AN INVESTIGATION INTO THE BUILDING PERFORMANCE IMPACT OF OCCUPANT BEHAVIOR THROUGH ENERGY SIMULATIONS

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by
Rümeysa DEMİR

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İZMİR

We approve the thesis of **Rümeysa DEMİR**

Examining Committee Members:

Prof. Dr. Mustafa Emre İLAL
Department of Architecture, İzmir Institute of Technology

Doç. Dr. Zeynep Durmuş ARSLAN
Department of Architecture, İzmir Institute of Technology

Prof. Dr. Ayça TOKUÇ
Department of Architecture, Dokuz Eylül University

8 December 2023

Prof. Dr. Mustafa Emre İlal
Supervisor, Department of Architecture,
İzmir Institute of Technology

Prof. Dr. Koray KORKMAZ
Head of Department of Architecture

Prof Dr. Mehtap EANES
Dean of the Graduate School of
Engineering and Sciences

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ABSTRACT

AN INVESTIGATION INTO THE BUILDING PERFORMANCE IMPACT OF OCCUPANT BEHAVIOR THROUGH ENERGY SIMULATIONS

The building industry greatly impacts worldwide energy consumption. Residential energy use is significant, making it a key area for energy efficiency and environmental concerns. Building simulation tools are used to predict energy consumption. One shortcoming of simulations that are employed is that building occupants are assumed to behave uniformly. This study explores the potential of including variability of occupant behavior in building simulation models and its impact on the accuracy and reliability of simulation results. Actual consumption data and energy simulation results are used in tandem to investigate this topic. The first phase involved a seven-week monitoring program in a dormitory where each room was equipped with an independent air-conditioning unit. The goal was to record and analyze electricity consumption that included this heating system. The second phase of the study explored occupant behavior. Each room was simulated using schedules representing three different behavior patterns: frugal, standard, and wasteful. Finally, simulation results are compared with actual data. The margin of error in the DesignBuilder standard scenario varies between 4% and 38%, while the average margin of error is 16%. In the frugal scenario, occupants could save 30% to 70% of their energy, with an average savings of 50% possible. For the standard scenario, rooms offer an average saving potential of 16%, and in the wasteful scenario, only one room offers a saving potential of 13%. The results of the study underlines the need for considering the variability in occupant behavior in simulation models.

ÖZET

KULLANICI DAVRANIŞLARININ BİNA PERFORMANSINA ETKİLERİNİN ENERJİ BENZETİMLERİYLE İNCELENMESİ

İnşaat sektörü dünya çapında enerji tüketimini ve sera gazı emisyonlarını büyük ölçüde etkilemektedir. Konutlarda enerji kullanımı önemlidir ve bu da onu enerji verimliliği ve çevresel kaygılar açısından kilit bir alan haline getirmektedir. Enerji tüketimini tahmin etmek için bina benzetim araçları kullanılır. Kullanılan benzetim modellerinin bir eksikliği, bina kullanıcılarının aynı şekilde davrandıklarının varsayılmasıdır. Bu çalışma, bina benzetim modellerine bina kullanıcılarının davranışının değişkenliğini dahil etme potansiyelini ve bunun benzetim sonuçlarının doğruluğu ve güvenilirliği üzerindeki etkisini araştırmaktadır. Konuyu araştırmak için gerçek tüketim verileri ve enerji benzetim sonuçları birlikte kullanılmıştır. İlk aşamada, her odanın bağımsız bir klima ünitesiyle donatıldığı bir yurtta yedi haftalık bir sürede tüketim verisi toplandı. Amaç, ısıtma sistemini de içeren elektrik tüketimini kaydetmek ve analiz etmekti. Araştırmanın ikinci aşamasında bina kullanıcılarının davranışları araştırıldı. Her odanın tutumlu, standart ve savurgan olmak üzere üç farklı davranış modelini temsil eden çizelgeler kullanılarak benzetimleri yapıldı. Son olarak benzetim sonuçları gerçek tüketim verileriyle karşılaştırıldı. Sonuçlara göre Design-Builder standart senaryosunda hata payı odalara göre %4 ile %38 arasında değişirken, ortalama hata payı %16'dır. Tutumlu senaryoda, bina sakinleri tükettikleri elektriği %30’dan %70'e kadar tasarruf edebilir ve ortalama %50'lik bir tasarruf mümkün olabilir. Standart senaryoda odalar ortalama %16'lık bir tasarruf potansiyeli sunarken, israf senaryosunda yalnızca bir oda %13'lük bir tasarruf potansiyeli sunuyor. Çalışmanın sonuçları, simülasyon modellerinde bina sakini davranışındaki değişkenliğin dikkate alınması gerektiğinin altını çizmektedir.

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CHAPTER 1

INTRODUCTION

1.1. Problem Definition

Since the building sector has a large share in the energy consumed worldwide, it offers significant energy saving potential. While the total final energy consumption of the global building sector is %35, CO_2 emissions from the operation of buildings, with the inclusion of emissions from the building construction industry, is 38% of total global energy-related CO_2 emissions (United Nations Environment Program, 2020). Building energy consumption in residential sector is responsible for a large part of the total energy consumption. In the sectoral distribution of final energy consumption in Turkey, the residential and services sector has increased every year. The residential and services sector, along with the industrial sector, accounted for the highest proportion of final energy consumption in Turkey in 2022. (Republic of Turkey Ministry of Energy and Natural Resources, 2022). In addition, electricity demand, which was approximately 305 TWh in 2020, is expected to be in the 545-636 TWh band with an annual average increase rate of 2.9-3.7% over the next 20 years.

Energy consumption in residential buildings is similarly increasing. This high energy use in buildings varies due to factors such as climate, building envelope, and activities of building occupants. These factors can be grouped under two main headings: First, the use of climatically incompatible designs, and second, the occupants' energy-unconscious behavior (Al-Mumin et al., 2003; Cheng & Vincent J. L., 2013). For the first factor, the problem can be overcome with construction techniques and quality building materials, but the second factor, user behavior and lifestyle choices, is often ignored (Bourgeois, Reinhart, and Macdonald 2006). Although design standards for energy efficient buildings become more stringent, overall building energy use does not decrease but rather increases, driven by the behavior and lifestyles of building occupants (Chen et al., 2015). Although, the field of detailed exploration into occupant behavior is relatively young, research has shown that there is significant potential for energy savings (Naylor et al., 2018). Therefore, in order to reduce energy use in buildings, it is important to consider building characteristics together with occupant behaviors and lifestyles.

1.2. Aim of The Study

The main objective of this study is two-fold. The primary objective is to evaluate the precision and dependability of energy simulation software through a comparative analysis of actual electricity consumption data and simulated outcomes. This assessment aims to offer an analysis of the accuracy and reliability of energy simulation tools, thereby confirming their efficacy as significant resources for predicting and improving energy efficiency in the construction industry. The secondary objective of this study is to examine the significant influence of occupant behavior on the energy performance of buildings. Through the examination of occupant behavior within enclosed spaces and the analysis of various occupant profiles, such as frugal, standard, and wasteful inhabitants, this study aims to reveal the underlying energy-saving potential associated with occupant actions. The study aims to emphasize the crucial importance of adopting a complete strategy for energy efficiency in the building industry by addressing these two objectives simultaneously. This statement underscores the need to take into account both the attributes of buildings and the actions of occupants while striving for sustainable and energy-efficient living environments. The study's primary contribution is in its utilization of simulation techniques to advance the modernization of the construction industry. By employing this approach, the research endeavors to create practical architectural elements that closely resemble those found in real-world scenarios. This, in turn, facilitates the reduction of energy consumption and the advocacy of sustainable living habits.

1.3. Research Questions

The study examines the impact of occupant behavior on the energy efficiency of buildings and investigates the varying degrees of energy-saving potential related with different occupant profiles, namely those characterized as frugal, standard, and wasteful occupants.

1- What is the extent of accuracy displayed by energy simulation tools in modeling and predicting the energy consumption of dwellings, and how do their outcomes compare with actual electricity consumption statistics in real-world scenarios?
2- How does the impact on building performance change as user behavior changes in simulation programs? How effective is user behavior in saving energy?

The comparison between real-world power usage data and the outcomes of energy simulations has yielded significant insights and conclusions. These findings have the potential to inspire policies aimed at enhancing energy efficiency in residential structures.

The study focuses on investigating the relationship between occupant behavior, energy simulation accuracy, and building energy performance. By addressing these research questions, the study aims to enhance our understanding of this relationship and its implications for energy conservation strategies in the construction industry.

1.4. Methodology

The study provides a comprehensive research approach that integrates monitoring and simulation techniques to examine the significant influence of occupant behavior on building performance. The study was carried out in the "İYTE Yaşam Merkezi" dormitory located at the Izmir Institute of Technology, A total of nine rooms were selected for the study. When choosing the rooms, care was taken to ensure that they were on different floors, had different numbers of users and different genders. The monitoring phase lasted for a duration of seven weeks, commencing on December 13, 2022, and ended on January 9, 2023. Actual electricity consumption data was provided by the dormitory administration. Daily data (in kilowatt-hours) was available. Multiple variables were taken into account, encompassing the selection of building materials, details of construction, the orientation of the building, the HVAC systems employed, and the number of residents inside individual rooms. The simulations carried out using DesignBuilder software involved three distinct scenarios for each room:

Frugal Scenario: Simulating rooms with occupants exhibiting energy-conscious, frugal behavior. In this scenario, cooling and heating set points and use of electrical appliances were adjusted to reflect more conservative usage.

Standard Scenario: Simulating rooms with occupants exhibiting typical, standard energy behavior. This scenario was chosen entirely from the templates offered by DesignBuilder software and the user data was not changed.

Wasteful Scenario: Simulating rooms with occupants exhibiting energy-wasteful behavior. In this scenario, cooling and heating set points use of electrical appliances were set to levels indicating excessive usage.

Each of the eight rooms was simulated with these three scenarios, resulting in 24 distinct simulations. This approach facilitated the extraction of user profiles within the rooms and allowed for an assessment of the potential variation in simulation results based on occupant behavior.

CHAPTER 2

LITERATURE REVIEW

2.1. Occupant behavior

Under the heading of Occupant Behavior, a number of studies exploring the effects of building occupant behaviors on energy performance have been examined. The literature hosts a wide range of research, from efforts to understand building occupant behavior to energy saving strategies and evaluation of psychological effects. As an example, the study by (Peschiera et al., 2010) represents an example where behavioral changes were examined by providing personal usage data to building occupants. Additionally, Kazar's (2015) study examining a student dormitory in Turkey evaluated changes in energy consumption using grouping methods. These studies highlight the complexity of building occupant behavior to energy performance while also revealing energy saving potential. This summary provides a comprehensive overview of research conducted to better understand the role of building occupant behavior in energy consumption.

Research on occupant behavior that can be characterized as the existence of people in the building and their activities that influence the indoor environment, is increasing (Hoes et al., 2009). Occupant behavior is determined in literature to be the main source of failure to save on energy consumption in buildings. Research varies in the exploration of occupant behavior and energy performance (Zhang et al. 2018) . These efforts can be collected under four headings: First one is related to the environmental psychology of occupant. Second one focuses on developing and testing strategies and methods to reduce energy use. The third one tries to characterize occupant attitudes. The fourth one focuses on energy efficient buildings by using models of occupant behavior.

Some studies focus on the occupancy of user before the occupant behavior, for example Mahdavi and Tahmasebi (2015) developed occupancy models for two different scenarios to predict future user behavior with monitored long-term historical data from the office. The prediction accuracy for its behavior turned out to be quite low. Results show low accuracy of strategies to predict the occupancy of office users with historical data. In another study conducted by Masoso and Grobler (2010), a monitoring study focusing on energy consumption during non - working hours was carried out in 5 different offices. It showed that while 44% of energy is consumed in total during working hours, the energy consumption is 56% during non - working hours and that energy consumption is higher when there is no occupancy. This is due to the user forgetting to turn off the equipment, revealing the occupancy role in energy consumption from buildings. It would be more efficient to improve user behavior rather than employ technological measures to reduce energy consumption (Ouyang & Hokao, 2009). It has been seen that electricity consumption can be reduced more than 10% by improving occupant behavior through energy-savings education.

Some studies focus on psychological aspects of occupant behavior in buildings that affect energy use. Peschiera et al. (2010) conducted a study on the alteration of occupant behavior, where data on personal electricity usage was provided to occupants. They examined 83 dormitory rooms located on the same floors and grouped the occupants into 3 groups. While the first group had the data of their own electricity use, the second group had the data of their own electricity and average use, on the other hand, the last group had the data of their own electricity with both average occupant utilization with the electricity use of their peer network in the building. Results showed that only the group which had the data of their peer network reduced their electricity use. Another similar research was conducted by Petersen et al. (2007). While they provided to first group dormitory residents with real-time web-based feedback on energy and water use, they provided to second group with residents once per week. Results show that first group of students reduced their electricity consumption by 55 percent compared to 31 percent for the second group in dormitories.

