SIMULATING THE ELECTRICITY CONSUMPTION OF OCCUPANTS IN DORMITORY BUILDINGS BY USING AGENT BASED MODELING

by

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B.S., Civil Engineering, University of Tabriz, 2018

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Master of Science

Graduate Program in Civil Engineering

Boğaziçi University

2022

ACKNOWLEDGEMENTS

First of all, I would like to express my deepest gratitude to my supervisor, Assist. Prof. Semra Çomu Yapıcı, for all her valuable lessons and guidance throughout my master's program. Dr. Çomu is a creative person and has great ideas in her mind, and with her various suggestions for research, I had the chance to study and learn different research topics related to construction management. I am also grateful to all my professors at Boğaziçi University, especially Prof. Beliz Özorhon, as her critical and constructive comments have always been helpful. Lastly, I wish to thank Assist. Prof. Yiğit Can Altan for accepting to be a member of my dissertation committee.

I am fortunate that I have found amazing friends during my time at Boğaziçi University. Güven Tezcan, Uğurcan Gürler, and Büşra Yücel are all amazing people who helped me a lot. We had memorable moments, and I wish them success in all their endeavors.

Living in a foreign country has its ups and downs. Having friends to help you in hard times and give moral support is priceless. Therefore, I am grateful to have Sina Mohammadzadeh Tutunchi, Pouya Sabokrouhie, Aref Entezari, Morteza Shokrani, and Mahsa Mohammadkhorshiddoust as friends. Thank you for always believing in me and having my back in every situation. I also feel lucky to have Ilyar Jafari, Nima Niyazpour, and Reza Faraji Dizaji as my flatmates. We shared great moments and laughed a lot, and without them, it would be unimaginably hard to pass the time in a foreign country during the pandemic.

Finally, I would like to mention that this study would not have been possible without the support of my family. I am deeply grateful to have my mother, father, and grandmother's love and support.

ABSTRACT

SIMULATING THE ELECTRICITY CONSUMPTION OF OCCUPANTS IN DORMITORY BUILDINGS BY USING AGENT BASED MODELING

Buildings are recognized for their significant role in electricity consumption and carbon emissions. Policymakers and researchers have addressed the necessity of realizing the underlying reasons behind buildings' colossal energy consumption. In this regard, many energy-efficiency strategies have been developed to achieve sustainability and lower energy consumption rates. Building energy performance is also proved to be significantly affected by occupant presence and behavior. However, understanding the dynamic relationship between occupants and buildings is not easy due to the complexities of human behavior. Until a few years ago, many building energy performance tools did not even consider occupant behavior in their analyses, resulting in noticeable gaps between actual and predicted energy performance. Strategies involving behavioral changes are considered low-cost and effective methods in reducing building energy consumption. Although researchers have investigated occupants' role in different building types, the number of studies focused on dormitory buildings is limited. Occupant-building interactions in dormitories are more complicated than office buildings because of the differences in students' lifestyles and daily behaviors. In order to examine the role of students in the energy consumption of dormitories, an agent-based simulation was developed and validated using real-time consumption data collected from a dormitory building located on the Kilyos Campus of Boğaziçi University. Results show satisfying accuracy, and this study explains how the model can be used for energy consumption prediction. Some scenarios are also simulated with the model to demonstrate its capabilities for recommending effective occupant-centric energy-saving strategies. The model is adjustable and can be modified to be employed in other similar buildings. Moreover, this study paves the way for other researchers to use the agent-based simulation for occupancy prediction and building energy analysis and gives recommendations on improving and achieving a more sophisticated model.

ÖZET

ETMEN TABANLI MODELLEME KULLANARAK YURT BİNALARINDA SAKİNLERİNİN ELEKTRİK TÜKETİMİNİN SİMÜLASYONU

Binalar, dünyadaki elektrik tüketimi ve karbon salınımında önemli paya sahiptir. Politika belirleyicilerin ve araştırmacıların, binalardaki yüksek enerji tüketiminin arkasındaki gerçek nedenleri anlamaları gerekmektedir. Bu bağlamda, daha düşük tüketim oranları ve sürdürülebilirlik elde etmek için birçok enerji-verimliliği stratejisi geliştirilmiştir. Bina enerji performansının da esas olarak bina sakinlerinin varlığı ve davranışından etkilendiği kanıtlanmıştır. Bununla birlikte, insan davranışının karmaşıklığı nedeniyle bina sakinleri ve binalar arasındaki dinamik ilişkiyi anlamak kolay değildir. Yakın zamana kadar, birçok bina enerji performans aracı, analizlerinde bina sakinlerini dikkate almadığından, gerçek ve tahmin edilen enerji performansı arasında gözle görülür uyumsuzluklar oluşmasına neden oluyordu. Ayrıca tüketici davranışlarını göz önünde bulunduran stratejiler, bina enerji tüketimini azaltmada düşük maliyetli ve etkili yöntemler olarak kabul edilmektedir. Birçok araştırmacı son yıllarda farklı bina tiplerini ve bina sakinlerini incelemesine rağmen yurt binalarına odaklanan çalışmaların sayısı literatürde sınırlıdır. Yurtlardaki sakin-bina etkileşimleri öğrenci yaşam tarzları ve günlük davranışlarındaki farklılıklar nedeniyle daha karmaşıktır. Öğrencilerin yurtların enerji tüketimindeki rolünü incelemek için Boğaziçi Üniversitesinin Kilyos Kampüsünde yer alan bir yurt binasından toplanan gerçek zamanlı tüketim verileri kullanılarak ajan tabanlı bir simülasyon geliştirildi ve doğrulandı. Bu çalışma kapsamında elde edilen ve tatmin edici bir doğruluğa sahip olan sonuçlar, önerilen modelin enerji tüketim tahmini için kullanılabileceğini göstermektedir. Modelin bina sakini-merkezli enerji tasarruf stratejileri geliştirme etkinliğini göstermek için bazı senaryolar simüle edilmiştir. Önerilen model diğer benzer binalarda kullanılmak üzere uyarlanabilir. Ayrıca bu çalışma, diğer araştırmacıların bina doluluk tahmini ve enerji analizi için ajan tabanlı simülasyon yönteminin kullanımını desteklemekte ve daha karmaşık bir modelin nasıl geliştirileceğine dair bazı önerilerde bulunmaktadır.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS / ABBREVIATIONS

ABM	Agent-Based Modeling
ABS	Agent-Based Simulation
ANOVA	Analysis of Variance
BREEAM	Building Research Establishment Environmental Assessment Methodology
CO2	Carbon Dioxide
DOE-2	Development of Energy - Version 2
EEM	Energy Efficiency Measures
GHG	Greenhouse Gas
HVAC	Heating, Ventilation and Air Conditioning
IEA	International Energy Agency
LED	Light Emitting Diode
LEED	Leadership in Energy & Environmental Design
MAPE	Mean Absolute Percentage Error
NPB	Net-Positive Building
RMSE	Root Mean Square Error
UK	United Kingdom
US	United States
ZEB	Zero Energy Building

1. INTRODUCTION

1.1. Motivation

In the past few decades, people's lifestyle has changed a lot due to technological developments. The advancement of technology has also increased people's life quality and comfort levels. The modern lifestyle requires utilizing various energy sources for dynamic personal and industrial activities, and societies demand as many resources as possible to maintain their quality of life. There are many sources of energy, but all of them can be grouped into two general categories; primary and secondary sources. Primary sources consist of fossil fuels, renewable sources, and nuclear energy. On the other hand, electricity can be categorized as a secondary source since it is generated from primary sources. Electricity is the foundation of modern civilization and has been the dominant form of energy, especially after the digital revolution. One needs no more than a few seconds of thinking to acknowledge the vital role electricity plays in our daily lives. Electricity is being consumed every second, from basic needs such as providing light for enclosed areas to generating power for microchips in all electrical devices. Even the Internet, without which most businesses and human connections could collapse, needs electricity to maintain functioning. Electricity use is not limited to individuals, and the industrial sector also consumes a significant amount of electricity. According to U.S. Energy Information Administration [1], only in 2020, about 3.88 trillion kWh of electricity was consumed, and 3.66 trillion kWh was billed to various sectors. According to electricity retail sales, residential buildings had the largest share in consumption with more than 38%, and the following major sectors are commercial and industry with around 34% and 25%, respectively [1]. The United States is not the only country with enormous energy consumption records; any country with overpopulated cities and large industrial and commercial sectors demands the same usage. High electricity demand, however, is not the main problem.

