap. As a result, their settling times are longer, approximately 30 minutes. In contrast, Room 3 begins the day already close to the reference value and reaches steady-state conditions within about 15 minutes.

Analyzing the energy balance plots, we observe that Rooms 1 and 2 consistently consume energy during the occupancy period (i.e., when the reference is set to 21 °C). However, Room 3, being smaller and more thermally stable, has certain periods during the day when no heating is required, and the local heating unit remains inactive.

Lastly, during the night, Room 2 shows the fastest temperature drop, while Rooms 1 and 3 exhibit smoother cooling trends. This is consistent with the energy plots, where Room 2 displays greater energy losses. This behavior can be attributed to the increased exposure to window-related and solar losses, which have a more pronounced impact during winter conditions, when the simulation is conducted.

We now present the results obtained using feedback control based on user input. As in the previous setup, user feedback is represented by a continuous slider ranging from -1 to +1, allowing each occupant to indicate their level of thermal

discomfort.

The control law is applied as described in the previous chapter. However, in contrast to the earlier configuration, the gain parameter  $k$  is no longer set equal to the room's thermal capacitance  $C_r$ . Instead,  $k$  serves as a tunable parameter that limits the maximum heating power supplied to the system. To ensure stable and realistic temperature evolution, we fix this value at  $k = 0.7$ .

In this initial simulation, we adopt a sampling interval of 15 minutes. Every 15 minutes, users receive the current room temperature and have the opportunity to send a new feedback signal to the controller.

As in the previous case, a smooth on/off controller is also implemented to manage passive heating during unoccupied periods. This controller activates only when no user is present and the room temperature falls below the lower comfort threshold of  $18^\circ\text{C}$ .

The temperature evolution for the three rooms is shown in Figures 5.8, 5.10, and 5.12, while the corresponding energy balances are presented in Figures 5.9, 5.11, and 5.13.