In the literature, the role of the user in energy consumption was investigated not only from survey data, but also using advanced technology. Kim et al. (2018) developed the PCS (Personal comfort systems) model, a new type of feedback, using 6 machine learning algorithms that can effectively predict individuals' thermal preferences to improve occupant satisfaction and energy use in buildings. Marzban et al. (2016) also developed a method to optimize the façade systems to minimize the cooling energy system. To achieve this, they studied the users' interaction with the facade using genetic algorithms and artificial neural networks.

Dormitories on university campuses are significant residential building types in energy retrofit studies because residents have free access to electricity, hot water, and other energy-intensive appliances, so they are less likely to think about energy efficiency in their daily routines and activities. One study analyzed the behavioral models of two dormitories at Oregon University in the United States and discovered no discernible differences in OEBs (Occupant Energy Behavior) between the newer and the older buildings (Collins, 2010). In Turkey Kazar, (2015) conducted a quantitative study analyzing the impact of the behavior of occupants on the annual energy consumption with 529 students. The users were divided into 3 different groups as A, B, and C through clustering. The first analysis was made assuming that all the users in the dormitory rooms were from group A, and the second analysis was made considering that all students belonged to group B and the third analysis was made accepting that they belonged to group C. In the 4th analysis, the actual distribution of students in the dormitory building was considered. The 5th and 6th analyses were made with the default assumptions of energy analysis programs such as DesignBuilder and Green Building Studio. The results showed that the effect of occupancy can create changes in energy consumption up to 81%. In another study conducted in China, energy saving scenarios under different strategies were simulated using the basic knowledge of students in the dormitory, their stay in the dormitory and their device usage behaviors. The findings reveal that occupancy is the most significant factor for dormitory energy consumption, reducing the amount of time an air conditioner is used, reducing computer standby time. Students' attitudes toward and awareness of energy conservation as well as communication and exchange of energy information among students are significant factors in energy conservation (Ding et al. 2019).

To summarize, the literature review on occupant behavior shows that studies have focused on a variety of aspects of the topic. From studies that attempt to predict how people will act in different situations (Mahdavi & Tahmasebi, 2015) to studies that look at how psychological factors affect energy use (Peschiera, Taylor, and Siegel 2010a), it is clear that the role of building occupants is an essential variable affecting how effectively buildings use energy. Most recently, researchers have started to use advanced technologies, such as machine learning methods (Kim et al., 2018).

2.2. Occupant Behavior Parameters

Occupant behavior parameters, which define the complex relationships between building occupants and adjustable elements, have a crucial impact on describing the indoor environment and affecting the energy efficiency of buildings. The complex character of occupant behavior can be described by three major parameters (Chen et al., 2015).

Occupancy by Users:

This parameter is fundamental to understanding the dynamics of building utilization. Occupancy, which is evaluated as a binary state of being either occupied or unoccupied, establishes the foundation for the utilization of different building services and energy systems. Building service and energy systems involve a range of tasks such as heating, cooling, ventilation, cooking, and using household electric equipment. The inhabitants' involvement with these systems reflects their different approaches, which can be characterized as frugal, standard, and wasteful (Yogi et al., 2017).

Operation modes of building and energy systems:

Second parameter is about how the building's energy and service systems work, including heating, cooling, ventilation, cooking, hot water, and electric tools in the residence. The operation of building services and energy systems is closely tied to occupant behavior. HVAC control strategies, such as ventilation, thermostat set points, and indoor thermal environment, significantly affect energy consumption. In addition to energy systems such as heating, cooling, and lighting, cooking and home appliances consume significant energy. Ovens, stoves, refrigerators, computers, hairdryers, and other household appliances should be carefully examined for energy efficiency. How building occupants use these devices has an important place in user behavior parameters, as it will greatly impact energy savings.

User-system interactions:

Occupants take an active role in adjusting the position of windows, curtains, and blinds to enhance thermal and visual comfort. These modifications have the potential to enhance comfort levels while also saving energy. In addition to occupancy and system operation, this parameter explores the physical adaptations that inhabitants make to the building environment.

The interaction of the occupier with adjustable windows, lights, blinds, thermostats, and plug-in devices is referred to as "occupant behavior" (Heydarian et al., 2015). To reach the desired level of comfort inside a building, an occupant interacts with the energy and systems of the building; this has a direct impact on how well building's function and how much energy they use.

Chen et al. (2015) categorized styles of occupant behavior into three. The actions of occupants in opening windows, changing curtains, and controlling blinds demonstrate a range of energy-use workstyles, spanning from energy-conscious frugal to typical practices, and at the opposite end, wasteful behaviors (Chen et al., 2015). Table 1 describes the differences between the three workstyles of "Frugal", "Standard", and "Wasteful" in terms of simulation parameters used in their study.

Table 1. Occupant behavior categorized into workstyles

	Frugality	**Standard**	**Wasteful**
Cooling set point	26	24	22
Heating set point	18	21	23
Adaptive comfort	yes	no	no
Occupancy controls	If unoccupied, turn off lights and HVAC, turn down plug load 30%	Scheduled	Leave everything. on: lights, HVAC, and plug load
Daylight controls	Dimming	no	no
HVAC operation time	Turn on 1 hour late and turn off 1 hour early: 9 am to 4 pm	Scheduled Follow	Same as whole building schedule Same

2.3. Building characteristics and occupant behavior

Although there are many parameters that affect user behavior, the characteristics of the building are one of the most important (Guerra Santin et al., 2009) . Bekö et al. (2011) analyzed the relationship between air change rate (ACR) data obtained from 500 bedrooms and data on occupant behavior obtained from questionnaires. Results of their regression showed that variables related to occupant behavior were stronger predictors of ventilation rate than those related to building characteristics. In addition, the smaller the room and the number of people sleeping in the room, the higher the habit of opening windows and doors, the higher the ACR rate.

Similar research has investigated the effect of decisions of occupants on building characteristics. Guerra Santin et al. (2009) shows that building occupants' characteristics and behavior significantly affect energy use (4.2%), but building characteristics still determine a large portion (42%) of energy use in a residence.

Another study was conducted by Commercial Building Energy Consumption Survey (CBES) in the US in 2003 to analyze the impact of occupant behavior on the energy performance. Building characteristics included number of floors, construction material, and window to wall ratio. Results showed that "heating temperature setpoint" is the most influential feature that affects the building energy performance.

2.4. Data collection methods

There has been significant progress in the area of data collection techniques to understand the impact of occupant behavior on energy consumption in buildings. This includes techniques for measuring (a) occupant movement and presence, (b) thermal comfort, (c) window shades and blinds, and (d) lighting and electrical equipment. This data is used to determine the influence of occupant behavior on the energy performance of buildings through energy simulation. The data collection process involves a variety of information sources such as weather stations, building energy and lighting management systems, and custom sensors (Hong et al., 2015).

2.5. Energy Simulation Software

Building simulation tools can be used to predict and study how much energy is used in buildings. These technologies allow evaluation of building performance, allowing researchers and professionals to evaluate the effects of different design and operational characteristics. Several modeling tools have been developed over the years to model and test building energy systems. DesignBuilder is one such comprehensive building simulation software that has gained popularity in the field of building performance analysis. DesignBuilder can be used to model environmental performance, thermal comfort, and energy use. With a user-friendly graphical interface, the software allows users to create detailed building models, define energy efficient strategies, and assess the overall sustainability of a structure.

DesignBuilder utilizes EnergyPlus as its simulation engine. The EnergyPlus v9.4 engine with several performance and feature improvements is included with DesignBuilder v7. ("DesignBuilder Software Ltd", 2023). EnergyPlus, the main building energy modeling engine developed by the Department of Energy, replaces DOE-2 and can be freely accessed as open-source software. This tool facilitates comprehensive examination of energy consumption, maximum power requirements, water utilization, and renewable energy sources for intricate architectural plans, specifically focusing on systems such as radiant cooling/heating, underfloor air distribution, natural ventilation, and window shading (Haves, Ravache, and Yazdanian 2020). Using the combination of DesignBuilder and EnergyPlus, building models and data can be entered, and thorough simulation results can be obtained.

In addition, DesignBuilder has successfully completed the validation test, validating its consistency in terms of temperatures and energy flow with other simulation software. Therefore, the results obtained from the simulations conducted in DesignBuilder are accurate and suitable for studies. Details of ANSI/ASHRAE standard 140-2020 (aka BESTTEST) validation test results for DesignBuilder and Energy Plus can be found in the documents section on DesignBuilder's website. (DesignBuilder. Download. ASHRAE 140-2020 / BESTEST Results for DesignBuilder v7.0, 15 August 2022. https://designbuilder.co.uk/download/documents (accessed 2023-12-30)).

2.6. Summary

The literature review indicates that occupant behavior is a significant determining factor in the energy efficiency of a building. However, it is challenging to predict how occupants will behave, leading to a large discrepancy between estimated and actual energy consumption. This has resulted in a lack of proper recognition of the impact of occupant behavior on building energy performance. The other factor identified in the literature review is that various workstyles associated with occupant behavior has been categorized according to the related level of energy consumption. The three categories are: frugal, standard, and wasteful. The other factor is related to specific parameters that are affected by occupant behavior, including cooling and heating set points, adaptive comfort, occupancy control, daylight control, HVAC operation time, and cooling startup control. This data for these parameters can be obtained from building management systems, energy management systems, surveys, case studies, and interviews with building occupants.

The studies all discuss the importance of understanding occupant behavior in relation to energy consumption in buildings. Occupant behavior refers to the interactions of the occupants with adjustable windows, lights, blinds, thermostats, and plug-in devices. These interactions have a direct impact on how well building’s function and how much energy they use. Studies have shown that adjusting occupant behavior can lead to significant energy savings. Some studies have also looked at the use of technology and advanced data analysis methods to predict and influence occupant behavior to improve energy efficiency. It is also mentioned that building occupants' characteristics and behaviours significantly affect energy use, but building characteristics still determine a large portion of energy use in a residence.

CHAPTER 3

RESEARCH METHODOLOGY

In order to better understand the uncertainties involved in building energy simulation due to occupant behavior, this research focuses on simulating a dormitory building where actual consumption data is readily available. The range of occupant workstyles adopted from literature are simulated and results are compared to actual data providing insight into energy savings potential as well as how occupant behavior should be included as a parameter in building energy simulation.

Collection of consumption data:

Electricity consumption data from the "ÜniYurt" dormitory was collected for winter 2022. In winter 2022, a seven-week period existed where outside temperatures were low enough to require heating and classes were in session. This was from November 22, 2022, to January 9, 2023. Rooms that were fully utilized in that time frame were identified and nine rooms were selected representing a wide range of orientations and adjacency conditions for modeling and simulations.

Energy Simulations:

Utilizing energy simulation tools, the study modeled the energy consumption behaviors of frugal, standard, and wasteful residents. This simulation strategy facilitated a comprehensive evaluation of both building performance and tenant behavior under varying energy usage scenarios.

3.1. The Dormitory

This research was conducted in a dormitory located in a region that displays the typical Mediterranean climate, which is categorized to have warm winters and extremely hot summers (CSA) according to the Köppen climatic classification system. (Figure 1)

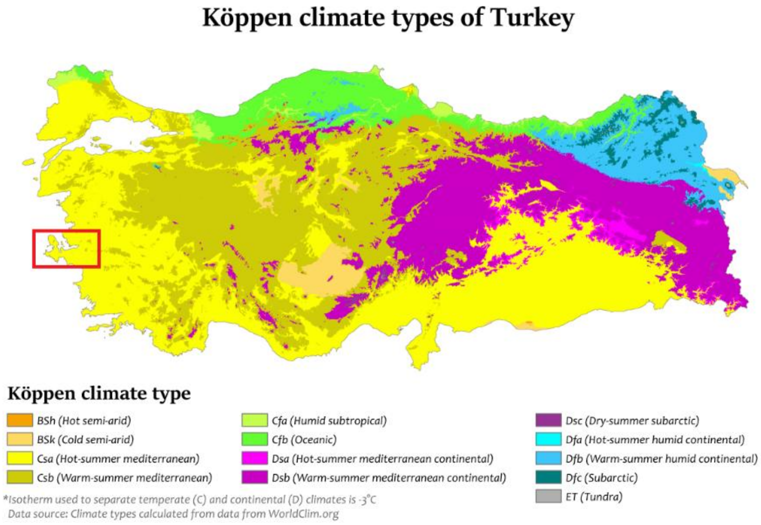


Figure 1. Köppen climate types of Turkey
(Source: Beck et al., 2018)

Within this geographical area, it is observed that the winter season has a much higher amount of precipitation compared to the summer season, therefore playing an important part in creating the climate pattern. The city of Izmir experiences an annual mean temperature of 17.1°C, accompanied by a total annual precipitation of 742 millimeters. Table 2 below shows the temperature and number of rainy days in Izmir.

Table 2. Temperature and precipitation values of Izmir province

City	Annual Average Mean Temperature (C)	Annual Average Lowest Temperature (C)	Annual Average Number of Rainy Days	Annual Average Total Precipitation (mm)
İzmir	17.1	14	7.4	12.8

The selected residence area, geographically situated in the Aegean region of Turkey, forms an integral part of the campus of İzmir Institute of Technology (İYTE).