A factor about energy consumption is the cost of using it; individuals and entities pay large sums of money for energy bills. The cost factor becomes even more pressing for energy-dependent countries since they import energy from abroad, which can have a considerable financial impact on the national economy. The more concerning factor is the environmental effects both generating and using electricity leave behind, which leads to global climate change. The environmental damage of electricity use is mainly related to utilizing fossil fuels rather than benefitting from renewable and sustainable resources. Although there has been a worldwide trend in recent years to harness energy from renewable resources, in countries such as China and United States (the top two electricity cosumers in the world), more than 60% of electricity is still produced by fossils fuels and only 20% from renewable sources [1, 2]. Countries may have different policies for adaption to renewable energies, but broadly speaking, there is still a long way to build sustainable cities and societies. An indicator to assess the environmental effects of energy consumption is "carbon footprint". Basically, it can be described as CO_2 or equivalent greenhouse gases (GHGs) emitted from an activity, operation, or any kind of process related to a product or service. Analyzing carbon footprint may not be the best method to understand the damage caused by energy consumption; however, due to its success at catching the public's attention, it is a good entry point for increasing energy usage awareness as well as fostering sustainability [3].

The building industry (not just residential buildings) has a significant share in energy use, and evidently, it also has a dominant share in the carbon footprint. Many studies have reported the same statement, mentioning that buildings are the primary source of GHG emissions [1, 4–6]. For example, the Chinese building sector produces 50% of the nations' GHG emissions [7]. In other developed countries, numbers are not much lower; 50% for the U.K. [8] and 23% for Australia [9]. As for the U.S., although there has been some improvement according to recent reports, the residential and commercial buildings still account for roughly 29% of total national indirect emissions [10]. These considerable numbers indicate one clear message; it is impossible to reduce GHG emissions without energy-efficient practices in the building industry. The efficiency measures are not limited to passive methods like sustainable design. There are also active energy-efficient practices that take into account the interactions humans have with buildings. This study focuses on active methods while considering the roles occupants can play in energy savings.

1.2. Problem Statement

All construction phases and the whole building lifecycle are taken into account when discussing the share building industry has in energy consumption. Nevertheless, the operation phase has a more significant role due to its inclusion of occupants. Buildings do not automatically consume energy; occupants are the ones who adjust the consumption rates according to their needs and comfort levels. Fenner et al. [11] mention that the operational phase of a building has the most contribution to emissions. The continuous operational GHG release represents 70% of total emissions per unit when it is compared together with embodied emissions. According to International Energy Agency [12], 20% of global carbon emission can be reduced by 2030 with some basic energy efficiency measures such as using energy-friendly home appliances and lighting systems.

As a result, energy consumption in the building sector must be analyzed thoroughly as an essential issue for both policymakers and researchers [13]. Only after acknowledging the role occupants have in energy consumption during the operation phase of buildings would it be possible to develop appropriate strategies to save energy and reduce emissions. Not until a long time ago, professionals in the industry did not consider occupants in their energy analyses. Even later, when studies in the literature proved the significance of the relationship between occupants and buildings, professions started to incorporate occupant presence in their models, but with fixed occupancy schedules and very simplified assumptions [14, 15]. However, it had also resulted in noticeable errors compared with the building's actual energy performance. Complex human behaviors and their occupancy schedules have more influence on energy consumption than what was assumed in the past. Therefore, analyzing energy-related occupant behavior and presence prediction in buildings are hot research topics as incorporating detailed human actions into building energy performance analyses is still a challenge.

1.3. Aims and Objectives

This study aims to develop a model that can predict energy consumption in a dormitory building located in Istanbul, Turkey. Studies regarding student residents are limited in the literature, and researchers mainly analyzed other building types with smaller spaces with fewer occupants. Unlike other building types, occupancy schedules are completely irregular in student residents, and occupants have different daily activities, making the situation more complex. In addition to developing a prediction model, this thesis also has the following objectives.

The first objective of the thesis is to propose a simple yet robust model to study and analyze the role students play in a dormitory's energy consumption. The second objective is to understand the differences between the energy behaviors of male and female students and observe how much each behavior influences the total consumption. The third objective is to build a reproducible model for other researchers and explain the necessary steps for constructing it. Finally, the last objective is that the proposed model should be relatively simple, adjustable, and useable in other similar student residents.

1.4. Research Methodology

Information about the building and its occupants is always required before developing a proper building energy performance model; therefore, two datasets are gathered. The first dataset provides basic information about occupancy schedules and energy use behaviors, and it was collected through questionnaires. The second dataset includes the actual electricity consumption that was monitored for some dormitory rooms. The purpose of the developed model is to simulate occupancy schedules in rooms and calculate electricity consumption based on the predicted indoor hours. The chosen method is an agent-based simulation, and for this reason, agents represent dormitory students. Agents are divided into two groups, male and female. All agents have similar interactions with the building, but their daily behaviors and decisions are different. In the model, consumptions values of male and female students are calculated separately to study how each group affects the total consumption. NetLogo, an open-source programming language, is selected as the agent-based simulation tool. The overall concepts of agent-based modeling and all the necessary details for constructing computerized agents are explained in this study. Initially, collected survey data are used for building agents and their energy-related behaviors. On the other hand, the monitored consumption values are first used to calibrate the model and then validate the final simulation results. After achieving acceptable accuracy in simulation results, the model is utilized for some occupant-related experiments. This step analyzes several energy-saving scenarios and their subsequent effectiveness in potential savings.

1.5. Scope and Limitations

The current study analyzes only the electricity consumption of occupants in a student resident in Istanbul, Turkey, and does not consider other energy forms related to heating or water consumption. Also, the location and weather conditions of the area affect the time students choose to stay in their rooms. Although the proposed can be utilized for other student dormitories with some modifications, the overall data for constructing the model came from a single building and its occupants. It is recommended to conduct a new survey for each new building to gather appropriate information regarding the occupant's energy behaviors. All occupants in the monitored building are newly admitted university students and only have English preparatory lessons. Unlike senior students, they do not know each other before arriving there, and students with different lifestyles stay together in rooms. The situation adds to the diversity and complexity of occupant behavior and may be different from other dormitories. Moreover, the actual measurements used for model validation cover only three months. Hence, if used to predict consumption values in the spring semester, the model may predict results with an increased error rate. However, if additional data can be collected during the spring semester in future works, the model can be easily modified, calibrated, and turned into a valid model for an entire year's predictions.

1.6. Thesis Organization

The structure of the thesis is as follows:

- Chapter 2 provides the background knowledge for understanding the rest of the thesis. It starts with reviewing the concept of energy efficiency and how energy consumption is measured in buildings. Next, it reviews the works in the literature regarding the gaps in predicting the building energy performance and occupants' role in it. Lastly, it provides information about modeling and simulation and reviews the models proposed in the literature about occupancy prediction.

- Chapter 3 explains the methodology of the thesis and covers data collection, model development, and model calibration.
- Chapter 4 first presents the results and illustrates the outputs of the simulation, then explores the validity of the model. In the last section of the chapter, some energy-saving scenarios are investigated using the proposed model.
- Chapter 5 discusses the quality of collected data and simulated results in greater detail. Also, the study's limitations and recommendations for future work are mentioned in its last section.
- Chapter 6 provides a summary of the thesis and concludes the study.

2. BACKGROUND

There is a growing worldwide interest in energy efficiency and sustainability due to climate change and the limitation of natural resources. Climate change has been acknowledged as an urgent global issue, especially after the steps taken by United Nations in 1992 and Kyoto Protocol in 1997. In recent years, the Paris Agreement was another milestone to prevent the continuation of global warming and mitigate GHG emissions [16, 17]. Therefore, developing and implementing novel ways of production and operation has become a necessity in every industrial sector. However, despite its significant influence on the economy and environment, the construction and building sector still has not opted to use the most efficient practices in the industry. The building sector has a considerable effect on the environment. It holds about 40% of total energy consumption and releases around 30% of GHG emissions worldwide [4–6]. In addition, population growth demands even more space for living and working, resulting in more construction and energy consumption. Therefore, it is necessary to understand the reasons behind the huge share of the building industry in energy consumption and to provide practical solutions for reducing the consumption rate and consequent environmental effects.