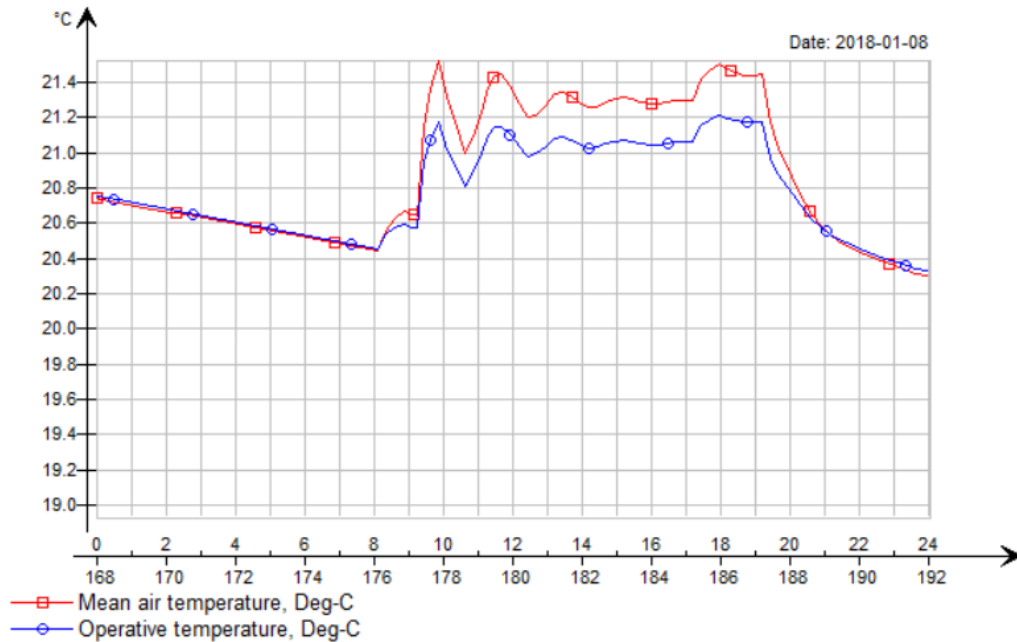


Figure 5.8: Temperature Evolution in Room 1 under Feedback Control

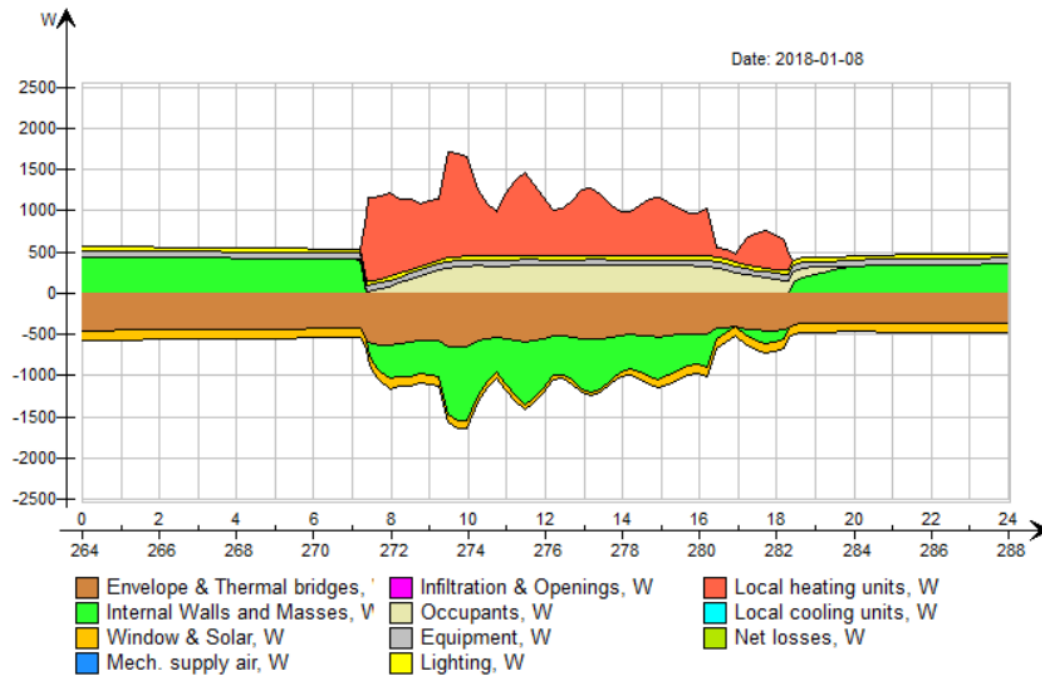


Figure 5.9: Energy Flow Analysis in Room 1 under Feedback Control

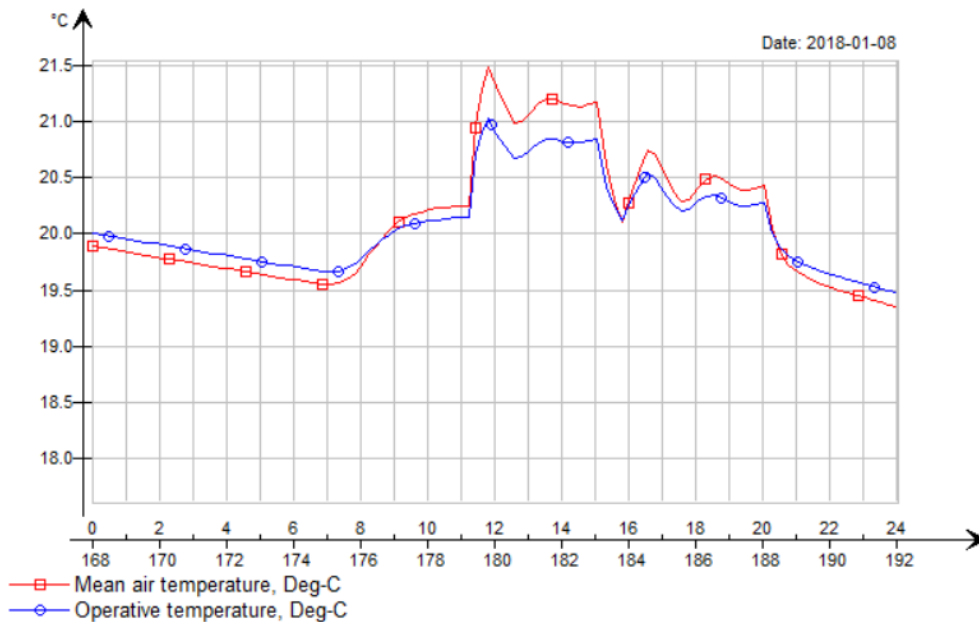


Figure 5.10: Temperature Evolution in Room 2 under Feedback Control

## 5.2. A COMPARISON BETWEEN SIMULINK AND IDA-ICE

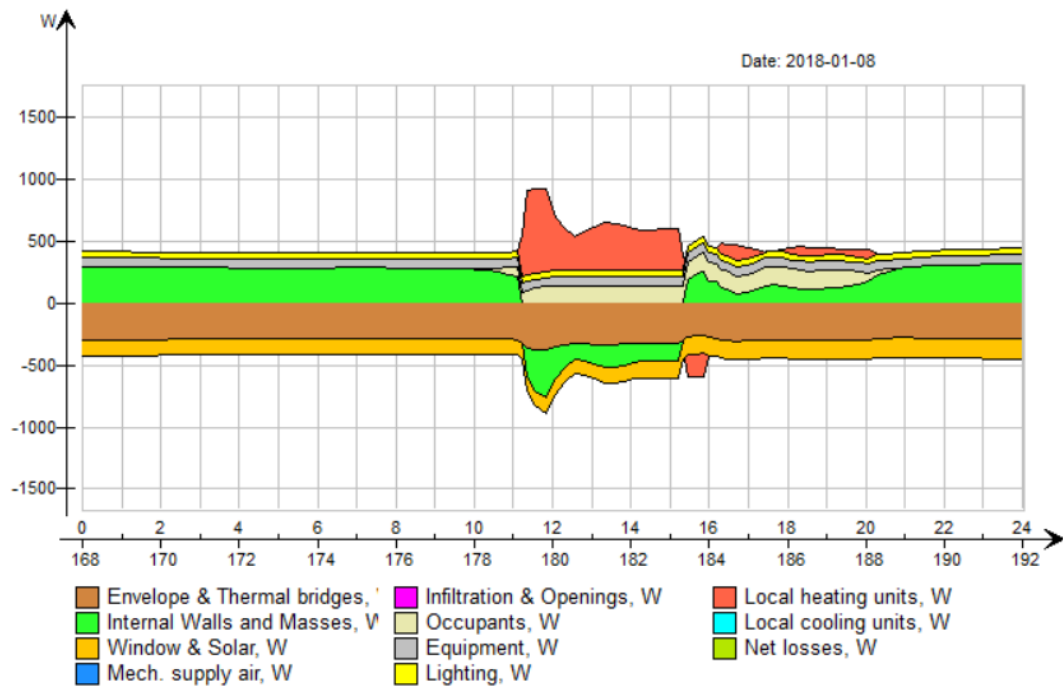


Figure 5.11: Energy Flow Analysis in Room 2 under Feedback Control

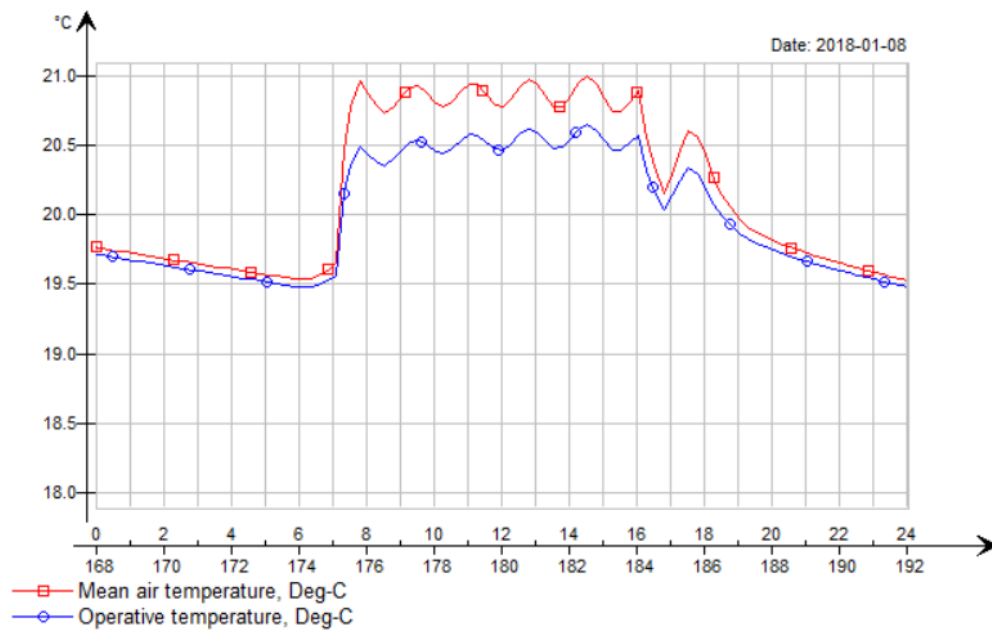


Figure 5.12: Temperature Evolution in Room 3 under Feedback Control

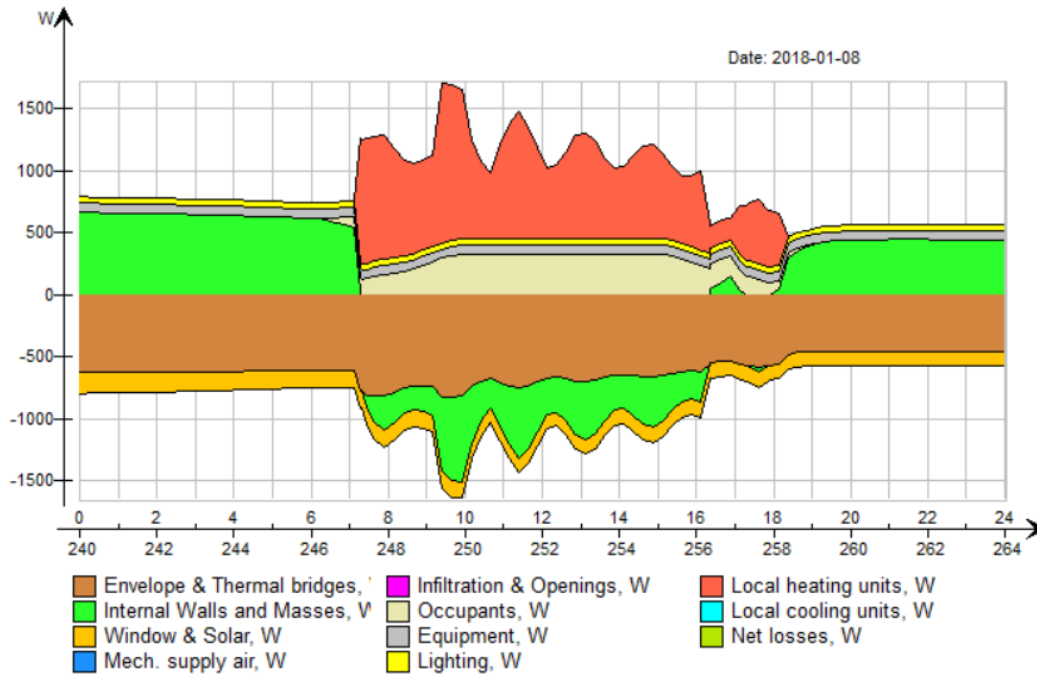


Figure 5.13: Energy Flow Analysis in Room 3 under Feedback Control

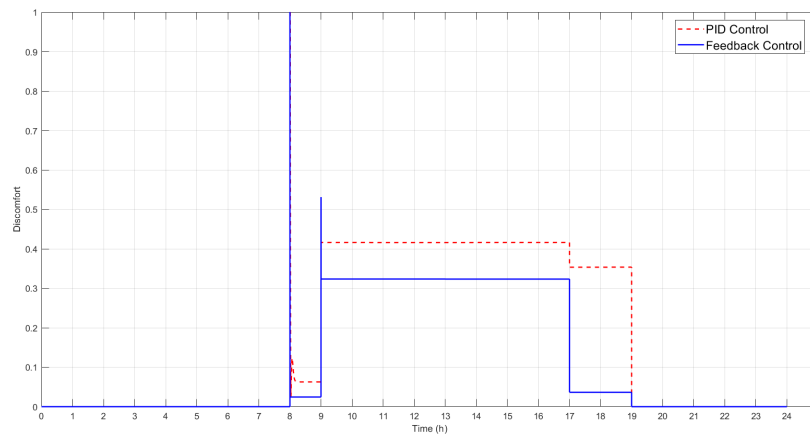
The results of this simulation reveal several important insights. First, the smooth on/off controller was never activated, as the temperature in all three rooms consistently remained above the lower threshold of  $18^{\circ}\text{C}$ . More significantly, the temperatures in each room stayed within the comfort range where users report the highest satisfaction. As a result, the feedback signals remained small in magnitude, leading to a sustainable level of energy consumption.

It is important to emphasize that, unlike in Simulink where the temperature evolution may appear linear or idealized, the use of IDA-ICE yields temperature profiles that are more realistic and dynamic. This is due to the software's high fidelity in modeling building physics, making it a superior tool for producing accurate simulations and obtaining more reliable results.

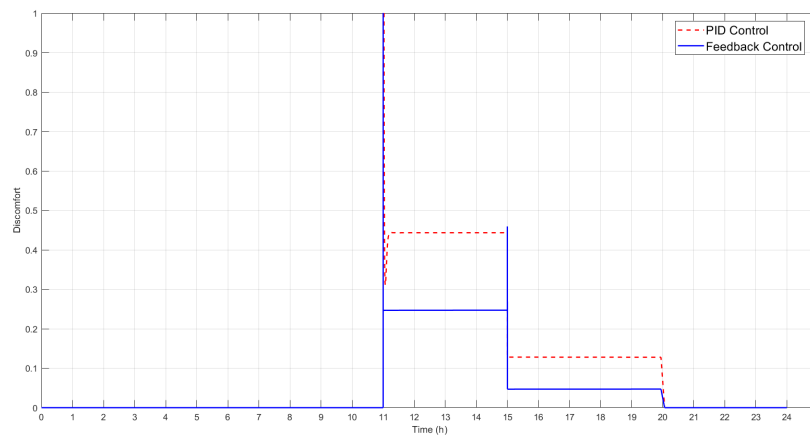
Nevertheless, some subtle step-up or step-down patterns in temperature can still be observed, which are attributable to the varying user schedules and individual comfort preferences. These transitions, although less pronounced, reflect the complex interaction between occupancy and thermal dynamics.