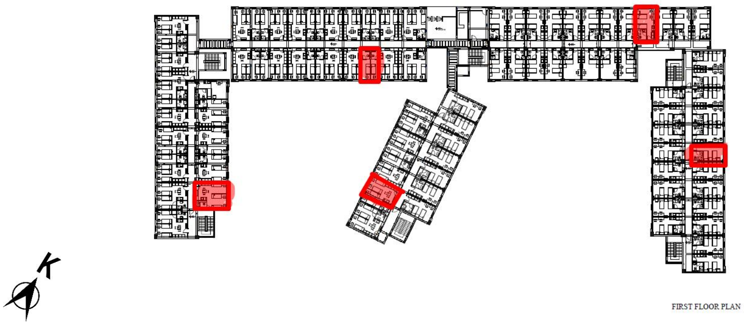
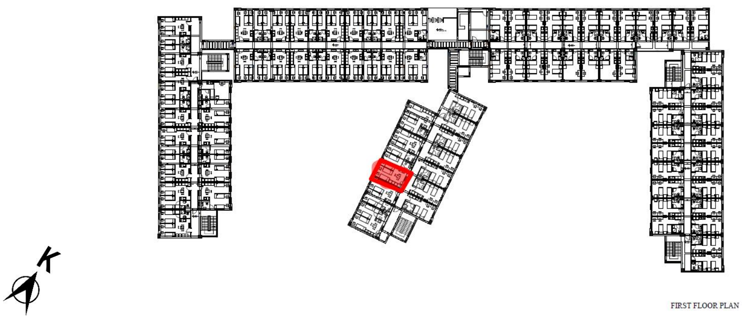
(Figure 2 and Figure 3) The dormitory is situated at a latitude of 38°.18' and a longitude of 26°.38', with an elevation of 39 meters above sea level. The dormitory consists of three levels, namely the ground floor, first floor, and second floor. It provides residential services only for students of İYTE and has a maximum capacity of 600 beds.

Figure 2. Location of İzmir in Turkey

Figure 3. Location of the dormitory

The dormitory has been built for students, providing a range of housing choices, such as single occupancy, triple occupancy, and quadruple occupancy. The facility is divided into two sections, accommodating students of both genders. The dormitory consists of a total of 221 rooms, which together offer a varied representation of physical and demographic attributes. The intentional choice of rooms based on many aspects enhances the research, enabling a detailed analysis of how spatial and demographic factors impact the energy efficiency of the building. Table 3 show the arrangement of the selected rooms based on their respective floor layouts. In order to carry out comprehensive observations, a selection process was employed to identify nine specific rooms within the student residence for simulation purposes. The subsequent section, titled "3.2. Data Collection Process," will provide further details on the analysis of the data obtained from the observed rooms.

Table 3. Selected rooms based on their respective floor layouts

Ground Floor	
1st Floor	
2nd Floor	

3.2. Data Collection Process

The specified accommodations are located within a university residence hall that has been specifically constructed to adapt to the needs of students studying at the Izmir Institute of Technology, situated in the Izmir province of Turkey. The dormitory consists of three levels, including the ground floor, the first floor, and the second floor. To get a comprehensive dataset, a systematic selection process was employed to choose rooms from various floors. This selection included 3 rooms on the ground floor, 5 rooms on the first floor, and 1 room on the second floor.

The data collection process focused on a duration of seven weeks, beginning on November 22, 2022, and concluding on January 9, 2023. This period coincides with the winter season in Izmir, wherein residents depended on air conditioning systems to fulfil their heating requirements. After the second week of January students left the campus since the semester ended.

In the study, 9 rooms were monitored. 5 rooms were designated as female dorms, while the other 4 rooms were designated as male dormitories. No mixed-gender rooms were available for the study. The observed rooms exhibited a range of occupancy levels, including arrangements accommodating one person, three people, and four people. The observations comprised of two rooms with single occupancy, three rooms with triple occupancy, and four rooms with quadruple occupancy.

The data gathering procedure included the regular monitoring of electricity usage within the specified rooms. The utilization of a detailed technique facilitated a comprehensive examination of energy usage trends across various room categories, degrees of occupancy, and gender differentiations.

Table 4. Information about selected rooms

Room number		**1005**	**3003**	**4003**	**1113**	**2110**	**3102**	**4110**	**5113**	**3203**
Floor	Ground floor	x	x	x						
	1^{ST} Floor				x	x	x	x	x	
	2^{ND} Floor									x
Occupant Number	1		x						x	
	3					x		x		x
	4	x		x	x		x			
Gender	Women			x			x	x	x	x
	Man	x	x		x	x				
Orientation		SW	W	SE	NE	SE	W	NW	NE	W

During the course of data collection, it was seen that the data obtained from one out of the nine rooms that were selected exhibited an unexplained anomaly. The room designated as Room 3003, located on the ground floor, had a total electricity use of only 51 kWh for the course of the experiment. As a result, that particular room was removed from the analysis, and simulations were performed on the remaining eight rooms.

The rooms are heated through the utilization of air conditioning systems. On the other hand, interviews with individuals inhabiting the rooms revealed that, owing to the limited dimensions of the spaces and periodic cooking actions, the rooms maintained sufficient heat without necessitating excessive use of air conditioning even during colder seasons. However, the heating demands exhibited significant variations depending on factors such as the dimensions of the room, the number of occupants, and the orientation of the room.

The inhabitants, individuals attending higher education institutions, have academic commitments for five consecutive days each week, which results in their extended absence from their living quarters. The rooms experience high utilization throughout weekdays after 6:00 pm and throughout the weekends. The apartments are furnished with dual electric stoves, which are frequently utilized by the tenants for food preparation. Furthermore, it should be noted that every room is equipped with an appropriate number of tables and closets that correspond to the total number of individuals occupying the space.

Figure 4. “ÜniYurt” Dormitory photo

Figure 5. Sample room photos

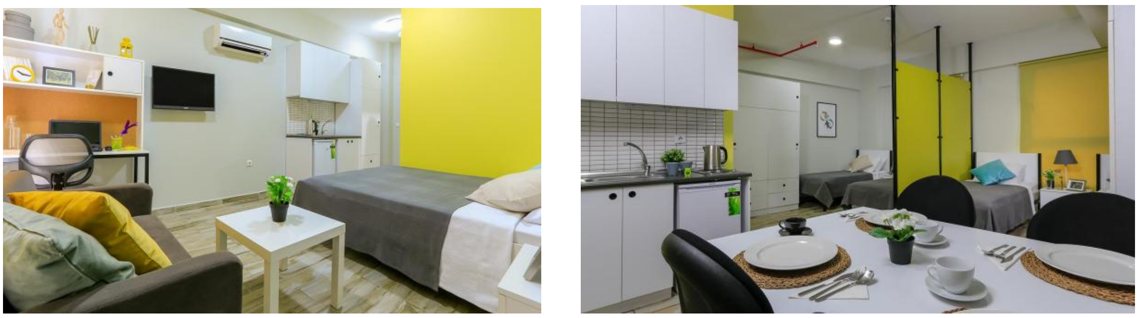


Figure 6. Sample room photos

3.3. Modeling Process and Simulation Settings

The energy simulations in this study were performed using Design Builder software version 7.0.0.116. The simulation method included the separate modeling of eight distinct rooms, with each of them being simulated independently into the observed period running from November 22, 2022, to January 9, 2023. It is worth noting that calibration was not conducted during the modeling procedure, since the rooms were occupied by students and it was their energy consumption behavior that was being evaluated.

The floor layouts showing the rooms that were subject to research are shown in table 5. Following this, the room plans were imported to the DesignBuilder tool in CAD format. The external walls, separating walls, doors, windows, and the staircase hall adjacent to the stairs, as well as the room on the attic floor, were modeled individually based on the CAD plans provided in the original project.

3.3.1. Detailed Room Plans

In this section, the plans of the rooms in the dormitory building where electricity usage data was collected from are given. Table 5 shows the locations and floor plans with respective areas of the rooms. Every student is provided with a study desk, chair, and personal wardrobe in each room. Additionally, each room contains a bathroom, toilet, and kitchen counter. The sleeping arrangements in four-person rooms consist of bunk beds. Certain room layouts utilize internal dividers. The construction and opening settings of the rooms are provided in Section 3.3.3, specifically addressing wall materials.

Table 5. Plans and areas of observed rooms

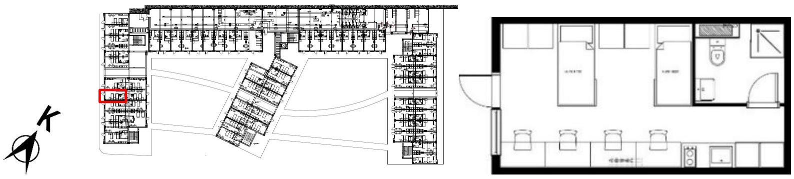
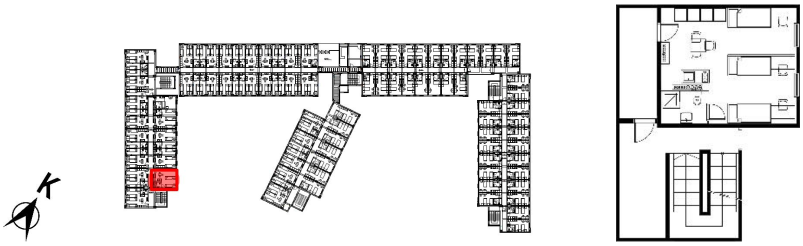
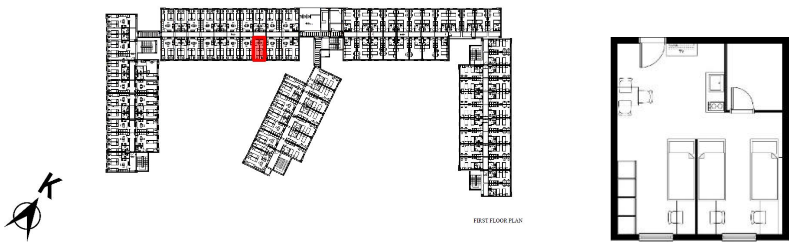
Room Number	**Floor Plan**	**Total Area**
1005		19.18m^2
4003		19.10m^2
1113		29.67m^2
2110		23.10m^2

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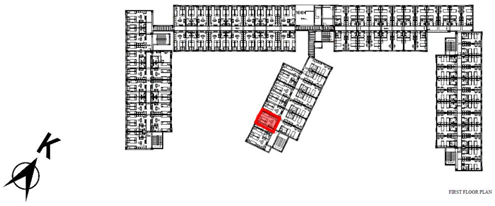
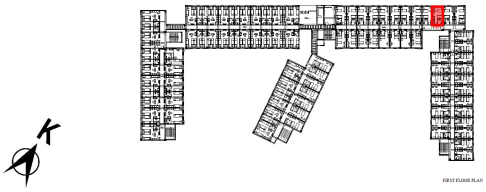
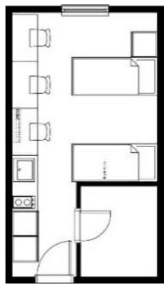
Table 5 (cont.)

3102 **27.96m^2**

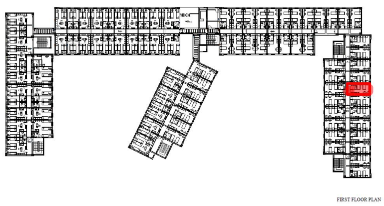


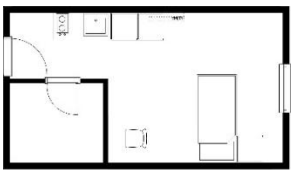
4110 16.75m^2



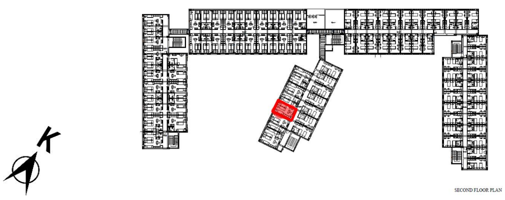


5113 16.63m^2





3203 27.96m^2



3.3.2. Thermal zones in DesignBuilder

1113	

The models, thermal zone plans and axonometric images of the 8 rooms selected for simulation in DesignBuilder are given in Table 6 below. In the two rooms on the ground floor, there is heat transfer through the floor, corridor doors and windows, and the side room walls are modeled as adiabatic. The side, upper and lower surfaces of the rooms on the first floor were modeled as adiabatic, with heat transfer through the stairs, corridor doors and windows. For the room on the top floor, heat exchange occurs from the roof, corridor and gaps in doors and windows.