2.1. Energy Efficiency in Buildings

After acknowledging the role of buildings in energy consumption and their impact on global carbon footprint, it is essential to understand the meaning of efficiency in the building industry. Three general characteristics in buildings can be taken into account to consider it as energy-efficient: (1) sustainable design, (2) use of energy-efficient material and smart devices, and (3) cost-effective and optimal building service system. Sustainable design mainly deals with steps taken during the design phase of the building lifecycle before the construction begins. The second factor considers measures regarding implementing new materials and tools in all three phases of design, construction, and operation. The last characteristic mainly applies during the operation phase with systematic management approaches and optimized control of HVAC and lighting systems of the whole building. In this regard, several agencies and organizations developed certifications to assess the level of efficiency in buildings. BREEAM, Energy Star, and LEED are some examples, to name a few. In recent years, however, new targets for sustainability have gained interest, especially in the academic world, to achieve Zero Energy Buildings (ZEB) and Net-Positive Buildings (NPB). The overall idea is to have self-sufficient buildings in terms of energy. Although the definitions and standards are not fully completed yet, the ideas are regarded as realistic approaches and not concepts of the distant future [18].

On the other hand, various actions result in waste of energy and prevent the industry from becoming a sustainable sector. It is necessary to examine and find the roots of inefficiency in the construction sector. To provide a general overview, actions such as implementing old practices in the industry, ineffective technical control systems, and using inefficient material and appliances are the primary examples of energy waste, which lead to inefficiency [16]. In order to prevent energy loss and achieve energy efficiency, several approaches have been proposed as Energy Efficiency Measures (EEMs) [19, 20]. For example, space heating and cooling demand can be reduced with modern glazing solutions, thermal insulation, and the utilization of efficient HVAC systems [4, 21]. In general, these measures can be divided into two approaches: passive and active.

Passive methods include optimal use of thermal mass and optimized space design to provide comfort with natural ventilation and good lighting; thus, resulting in less energy demand [21, 22]. Researchers have studied different elements of design such as orientation and shading [23, 24] and envelop design [4, 25] to develop more efficient designs and analyze their effects on energy savings. Active building system controls, such as lighting and HVAC management, take place during the operation phase of the building. The building is in service, and occupants are present during this time; therefore, modifications can result in significant energy preservation. Changing old electrical devices to smart and energy-friendly ones, for example, electric appliances with an A+ energy class or LED bulbs, are also simple steps in applying active measures. Another active measure that has gained attention in recent years is informing occupants of buildings about their energy consumption through feedback. By reminding their usage patterns and consumption rates, it is possible to improve occupants' awareness and guide them to more energy-efficient behaviors [26]. In another similar yet more complex system, consumption rates can be adjusted automatically with the help of sensors. For example, the system minimizes or even stops the energy consumption while the occupants are outside the building or when some spaces are vacant.

2.2. Energy Performance Monitoring

Evaluating the energy performance of a building is an essential step in understanding the saving potentials of energy consumption. Before going into details, it is important to have a general look at the main sources of consumption in buildings. Without knowing the source of the problem, any resolution to overcome the efficiency obstacles would be in vain. Furthermore, researchers and professionals in the domain of energy inspection have expressed their concern regarding the evident gap between the estimated energy use, usually in the design phase, and the actual amounts monitored during the operation phase of buildings. In the following sections (Section 2.2.2), the gap and related causes are reviewed only after gaining some ideas about the major sources of energy consumption in buildings.

2.2.1. Main Sources of Energy Consumption

By reviewing the literature and governmental reports, it can be easily understood that air conditioning, space heating, and water heating are the most dominant source of energy consumption [1, 27, 28]. Figure 2.1 shows the shares of major energy sources in both residential and commercial buildings.

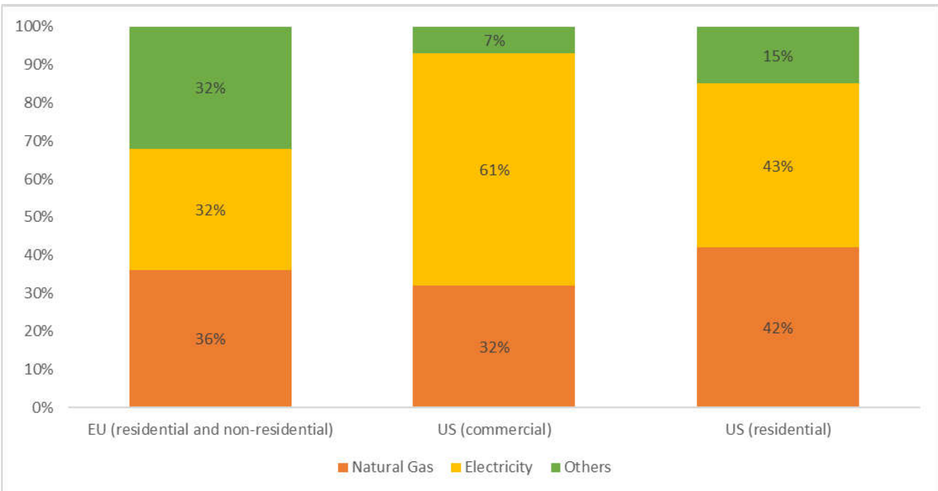


Figure 2.1. Shares of Major Energy Sources.

As the primary energy source in buildings, electricity holds a significant share and is utilized for various purposes. According to Figure 2.2, which illustrates the energy consumption by end-use, HVAC systems of residential buildings consume more than 50% of the total building energy use. Lighting and electrical appliances can be considered the second most dominant sources of end-use consumption in buildings, with roughly 30% of total energy in the United States and about 20% in EU countries [1, 28].

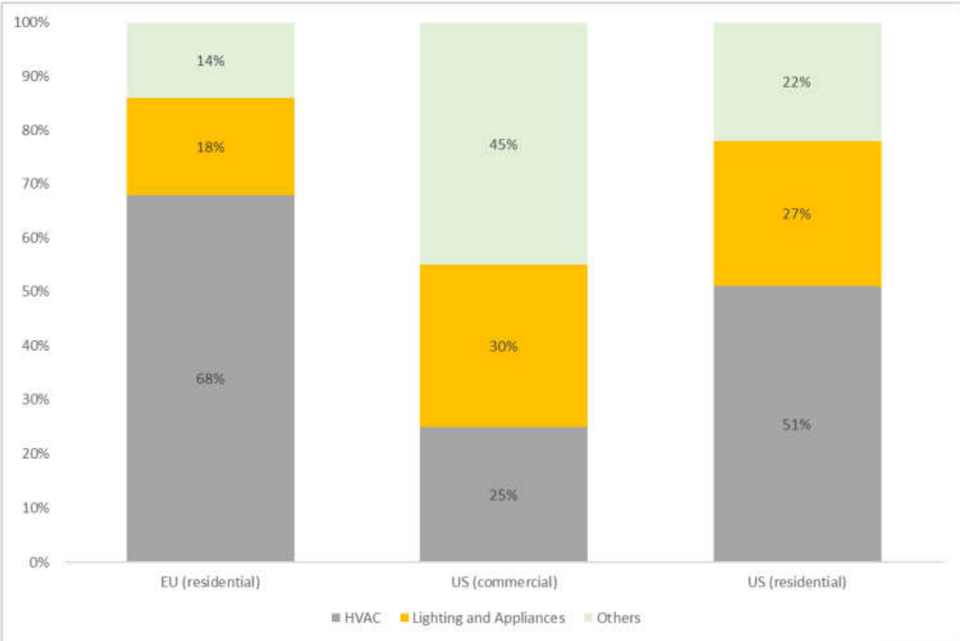


Figure 2.2. Energy Consumption by End-use.

For heating purposes, fuel (natural gas) has a significant role in many areas of the world, but electricity is also consumed for space and water heating. As a secondary source of energy, electricity automatically holds the account of fuels regarding carbon footprint and total energy use in the sector as a vast amount of electricity is generated from fuels. Electricity is consumed in various ways in buildings, from air conditioning and space heating to kitchen appliances and personal electronic devices. Air conditioning and heating have the most shares of electricity use, nearly 17% and 15%, respectively [1]. However, according to IEA's report, the use of air conditions will increase in the following years. This prediction especially applies to the Middle Eastern regions, where space cooling can represent 70% of total electricity use in a building on hot summer days and single-handedly cause environmental and financial impact [29]. Considering the environmental aspects, Fenner [11] states that the operational phase has the most contribution to emissions. The continuous operational GHG release represents 70% of total emissions per unit compared with embodied emissions.