In conclusion, we also present the evolution of discomfort over time for each room in this case. The approach used is the same as the one described in Section 4.3. The results are shown in Figure 5.14 and in Table 5.2.

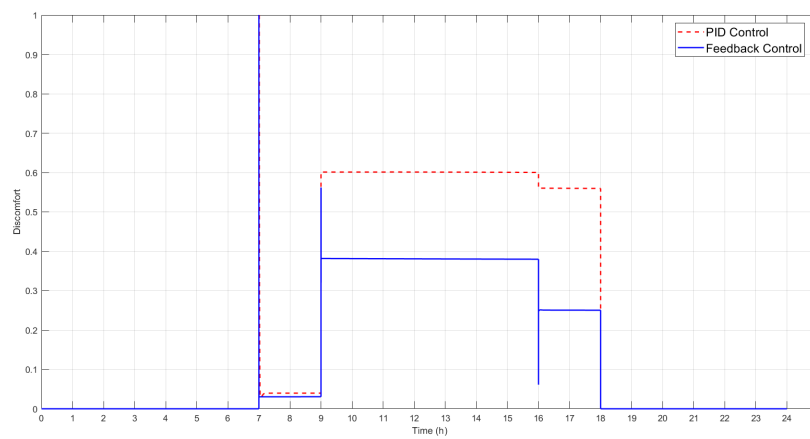
## 5.2. A COMPARISON BETWEEN SIMULINK AND IDA-ICE



(a) Discomfort Evolution Over Time in Room 1



(b) Discomfort Evolution Over Time in Room 2



(c) Discomfort Evolution Over Time in Room 3

Figure 5.14: Discomfort Evolution Over Time via Different Controls

Table 5.1: Total Discomfort for Each Control Strategy Across Rooms

| Control Strategy      | Room 1      | Room 2      | Room 3      |
|-----------------------|-------------|-------------|-------------|
| PID Control           | 0.3961 °C·s | 0.5312 °C·s | 0.5843 °C·s |
| User Feedback Control | 0.1846 °C·s | 0.3352 °C·s | 0.3527 °C·s |

In conclusion, the results obtained with IDA ICE are more realistic, as they account for the building's physical and thermal dynamics in greater detail. As a result, they show a slightly higher level of discomfort compared to the values obtained with the simplified Simulink model. This small increase reflects a more accurate representation of real-world conditions. However, also in this case, the feedback control highlights greater values of comfort compared to the PI control. Lastly, for this simulation as well, the results are presented in a two-dimensional plot, where the x-axis represents user comfort and the y-axis represents energy consumption. The corresponding plot is shown in Figure 5.15.

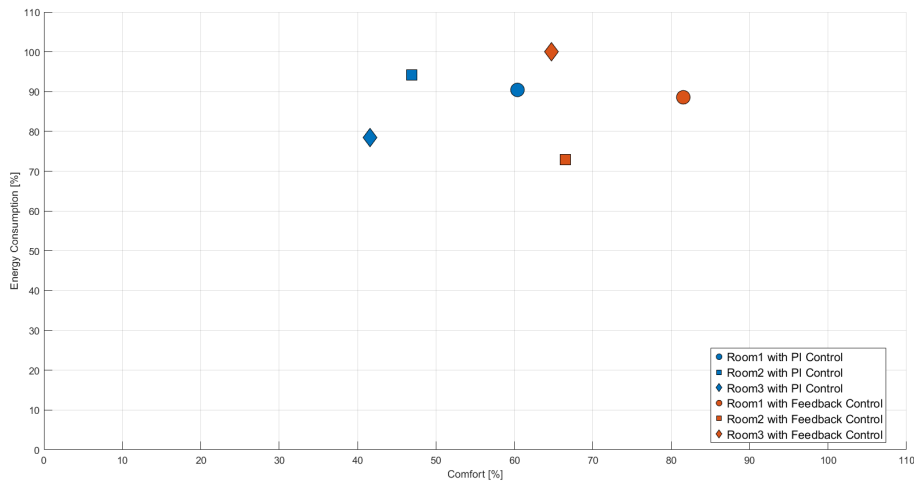


Figure 5.15: Results in percentages of comfort and energy consumption

### 5.3 AN OVERVIEW OF THE LIVE-IN-LAB STRUCTURE

As already mentioned in Section 1.7, the KTH (LIL) is a residential building located at the KTH Campus. The structure layout that was analyzed is illustrated in Figure 5.16 and in Figure 5.17.

On the east side of the plan, there are four residential rooms, each with a private

### 5.3. AN OVERVIEW OF THE LIVE-IN-LAB STRUCTURE

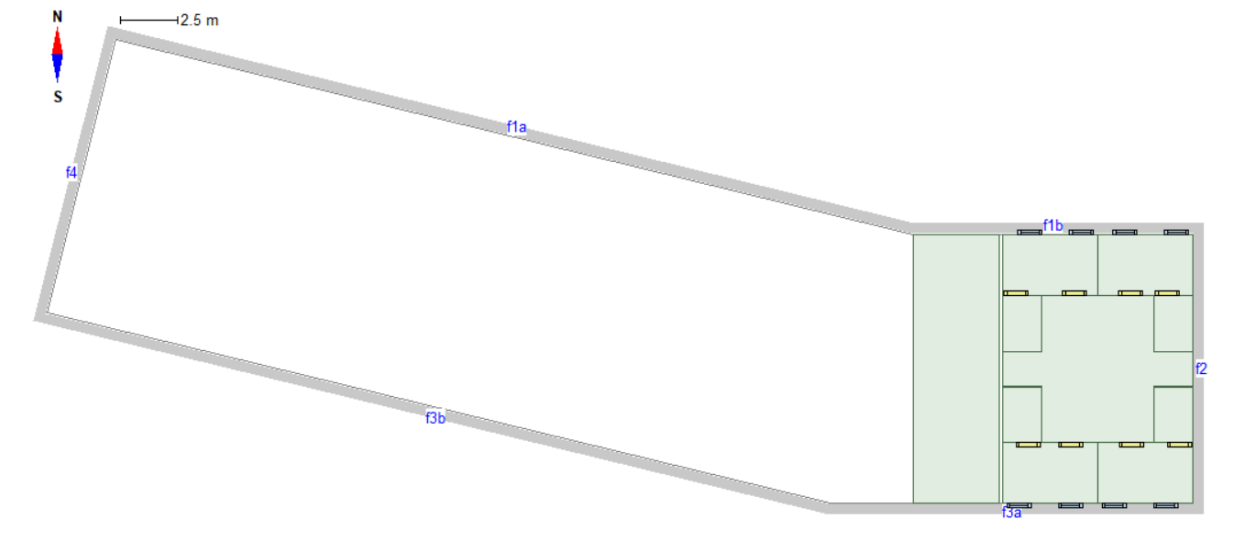


Figure 5.16: Floor plan of the KTH (LIL) building

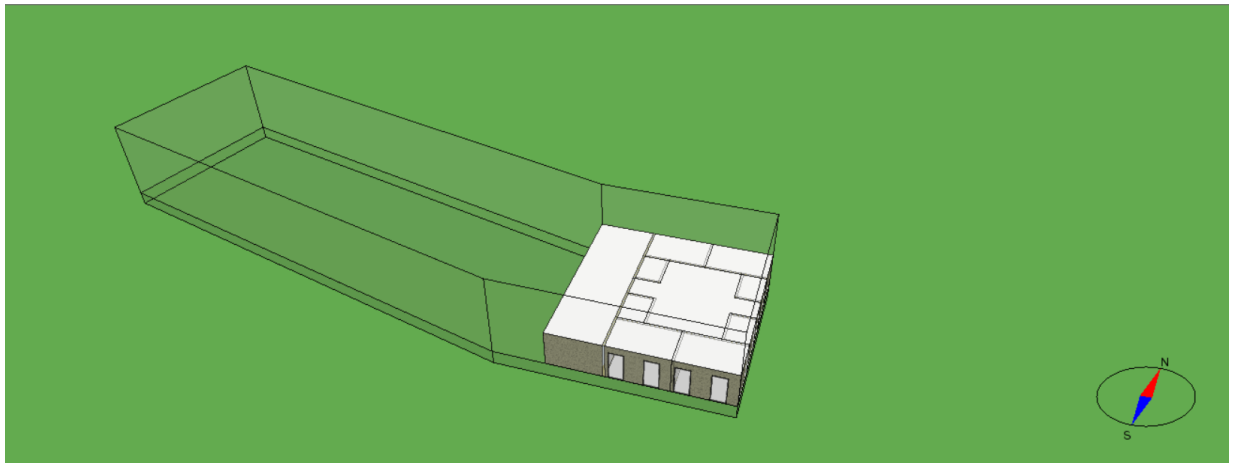


Figure 5.17: 3D representation of the KTH (LIL) building

bathroom, capable of accommodating between zero and two people. At the center of this area lies a shared kitchen, represented by the inner room, which can host up to six people at a time. On the west side of the layout, there is a rectangular office space, oriented along the longer axis of the building. This room is separated from the residential area and is slightly angled relative to the main structure.