Table 6. DesignBuilder model images

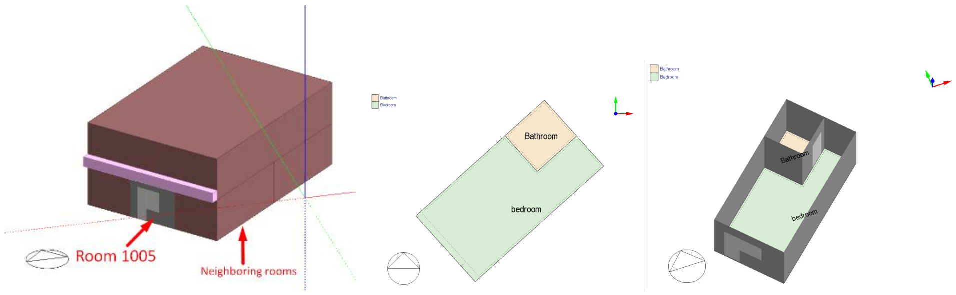
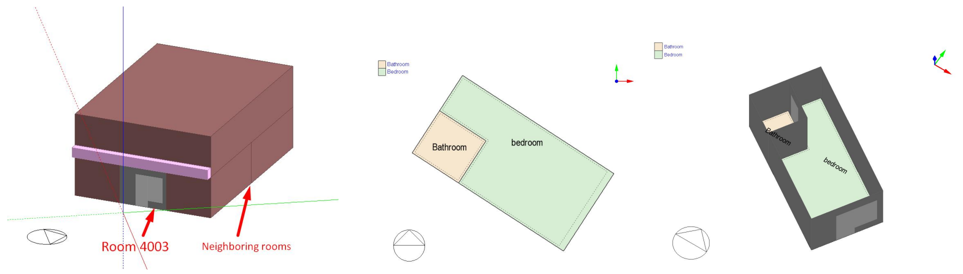
Room Number	**Floor Plan**
1005	
4003	

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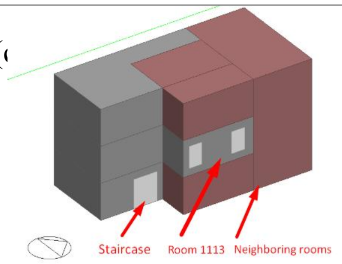
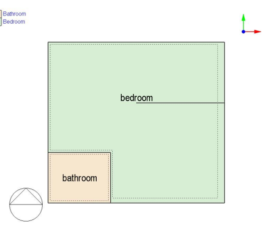
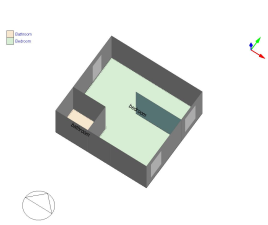
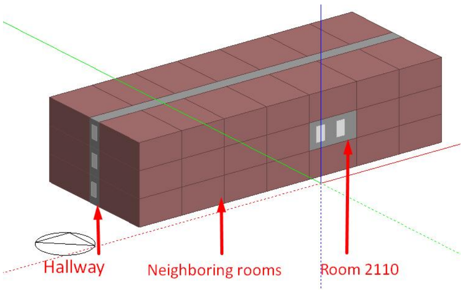
Table 6 (

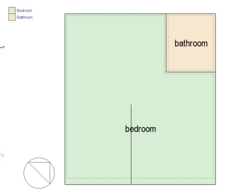


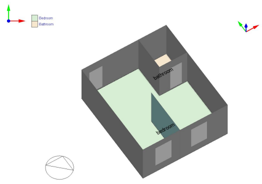




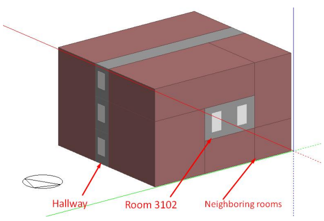
2110

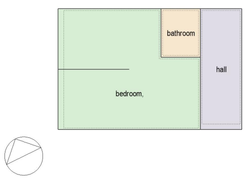


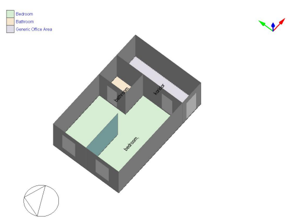




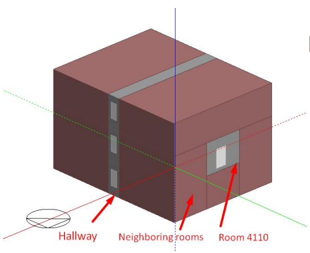
3102

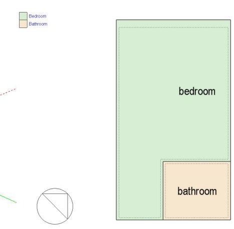






4110





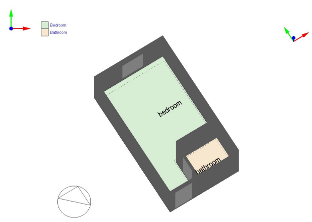


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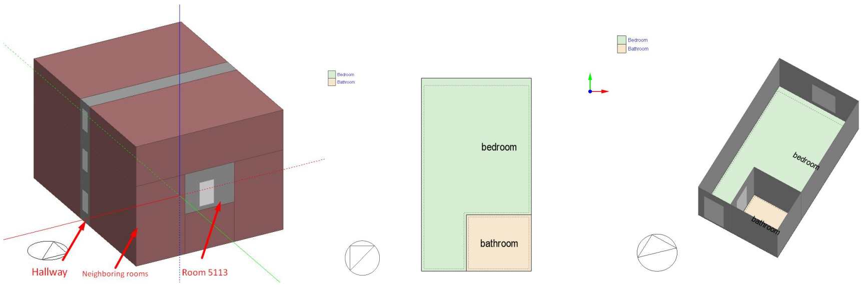
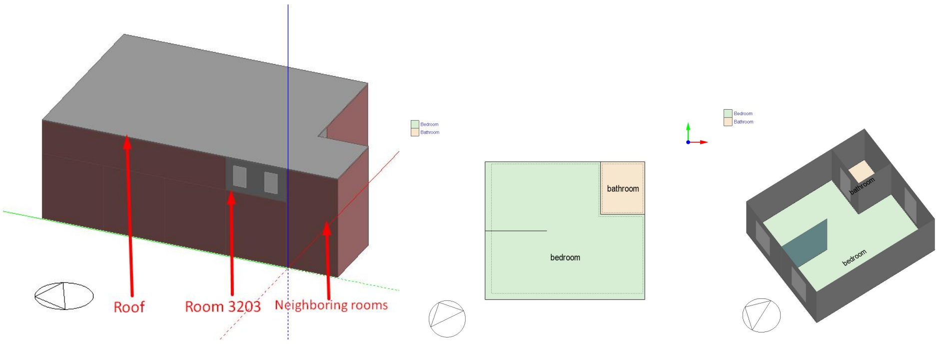
Table 6 (cont.)

5113



3203



3.3.3. Construction and Opening Settings

During the modeling phase, the DesignBuilder model was populated with building materials after the project's implementation. While preparing the models, first, a construction template was created from the construction tab in DesignBuilder. This template is included in the model file for all models. The template contains information about external floor, external wall, internal partitions, and flat roof. Conductivity, specific heat, density of the materials and u-values for the constructions are shown in table 7 below.

Table 7. Material chart of the dormitory

	U VALUE (W/m². K)	POSITION	LAYER NAME	CONDUCTIVITY (W/MK)	SPECIFIC HEAT (j/Kg-k)	DENSITY (Kg/m3)	THICKNESS (M)
External Floor	0.264	Outermost	Urea Formaldehyde Foam	0.04	1400	10.00	0.132
			Cast Concrete	1.40	840	2100.0	0.10
			Floor Screed	0.41	840	1200.0	0.07
		Innermost	Ceramic floor tiles	0.8	850	1700.0	0.03
Exterior Wall	0.728	Outermost	External rendering	0.50	1000	1300	0.0190
			EPS Expanded Polystyrene	0.04	1400	15	0.03
			Brickwork Inner	0.62	800	1700	0.220
		Innermost	Plaster (Lightweight)	0.16	1000	600	0.013
Glazing	2.178	Total Solar Transmission	Direct Solar Transmission	Light Transmission			
		0.682	0.595	0.738			
Internal Partitions	1.639	Outermost	Gypsum Plasterboard	0.25	1000	900	0.025
			Air Gap	Thermal Resistance: 0.15			0.10
		Innermost	Gypsum Plasterboard	0.25	1000	900	0.025
Roof	0.481	Outermost	Asphalt 1	0.7	1000	2100	0.05
			EPS Expanded Polystyrene	0.04	1400	15	0.06
			Cast Concrete (Lightweight)	0.38	1000	1200.00	0.10
		Innermost	Plasterboard	0.2500	896.0	2800.00	0.013

The term "U-value" refers to the thermal transmittance of a building component, which quantifies its ability to conduct heat. The U-value, also known as thermal transmittance, quantifies the rate of heat transfer across a certain area of a material during a specific time. The standard unit of measurement for this quantity is commonly expressed as Watts per square meter per Kelvin. Materials with lower U-values provide superior thermal insulation performance. The U-value holds significant importance in evaluating the thermal insulation characteristics of building materials, specifically in relation to structural components such as walls, roofs, and floors. This parameter plays a vital role in enhancing energy efficiency within the built environment.

Within this framework, the U-values pertaining to the external walls, internal walls, floor, door, and window were computed and subsequently juxtaposed against the U-values stipulated by the TS-825 regulation. It is noteworthy that the TS-825 regulation serves as the official regulatory framework in Turkey pertaining to building insulation. The U-values necessary for building components are documented in Table 8 (TMMOB Chamber of Mechanical Engineers, 2009). U-values are derived through the computation of R-values as stipulated in the TS-825 Insulation Regulation.

Table 8. U-values of the case building and required for 1st region

	Wall(external) U_w (W/m^2K)	**Roof U_r (W/m^2K)**	**Slab on ground U_c (W/m^2K)**	**Window U_w (W/m^2K)**
Required (TS 825)	0.70	0.45	0.70	2.40
Case value	0.728	0.481	0.264	2.178

The information provided establishes the groundwork for a thorough modeling procedure, encompassing the particularities of room arrangements, material attributes, and thermal qualities. Additional information pertaining to the models will be expounded upon in the following sections.

3.3.4. Activity Settings and Schedule Development

During the modeling process, templates were entered according to zones in the activity section. For example, while the bathroom template was chosen for bathrooms, the bedroom template was chosen for the room where students sleep and study. This template is provided by DesignBuilder, and is located under the selected bedroom and bathrooms, universities, and colleges file.

Room Number	1005	4003	1113	2110	3102	4110	5113	3203
Occupancy Density (people/m^{2})	0.208	0.209	0.134	0.129	0.143	0.179	0.060	0.107

Table 9. Occupancy density per rooms

Data regarding occupancy is as follows; For occupancy density, the number of people staying in the room is found by dividing by the square meters of the room. (Table 9) Occupancy schedules were designed in 3 different ways depending on the number of people staying in the room. Schedules are prepared separately for 1-person, 3-person and 4-person rooms; Schedule for 1 person is given in Table 10. It is assumed that the user is in class between 8 am and 5 pm on weekdays, uses the room after 5 pm, and spends a full outside from 1 pm to 11 pm on the weekend. For a 3-person room, it is designed that 1 person will stay in the room between 8 am and 5 pm on weekdays, the other 2 people will be in class and all users will be in the room after 5 pm. On the weekend, it is planned that all users will leave the room at 1 pm and will start coming to the room every 1 hour at 9 pm. In this case, according to the scenario, 3 users too will be in the room 12 am. The 4-person room scenario is set up similarly to the 3-person room scenario. On weekdays, between 8 am and 5 pm, there is 1 person in the room, and after 5 pm, 4 people are in the room. On weekends, everyone leaves the room at 1 pm and they start returning to their rooms at 9 pm.

Table 10. Occupancy schedules for 1,3 and 4-person rooms

Uni_Bed_Occ_1-person schedule	Uni_Bed_Occ_3-person schedule	Uni_Bed_Occ_4-person schedule
Uni_Bed_Equip,For Weekdays Until: 08:00, 1, Until: 17:00, 0, Until: 24:00, 1, For: Weekends Holidays, Until: 13:00, 1, Until: 21:00, 0, Until: 24:00, 1,	For Weekdays Until: 08:00, 1, Until: 17:00, 0.33, Until: 24:00, 1, For: Weekends Holidays, Until: 13:00, 1, Until: 21:00, 0, Until: 22:00, 0.33, Until: 23:00, 0.66, Until: 24:00, 1,	For Weekdays Until: 08:00, 1, Until: 17:00, 0.25, Until: 24:00, 1, For: Weekends Holidays, Until: 13:00, 1, Until: 21:00, 0, Until: 22:00, 0.25, Until: 23:00, 0.75, Until: 24:00, 1,

In the DesignBuilder program, computers and office equipment are created in separate programs in the activity section. Within the scope of this thesis, it is assumed that each room user has a computer. Considering that an average computer consumes 100 watts of energy, in this case, 400 watts were calculated from computers alone for a room of 4 people. This value is divided by the square meter of the room, the power density value of the computers is included in the modelling for each room. These values are shown in Table 11 for each room. Furthermore, taking into account everyday routines, electrical devices are employed in many scenarios, including hair dryers, bedside lamps, and coffee makers. For the purpose of this thesis, it is assumed that each individual utilizes personal electrical equipment with a total energy consumption of 50 kWh. This assumption is incorporated into the simulation inside the office equipment section of DesignBuilder.