2.2.2. The gap between theoretical and actual consumption data

As mentioned earlier, experts stated many times that there is an energy performance gap between theoretical (calculated) and actual (measured) consumption data [30, 31]. The calculated values are expected energy performance based on buildings' characteristics, and the measured data are values gathered through the operation phase of the building, with occupants' daily activities. Although energy policies still do not acknowledge the difference in many countries, it is an essential topic that needs to be analyzed thoroughly for transforming the building sector into an efficient and carbon-zero industry [32]. The gap can be divided into two kinds. The first gap is the difference between simulated performance, usually set as a target by owner and designer, and the actual (measured) values. The second kind stems from the difference between actual monitored values and a target set by governments in the forms of policies and standards [33]. The second gap is more lenient and automatically will be resolved if the first one is filled. Figure 2.1 demonstrates the gaps more clearly.

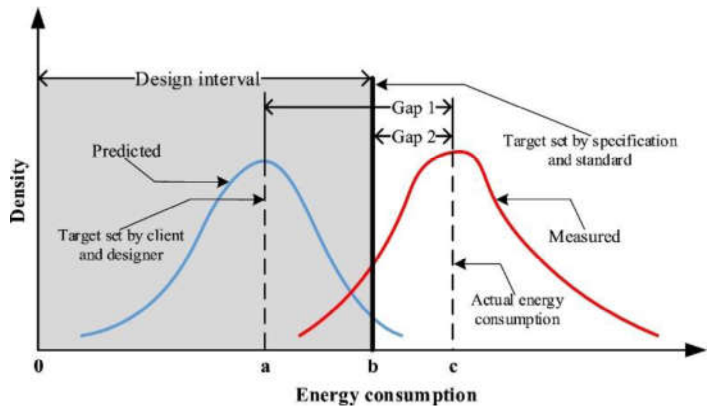


Figure 2.3. Gaps Between Actual and Predicted Energy Consumptions, Reprinted From [33], with Permission from Elsevier [Appendix F].

Researchers have expressed many causes and reasons for the root of gaps. The causes can be separated into three different categories by taking the building lifecycle into account;

causes arising from design, construction, and operation stages [34]. Most of the explanations in the literature attribute the problems to unrealistic assumptions and how the energy modeling is performed [32, 35]. Therefore, the reliability of assumptions, assessment tools, and methods is crucial.

In the design stage, inappropriate assumptions due to lack of experience and inadequate data are the leading causes of the energy performance gap. Another cause of the gap in design is associated with the modeling and simulation process as it turns the complex reality into a simplified representation [33]. In addition to the causes mentioned above, another interesting source of the gap is related to complex design and excessive use of technology. According to a study by [36], 28-35% of LEED-certified buildings consumed more energy than their conventional similitudes. The miscalculations in these certified buildings arise mainly because of overestimation of equipment performance, unpredicted occupant behavior, and lack of knowledge on controlling and operating energy systems [34, 36, 37].

During the construction period, negligence or low-quality work of the contractor can be the source of the energy performance gap. Poor workmanship or lack of experience, unconscientious work or cheating to reduce the cost, and multiple change orders are some other examples that can influence the final energy performance [34, 35, 38].

The critical stage of building operation plays a big part in the building energy performance gap. Up to a considerable degree, occupants are responsible for the appearance of this gap. Occupants’ presence and behaviors greatly influence a building’s energy consumption as they control home appliances, lighting systems, as well as temperature and ventilation to provide a comfortable space for themselves. Lots of studies in the literature analyzed the role of occupants in the energy performance of a building, and each study has focused on a different aspect(s) of occupant behavior. The following section explains occupants' roles on buildings’ energy performance in greater detail.

2.3. Role of Occupants in Buildings' Energy Performance

The previous section mentioned that the operation stage of a building's life cycle has a significant role in its energy performance. According to estimates, more than 80% of total energy is consumed during this period [39, 40]. The reason behind this significant value is the close connection between the building and its occupants. People spend most of their time working, doing daily practices, relaxing, and sleeping inside buildings. Generally, it does not matter where someone is during the day. During work time, as individuals, they consume energy at the workplace. If they come back home or go to another facility, they directly or indirectly influence consumption at that place. In all situations, electricity is continuously consumed, and HVAC systems operate to provide comfort for occupants. An exhaustive literature review by Chen et al. [41] revealed that studies mainly focused on occupant behavior in office and residential buildings, holding a share of 45% and 29% of the literature, respectively. The other building types that have attracted researchers' attention are commercial and university buildings; however, both these buildings represent less than 25% of the literature together. In addition to analyzing a specific building type, the location and region of a building must be taken into account. Occupants expect various comfort levels in each building type and region, and the operation interfaces are noticeably different in homes and workplaces [42]. However, in the past two years, people's daily routine has changed due to the Covid-19 pandemic. Many people have started to work remotely, and the energy consumption of residential buildings and private houses has increased compared to previous years. Besides the energy performance of the building, the comfort and health of occupants are also vital factors. Considering both energy efficiency and occupant comfort, researchers may shift their focus on residential buildings and study it more than before now that occupants spend excessive time in their houses.

Understanding occupant behavior is no simple task, and most of the studies in the literature have focused on a single behavior to analyze the human-building interaction deeply. Studies that have taken into account multiple behaviors and various actions are limited because analyzing every action occupants perform requires a tremendous amount of data. Besides, the consequent model for analysis becomes more complex and needs greater expertise. Many researchers have analyzed the role of occupants and acknowledged its influence on building energy performance [41, 43–47]. According to Chen et al. [41], occupants affect the building energy performance in three general steps: (1) acknowledging and including their presence in the energy models, (2) understanding the interaction between occupants and buildings, (3) invoking behavioral efficiency by increasing usage awareness. The following sections review these steps in greater detail.

2.3.1. Presence of Occupants

The presence of occupants has been regarded as a significant parameter in building energy consumption, but it is not enough to consider only the number of occupants, and more detailed occupancy information is needed for energy estimates [35, 48]. In reality, the number of occupants is not fixed and changes with time. There are several ways to represent occupancy information; prototype schedules suggested by governmental agencies, surveys, probabilistic methods, and with the help of smart devices. Fixed and basic schedules may lead to considerable discrepancies in some cases. There can be a 36-51% variance between fixed and actual schedules [49]. In addition, a study by Ehuaraz-Martinez et al. [50] shows that including the actual behavior of occupants results in considerable differences of up to 30% in building energy simulations. Occupant presence information is generally divided into two major dimensions: spatial and temporal [41]. The occupants can also have various statuses in each spatial and temporal dimension. A three-dimensional model, having occupancy (e.g., status, number, activity) as a separate dimension, is also suggested by some researchers [44]. For example, at a residential building, occupants can have states such as "at home and awake" or "at home and sleeping." Transition between rooms or floors is regarded as a change in spatial information. The time that an occupant is involved in an activity is stored as temporal information. It can also refer to the duration of being in a specific state or being inside a space.

2.3.2. Human-Building Interaction

The interaction of occupants with buildings is another subject of study by researchers to achieve energy efficiency. Occupants have great control over energy consumption in the buildings they live in or work. Adjusting HVAC system to reach a comfortable temperature [51], turning on and off the lighting systems [52], use of electrical appliances [53, 54], window and curtain openings [55], and demand for hot water [56] are some examples of occupant interactions with buildings. Research also focuses on the differences between manual and automated adjustments in smart buildings. In some cases, automatic control of the mentioned interactions can lead to noticeable reductions in energy consumption compared to manual control by occupants [45, 57]. Another method is to benefit from user feedback in order to understand the energy demand and the comfort level of occupants. Providing feedback to facility managers results in more optimized control and supply of HVAC systems, thus leading to energy savings in the whole building. Moreover, the difference in individuals' preferred comfort levels adds to the complexity of analyzing occupant behavior. In offices and commercial buildings, where several people occupy public spaces, individuals' behavior and perception of comfort may differ. Various studies highlighted the differences in preferred lighting and temperature options in commercial and residential buildings. For example, individuals prefer different illumination intensities, ranging from 230 to 1000 lux, in their workplace. In residential buildings, discrepancies of more than 6°C in thermostat setpoints were also observed [14, 44, 58]. External factors such as weather and window view also affect occupants' decisions. Several reasons can stimulate occupants to open and close windows. On cold days of the year, occupants usually open the windows to let fresh air come into the buildings. On warmer days, the motivation can be slightly different because it is not just for ventilation but also, in some cases, to reduce the outside noise. Other factors also influence the occupant's choice of actions and they should not be neglected, although they may not have noticeable effects. For example, psychological factors such as privacy concerns may lead to closing shades (blinds) and dimming lights [59].