## 5.4 CLIMATE DATA

To evaluate the system under realistic and challenging conditions, the simulation was conducted during the winter season. Stockholm Bromma was selected as the reference location, and a corresponding .Pnr climate file was downloaded and imported into IDA ICE.

This file provides essential environmental parameters, including air temperature, relative humidity, and solar irradiance. Among these, the outdoor air temperature is particularly critical and is illustrated in Figure 5.18, representing the conditions from January 18<sup>th</sup> to January 24<sup>th</sup>, 2021. The climate related input data used in IDA ICE for this location is shown in Figure 5.19.

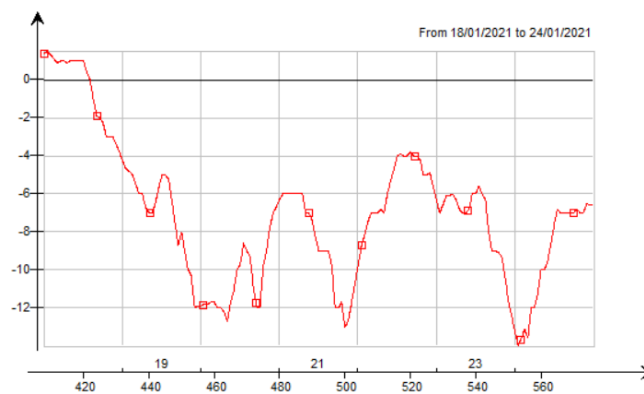


Figure 5.18: Outdoor air temperature over a week

## 5.5 ZONES

A realistic model requires rooms with accurate intended use and usage patterns. We begin by analyzing the geometrical properties of the room, as illustrated in Figure 5.20. This figure provides an overview of the rooms dimensions, including its height and floor area in square meters.

Another significant advantage of using the IDA-ICE software lies in its ability to accurately model the geometrical and structural layouts of floors, walls, and roofs. Since these configurations play a crucial role in the simulation of temperature dynamics, we briefly describe how each component has been implemented in the model.

We start by the ceiling, which is directly exposed to outdoor conditions and

## 5.5. ZONES

|                |       | Winter | Summer |     |
|----------------|-------|--------|--------|-----|
| Dry-bulb min   |       | -16.1  | 15.3   | °C  |
| Dry-bulb max   |       | -10.5  | 27.8   | °C  |
| Wet-bulb max   |       | -10.9  | 18.2   | °C  |
| Wind direction |       | 290    | 210    | °   |
| Wind speed     |       | 1.5    | 3.8    | m/s |
| Clear-sky      | tau_b | 0.316  | 0.337  |     |
| optical depth  | tau_d | 2.497  | 2.409  |     |

Figure 5.19: Location data for IDA ICE model

plays a significant role in heat exchange due to solar radiation and external temperature fluctuations. Its thermal transmittance is relatively high, with a U-value of  $U_{\text{ceiling}} = 2.385 \text{ W/m}^2\text{K}$ , making it a critical surface in terms of heat loss and gain.

The overall thickness of the roof (ceiling) is 0.175 m, obtained from the combination of three different layers: a 0.15 m thick layer of concrete, followed by 0.02 m of lightweight concrete, and finally a 0.005 m floor coating.

The floor shares the same overall thickness and material configuration as the ceiling. As a consequence, it also exhibits the same U-value of  $U_{\text{floor}} = 2.385 \text{ W/m}^2\text{K}$ . In this analysis, the floor is assumed to be in direct contact with the ground, which is modeled as a constant-temperature boundary condition.

Regarding the walls of the room, we distinguish between external and internal types. The external walls have a total thickness of 0.5 m and a U-value of  $U_{\text{ext. wall}} = 0.1838 \text{ W/m}^2\text{K}$ . Their construction consists of three main layers: a 0.25 m outer concrete layer, followed by 0.15 m of light insulation, and a final

| Name            | Group | Floor height, m | Room height, m | Floor area, m2 |
|-----------------|-------|-----------------|----------------|----------------|
| Kitchen         | LGH_3 | 0.0             | 2.6            | 36.53          |
| LGH_1_Bathr...  | LGH_1 | 0.0             | 2.6            | 4.09           |
| LGH_1_Living... | LGH_1 | 0.0             | 2.6            | 11.01          |
| LGH_2_Bathr...  | LGH_2 | 0.0             | 2.6            | 4.09           |
| LGH_2_Living... | LGH_2 | 0.0             | 2.6            | 11.01          |
| LGH_3_Bathr...  | LGH_3 | 0.0             | 2.6            | 4.09           |
| LGH_3_Living... | LGH_3 | 0.0             | 2.6            | 11.01          |
| LGH_4_Bathr...  | LGH_4 | 0.0             | 2.6            | 4.09           |
| LGH_4_Living... | LGH_4 | 0.0             | 2.6            | 11.01          |
| Office          |       | 0.0             | 2.6            | 44.2           |

Figure 5.20: Geometrical values of the rooms

inner concrete layer of 0.10 m.

In contrast, the internal walls are thinner and exhibit a higher thermal transmittance, with a U-value of  $U_{\text{int. wall}} = 0.5569 \text{ W/m}^2\text{K}$ . Their total thickness is 0.146 m. The composition of internal walls is more articulated and symmetrical, consisting of a 0.026 m layer of gypsum, followed by 0.032 m of air insulation, then a central core of 0.030 m light insulation, and the same layering in reverse order: air insulation and gypsum.

Another key aspect that significantly influences the temperature evolution within the building is the presence of windows on the south and north facades. Each window has a width of 1m and a height of 2.12m, resulting in a total surface area of  $2.12\text{m}^2$ .

In the thermal analysis of the building envelope, windows represent a critical point of heat exchange. Each window consists of two main components with distinct thermal properties: the glazing and the frame. The thermal transmittance (U-value) of the glazing is  $U_{\text{glazing}} = 1.4 \text{ W/m}^2\text{K}$ , indicating relatively good insulation performance. In contrast, the window frame has a higher U-value of  $U_{\text{frame}} = 2.0 \text{ W/m}^2\text{K}$ , allowing more heat to pass through compared to the glazing. These values are essential in determining the overall heat loss through the window and are incorporated into the thermal model.

Lastly, IDA-ICE also provides the possibility to define window opening schedules based on indoor temperature and user occupancy. However, in this analysis, we assume that all windows remain closed throughout the simulation.

### 5.6 OTHER CRITICAL PARAMETERS

In addition to the primary thermal and control parameters, several secondary but important factors significantly influence the indoor thermal dynamics. These critical parameters must be accounted for to ensure an accurate and realistic model of the environment.

As mentioned earlier in this work, internal gains represent one of the most significant factors influencing the thermal behavior of the system. Internal gains refer to the heat generated within the room by non-HVAC sources.

These include heat released by occupants, lighting systems, and electrical equipment. Occupants contribute both sensible and latent heat through their metabolic processes, depending on their activity levels. Lighting systems, particularly those that are not energy-efficient, emit significant heat during operation. Similarly, computers, appliances, and other devices add to the internal heat load while in use. These internal gains are often time-dependent and vary according to occupancy schedules and usage patterns. Accurately modeling them is essential to avoid incorrect estimations of the HVAC system's performance.

In our IDA-ICE simulation, we set the following internal gain values: in the office and kitchen, the equipment generates 250 W and the lighting contributes 100 W. In the four bedrooms, the equipment produces 150 W and the lighting adds 50 W. Finally, in the bathrooms, the equipment accounts for 75 W, while the lighting once again contributes 100 W.

Another feature available in IDA-ICE is the modeling of openings, commonly represented by doors. Doors connecting adjacent rooms play a vital role in facilitating thermal exchange between spaces. Unlike walls, which generally act as thermal barriers, open or partially open doors enable the transfer of air and heat, influencing both local temperatures and the overall thermal balance of the building.

Finally, the presence of furniture in each room is also taken into account. Furniture contributes to the rooms thermal mass, as materials like wood, fabric, and metal have the ability to absorb, store, and release heat. This effect can slightly delay the rooms temperature response to heating or cooling. Although often overlooked in simplified models, the quantity and material properties of furniture can significantly influence the thermal inertia, particularly in rooms with a high density of furnishings.