The primary objective of this thesis is to investigate the impact of users with varying behavioral habits on the performance of buildings. Scenarios were generated in this context by modifying users' computer usage, electrical appliance usage, and heating-cooling set point options. The schedules for regular users in Scenario 2 have maintained the original schedule provided by DesignBuilder without any modifications.

Table 11. Power density for each room

Room Number	1005	4003	1113	2110	3102	4110	5113	3203
Computers power density	20.85	20.85	13.70	12.98	14.30	17.91	6.04	10.72
Electrical Appliances power density	10.42	10.42	6.85	6.49	7.15	8.95	3.00	5.38

The "Uni_Bed_Equip" template was chosen from the university and colleges file for standard Schedule of computers and electrical appliances. No changes were made to it for standard schedule in scenario 2. Computers are utilized for a total of 2 hours every day during the observation period. This occurs specifically between 7 and 10 in the morning, following DesignBuilder's standard schedule.

In the Wasteful scenario, computers and electrical appliances are consumed continuously throughout the night from December 31st to January 3rd, a total of 4 days during the simulation period. On the remaining days, computers are actively used for 2 hours each day. In summary, during a period of 7 weeks, users spend an additional 24 hours using both computers and electrical appliances compared to the regular schedule in the wasteful scenario.

In the frugal scenario, occupants save energy by avoiding using any electrical equipment, whether actively or while charging, from January 3 to January 9, in order to save money. In other words, in a total of 7 weeks of monitoring, occupants save 6 days by not using electrical appliances at all. During the creation of the scenarios, the dates for saving money or spending it heavily were chosen at random.

Cooling set point and heating set points were selected adopting assumptions from literature (Yogi et al. 2017, Hong and Lin 2013). Information about the scenarios is given in Table 12.

One of the main purposes of this thesis is to investigate the effect of users with different behavioral habits on building performance. Scenarios were generated in this context by changing users' computer usage, electrical appliance usage, and heating-cooling set point decisions.

Table 12. Comparative table of scenarios

	SCENARIO 1 FRUGAL	**SCENARIO 2 STANDARD**	**SCENARIO 3 WASTEFUL**
Schedule of computers and electrical appliances	Through: 22 November 2022, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 23:00, 0.24628, Until: 24:00, 0.05785; Through:3 January 2023, For: AllDays, Until: 08:00, 0, Until: 24:00, 0, Through: 9 January 2023, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 23:00, 0.24628, Until: 24:00, 0.05785;	Through: 22 November 2022, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 23:00, 0.24628, Until: 24:00, 0.05785; For: AllDays, Through: 9 January 2023, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 23:00, 0.24628, Until: 24:00, 0.05785;	Through: 22 November 2022, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 23:00, 0.24628, Until: 24:00, 0.05785; Through: 31 December 2022, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 23:00, 0.24628, Until: 24:00, 0.05785; Through:3 January 2023, For: AllDays, Until: 08:00, 1, Until: 19:00, 0.05785, Until: 24:00, 1, Through: 9 January 2023, For: AllDays, Until: 07:00, 0.05785, Until: 10:00, 1, Until: 19:00, 0.05785, Until: 24:00, 1;
Heating setpoint	18°C	21°C	23°C
Cooling setpoint	26°C	24°C	22°C

Within the scope of this thesis, once the rooms were modelled and templates were created for the scenarios, individual simulation results were generated for each scenario per room. The simulation period corresponds to the monitored period and runs from November 22, 2022, to January 9, 2023. The simulation options are as follows: All buildings are included in shading calculations. Model reflections and shading of ground reflected solar included. Solar distribution is full exterior. Shadowing intervals are 20 days. HVAC options at the building level. Mechanical and natural ventilations are turned off. Heating is set to electric heating. The heating schedule is always on. Cooling is set to electricity. Domestic hot water is turned off.

CHAPTER 4

RESULTS

4.1. Analysis of Consumption Data

Daily monitoring data for electricity consumption between November 22, 2022, and January 9, 2023, was collected for the nine rooms, unveiling interesting patterns and variations in kilowatt-hours (kWh). The maximum electricity consumption across all rooms reached its peak at 35.939 kWh in Room 3102 on January 3, 2023, while the minimum was remarkably low at 0.278 kWh, recorded in the same room on December 14, 2022. Examining average daily consumption, each room displayed distinct behaviors. For instance, Room 2110 consistently showed higher averages, ranging from 0.813 to 13.256 kWh, while Room 3203 fluctuated between 2.361 and 27.534 kWh. Comparing the days of maximum consumption, we observed specific days where multiple rooms shared peak usage, raising questions about shared influences. Based on the observation, it was noted that room 3003 consumed more than 2 kilowatt-hours (kWh) only two times. This suggests that this particular student room was unoccupied for most of the time. For this reason, it was decided not to include room 3003 in the analyses.

Table 13. Results of monitored electricity consumption data

Room number	1005	3003	4003	1113	2110	3102	4110	5113	3203
Max electricity Consumption Amount(kWh)	10.08	2.69	10.53	11.44	13.25	35.93	7.22	11.00	27.53
Min electricity consumption Amount (kWh)	0.20	0.22	0.59	0.66	0.81	0.27	1.02	0.42	2.36
Average Daily Electricity consumption (kWh)	4.47	1,059	3.87	5.06	6.53	7.59	3,.55	5.23	13.18
Total Room Area (m^2)	19.18	20.32	19.10	29.67	23.10	27.96	16.75	16.63	27.96
Occupancy number (person)	4	1	4	4	3	4	3	1	3
Orientation	SW	W	SE	NE	SE	W	NW	NE	W

Table 14. Max and Min days of monitored electricity consumption

Room number	1005	3003	4003	1113	2110	3102	4110	5113	3203
Max electricity Consumption Day	12.12.2022	8.12.2022	4.01.2023	9.01.2023	22.12.2022	03.01.2023	25.12.2022	8.01.2023	27.12.2022
Min electricity consumption day	13.12.2022	5.12.2022	10.12.2022	28.11.2022	29.11.2022	14.12.2022	16.12.2022	26.11.2022	16.12.2022

4.1.1. Comparative Analysis of Room Electricity Consumption

The following section provides electricity usage data for 8 rooms observed between November 22, 2022, and January 9, 2023, comparing rooms with similar features. At the same time, information about maximum electricity consumption, minimum electricity usage days and square meters of the rooms are given in table 13 and 14. The simulation results are given in section 4.2.

Comparative analysis of rooms 1005 and 4003.

Over the course of the 7-week period, comparison of Room 1005 and Room 4003, both situated on the ground floor and both with 4 occupants shows that average consumption differs by 15%. The mean electricity usage during this period was 4,474 kWh for Room 1005 and 3,876 kWh for Room 4003. (Table 15) Room 1005 faces southwest, while Room 4003 faces southeast. Room 1005 is where more consumption took place.

Additionally, variation in electricity consumption in Room 1005 followed a pattern distinctly different from the one displayed in Room 4003. In Room 1005 consumption reached its peak on December 12th and its lowest point on the subsequent day, December 13th. On the other hand, Room 4003 had its lowest consumption on December 10th and the highest on January 4th, highlighting the unpredictable nature of user behavior. (Table 16)

Table 15. Comparative analysis of room 1005 and 4003

Common features		**Unique features**		
			1005	4003
Level of Rooms	Ground	Gender	Men	Women
Number of Occupancy	4	Area	19.17 m^2	19.10 m^2
		Orientation	Southwest	Southeast

Table 16. Comparative analysis of room 1005 and 4003

Number of Room	**1005**	**4003**
Max electricity consumption(kWh)	10.08	10.53
Min electricity consumption(kWh)	0.20	0.59
Average electricity consumption(kWh)	4.74	3.87
Min electricity consumption day	13.12.2022	10.12.2022
Max electricity consumption day	12.12.2022	04.01.2023

Comparative analysis of rooms 1113 and 2110

Within the 7-week observation time, different patterns of energy use were also seen in Rooms 1113 and 2110, both of which were on the first floor and were designated as male dormitories. Room 1113, facing northeast, which had four people living in it, used an average of 5,064 kWh. Room 2110, facing southeast, which had three people living in it, had a 29% higher average consumption of 6,530 kWh.

Examining consumption variation across days shows both rooms used the least power on close dates, on December 28th and 29th for Room 1113 and Room 2110 respectively. However, maximum consumption happened on dates that were far apart on January 9th and December 22nd indicating the impact of occupants' usage patterns (Table 18).

Table 17. Comparative analysis of room 1113 and 2110

Common features		**Unique features**		
			1113	2110
Level of Rooms	1st	Number of Occupancy	4	3
Gender	Man	Area	29.67 m^2	23.10 m^2
		Orientation	Northeast	Southeast

Table 18. Comparative analysis of room 1113 and 2110

Number of Room	**1113**	**2110**
Max electricity consumption(kWh)	11.44	13.25
Min electricity consumption(kWh)	0.66	0.81
Average Electricity consumption(kWh)	5.06	6.53
Min electricity consumption day	28.11.2022	29.11.2022
Max electricity consumption day	09.01.2023	22.12.2022

Comparative analysis of rooms 1113 and 3102

During the 7-week period, comparing energy consumption in Room 1113 facing northeast and Room 3102 facing west, both 4-person rooms, both located on the 1st floor, shows the most drastic difference. It was found that Room 1113 used an average of 5,064 kWh of electricity, while Room 3102 used an average of 7,591 kWh of electricity. A 50% higher consumption while receiving more sunlight.

Again, each Room had a very different variation pattern in consumption across days. Room 3102 is also responsible for the highest maximum daily consumption that was more than three times as much as the maximum consumption in Room 1113.The comparison results are shown in Tables 19 and 20.

Table 19. Comparative analysis of room 1113 and 3102

Common features		**Unique features**		
			1113	3102
Level of Rooms	1st	Gender	Man	Women
Number of Occupancy	4	Area	29.67 m^2	27.96 m^2
		Orientation	Northeast	West

Table 20. Comparative analysis of room 1113 and 3102

Number of Room	**1113**	**3102**
Max electricity consumption(kWh)	11.44	35.93
Min electricity consumption(kWh)	0.66	0.27
Average Electricity consumption(kWh)	5.06	7.59
Min electricity Consumption Day	28.11.2022	14.12.2022
Max electricity Consumption Day	09.01.2023	03.01.2023

Comparative analysis of rooms 4110 and 5113:

A comparison between rooms with different number of occupants was carried out between Room 4110 facing NW and Room 5113 facing NE. Both rooms are on the first floor and both had female occupants. They have almost the same area. The only major difference was that Room 4110 had 3 occupants while Room 5113 had a single occupant. However, the single occupant had a significantly higher energy consumption as observed in Table 21 and 22. Three inhabitants in Room 4110 had an average electricity use of 3,556 kWh. On the other hand, Room 5113, which was occupied by a single person, had a 47% higher average usage of 5,231 kWh. Room 5113 uses significantly more electricity with just one resident as compared to Room 4110 with three occupants. More load is placed on the air conditioning system when there is a single occupant. The extra computer usage in the more crowded room does not offset the heating electricity consumption. Yet, Room 5113 still aligns more closely with its wasteful scenario. This highlights the complexity of individual user behavior and suggests the importance of considering behavior variations with occupant densities in energy efficiency strategies. Recommendations should also address individual behavior rather than just depending on occupancy as a determining factor for energy conservation strategies.

Table 21. Comparative analysis of room 4110 and 5113

Common features		**Unique features**		
			4110	5113
Level of Rooms	1st	Number of Occupant	3	1
Gender	Women	Area	16.75 m^2	16.63 m^2
		Orientation	Northwest	Northeast

Table 22. Comparative analysis of room 4110 and 5113

	4110	**5113**
Max electricity consumption (kWh)	7.22	11.00
Min electricity consumption (kWh)	1.02	0.42
Average Electricity consumption (kWh)	3.55	5.23
Min electricity Consumption Day	16.12.2022	26.11.202
Max electricity Consumption Day	25.12.2022	08.01.2023

Comparative analysis of rooms 4110 and 3203:

To compare consumption on different floors a detailed comparison between Rooms 4110 facing northwest and 3203 facing west, both three-person female dormitories, again reveals differences in energy consumption patterns. Room 4110, situated on the first floor, recorded a comparatively lower average electricity consumption of 3,556 kWh, while Room 3203, located on the second and top floor, exhibited a higher consumption at 7,591 kWh. However, it should be noted that Room 3203 is significantly larger, covering an area of 27 m2, whereas Room 4110 spans 16 m^2. (Table 23)

The observed disparity in electricity consumption is attributed to both the larger size of Room 3203 and its location on the top floor, which may lead to increased energy demands, possibly associated with heat loss through the roof. (Table 24)

Table 23. Comparative analysis of room 4110 and 3203

Common features		**Unique features**		
			4110	3203
Number of occupants	3	Level of Rooms	1st	2nd
Gender	Women	Area	16.75 m^2	27.96 m^2
		Orientation	Northwest	West

Table 24. Comparative analysis of room 4110 and 3203

	4110	3203
Max electricity consumption(kWh)	7.22	27.53
Min electricity consumption(kWh)	1.02	2.36
Average Electricity consumption (kWh)	3.55	13.18
Min electricity Consumption Day	16.12.2022	16.12.202
Max electricity Consumption Day	25.12.2022	27.12.2022

Examining the consumption data, notable variations in energy consumption among different dormitory rooms have been identified. Room 3203, situated on the top floor with a larger square footage, exhibited substantially higher electricity consumption compared to Room 4110, emphasizing the impact of both physical space and environmental factors on energy usage. Additionally, Room 5103, despite having a single occupant, consumed more electricity than the three-person Room 1113, challenging the conventional assumption of a linear relationship between occupancy and energy consumption. These findings underscore the importance of considering room characteristics and individual behavior in understanding and optimizing energy usage within the building. Section 4.2 will delve into the results of simulations, exploring various user scenarios to further inform energy efficiency strategies.