2.4. Modeling and Simulation

A model is a less simple representation of a real-world system. A model is created to analyze and predict the effects of changes in a system when, in real life, the system is complicated, or it is impossible to conduct the necessary experiments. An ideal model should neither be too simple nor too complex as simplicity will cause the model to miss the essential elements of the system, and complexity will make it hard to analyze and understand the ongoing phenomena in the system. Simulation, however, is what puts a model into operation [60]. The two terms are sometimes used interchangeably. In a simulation, the model can be modified and experimented on to analyze the effects of changes in the system and understand the system's behavior. Simulations come in handy when it is not practical to do tests in the real world because of time, financial, or physical constraints. In a computerized simulation, it is possible to visualize and practically understand how the system works. It can also inform us whether a system works correctly or needs further modifications. In addition, simulations can test various changes and different scenarios if modifications are required in an actual physical system. After analyzing simulation results, researchers can choose the most appropriate way to implement it in the real system [61, 62].

It is necessary to have some general ideas about scientific models before understanding the process behind the design of a building energy simulation. An energy system model consists of three main parts; inputs, outputs, and system structure. These three parts are always linked together, and the purpose is to understand the underlying connection between the parts of a system. Input variables can be grouped into controllable and uncontrollable variables. Temperature setpoints, for example, are controllable values that can be changed either by the system manager or occupants in the buildings. In contrast, weather data (radiation, temperature, wind, etc.) are uncontrollable variables, although they influence the model output. Output variables are directly related to energy consumption. They can include room temperature, humidity, and illuminance. The system structure of the model connects the inputs to outputs and describes the relationship. Mathematical equations and physics formulas can be utilized to build the modeling structure [63].

2.4.1. Approaches to Building Energy Modeling

The models can be categorized depending on their purpose and built. Considering purpose, models of energy simulations can be either *Diagnostic* or *Prognostic* [64]. A diagnostic approach is utilized if an analyst wants to perceive how the system works and discover the roots of a phenomenon. In prognostic models, however, researchers and analysts do not focus on the underlying laws of the system; they use the governing laws to predict the outcomes. The other categorization depends on how a model is built, and it can be put into two distinctive approaches: *Law-Driven* or *Data-Driven*.

<u>2.4.1.1. Law-Driven (forward) Approach.</u> A law-driven approach works according to a given set of system laws and predicts the system outcome depending on the specified

conditions (input variables). Simulations based on this model produce accurate results because many sophisticated system structures have been developed to do the process. Some widely-used building simulation programs like TRNSYS and EnergyPlus operate under the same approach [63, 65]. This modeling approach is also called *White-Box* modeling. The first step in developing this kind of model is to get as much information as possible from the building layout, although it may not be possible to get every detail of the building in real life. Then, the modeling expert must set some parameters based on the gathered information and geometries so that the energy simulation programs mentioned above can use it. Lastly, to tune the parameters, the simulated outputs must be matched against actual (measured) data from the building. Employing this approach can be cost and time prohibitive and not really suitable for diagnostic purposes. However, forward approach modeling can be utilized for prognostic approaches if well-defined laws and inputs are provided [63–65]

2.4.1.2. Data-Driven (inverse) Approach. In a data-driven approach, the goal is not to predict the outputs but to understand system properties and behaviors. In order to develop the inverse model, both input and output data must be available through measurements. In contrast to the forward approach, where it requires excessive input data for greater detail, data-driven models can be constructed with minimal inputs. This method can be divided into two general categories: *Grey-Box* and *Black-Box* modeling.

Grey-box modeling is in some aspects similar to White-box modeling, although they have fundamental differences. Firstly, there is no need for detailed building layouts, and aggregated physical parameters are used instead. This method is relatively more complicated as it requires the development of a mathematical structure of the building based on formulas and laws of physics such as thermodynamic equations. Also, to tune the parameters, variables and inputs need to be adjusted with measured data [64]. Constructing a Grey-box model is not an easy job; it needs expertise and a sufficient amount of time to build the model. Another problem with this method is that a new model must be developed for each building. In addition, if the operational function of the building changes during its lifecycle, lots of parameters should be modified [65]. This modeling, however, is appropriate for diagnostic approaches but may not be the best choice for the whole building energy modeling due to its complexity mentioned above [63].

Lastly, the Black-box modeling is an approach that only relies on data and does not deal with physic principles. The idea is that gathered data are used to learn a predictive model for energy consumption of the buildings [63]. Accordingly, implementing this method is not suggested for diagnostic approaches, HVAC system control, and understanding how the system works. Black-box models use relatively simple mathematical and statistical techniques to understand the connection between inputs (e.g., occupancy, solar, and wind data) and outputs (measured consumption). Regression analysis methods and some artificial intelligence techniques such as neural networks are widely used in this approach [63, 64]. Here, data quality is an essential factor for developing a proper model; therefore, time and money must be served to accumulate accurate data. An excellent example of this method is Golestan et al.'s [66] work, where they applied it to estimate occupancy information. They only used a data-driven method, using some sensors to gather the required data, and applied particle filtering and time series neural networks without the need for building complex physics-based models. The performance of their black-box models was promising and resulted in accurate estimates.

2.4.2. Occupancy models

After acknowledging the two facts from previous sections, the gap between actual and predicted consumption in buildings and the role occupants play in energy consumption, the next step is to understand how researchers have adopted various models to analyze the connection between people and buildings in greater detail. Several empirical and simulation models have been proposed to predict energy use, but the older models sometimes had differences up to 30% from actual values [48]. Turner and Frankel [38] also stated that in some extreme cases where high electrical activities are utilized, the difference could even reach 100%. This discrepancy is mainly attributed to ignoring occupants or underestimating their effect. Energy models, nowadays, take into account the importance of occupant behaviors. However, admitting their presence in a building is not enough; therefore, their interactions with the building should also be considered.

It should be noted that occupants do not have a fixed behavior or characteristics; their patterns of actions alter over time. Additionally, Sorrel et al. [67] highlight an interesting fact regarding variations in behaviors due to changes in surroundings. They mentioned that some bad habits could arise after energy-saving retrofits in buildings. For example, substituting old light bulbs with energy-friendly LEDs results in energy saving; however, occupants may end up using more energy due to the notion that their lighting usage is no longer as influential as it used to be. This phenomenon is called the “rebound effect”. There is another phenomenon called “word of mouth” in the literature, where occupants influence each other with verbal communication. By observing, talking, and learning from each other, occupants may change their consumption behaviors [48].

To address the mentioned complexities, researchers have utilized different methods to estimate occupant presence and their respective behaviors. The models vary in required data, complexity, and implementation levels [68]. Occupant movement and behavior patterns can be generally categorized into static and stochastic schedules. Static schedules are commonly used in the industry as many established energy simulation engines and software programs utilize this method. EnergyPlus, DOE-2, Green Building Studio, and Design Builder are some examples of tools that perceive occupant presence and behavior based on a fixed routine. The schedule data is usually gathered through surveys and observations. Although fixed occupancy pattern is the dominant method used in industry, it has been reported that occupancy presence and number estimates have substantial errors compared with actual monitored data [69, 70]. On the other hand, stochastic models do not presume that occupants have completely fixed schedules; therefore, the proposed models are more sophisticated than static ones. Diverse stochastic models can be found in the literature, and each utilizes a different statistical and mathematical method, including logistic regression, survival analysis, Markov chains (especially discrete-time version), data mining, and agent-based modeling.

2.4.2.1. Statistical Analysis. Statistical analysis is not a single method but some quantitative tools to determine relationships among variables influencing each other. It is still the simplest and most used tool in various science and engineering domains. In occupancy models, it can be used to understand the connection between occupants and the building’s indoor and outdoor parameters. For example, Haldi and Robinson [71] used logistic regression to analyze the environment’s thermal situation and its effect on occupant actions (e.g., opening doors, windows, and turning on fans). In another study, researchers found out that occupant behavior has more correlation with personal needs rather than just with external factors [72]. They used random functions in general but also used S-curve method for activities that heavily rely on the time passed since last happened. Multi-factor analysis of variance (ANOVA) is another method that can be found in many studies. It is utilized to understand the significance of the relationship between various factors and a specific human activity such as window opening or lighting system use. Li et al. [73], used this method to analyze the connection between window opening and various indoor and outdoor parameters. After finding the most significant factor (in this case, outdoor temperature), they came up with a model to show the probability of window opening and the mentioned factor. In addition, they also compared their result with window activity probability distribution, which was produced from another method, Monte Carlo simulation.