In conclusion, we can now assign numerical values to this factor. For simplicity,

the heat transfer coefficient is assumed to be the same for all rooms and set to  $6\text{W}/\text{m}^2\text{K}$ . The varying parameter between rooms is the surface area covered by furniture. Specifically, the office has a furniture surface area of  $2.124\text{m}^2$ , the bedrooms each have  $2\text{m}^2$ , the kitchen has  $1.276\text{m}^2$ , and the bathrooms have a constant area of  $0.8328\text{m}^2$ .

## 5.7 SIMULATION

To proceed, we first present the configuration of our simulation model. In this implementation, each room is equipped with either an ideal heating/cooling device or a simpler, more energy-efficient panel system. Specifically, ideal heating and cooling systems were assigned to the main rooms, while the bathrooms were fitted with basic heating-cooling panels to reduce energy use and simplify the setup.

In both the PI and feedback control simulations, the kitchen was modeled using a simple PI controller combined with an ideal heating-cooling device. This modeling choice was motivated by the difficulty of accurately defining user occupancy schedules in the kitchen; therefore, a conventional PI strategy was adopted for simplicity. Similarly, the bathrooms were equipped with panel-based heating-cooling systems in both scenarios, also regulated by a PI controller.

The key comparison between the two control strategies was conducted in the four bedrooms and the office, where the respective PI and feedback-based control laws were applied to evaluate performance differences.

Another important aspect of the building setup concerns the ventilation and heating/cooling systems. In both the kitchen and the bedrooms, a Variable Air Volume (VAV) system is present. By default, when both a VAV system and other heating/cooling devices are defined within a zone, IDA-ICE prioritizes the use of the VAV unit. Consequently, the setpoints of the additional room units are automatically offset by  $1.0^\circ\text{C}$  to avoid overlap and ensure sequential activation. This configuration specifically applies only to rooms governed by units with PI control, where temperature references are explicitly imposed.

In contrast, the office and bathrooms are directly served by the assigned room unit devices, as no VAV system is installed in those spaces.

To define the reference signals for the PI-controlled rooms, we adopt fixed temperature setpoints, consistent with the complexity and realism of the building model under implementation. Specifically, in the office, kitchen, and bedrooms,

## 5.7. SIMULATION

the heating controller is assigned a setpoint of 21 °C, while the cooling controller is activated if the temperature exceeds 22 °C.

For the bathrooms, which utilize a more energy-efficient heating/cooling panel, the heating setpoint is slightly lower at 20 °C, and the cooling setpoint is set to 21 °C. These reference values ensure appropriate thermal comfort across different room types while accounting for the nature of the installed devices.

These same fixed setpoints are also applied in the feedback control formulation for those zones where no user feedback has been implemented, namely the kitchen and bathrooms.

The internal heat gains for each zone are configured based on realistic user presence, lighting, and equipment schedules. Below is a detailed description of the setup for each room:

- **Office:** The office hosts a total of five users. Three users are present from 8:00 to 12:00, Monday through Friday, while the remaining two are present from 8:00 to 19:00 during the same weekdays. No occupants are present during the weekends. Lighting and equipment (e.g., computers, monitors) are activated only when the room is occupied.
- **Kitchen:** The kitchen is assumed to contain always-active appliances such as fridges and freezers; hence, the equipment gains are set to be constantly on. Lighting in the kitchen is active daily from 7:00 to 22:00.
- **Bedroom 1:** This room is occupied by two users who share the same schedule: they are absent from 8:00 to 18:00 from Monday to Friday and are away all day during the weekend.
- **Bedroom 2:** One user occupies this room. The user is away from 10:00 to 20:00 from Monday to Friday, and present at all hours during the weekend.
- **Bedroom 3:** This room has a user who is absent from 8:00 to 19:00 on weekdays, and fully present on weekends.
- **Bedroom 4:** The occupant is away from 10:00 to 20:00 on weekdays and remains inside during the weekend.
- **Bathrooms and Bedrooms (general settings):** Lighting is assumed to be always off, while equipment (e.g., small appliances) is considered to be always on.

The following discussion presents the analysis of energy consumption under the PI control strategy. Figures 5.23a and 5.24a illustrate the building's energy performance and the HVAC system's power dynamics during the winter simulation period. The total delivered energy is 742 kWh, corresponding to an energy intensity of 5.3 kWh/m<sup>2</sup>. As depicted in Figure 5.23a, the largest share of energy

is used for *fuel heating* (437 kWh, 59%), followed by *tenant equipment* (200 kWh, 27%) and *electric cooling* (77 kWh, 10%). Lighting and HVAC auxiliaries account for only 4% of the total.

Figure 5.24a shows the time-resolved HVAC power demand from January 18 to January 24. The dominant component is the air handling unit (AHU) heating coil (red line), which operates with strong daily variation, peaking around 3000 W. Cooling is active mostly during specific daytime periods, with ideal local units (blue crosses) engaging mainly between 9:00 and 18:00. Water-based heating exhibit negligible usage, confirming that local radiant devices were not significantly involved. Finally, domestic hot water consumption is zero, as no DHW systems are included in the model.

Overall, the results confirm that the PI control strategy maintains thermal comfort while minimizing unnecessary energy consumption, particularly by centralizing heating demand through the AHU.

We now present the results obtained using the feedback control strategy. The quantitative summary is provided in Figure 5.23b, which shows a total energy demand of 785 kWh, corresponding to an energy intensity of  $5.6 \text{ kWh/m}^2$ , over the simulated period. The majority of the consumption comes from *fuel heating* (520 kWh, 66%), followed by *tenant equipment* usage (200 kWh, 25%) and *electric cooling* (36 kWh, 5%). Lighting and HVAC auxiliaries account for only 4% of the total. The building demonstrates also no overheating above  $27^\circ\text{C}$  in any zone, confirming satisfactory comfort compliance.

Then, Figure 5.24b illustrates the temporal evolution of thermal energy consumption across the building during the baseline simulation week.

The red line, representing the power required by the AHU heating coil, dominates the energy profile. Peaks in demand are clearly visible around the mornings and evenings, reaching above 3000 W, which aligns with expected occupancy and temperature setback recovery patterns. Minor contributions are observed from water-based zone heating, cooling systems, and local ideal coolers.

An interesting aspect observable in Figure 5.24b is the presence of negative power values for the ideal heaters and other local units (orange curve). This behavior is caused mostly by the office zone, which, due to its location and relatively well-insulated structure, tends to retain internal heat gains from occupants and equipment, making it less susceptible to external thermal losses.

It is important to clarify that this negative heating power does not imply actual

## 5.7. SIMULATION

heat removal by a dedicated cooling system. Instead, it results from the way the heating/cooling signal is managed in our simulation setup. Specifically, the control signal was computed in MATLAB and then sent to IDA-ICE as a heating input. Since IDA-ICE allows only one control channel per zone, either for heating or cooling but not both simultaneously, we chose to interpret this signal as heating power.

Consequently, when users send a negative feedback value (indicating overheating), the controller computes a negative heating signal, which effectively corresponds to a cooling demand. Therefore, negative heating values in the plots should be interpreted as localized cooling, reflecting the system's attempt to maintain thermal comfort even during winter conditions.

Finally, by comparing the two control strategies applied to our building, we observe a moderate increase in total energy consumption with the feedback control law, specifically an increase of approximately 5.8%.

As discussed at the end of Chapter 4, we also aim to present the discomfort experienced by each user, providing an overview of the trade-off between thermal comfort and energy consumption.

For the sake of simplicity, we considered the temperature evolution over a typical working day, so that users are present in the office, in order to calculate their discomfort. The results are represented in Figure 5.21 and in Figure 5.22 and in Table 5.2.

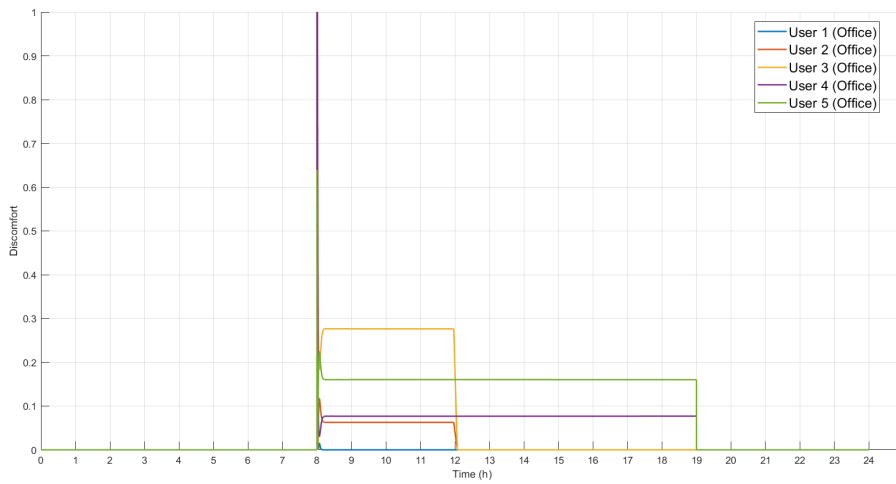
Looking at the discomfort plots, we can make several observations. First, we observe that discomfort converges toward zero in the bedrooms where users are present. This is because the room temperature gradually approaches each user's ideal temperature. This effect is particularly evident in the bedrooms, where, except for Bedroom 1 which hosts two users, there is only a single occupant per room. In these cases, the user can individually influence the temperature by sending feedback signals, allowing the system to quickly adjust to their comfort preference.