Electricity consumption in rooms located on the same floor:

Consumption time graph of rooms 1005 and 4003 on the ground floor is given in figure 7. Rooms 2110, 4110, 1113 and 3102 are located on the first floor and their comparative chart is given in figure 8. Since there is only one room on the 2nd floor, room 3203 is shown together with the rooms on the 1st floor (Figure 9). It should be noted that even though the rooms have the same floors, their orientations are different.

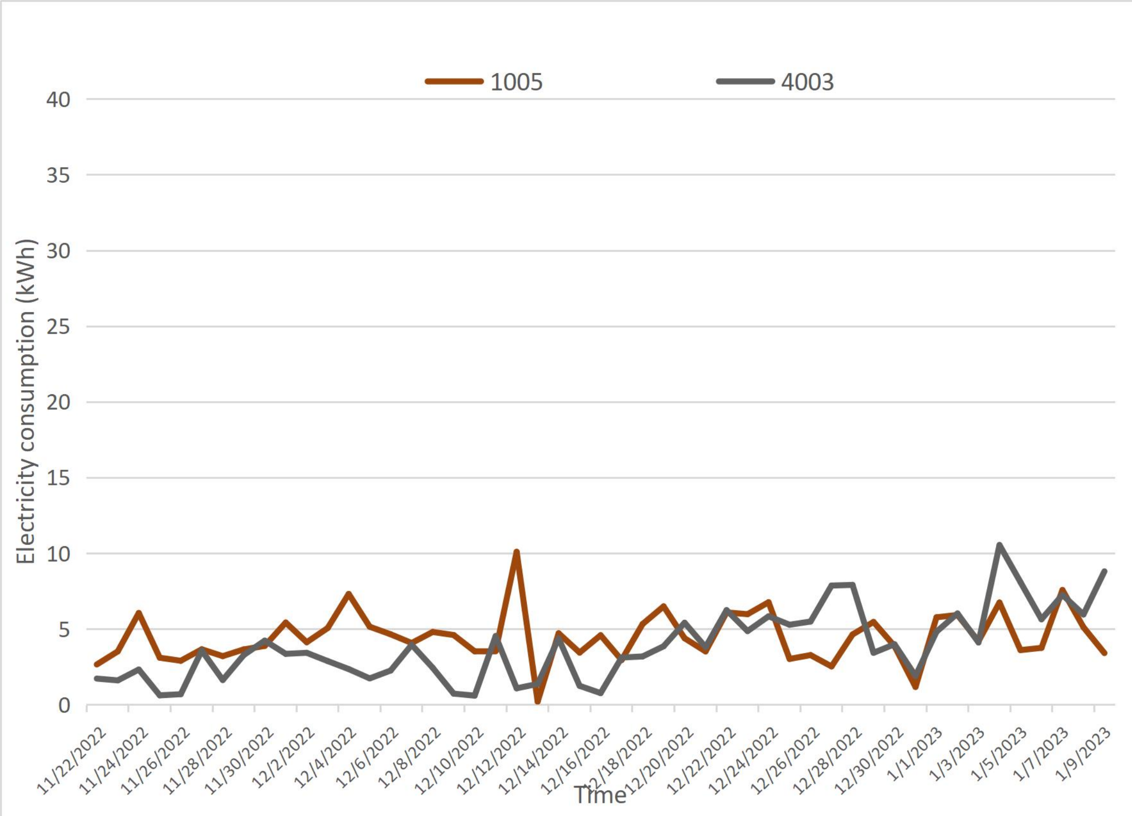


Figure 7. Consumption time graph of ground floor rooms

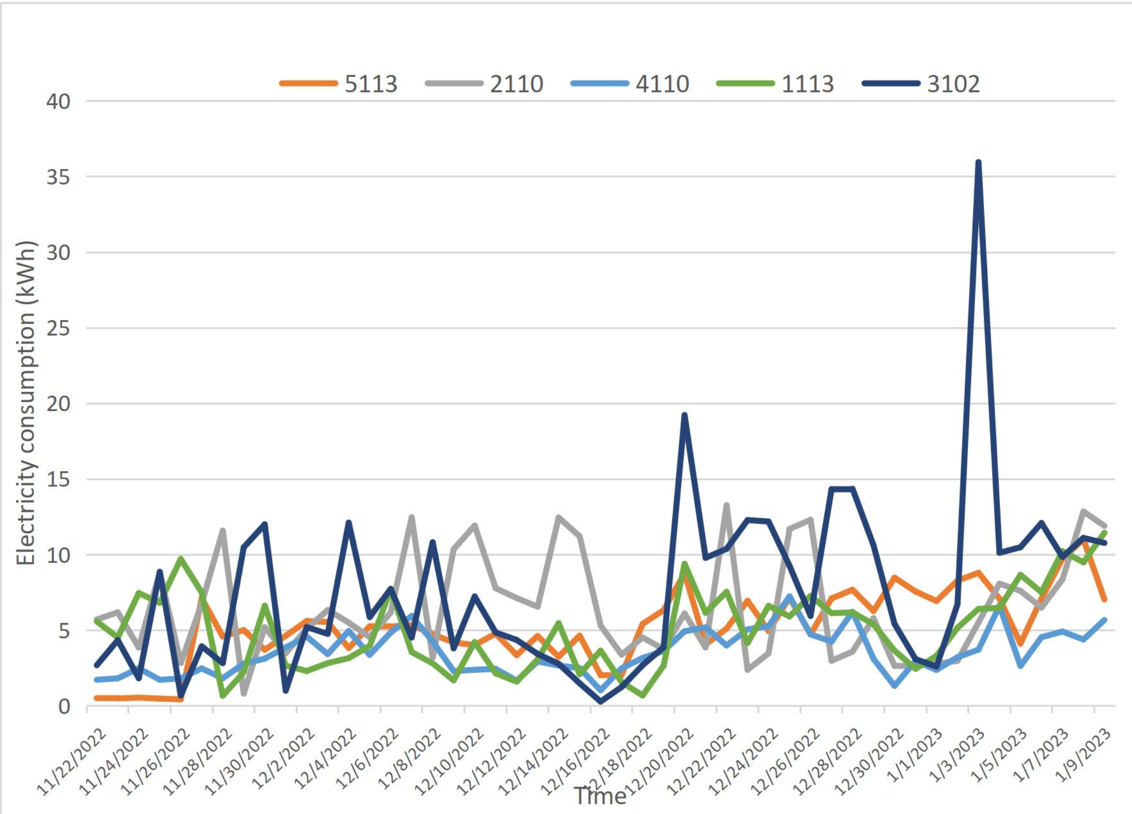


Figure 8. Consumption time graph of 1st floor rooms

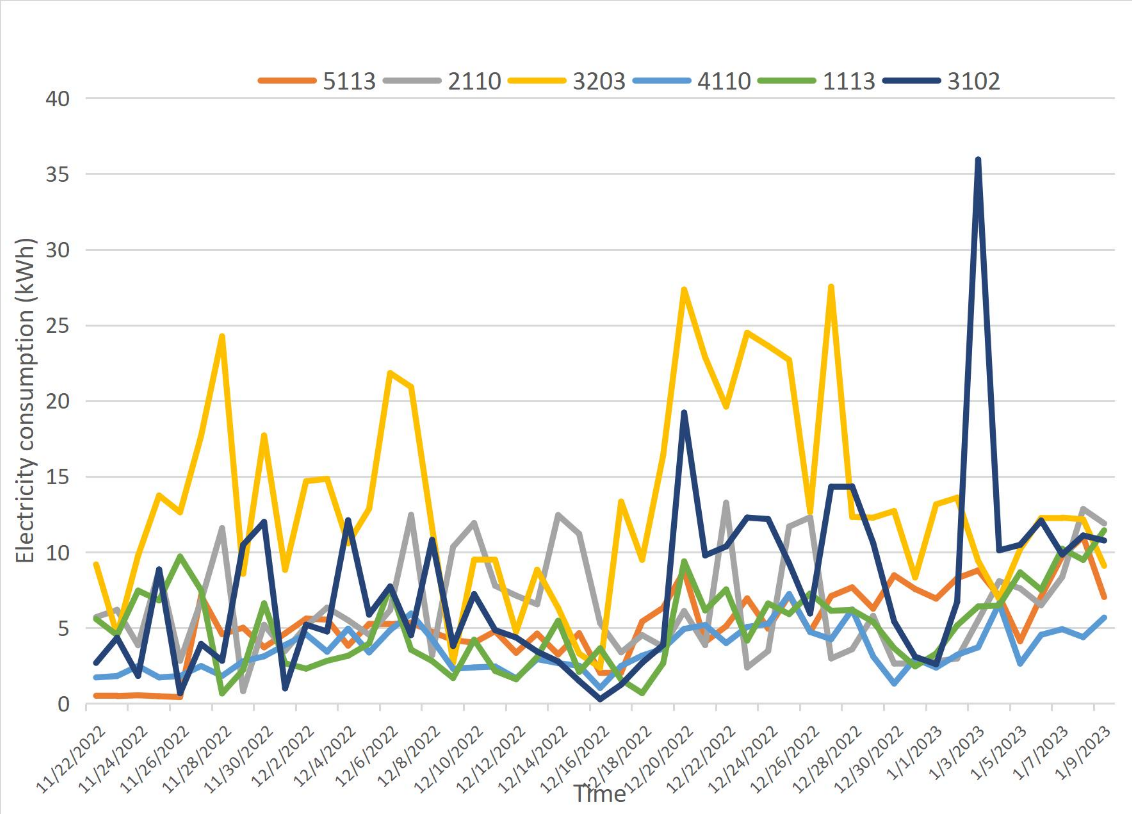


Figure 9. Consumption time graph of rooms on the 1st and 2nd floor.

Electricity consumption in rooms with equal number of occupants:

Although there were two single rooms among the initially observed rooms, the data of room 3003 was excluded from the results because it was considered erroneous. For this reason, a comparison of single rooms is not included. The comparative graph of 3 and 4-person rooms is shown in figures 10 and 11.