2.4.2.2. Markov Chains. When talking about random behaviors and stochastic modeling, Markov Chains can be regarded as the most dominant method in the literature. Markov chain process is also one of the most established methods used for occupancy prediction due to its high accuracy and great implementation. The idea behind this method is that the history of transitions among states does not really matter, and the probability of the current state solely depends on the previous step (one step back in time). In a study by Erickson et al. [74], they utilized the Markov chain method to save more than 40% energy consumption in the HVAC system by accurately predicting occupancy patterns. Researchers have also benefitted from various algorithms to increase the accuracy of transitional probabilities in Markov chains. Therefore, some optimized Markov chains could outperform agent-based models and other well-known methods [47] .

2.4.2.3. Data-mining. It is possible to state that electricity usage or energy consumption generally reflects the occupant's behavior. Considering this idea, researchers proposed using data mining and finding patterns of behavior through consumption values, especially when there is no scarcity of data. In this method, consumption values are gathered from various electrical appliances. Researchers train the data with appropriate algorithms and then test it. This method is used by various experts and results in good predictions of occupancy and device use schedules [49, 75]. Baptista et al. [76] showed that implanting this method into an agent-based simulation can outperform a Markov chain model.

2.4.2.4. Agent-based Modeling. A proper model for occupant occupancy and behavior needs to simulate human interactions as individuals and groups. Agent-based modeling (ABM) is another well-known technique capable of representing most human behaviors in a simplistic form. In such a model, agents behave based on a set of rules and states assigned to them. Although ABM is used in the literature for occupancy presence prediction [45, 77], it can be seen that researchers applied this method for analyzing human-human or human-building interactions. Azar and Menassa [78] utilized ABM to analyze the "word of mouth" effect on agents' behavior and consumption characteristics. They wanted to see what happens if occupants influence each other and alter into lower or higher energy consumers. Their ABM model combined with *eQues*t energy simulation software resulted in more than 20% energy saving. Zhang et al. [79] constructed an agent-based simulation to compare automatic lighting management with manual (staff-controlled) lighting strategy in an office building. Lee and Malkawi [80] used ABM to study occupants' comfort level. They analyzed how an agent considers among five different behaviors to achieve comfort based on a decision process. Besides, their simulation revealed agents' sensitivity to different climate conditions how an agent adapts to the dynamic thermal changes. Langevin et al. [81] developed a novel ABM based on "Perceptual Control Theory" which they argue is an appropriate method for building agents. The theory works based on negative feedback due to discomfort and choosing the most immediate and unconstrained action to return to a satisfying comfort level. Besides, the researchers benefitted from a one-year field study to validate their final results. Azar et al. [82] used a surrogate regression model to analyze an urban area's energy performance in their ABM. Their objective was to reduce energy consumption without sacrificing occupants' thermal comfort. They implemented various interesting methods for each part of their study as there were no field data at hand for analysis and validation. Therefore, they generated the whole data required for the analysis, including occupancy characteristics and their respective consumption values, both for training and testing the dataset for surrogate models. Their energy management framework resulted in about 19% reduction without sacrificing occupants' thermal comfort. Ding et al. [39] built an ABM model to study students' energy consumption behaviors in a university's student residences. They also considered students' energy-saving awareness levels and explored measures for increasing agents' awareness via interaction in their model.

There are many studies in the literature regarding buildings' energy performance. However, until recent years, the energy analysis was conducted without considering the role occupants can play in the energy performance. It is not the building itself that consumes energy but the people residing in it. As a result, researchers have started to include occupants in their analysis and studied how people's presence and behavior can affect energy consumption. Accordingly, several types of buildings were studied, and occupants' roles were analyzed with various methods. ABM is shown to be a proper method to study the complexities of occupant behavior. In most studies, small rooms such as offices or classrooms with a limited number of people were studied. Generally, the occupants have a relatively fixed movement schedule and limited actions in these spaces. Nevertheless, in buildings like dormitories, complexity increases as each individual has their own schedule. The number of studies regarding student residents is limited, and this study aims to fulfill the gap by analyzing students' role in dormitories' energy performance. Besides, the differences in consumption behaviors of male and female students are separately analyzed to gain a better understanding of each group's impact on energy performance. Thus, a robust yet straightforward ABM model is proposed, which does not take the geometry of the building into account. The model uses ABM in its simplest form; therefore, it can be easily understood, modified, and efficiently utilized for other buildings.

3. RESEARCH METHODOLOGY

As mentioned previously (Section 2.3), occupants significantly impact the energy consumption in buildings. In office buildings, most employees arrive and leave the building on fixed hours; therefore, making it easier to model their occupancy schedule. However, in the case of student residents, the situation gets more complex because of their various class schedules and flexible lifestyles in general. This complexity explains the noticeable discrepancies reported between predicted and actual energy consumption in dormitory buildings. The gap in energy values stems from neglecting the role occupants (students) play in buildings' energy consumption. Many university students live in dormitories, and these buildings consume a great amount of energy. The 3rd Kilyos Dormitory of Bogazici University is selected to study the relationship between building energy consumption and occupant behavior. For this purpose, an agent-based simulation is developed to model the students' daily actions and energy use habits. The following sections explain the data collection, modeling, simulation, and validation processes.

3.1. Data Collection

Data acquisition is the first step in studying the energy performance of a building and how occupants can impact it. There are many ways to gather data about the presence and activities of occupants. A standard method to understand occupant behavior is conducting a survey, especially if smart devices are not available or the budget for research is limited. More advanced tools can also be utilized to gather accurate data, such as cameras, sensors, and smartphones [45, 83, 84]. However, in this research, devices are not used for occupancy detection, but smart meters are installed in rooms for energy monitoring. It is important to note that a more profound understanding of occupant behavior can be achieved by using both surveys and energy monitoring devices. The main downside of using an advanced monitoring tool is the cost and time of implementation and operation, which can sometimes exceed the duration and budget of research. If there are no limits regarding the mentioned obstacles, utilizing smart tools for the whole data gathering process is the best option. The survey was conducted to gather the preliminary information for developing the occupant behavior model in this research. On the other hand, the monitored energy data is used for validating the proposed model's outputs.

3.1.1. 3rd Kilyos Dormitory

The whole data of this study came from the 3rd Kilyos Dormitory of Bogazici University. The dormitory is in the university's Saritepe campus. It is located in Kilyos, an area in the north of the European side of Istanbul, Turkey. Figure 3.1 and Figure 3.2 show where the Kilyos area and the dormitory building are located. The campus is adjacent to the Black Sea and houses different facilities such as dormitories, research labs, a hotel, and the foreign language school of the university. Maps are downloaded from OpenStreetMap, which provides data under the Open Database License [85, 86].

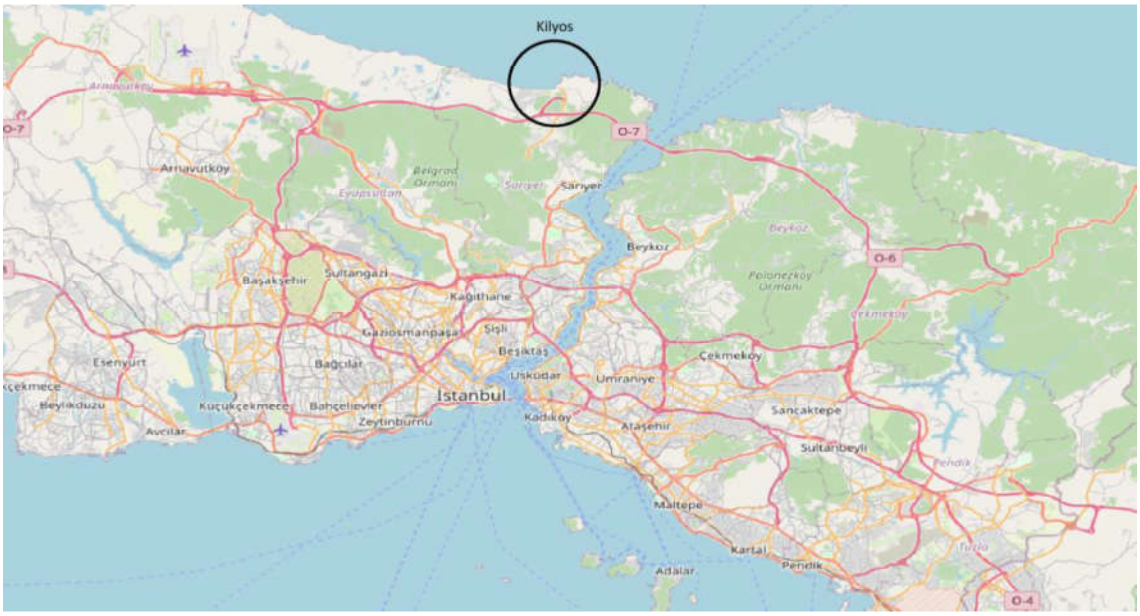


Figure 3.1. Location of Kilyos Area on Map of Istanbul.