This behavior is not observed in shared spaces like the office, where the discomfort remains relatively constant throughout the day and changes only when someone enters or leaves the room. In these environments, since multiple users may have different ideal temperatures, the system cannot perfectly match everyone's preference at the same time.

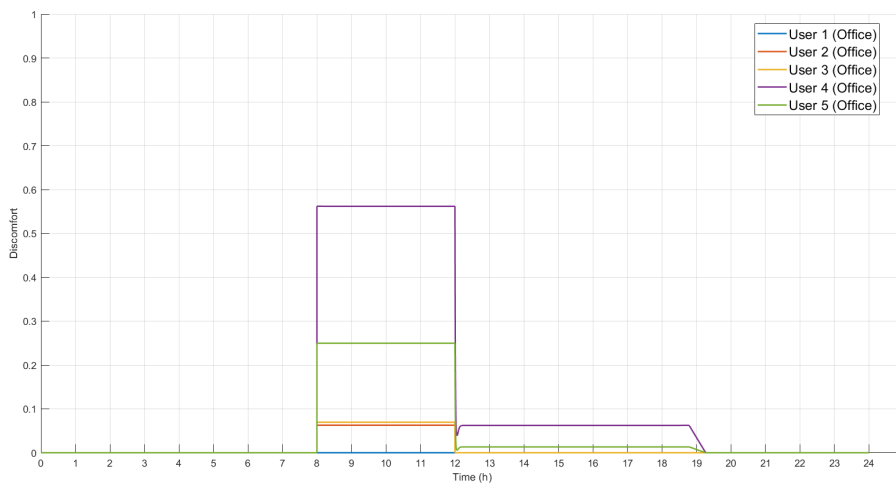
Moreover, even in this more complex model, we observe that on this particular day, the feedback control generally results in lower discomfort values across

all rooms compared to the simple PI controller, except for Bedroom 1, where the PI controller performs slightly better. This is because user 1 has an ideal temperature that exactly matches the fixed temperature reference used in the PI control, meaning that his discomfort is always zero.

In conclusion, aside from some isolated cases like Bedroom 1, the feedback control approach performs better overall in terms of maximizing user comfort, particularly in shared spaces where preferences may vary.



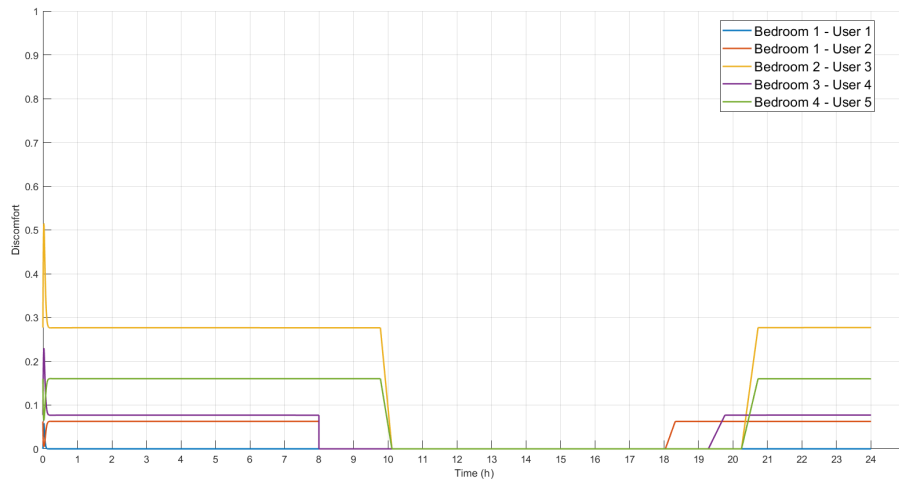
(a) Discomfort Evolution Over Time in the Office via PI Control



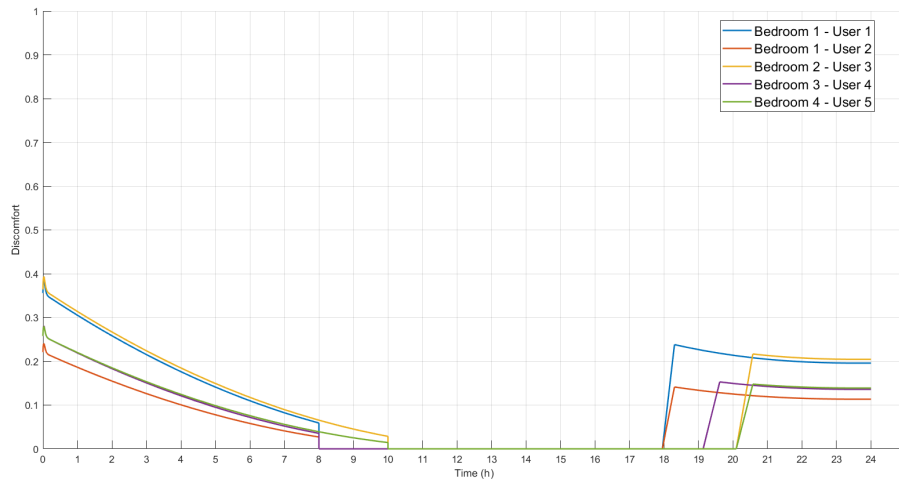
(b) Discomfort Evolution Over Time in the Office via Feedback Control

Figure 5.21: Discomfort Evolution Over Time in the Office

## 5.7. SIMULATION



(a) Discomfort Evolution Over Time in the Bedrooms via PI Control



(b) Discomfort Evolution Over Time in the Bedrooms via Feedback Control

Figure 5.22: Discomfort Evolution Over Time in the Bedrooms

Table 5.2: Total Discomfort for Each Control Strategy Across Rooms

| Control Strategy      | Office      | Bedroom 1   | Bedroom 2   | Bedroom 3   | Bedroom 4   |
|-----------------------|-------------|-------------|-------------|-------------|-------------|
| PID Control           | 0.8324 °C·s | 0.3673 °C·s | 0.5231 °C·s | 0.3831 °C·s | 0.4880 °C·s |
| User Feedback Control | 0.7986 °C·s | 0.4143 °C·s | 0.3501 °C·s | 0.3152 °C·s | 0.2920 °C·s |

|                                                                                   |                                                 |                                |                                       |
|-----------------------------------------------------------------------------------|-------------------------------------------------|--------------------------------|---------------------------------------|
|  |                                                 | <b>Delivered Energy Report</b> |                                       |
| <b>Project</b>                                                                    |                                                 | <b>Building</b>                |                                       |
| Customer                                                                          |                                                 | Model floor area               | 141.1 m <sup>2</sup>                  |
| Created by                                                                        |                                                 | Model volume                   | 367.0 m <sup>3</sup>                  |
| Location                                                                          | Stockholm (Bromma Airport)_024640 (ASHRAE 2013) | Model ground area              | 0.0 m <sup>2</sup>                    |
| Climate file                                                                      | [Default]                                       | Model envelope area            | 93.1 m <sup>2</sup>                   |
| Case                                                                              | Testbed_KTH floor_Winter_Occ Testbed 2.0        | Window/Envelope                | 18.2 %                                |
| Simulated                                                                         | 13/06/2025 09:55:10                             | Average U-value                | 0.4521 W/(m <sup>2</sup> K)           |
|                                                                                   |                                                 | Envelope area per Volume       | 0.2537 m <sup>2</sup> /m <sup>3</sup> |

**Building Comfort Reference**

|                                                                              |      |
|------------------------------------------------------------------------------|------|
| Percentage of hours when operative temperature is above 27°C in worst zone   | 0 %  |
| Percentage of hours when operative temperature is above 27°C in average zone | 0 %  |
| Percentage of total occupant hours with thermal dissatisfaction              | 10 % |

**Delivered Energy Overview**

|                          | Purchased energy |                    | Peak demand |
|--------------------------|------------------|--------------------|-------------|
|                          | kWh              | kWh/m <sup>2</sup> | kW          |
| ■ Lighting, facility     | 16               | 0.1                | 0.2         |
| ■ Electric cooling       | 77               | 0.5                | 0.94        |
| ■ HVAC aux               | 12               | 0.1                | 0.08        |
| Total, Facility electric | 105              | 0.7                |             |
| ■ Fuel heating           | 437              | 3.1                | 3.57        |
| ■ Domestic hot water     | 0                | 0.0                | 0.0         |
| Total, Facility fuel*    | 437              | 3.1                |             |
| Total                    | 542              | 3.8                |             |
| □ Equipment, tenant      | 200              | 1.4                | 1.4         |
| Total, Tenant electric   | 200              | 1.4                |             |
| Grand total              | 742              | 5.3                |             |