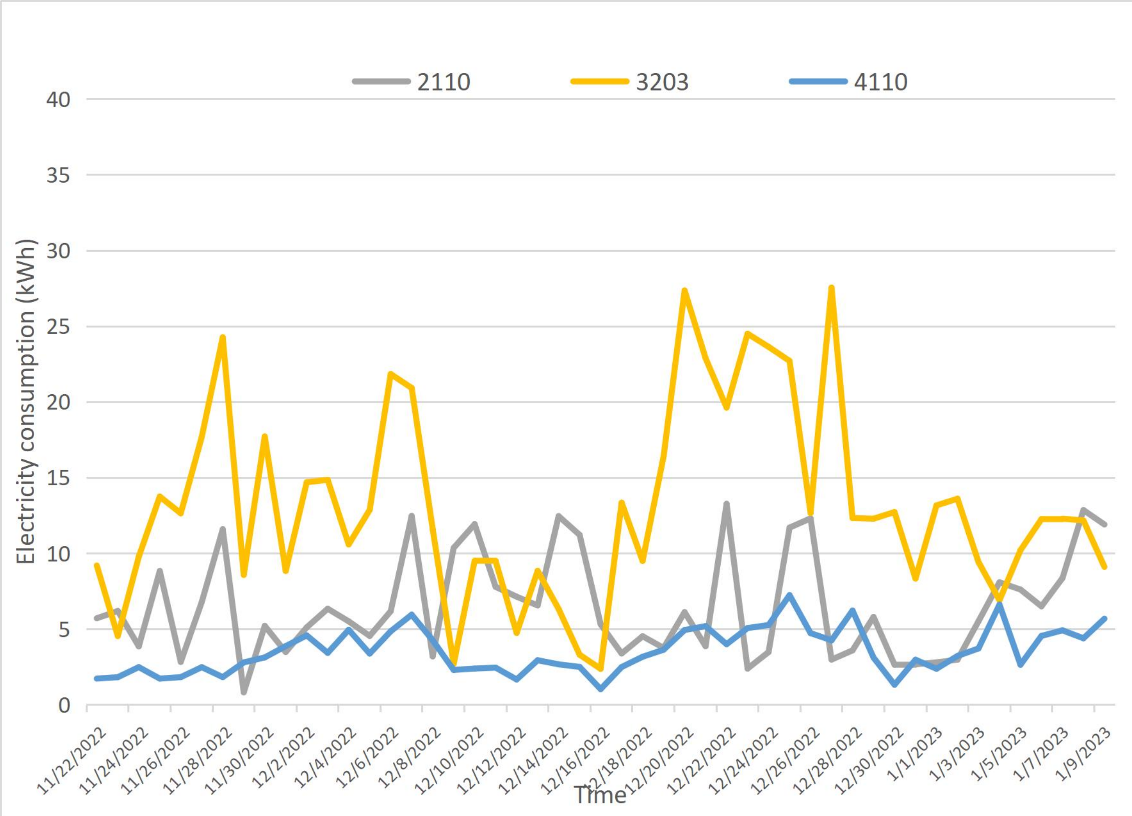


Figure 10. Consumption time graph of 3-person rooms

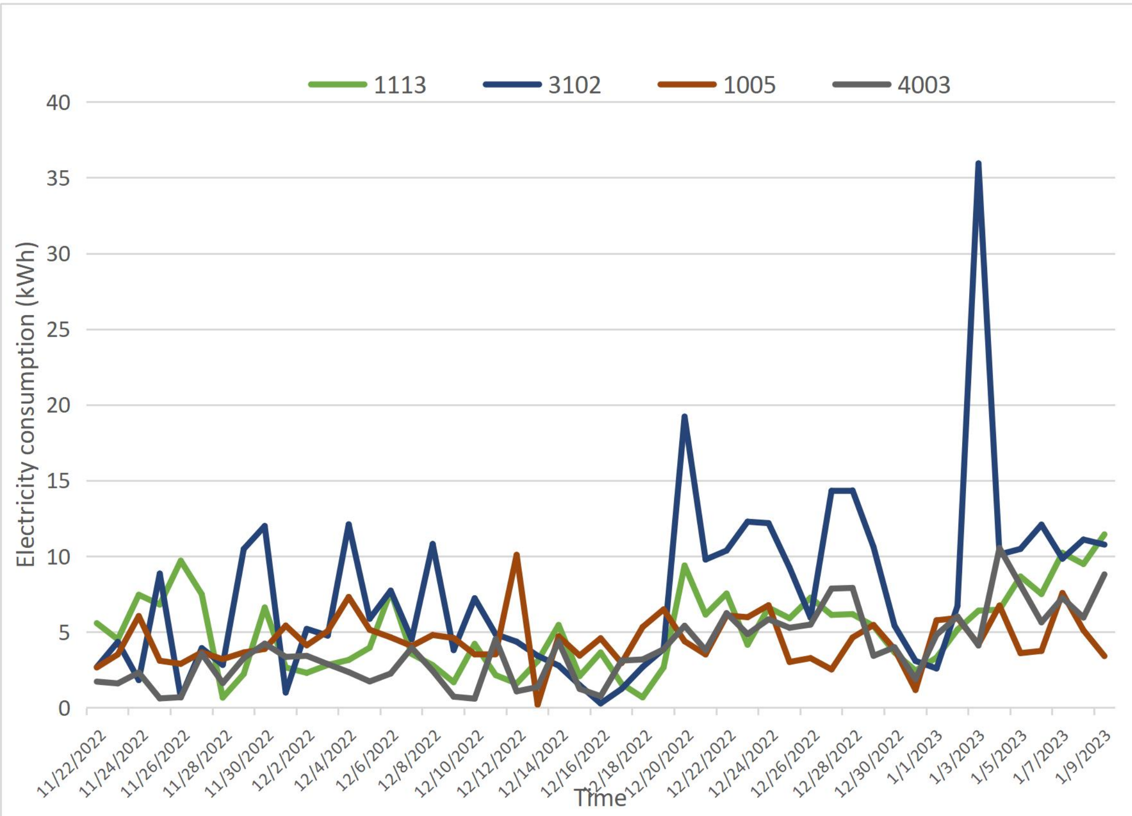


Figure 11. Consumption time graph of 4-person rooms

4.2. Simulation Results

Selected rooms were simulated for the period November 22, 2022, to January 9, 2023, in order to model and assess the electricity consumption under three distinct user scenarios: Frugal, Standard, and Wasteful. The simulation models were built on the assumption that user actions align with these scenarios.

This comparative analysis aims to investigate the accuracy and reliability of the simulation software under real-life usage by evaluating the close relationship between the simulated results and the actual consumption data. Furthermore, it aims to determine the energy-saving potentials related to various user scenarios. The results of this simulation study will provide significant knowledge for developing effective guidance for building energy management, highlighting the significance of considering various user behaviors in sustainable energy practices.

Simulation Results of Room 1005:

During the observation period, Room 1005 demonstrated distinct electricity consumption patterns under different user scenarios. The simulation, based on standard user behavior, wasteful user behavior, and frugal measures, projected anticipated consumptions of 152 kWh, 240 kWh, and 65 kWh, respectively. Conversely, the monitored data revealed an actual consumption of 219.25 kWh (Table 25). The disagreement between simulated and observed values is expected as a result of the diverse nature of user behavior. Consequently, the real-world data of 1005 room members is perceived to be situated between the standard and wasteful user profiles. Another noteworthy observation is that, had the user adhered to a frugal scenario, a substantial energy-savings of approximately 70% is anticipated in electricity consumption (Table 26).

Table 25. Results and monitored data of room 1005 according to scenarios

1005 Room	**SCENARIO 1 Frugal Schedule**	**SCENARIO 2 Standard Schedule**	**SCENARIO 3 Wasteful Schedule**	**Monitored Data**
Total Electricity Consumption kWh (during 7 weeks)	65.53	152.51	240.81	219.25

Table 26. Energy saving potential percentage in different user scenarios room 1005

	SCENARIO 1 Frugal	**SCENARIO 2 Standard**
Occupant can save %	%70.1	%30.4

Simulation Results of Room 4003:

In the frugal scenario, Room 4003 is estimated to consume 82 kWh, while under the standard schedule, the projected consumption increases to 161 kWh. In the wasteful scenario, the simulation indicates a higher consumption of 294 kWh. However, the actual monitored data records a consumption of 189 kWh. Notably, the user profile in the simulation appears to align more closely with the standard scenario predicted by DesignBuilder (Table 27). In the observed data, Room 4003 recorded an electricity consumption of 189 kWh. If the user had adhered to the frugal scenario, the estimated consumption would have been 82 kWh. This signifies a potential energy-saving of approximately 56.08% (Table 28).

Table 27. Results and monitored data of room 4003 according to scenarios

4003 Room	**SCENARIO 1 Frugal Schedule**	**SCENARIO 2 Standard Schedule**	**SCENARIO 3 Wasteful Schedule**	**MONITORED Data**
Total Electricity Consumption kWh	82.14	161.74	294.10	189.94

Table 28. Energy saving potential percentage in different user scenarios room 4003

	SCENARIO 1 Frugal	**SCENARIO 2 Standard**
Occupant can save %	%56.08	%14.8

Simulation Results of Room 1113:

According to the simulation data, Room 1113 demonstrates a consumption of 113 kWh under the frugal scenario, 284 kWh under the standard schedule, and 443 kWh under the wasteful scenario. The monitored data reveals an actual consumption of 248 kWh. This indicates that the users in Room 1113 are fairly energy-conscious and fall between the frugal and standard user profiles. (Table 29)

Table 29. Results and monitored data of room 1113 according to scenarios

1113 Room	**SCENARIO 1 Frugal Schedule**	**SCENARIO 2 Standard Schedule**	**SCENARIO 3 Wasteful Schedule**	**MONITORED DATA**
Total Electricity Consumption kWh	113.40	284.63	443.32	248.16

Table 30. Energy saving potential percentage in different user scenario room 1113

	SCENARIO 1 Frugal	**SCENARIO 2 Standard**
Occupant can save %	%54.3	N/A

Simulation Results of Room 2110:

In the simulation scenarios for Room 2110, the anticipated electricity consumption stands at 127 kWh for the frugal scenario, 198 kWh for the standard scenario, and 276 kWh for the wasteful scenario. The monitored data shows that 320 kWh of power was used. Particularly, the amount of energy used is higher than what was expected, even in the wasteful scenario. This means that the room needs more energy than expected. A deeper exploration of the daily electricity usage patterns uncovers a distinctive trend. Specifically, two days of the week exhibit electricity consumption levels that are twice the weekly average. This exceptional case is one example of how unpredictable and complicated people's behavior is (Table 31).

The difference between what was expected based on simulations and what was actually observed shows how hard it is to correctly model user behavior and how important it is to take into account how complicated and unpredictable user habits are. These findings contribute valuable insights to the ongoing discourse on refining simulation models for improved accuracy in energy management strategies within residential spaces (Table 32).

Table 31. Results and monitored data of room 2110 according to scenarios

2110 Room	**SCENARIO 1 Frugal Schedule**	**SCENARIO 2 Standard Schedule**	**SCENARIO 3 Wasteful Schedule**	**MONITORED DATA**
Total Electricity Consumption kWh	127.45	198.39	276.93	320.006

Table 32. Energy saving potential percentage in different user scenarios room 2110

Room 2110	**SCENARIO 1 Frugal**	**SCENARIO 2 Standard**	**SCENARIO 3 Wasteful**
Occupant can save %	%60.1	%38.0	%13.4

Simulation Results of Room 3102:

Simulation results for Room 3102 showed that in the frugal scenario where people are assumed to be careful with their energy use, the expected consumption is 161 kWh. On the other hand, the standard scenario predicts a consumption of 355 kWh, which is closer to normal and balanced energy use. In the wasteful scenario, the simulation predicts a higher consumption of 472 kWh, which points to a possible tendency toward less energy-efficient behaviors (Table 33).

Upon comparing these calculated projections with the observed data, which is 371 kWh for Room 3102, it is understood that the occupants of this room spent slightly more energy than what is expected under normal usage. The difference of approximately 5% suggests that the users in this room display behavior that is more in line with the typical user profile expected by the simulation model (Table 34).

Table 33. Results and monitored data of room 3102 according to scenarios

3102 Room	**SCENARIO 1 Frugal Schedule**	**SCENARIO 2 Standard Schedule**	**SCENARIO 3 Wasteful Schedule**	**MONITORED DATA**
Total Electricity Consumption kWh	161.12	355.86	472.11	371.965

Table 34. Energy saving potential percentage in different user scenarios room 3102

3102	**SCENARIO 1 Frugal**	**SCENARIO 2 Standard**
Occupant can save %	%56.6	%4.3

Simulation Results of Room 4110:

The simulation results for Room 4110 show how electricity use is expected to change depending on the user situation. The models show that 112 kWh will be used in the frugal scenario, 169 kWh in the standard scenario, and 234 kWh in the wasteful scenario. On the other hand, the monitored data shows that 174 kWh of power were actually used (Table 35).

It's worth mentioning that the amount of energy used matches more closely with the standard scenario. This means that the people in Room 4110 use energy in a way that is more balanced and usual. Even though it might be hard to get exact matches between simulated and observed data, the fact that observed consumption is closely related to the standard situation shows how important it is to use real-world data to improve simulation models. This result shows how important it is to recognize that user behavior is naturally variable and that it might be helpful to change energy management strategies to fit patterns that have been seen (Table 36).

Table 35. Results and monitored data of room 4110 according to scenarios

4110 Room	SCENARIO 1 Frugal Schedule	SCENARIO 2 Standard Schedule	SCENARIO 3 Wasteful Schedule	MONITORED DATA
Total Electricity Consumption kWh	112.52	169.57	234.20	174.27

Table 36. Energy saving potential percentage in different user scenarios room 4110

	SCENARIO 1 Frugal	SCENARIO 2 Standard
Occupant can save %	%35.4	%2.6

Simulation Results of Room 5113:

The simulation outcomes for Room 5113 project varying electricity consumption scenarios under different user profiles. The estimations indicate an expected consumption of 170 kWh for the frugal scenario, 225 kWh for the standard scenario, and 274 kWh for the wasteful scenario. However, the monitored data reveals an actual electricity consumption of 256 kWh (Table 37).

Even though the actual energy use doesn't exactly match any simulated situation, the fact that it's close to the wasteful profile makes us think about how user behavior might affect energy use. This more complex understanding shows how user habits change over time, which makes it hard to accurately predict energy use using only simulation models. The fact that the observed data was close to the wasteful situation shows how important real-world data is for making simulation models more accurate and for making sure that energy management strategies are based on how people actually use energy (Table 38).

Table 37. Results and monitored data of room 5113 according to scenarios

5113 Room	SCENARIO 1 Frugal Schedule	SCENARIO 2 Standard Schedule	SCENARIO 3 Wasteful Schedule	MONITORED DATA
Total Electricity Consumption kWh	170.56	225.14	274.54	256,333

Table 38. Energy saving potential percentage in different user scenarios room 5113

	SCENARIO 1 Frugal	SCENARIO 2 Standard
Occupant can save %	%33.4	%12.1

Simulation Results of Room 3203:

Room 3203's simulation outcomes unveil distinct electricity consumption scenarios across different user profiles. The simulations of this top floor space project an expected consumption of 402 kWh for the frugal scenario, 557 kWh for the standard scenario, and 793 kWh for the wasteful scenario. In contrast, the monitored data reveals an actual electricity consumption of 646 kWh (Table 39).

The observed consumption aligns notably with the wasteful scenario, indicating that the users in Room 3203 exhibit a behavior profile that closely resembles wasteful consumption patterns (Table 40).