Figure 3.2. Location of 3rd Kilyos Dormitory on Map of Saritepe Campus.

Most of the residents on the campus are newly accepted students studying English preparatory courses. Students from other cities are not the only ones who stay in dormitories. Due to the campus location, which is far away from the city center, even some students who live in Istanbul with their families prefer to stay at dormitories during the week. The campus has various social facilities so that students can interact with each other after their classes and get familiar with university life. The campus location may create some difficulties for the students in terms of weather as it is built near the sea. In cold months of the year, the weather can get freezing and windy in Kilyos. Therefore, students spend most of their time in rooms or inside buildings. It is worth mentioning that the university has benefited from the strong winds in the area and installed a wind power plant to generate its own electricity, adopting sustainability in energy management.

The 3rd Kilyos dormitory is not the only dormitory on Saritepe campus. However, it is the main dormitory due to its capacity to house more than 400 students. Both male and female students reside in it, although they stay on different floors. The building has five floors with an attic. Each floor has several flat-type rooms, and each flat contains a bathroom, toilet, and kitchen shared by some students. All flats do not have the same number of bedrooms. There are different types of flats with two to ten beds. Rooms and flats have several pieces of furniture and some appliances, including a wardrobe, table, chair, and bed in each room and a kettle, refrigerator, and electric stove in each flat.

3.1.2. Energy consumption data

Bogazici University has installed energy monitoring devices in the 3rd Kilyos dormitory for research purposes. Smart electricity meters in rooms collect and store consumption data in a cloud-based IoT system. The service was provided by a private energy monitoring company, Reengen, and allows users to access and download their data. The electricity measurements are gathered from 20 different rooms and stored as kilowatt-hours (kWh) in 5 minutes intervals. Although the cloud service and IoT platform have made it easier to store and access data, two issues were encountered during the electricity monitoring process.

The main issue that completely changed the course of the study was the emergence of Covid-19 pandemic. Due to the pandemic, universities worldwide had to cancel their face-to-face lessons and limit access to university campuses to control the spread of the virus. Many dormitories had to close and asked students to return to their hometowns and stay with their families. The residents of the 3rd Kilyos Dormitory were English prep students, and as the education system turned online, they had no reason to stay in dormitories. Rooms became empty, and the real-time energy monitoring process stopped. The restrictions continued for more than a year, and the measured electricity data turned out to be futile. In order to cover the damage and resume the study, another dataset was selected. Unfortunately, a dataset covering an entire year was not available in the servers, and the only useful and consistent electricity data belonged to 2016. The substitute data was collected for another study related to energy efficiency and covered the first semester of the 2016-2017 academic year, starting from the 21st of September to the 8th of January

The second issue is related to the quality of the data. The devices, which meter electricity use, sometimes fail to measure consumption or, in some cases, fail to send and store the data in the servers. Because of this issue, there are some missing values in the downloaded data from the servers. The connection problem occurred multiple times between devices and the server during the mentioned days. In some cases, the problem lasted only for some hours, and in others, it took several days to get fixed. Data covers 112 days; however, only 93 days had consistent measurements for an effective analysis. In general, the inconsistency in measurements reduces the quality of the data at hand and may lead to slight deviations in the validation process.

3.1.3. Survey

Energy consumption in the dormitory building is directly related to students' daily routines. Therefore, the first step is to gather enough information regarding their schedules and lifestyles. For this purpose, a completed survey that belonged to the study mentioned in the previous section was selected. The reason for not conducting a fresh survey, as stated before, was the pandemic. Also, the collected electricity measurements and the survey must belong to the same semester and student body. Researchers distributed paper-based questionnaires to 100 randomly chosen students in the 3rd Kilyos dormitory. They got permission from the university officials and dormitory management to hand out the questionnaires to students in person. Students were informed about the research theme and then requested to answer the questions without entering personal information. Questions were all in a 5-point Likert Scale format; therefore, making it easier to decide and answer. As a result, most of the questions were answered entirely and had no inconsistencies. The first part collects basic information about students, their rooms, and the number of roommates. The second part asks questions about the time students spend in their rooms. In the third section, questions are designed in a way to understand students' usage behaviors of electrical devices and kitchen appliances. The questionnaire used in this study is part of an exhaustive survey that was conducted during the same year and semester when previously mentioned real-time electricity consumption data were being collected. It was designed to collect various information about their detailed activities, comfort levels, and energy awareness in addition to the sections mentioned above. As the current study analyzes the electricity consumption behaviors, only the relevant sections are used to develop the model. The survey form containing pertinent questions is shown in Appendix A.

3.2. Model Development

In the next step, a model is developed depending on the collected information about students' daily routines through questionnaires and their actual energy consumption with the help of measurement devices. Utilizing both survey and smart monitoring methods helps to understand occupant behavior better and results in a more profound model. The survey results are used as a preliminary step in modeling the occupant behavior and their energy consumption rates. The actual electricity data is used for adjusting the model and its final validation. The model proposed in this study is an ABM. The following sections explain the fundamentals of ABM and how the model is built.

3.2.1. What is ABM?

The philosophy behind agent-based modeling is that real-world phenomena can be modeled via agents and an environment in which they can interact. Interactions occur in the forms of agent-agent and agent-environment [87]. How agents perform the interactions depends on how they are formulated. Agents are just autonomous individuals or objects with specific properties and actions coded into them. The method has been used in the literature with two different names; sometimes as agent-based modeling (ABM) and other times as agent-based simulation (ABS). These different terms should not confuse the reader as both mean the same method, but each can be used depending on the context. Besides, the general difference between modeling and simulations was mentioned in the background chapter (Section 2.4), and the same applies here. An agent-based simulation depicts a model of dynamic agent interactions, which is simulated repeatedly over time.

There are several reasons why ABM has become an established and widely used method in various domains of science [87, 88]. First of all, the world we live in is getting more complex every day, and analyzing it with conventional methods may not be possible anymore. Second, some systems have intrinsic complexity; therefore, many assumptions are made to simplify the modeling process. These assumptions include homogenous agents or modeling only at macro levels. However, ABM grants us the ability to model phenomena at the micro level with heterogeneous individuals and study the consequences at the macro level. Lastly, computational power was much lower in the past, and simulations were time-consuming. In addition, data collection was also costly, and access to a detailed database was limited. Nowadays, various types of data can be constantly collected in great detail and at lesser costs. The two expressed changes in technology make ABM a useful tool to quickly build agents and observe their behavior in multiple simulations. ABM is also an appropriate method for incorporating randomness into a model as an agent makes decisions and acts upon them based on random numbers or specified probabilities. Besides occupancy prediction and building's energy analysis, mentioned in the background chapter (Section 2.4.2), researchers have applied ABM in various fields of science, including healthcare and epidemiology, social sciences, transportation, supply chain, and planning [87, 89].

In the real world, occupants are heterogeneous individuals with various goals and behaviors. They may change behavior depending on the situation and act differently over time. Behavior is a complex system influenced by consciousness and environment [39]. All the occupy models mentioned in section 2.4.2 have some advantages and limitations, and each can be used according to the objective of the study; thus, it cannot be concluded that one method is more effective than the others. For example, Markov chains is a suitable method for long-term occupancy schedule prediction or classification, while for modeling the number of present occupants in the building and their detailed behaviors, ABM is recommended as the proper method. ABM is a bottom-up modeling method that considers each agent's behavior and decision separately and combines the micro-level actions to reflect the system and demonstrate its macro-level conditions and consequences [47]. The foundation of building occupant behavior simulation is the assigned rules for the agents and the system; however, ABM is more than a simple "if-then" rule because agents can interact and change behaviors in each simulation cycle.

It should be noted that actual data is needed instead of assumptions to have a dependable model and get the best result from an ABM. Building models based on assumptions can be regarded as a limitation of ABM as assumptions cannot be removed entirely, but it is possible to minimize them by providing the model with actual data as much as possible. Researchers are sometimes unable to successfully validate their results using ABM due to a lack of actual observational data. Jia et al. [47] reviewed various studies and different methods for building energy modeling and the connection occupants have with it. They expressed that ABM is a suitable method for real-time modeling for various building types, but the studies usually lack actual data to support their results.This study, however, utilizes the previously explained survey data and electricity measurements to achieve an acceptable model.