(a) Energy consumption breakdown under PI control

|                                                                                     |                                                 |                                |                                       |
|-------------------------------------------------------------------------------------|-------------------------------------------------|--------------------------------|---------------------------------------|
|  |                                                 | <b>Delivered Energy Report</b> |                                       |
| <b>Project</b>                                                                      |                                                 | <b>Building</b>                |                                       |
| Customer                                                                            |                                                 | Model floor area               | 141.1 m <sup>2</sup>                  |
| Created by                                                                          |                                                 | Model volume                   | 367.0 m <sup>3</sup>                  |
| Location                                                                            | Stockholm (Bromma Airport)_024640 (ASHRAE 2013) | Model ground area              | 0.0 m <sup>2</sup>                    |
| Climate file                                                                        | SWE_STOCKHOLM-BROMMA_024640 (IW2)               | Model envelope area            | 93.1 m <sup>2</sup>                   |
| Case                                                                                | Testbed_KTH floor_Winter_Occ Testbed 2.0        | Window/Envelope                | 18.2 %                                |
| Simulated                                                                           | 13/06/2025 10:38:08                             | Average U-value                | 0.4521 W/(m <sup>2</sup> K)           |
|                                                                                     |                                                 | Envelope area per Volume       | 0.2537 m <sup>2</sup> /m <sup>3</sup> |

**Building Comfort Reference**

|                                                                              |     |
|------------------------------------------------------------------------------|-----|
| Percentage of hours when operative temperature is above 27°C in worst zone   | 0 % |
| Percentage of hours when operative temperature is above 27°C in average zone | 0 % |
| Percentage of total occupant hours with thermal dissatisfaction              | 9 % |

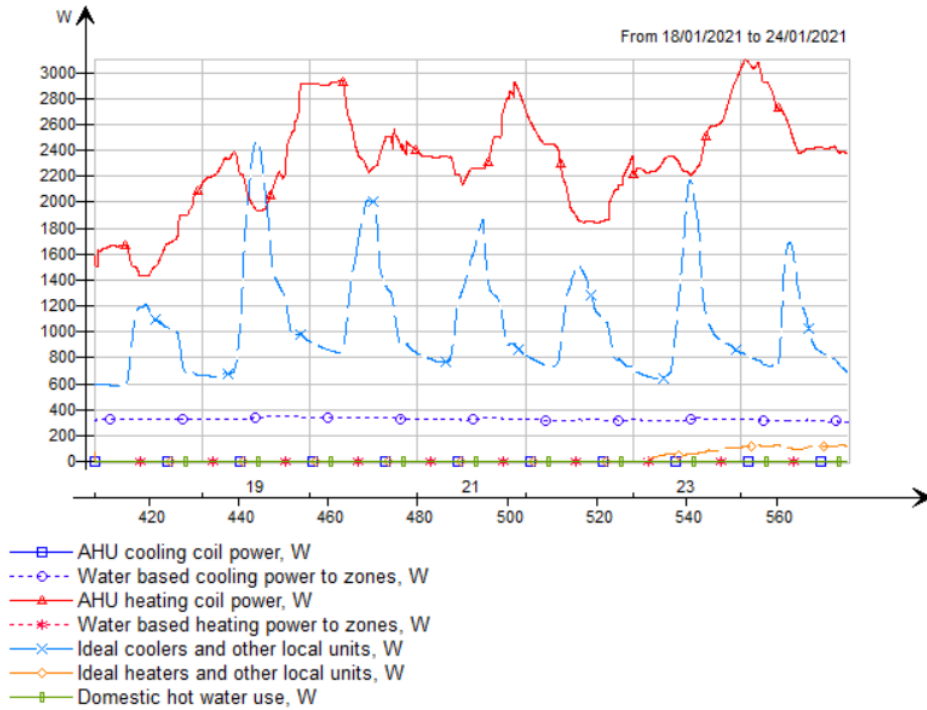
**Delivered Energy Overview**

|                          | Purchased energy |                    | Peak demand |
|--------------------------|------------------|--------------------|-------------|
|                          | kWh              | kWh/m <sup>2</sup> | kW          |
| ■ Lighting, facility     | 16               | 0.1                | 0.2         |
| ■ Electric cooling       | 36               | 0.3                | 0.25        |
| ■ HVAC aux               | 13               | 0.1                | 0.16        |
| Total, Facility electric | 65               | 0.5                |             |
| ■ Fuel heating           | 520              | 3.7                | 4.64        |
| ■ Domestic hot water     | 0                | 0.0                | 0.0         |
| Total, Facility fuel*    | 520              | 3.7                |             |
| Total                    | 585              | 4.1                |             |
| □ Equipment, tenant      | 200              | 1.4                | 1.4         |
| Total, Tenant electric   | 200              | 1.4                |             |
| Grand total              | 785              | 5.6                |             |

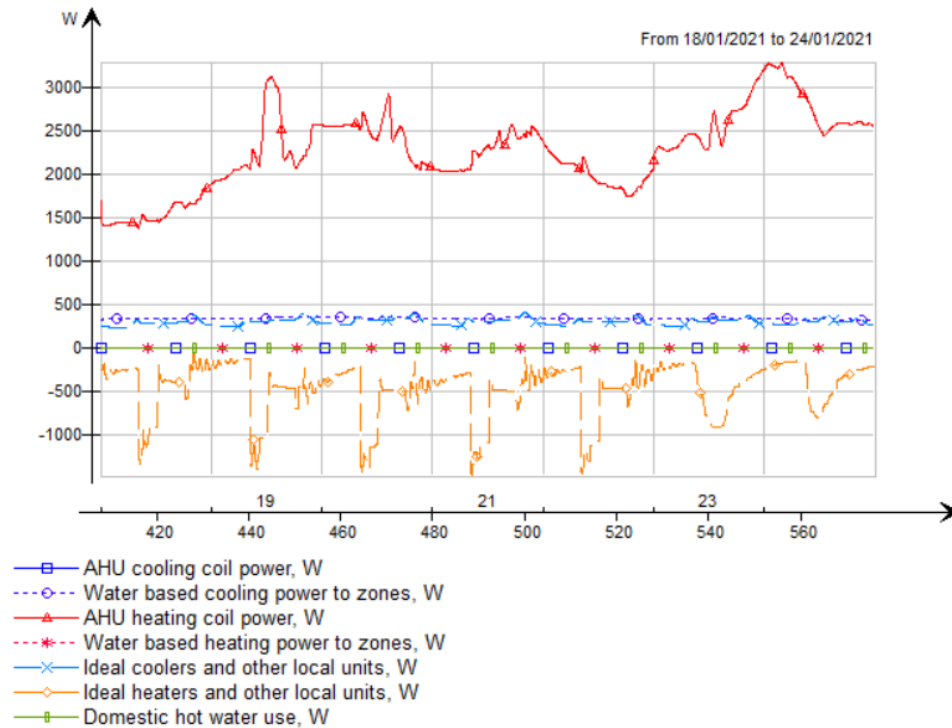
(b) Energy consumption breakdown under Feedback control

Figure 5.23: Energy consumption breakdown under different controls

## 5.7. SIMULATION



(a) HVAC system power demand over time under PI control



(b) HVAC system power demand over time under Feedback control

Figure 5.24: HVAC system power demand over time under different controls

# 6

## Conclusions and Future Works

### 6.1 CONCLUSION

The aim of this work was to explore advanced control strategies for optimizing thermal comfort in shared indoor environments, with particular attention to balancing user satisfaction and energy consumption.

Despite considerable energy usage, it is often observed that many building occupants still experience discomfort due to suboptimal thermal conditions. To address this issue, a Feedback Thermal control strategy was developed, with the goal of enhancing user comfort through improved temperature regulation.

Following the introduction of the motivations and the current research context in Chapter 1, Chapter 2 presented the methodology for developing building models using the 2R1C technique, supported by a physical derivation of the model. The focus then shifted from modeling the components of the building to analyzing the impact of external disturbances on indoor conditions.

The core of the work began with the formulation of a thermal model in Simulink, which integrated realistic building parameters and human thermal comfort preferences, as described in Chapter 3. Building upon this foundation, we implemented two different control strategies, PI control and a feedback-based approach, within the IDA-ICE simulation environment, as presented in Chapter 5. This allowed us to evaluate their performance under realistic building operation scenarios.

In summary, this thesis offers a solid foundation for user-centric climate control in buildings. By combining theoretical modeling, simulation tools, and control system design, the work contributes toward the development of more adaptive,

## 6.2. FUTURE WORK

responsive, and sustainable indoor environments.

### 6.2 FUTURE WORK

Building upon the results of this thesis, several promising directions for future research can be explored. One important development would be the integration of predictive control techniques, such as Model Predictive Control (MPC), which could enhance the management of thermal comfort by anticipating heating or cooling needs based on weather forecasts, user behavior patterns, and occupancy schedules. This would allow for more efficient energy use while maintaining comfort over time.

Another critical step would be the validation of the proposed control strategies in real-world settings. Implementing these approaches in an actual building with physical HVAC systems would help verify the simulation results, assess their practical feasibility, and identify challenges such as sensor inaccuracies, communication delays, and the variability of user behavior.

Additionally, the use of machine learning algorithms offers a promising avenue to better interpret user feedback. By analyzing patterns in occupant responses, the control system could adapt to individual thermal preferences over time, improving comfort and energy efficiency even with limited direct input from users.