Table 39. Energy saving potential percentage in different user scenarios room 3203

3203 Room	**SCENARIO 1 Frugal Schedule**	**SCENARIO 2 Standard Schedule**	**SCENARIO 3 Wasteful Schedule**	**MONITORED DATA**
Total Electricity Consumption kWh	402.26	557.04	793.99	646.122

Table 40. Energy saving potential percentage in different user scenarios room 3203

	SCENARIO 1 Frugal	**SCENARIO 2 Standard**
Occupant can save %	%37.7	%13.7

4.2 Discussion

According to the results of this study, where modeling and simulation studies were carried out in 8 different rooms, it was observed that while 7 of the 8 modeled rooms were within the prediction range of the simulation, only room 2110 consumed more electricity than the simulation predicted even in the wasteful scenario (Table 41). The simulation outcomes across various rooms exhibit distinctive trends in alignment with different user scenarios. Rooms 5113, 1005, and 3203 showcase a closer resemblance to the wasteful scenario, indicating a propensity for higher energy consumption habits. On the other hand, Rooms 4110, 3102, 1113, and 4003 demonstrate a closer alignment with the standard schedule, suggesting more balanced and typical energy utilization patterns. Room 1113 is the only room where energy consumption is between frugal and standard scenario expectations. Room 2110, however, significantly surpasses the wasteful scenario, highlighting an outlier in user behavior. Moreover, the exploration of potential energy savings reveals that none of the rooms are close to the frugal scenarios. Therefore, notable energy savings potentials exist. If users' behavior is adjusted to align with the frugal scenarios, substantial energy consumption reductions between 50% and 70% are possible in the dormitory. This underscores the significance of tailoring energy management strategies to user profiles for optimal efficiency.

In addition, when standard schedule results and monitoring data are compared, the simulation results show an error of 3-38% per room, and 16% in total (Table 42). Considering the frugal scenario, occupants could save 30% to 70% of their energy, with an average savings of 50% possible. Even under the standard scenario, energy savings from 2.6% to 38% are possible. The standard scenario can achieve an average of 16% electricity savings. Only one of the rooms consumed more electricity than in the wasteful scenario. There is an energy-saving potential of 13% in the wasteful scenario in that room (Table 43).

Table 41. Total Electricity Consumption (kWh) of each room according to scenario

Room	SCENARIO 1 Frugal Schedule	SCENARIO 2 Standard Schedule	SCENARIO 3 Wasteful Schedule	Monitored Data
1005	65.53	152.51	240.81	219.25
4003	82.14	161.74	294.1	189.94
1113	113.4	284.63	443.32	248.16
2110	127.45	198.39	276.93	320.006
3102	161.12	355.86	472.11	371.965
4110	112.52	169.57	234.2	174.27
5113	170.56	225.14	274.54	256.33
3203	402.26	557.04	793.99	646.12

Table 42. Margin of error of standard schedule

Room	Margin of error of standard Schedule
1005	30.4%
4003	14.8%
1113	12.8%
2110	38%
3102	4.3%
4110	2.6%
5113	12.1%
3203	13.7%

Table 43. Savings potential according to scenario

Room	Frugal scenario	Standard scenario	Wasteful scenario
1005	70.1%	30.4%	N/A
4003	56.08%	14.8%	N/A
1113	54.3%	N/A	N/A
2110	60.1%	38%	13.4%
3102	56.6%	4.3%	N/A
4110	35.4%	2.6%	N/A
5113	33.4%	12.1%	N/A
3203	37.7%	13.7%	N/A

CHAPTER 5

CONCLUSION

The varied energy usage patterns found in various rooms highlight the complex nature of human behavior in residential spaces. Rooms 5113, 1005, and 3203, which are more closely aligned with the wasteful scenario, indicate a probable tendency towards energy-intensive operations. Understanding and addressing the factors contributing to this behavior in these specific rooms become crucial for implementing targeted energy-saving actions.

On the other hand, the rooms that closely match the standard schedule - 4110, 3102, 1113, and 4003 - provide useful information about more regular and typical energy usage. This predictability makes it possible to come up with standard energy management plans that are tuned to the needs of these user profiles. Additionally, it emphasizes the possibility of setting standard reference points for energy efficiency in certain situations.

Room 2110 stands out as an exceptional case, surpassing the wasteful scenario. This outlier highlights the importance of considering user behaviors that may diverge dramatically from typical models. It is crucial to identify and understand these exceptional data points in order to create strong and flexible energy management plans that accommodate a wide variety of user behaviors.

Communicating how much energy can be saved utilizing simulations with various economic scenarios to the occupants in real-time has the potential to save a lot of energy and may possibly be a new way to get people to change their habits to be more energy efficient. Strategies to alter people's behavior toward "frugal scenarios" might work to get large reductions in the amount of energy used. Behavioral changes can have a real effect on overall energy efficiency, as shown by the possibility for up to 70% decrease in energy use for this dormitory case.

In summary, this thesis had two research questions to investigate the relationship between energy simulation accuracy and occupant behavior and the building's energy performance.

1- What is the extent of accuracy displayed by energy simulation tools in modeling and predicting the energy consumption of dwellings, and how do their outcomes compare with actual electricity consumption statistics in real-world scenarios?

In seven out of eight rooms, the simulated results, generated with diverse user profiles, closely aligned with actual data within the predicted range. However, in a single room, a wasteful scenario exhibited results surpassing the anticipated outcomes.

Comparing simulation outcomes with real data, a margin of error ranging from 3% to 38% for all rooms in standard user scenarios was observed, culminating in an average error of 16%. This shows how important it is to improve the way user data is integrated so that there are fewer errors, and the modelling results are more accurate.

2- How does the impact on building performance change as user behavior changes in simulation programs? How effective is user behavior in saving energy?

The results show that user behavior is very important in the performance of the building. It has been observed that users can save energy from 12% to 70% in the designed wasteful standard and frugal user scenarios.

The results emphasize the effectiveness of energy simulation tools in accurately predicting residential energy consumption, emphasizing the crucial role of their active utilization, particularly by designers. Furthermore, observations regarding the impact of user behaviors on building performance highlight the necessity for a more focused inclusion of detailed user profiles within simulation programs. Combining more extensive data on user behaviors into simulation tools can be an effective method to improve and apply energy-saving measures in architectural design.

The duration of the seven-week monitoring period does not comprehensively capture variability due to occupant behavior. In a dormitory that has full occupancy throughout the year, the period of observation can be a full year and could help us learn more about how seasonal and temporal changes affect the relationship between occupant behavior and energy consumption.

The dynamic nature of student housing, with occupants coming and going, introduces challenges in maintaining a consistent user profile. Based on the students' class schedules, this study assumed that users would not be in the room from 8 am to 5 pm on weekdays. However, we do not have accurate data on whether users were in the room or not. The dormitory management did not allow occupant sensing equipment.

Simulation techniques offer useful insights, but the accuracy of these models is limited by inherent uncertainties even without considering occupant behavior. The study would have benefitted from calibrating the simulations using actual data from an unoccupied room, however, this was not possible due to time constraints and the lack of an appropriate unoccupied room.

People are naturally complicated, and the study's limited focus on three simple scenarios (frugal, standard, and wasteful) might not fully capture the complex and varied ways people deal with energy systems. Future studies should look into capturing a wider range of variations in occupant behavior.

One other potential area for future investigation that can build on the knowledge gained from this study and enhance the field of residential energy management is the long-term analysis of occupant behavior. Participating in extended monitoring periods, encompassing many seasons and years, might yield a more complex understanding of how the occupant behavior adjusts over an extended duration. Such a campaign has the potential to reveal trends that are influenced by seasonal variations.

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APPENDIX A

ELECTRICITY CONSUMPTION DATA

Table A.1. Monitored daily electricity consumption in rooms (kwh)

Time	Room 3003	Room 5113	Room 2110	Room 3203	Room 4110	Room 1113	Room 3102	Room 1005	Room 4003
11/22/2022	1.399	0.508	5.702	9.184	1.718	5.579	2.678	2.65	1.719
11/23/2022	1.381	0.488	6.183	4.533	1.811	4.508	4.339	3.515	1.599
11/24/2022	1.278	0.538	3.846	9.766	2.475	7.453	1.82	6.049	2.318
11/25/2022	0.957	0.474	8.824	13.739	1.718	6.806	8.853	3.095	0.613
11/26/2022	0.628	0.421	2.82	12.632	1.814	9.702	0.674	2.896	0.688
11/27/2022	1.738	7.105	6.776	17.68	2.472	7.484	3.93	3.652	3.572
11/28/2022	0.237	4.58	11.579	24.256	1.816	0.663	2.821	3.201	1.625
11/29/2022	0.453	5.001	0.813	8.569	2.787	2.221	10.474	3.645	3.272
11/30/2022	0.423	3.706	5.199	17.705	3.116	6.612	11.994	3.876	4.226
12/1/2022	0.239	4.623	3.475	8.827	3.863	2.654	0.998	5.418	3.353
12/2/2022	0.435	5.603	5.101	14.684	4.57	2.297	5.201	4.118	3.421
12/3/2022	0.707	5.539	6.332	14.842	3.417	2.818	4.756	5.057	2.875
12/4/2022	0.517	3.817	5.497	10.577	4.941	3.151	12.103	7.309	2.347
12/5/2022	0.229	5.253	4.535	12.859	3.369	3.96	5.867	5.144	1.73
12/6/2022	1.057	5.234	6.168	21.829	4.842	7.688	7.726	4.642	2.252
12/7/2022	1.793	5.341	12.46	20.908	5.938	3.548	4.517	4.068	3.951
12/8/2022	2.693	4.731	3.184	11.604	4.251	2.805	10.807	4.796	2.435
12/9/2022	1.091	4.184	10.346	2.694	2.291	1.681	3.8	4.596	0.724
12/10/2022	1.343	4.013	11.916	9.498	2.38	4.208	7.224	3.52	0.593
12/11/2022	1.343	4.774	7.775	9.474	2.441	2.148	4.845	3.552	4.527
12/12/2022	1.284	3.346	7.126	4.733	1.66	1.595	4.355	10.089	1.077
12/13/2022	1.093	4.614	6.549	8.834	2.93	3.07	3.424	0.2	1.364
12/14/2022	1.023	3.239	12.444	6.313	2.66	5.459	2.778	4.71	4.369
12/15/2022	0.683	4.635	11.205	3.295	2.489	2.086	1.489	3.436	1.24
12/16/2022	0.394	2.023	5.303	2.361	1.021	3.643	0.278	4.582	0.759
12/17/2022	0.501	2.047	3.375	13.333	2.48	1.569	1.239	2.943	3.107
12/18/2022	1.528	5.411	4.514	9.491	3.16	0.679	2.685	5.322	3.181
12/19/2022	0.926	6.322	3.742	16.391	3.624	2.657	3.867	6.486	3.852
12/20/2022	0.492	8.761	6.106	27.346	4.924	9.386	19.218	4.383	5.407
12/21/2022	0.798	4.059	3.856	22.875	5.183	6.148	9.78	3.513	3.796
12/22/2022	0.906	5.1	13.256	19.616	3.989	7.535	10.373	6.089	6.238
12/23/2022	1.078	6.941	2.38	24.491	5.055	4.156	12.279	5.971	4.855
12/24/2022	1.344	4.942	3.471	23.626	5.256	6.605	12.182	6.761	5.832

(cont. on next page)

Table A.1 cont.

12/25/2022	1.152	7.155	11.688	22.695	7.227	5.904	9.251	3.017	5.275
12/26/2022	1.99	4.729	12.298	12.658	4.72	7.261	5.944	3.27	5.485
12/27/2022	0.311	7.093	2.973	27.534	4.247	6.124	14.317	2.522	7.862
12/28/2022	2.101	7.67	3.582	12.322	6.209	6.174	14.348	4.63	7.906
12/29/2022	0.66	6.263	5.787	12.275	3.105	5.388	10.605	5.459	3.421
12/30/2022	0.564	8.467	2.635	12.716	1.315	3.647	5.417	3.864	3.986
12/31/2022	1.574	7.558	2.662	8.322	2.964	2.446	3.085	1.167	1.893
1/1/2023	1.662	6.926	2.788	13.156	2.367	3.301	2.589	5.767	4.812
1/2/2023	1.25	8.272	2.967	13.595	3.213	5.157	6.715	5.918	6.018
1/3/2023	1.134	8.793	5.507	9.412	3.711	6.405	35.939	4.186	4.105
1/4/2023	0.627	7.079	8.076	6.895	6.606	6.469	10.115	6.741	10.539
1/5/2023	1.068	4.113	7.599	10.194	2.633	8.66	10.481	3.6	8.087
1/6/2023	1.911	7.076	6.492	12.249	4.536	7.503	12.084	3.747	5.635
1/7/2023	1.461	9.73	8.356	12.278	4.906	10.22	9.838	7.569	7.248
1/8/2023	1.505	11.009	12.845	12.159	4.38	9.485	11.098	5.11	5.95
1/9/2023	0.97	7.027	11.893	9.097	5.674	11.443	10.765	3.402	8.801