It would also be valuable to investigate the design and usability of the user interface used for feedback collection. Studying how occupants interact with the system, whether through mobile applications, physical controls, or other interfaces, can help improve engagement and ensure the feedback collected is meaningful and consistent.

Finally, future research could focus on refining the discomfort function used in both simulation and control. Moving beyond simple metrics like temperature deviation, more sophisticated discomfort models could incorporate factors such as humidity, air velocity, clothing levels, and the users recent thermal history. A more accurate representation of discomfort would enable the design of smarter and more responsive thermal comfort systems.

## References

- [1] Caruso Acoustic. “Acoustic comfort in indoor areas: why is it important?” In: 2021.
- [2] Yousef Al Horr et al. “Impact of indoor environmental quality on occupant well-being and comfort: A review of the literature”. In: *Journal of Building Engineering*. Elsevier, 2016.
- [3] American Society of Heating, Refrigerating and Air-Conditioning Engineers. “ASHRAE Standard 55-2010: Thermal Environmental Conditions for Human Occupancy”. In: *ASHRAE Standards and Guidelines*. 2010.
- [4] A. M. Annaswamy et al. “Cyber-Physical-Human Systems: Fundamentals and Applications”. In: 2022.
- [5] ArchDaily. “Lighting and Visual Comfort Solutions in Residential Projects”. In: 2021.
- [6] K. Arendt et al. “Comparative analysis of white-, gray- and black-box models for thermal simulation of indoor environment: Teaching building case study”. In: *Proceedings of the 2018 Building Performance Modeling Conference and SimBuild co-organized by ASHRAE and IBPSA-USA, Chicago, IL, USA*. 2018, pp. 26–28.
- [7] A. Aryal and B. Becerik-Gerber. “Energy consequences of comfort-driven temperature setpoints in office buildings”. In: *Energy and Buildings*. Vol. 177. Oct. 2018, pp. 33–46. doi: 10.1016/j.enbuild.2018.08.025.
- [8] S. Attia. “NZEB Case Studies and Learned Lessons”. In: *Net Zero Energy Buildings (NZEB)*. Elsevier, 2018, pp. 303–341. doi: 10.1016/b978-0-12-812461-1.00011-3.
- [9] N. Björnsell et al. “IDA indoor climate and energy”. In: *Proceedings of the 6th IBPSA Conference*. 1999, pp. 1035–1042.

## REFERENCES

- [10] Boverket. "Energy use in buildings". In: *Energy use in buildings*. 2021. URL: <https://www.boverket.se/sv/byggande/hallbart-byggande-och-forvaltning/miljoindikatorer---aktuell-status/energianvandning>.
- [11] P. Bröde et al. "Heat Gain From Thermal Radiation Through Protective Clothing With Different Insulation, Reflectivity and Vapour Permeability". In: *International Journal of Occupational Safety and Ergonomics*. Vol. 16. 2. Jan. 2010, pp. 231–244. DOI: 10.1080/10803548.2010.11076842.
- [12] A. Bryson. "Applied Optimal Control: Optimization, Estimation, and Control". In: *Hemisphere Pub. Corp. Distributed by Halsted Press*. Washington, New York, 1975. ISBN: 9780891162285.
- [13] T. Cheung, W. T. de Dear, and R. C. D. Parkinson. "Effect of Thermal Comfort on Productivity and Health: A Systematic Review". In: *Buildings*. Vol. 7. 2. 2017, p. 36. DOI: 10.3390/buildings7020036. URL: <https://www.mdpi.com/2075-5309/7/2/36>.
- [14] European Environment Agency. "Energy and Buildings". In: *European Environment Agency - Climate & Energy*. 2021. URL: <https://climate-energy.eea.europa.eu/topics/energy-1/energy-and-buildings>.
- [15] Yuan Fang et al. "Study of Human Thermal Comfort for CyberPhysical Human Centric System in Smart Homes". In: *Sensors*. MDPI, 2020. DOI: 10.3390/s20020372. URL: <https://www.mdpi.com/1424-8220/20/2/372>.
- [16] P. O. Fanger. "Thermal Comfort: Analysis and Applications in Environmental Engineering". In: *McGraw-Hill*. New York, 1972. ISBN: 9780070199156.
- [17] William J Fisk. "Health and productivity gains from better indoor environments and their relationship with building energy efficiency". In: *Annual Review of Energy and the Environment*. Annual Reviews, 2000.
- [18] G. Fraisse et al. "Development of a simplified and accurate building model based on electrical analogy". In: *Energy and Buildings*. Vol. 34. 10. Nov. 2002, pp. 1017–1031. DOI: 10.1016/s0378-7788(02)00019-1.
- [19] I. Hazyuk, C. Ghiaus, and D. Penhouet. "Optimal temperature control of intermittently heated buildings using Model Predictive Control: Part I Building modeling". In: *Building and Environment*. 2012.
- [20] W. Hes. "The dependent variable in thermal comfort research: some psychological considerations". In: *Building Research Establishment Reports*: Vol. 264. 1994.

- [21] IAQ.Works. "Carbon Dioxide: Indoor Air Quality Explained". In: 2021.
- [22] TSI Incorporated. "Enhancing Indoor Environmental Quality: Understanding the Significance of Sound and Noise". In: 2021.
- [23] Frank P. Incropera et al. "Fundamentals of Heat and Mass Transfer". In: Hoboken, NJ: Wiley, 2007.
- [24] Svenska institutet. "Svenska institutet: 1945-1960: 15 års upplysningsarbete, utveckling, förnyelse, resultat". Swedish. In: *Svenska institutet*. Stockholm, 1960, p. 29.
- [25] H. Johra, P. Heiselberg, and J. Le Dréau. "Numerical analysis of the impact of thermal inertia from the furniture/indoor content and phase change materials on the building energy flexibility". In: *Proceedings of 15th IBPSA Conference, International Building Performance Simulation Association*. San Francisco, CA, USA, 2017. doi: <https://doi.org/10.26868/25222708.2017.012>.
- [26] W. Jung and F. Jazizadeh. "Human-in-the-loop HVAC operations: A quantitative review on occupancy, comfort, and energy-efficiency dimensions". In: *Applied Energy*. 2019.
- [27] Targo Kalamees, Jarek Kurnitski, and L. Eskola. "IDA-ICE: The simulation tool for whole-building energy and HAM analysis". In: *ResearchGate*. 2006. URL: [https://www.researchgate.net/publication/241254031\\_IDA\\_ICE\\_the\\_simulation\\_tool\\_for\\_making\\_the\\_whole\\_building\\_energy\\_and\\_HAM\\_analysis](https://www.researchgate.net/publication/241254031_IDA_ICE_the_simulation_tool_for_making_the_whole_building_energy_and_HAM_analysis).
- [28] KTH Live-In Lab. "Testbeds for Increased Innovation in the Construction and Real Estate Sector". In: 2021.
- [29] Huibert Kwakernaak and Raphael Sivan. "Linear Optimal Control Systems". In: New York: Wiley-Interscience, 1972.
- [30] Edward A. Lee. "Introduction to Embedded Systems: A Cyber-Physical Systems Approach". In: *MIT Press*. Cambridge, MA, 2017.
- [31] X. Li and J. Wen. "Review of Building Energy Modeling for Control and Operation". In: *Renewable and Sustainable Energy Reviews*. 2014. doi: [10.1016/j.rser.2014.05.056](https://doi.org/10.1016/j.rser.2014.05.056).

## REFERENCES

- [32] P. Lyons, D. Arasteh, and C. Huizenga. "Window performance for human thermal comfort". In: *Transactions-American Society of Heating Refrigerating and Air Conditioning Engineers*. Vol. 106. 1. 2000, pp. 594–604.
- [33] Norsk Standard. "Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria (ISO 7730:2005)". In: [Online]. Mar. 2006.
- [34] Rajesh K Rajkumar et al. "Cyber-Physical Systems: The Next Computing Revolution". In: *Design Automation Conference*. IEEE, 2010, pp. 731–736.
- [35] D. Rolando, W. Mazzotti Pallard, and M. Molinari. "Long-Term Evaluation of Comfort, Indoor Air Quality and Energy Performance in Buildings: The Case of the KTH Live-In Lab Testbeds". In: *Energies*. 2022. doi: 10.3390/en15144955.
- [36] P. Sahlin and E.F. Sowell. "A Neutral Format for Building Simulation Models". In: 1989.
- [37] P. H. Shaikh et al. "A review on optimized control systems for building energy and comfort management of smart sustainable buildings". In: *Renewable and Sustainable Energy Reviews*. Elsevier, 2016.
- [38] P. Strachan. "Energy use and environmental impact of buildings: A detailed simulation approach". In: *Building and Environment*. 2000.
- [39] Austrian Institute of Technology. "Advanced modeling techniques in IDA-ICE for HVAC simulation". In: *AIT Research Paper*. 2014.
- [40] uHoo. "Understanding CO2 Levels: A Key Indicator of Indoor Air Quality". In: 2021.