3.2.2. Understanding the Model

Since each student has a different lifestyle and daily routines, ABM is selected as a suitable tool for the modeling process as this method is most useful when agents are not homogenous. For this purpose, NetLogo software program was selected to construct the agents and their environment. NetLogo is an open-source programming language and modeling environment designed by Uri Wilensky in 1999 [90]. It was initially developed for educational purposes and used as a teaching material. Nowadays, it is acknowledged and used by many students, scientists, and researchers worldwide. Unlike AnyLogic, a multi-method simulation tool primarily used in the industry, NetLogo is not a professional program and has kept its user interface simple and easy to understand. Therefore, it may not be suitable for industry-level problems. However, NetLogo has improved a lot in the last two decades, and once in a while, developers add new functionalities and extensions to it. There is no need to have a strong programming background to work with NetLogo, and due to its similarity to natural human language, the coding language can be learned within some weeks of training.

Before constructing the model, it should be noted that every ABM must have three components defined; agents, environment, and interactions [87]. Agents are representatives of students in this study. Agents have classes (types) and attributes. Here, we have two types of agents: male and female. However, several attributes were defined for each class. Agents have five attributes coded into them. Each student agent keeps track of the energy they consume and records it in the attribute variable named “e-cons”. Two different attributes indicate their sleeping status and location. Each of these attributes has two alternatives; the former can be either “sleeping” or “awake” and the latter, “indoor” or “outdoor”. Agents also decide how long they will stay inside their rooms based on the data collected from the survey. “M-in-hour” and “N-in-hour” attributes are introduced to save indoor hour values for daytime and nighttime, respectively. “M-in-hour” indicates the maximum time an agent spends inside a room in the morning when they do not have a class on a specific day. “N-in-hour" shows the maximum hours an agent chooses to spend in his or her room after finishing their classes up to 2 o'clock after midnight. After 2 A.M. all agents are assumed to be asleep. This assumption had to be made to simplify the model as there was no data related to the time students go to bed. Even if such data were gathered with questionnaires, it would be unreliable since newly admitted university students have flexible and eccentric lifestyles and do not have a fixed sleep time. The values for the two mentioned time attributes are not imported directly from the questionnaires. Agents in Netlogo choose the required values from a pool of numbers that were generated with Python programming language. The questions in the 2016 survey were mainly in a 5-point Likert Scale format. Answer choices for the questions about time spent indoors could not be directly used in NetLogo. Thus, new useable values for the model are created.

In order to come up with more practical indoor hour data, answers from the questionnaires were taken in 5-point format, and their distributions were calculated and plotted. Figure 3.3 is a sample plot showing the distribution of answer choices for the first question regarding the time spent inside rooms during the week. The plot below shows that, for example, around 33% of respondents in the main questionnaire chose the first answer (1), and 4% chose the last answer (5). It must be noted that values 1 to 5 are not considered as hours here; therefore, they need to be modified.

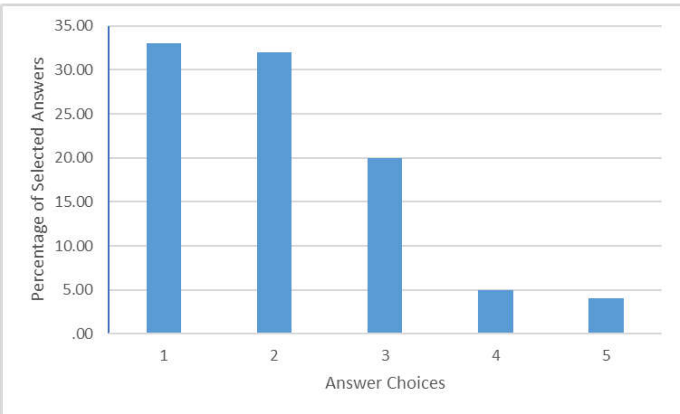


Figure 3.3. Distribution of Answers for a Sample Question from the Questionnaire.

Specific values in terms of hours are needed for agents in NetLogo. Generating completely random hours is a possible method; however, it would neglect the survey results.

Hence, the percentages in Figure 3.3 are used as weights to produce random numbers, and the generated numbers indicate the hours an agent may choose to spend in their room. In addition, NetLogo has a limited number of random functions and does not include weighted random distribution. Thus, Python is used to generate 1000 random values based on the weighted probabilities. The generated values (as hours) have a similar distribution to the survey data but have a different range. Figure 3.4 shows a sample plot created based on Figure 3.3 and represents the numbers required for NetLogo agents. The plot shows that each answer choice, except the first one, is turned into two discrete hours, but the summation of their distributions is kept close to the original value. In this example, values “0” and “1” have a total probability of 35% for being selected, compared with 33% of the first answer choice in Figure 3.3. Similarly, the chances of being indoors for seven or eight hours are 2% and 3%, respectively. Their summation is 5%, which is very close to the original distribution of the answer choice “5” in Figure 3.3.

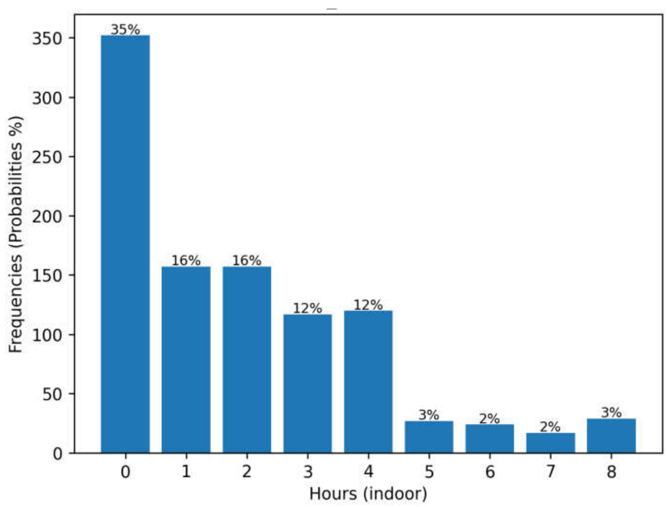


Figure 3.4. Distribution of Generated Answers Based on the Values from Figure 3.3.

It is not mandatory to plot the hourly values for all the questions, but visualization makes it easier to check whether the resulting values follow the original data or there is a mistake in the codes. The produced hours are saved into a text file because NetLogo has a built-in function to read and import data from text files and use them in the model.

After building the agents and identifying their attributes, the next step is to design an environment. Agents act and interact in the environment surrounding them. Agents and the environment are always connected as each can affect the other. In general, there are two kinds of environments in NetLogo; spatial and network-based [87].

Spatial environments represent physical areas such as a building, a farm, or a country. Network-based environments, however, do not model physical distances. It provides an environment where agents are linked and share information without being present in a specific location. For example, a network-based environment is utilized to model how rumors spread in a given society. There is no need for agents to be in specific geographical positions in order to communicate, as in real life, information exchange can be done via telecommunication devices. In our case, however, the modeled area is a dormitory building, and the positioning of students is important, and only a spatial environment is built. Figure 3.5 shows the graphical environment built for this study. The white section represents the outdoor area. The indoor area here is divided into two parts since the energy consumptions of male and female students are analyzed separately.

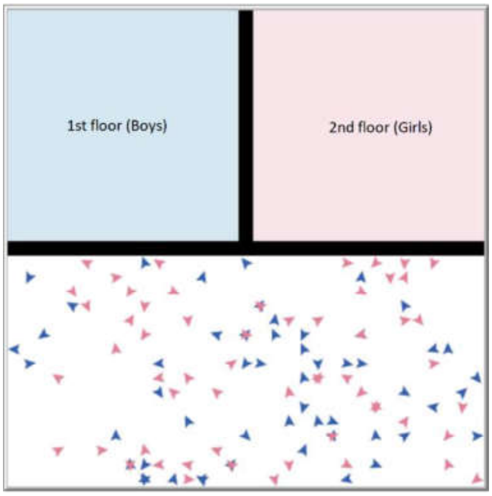


Figure 3.5. NetLogo Environment of the Proposed Model.

The level of detail is another essential factor in building the environment, and it depends on the purpose of the study. It is possible to model the whole building as a single solid environment or even increase the complexity and build each room and hallway separately. Since being indoors (inside rooms) triggers electricity consumption in our model, constructing only two different areas would be enough. Besides, unlike some studies where only a single office was modeled and analyzed, it is neither logical nor practical to build many separate rooms when there is no knowledge of the relationship and interaction among their occupants.

Next, the electrical devices that students use in the dormitory flats need to be added to the model. The power demand (wattage) of kitchen appliances, personal devices, and lighting bulbs were gathered from various sources on the internet, and an average wattage was used [91, 92]. Energy demand for all the electrical devices used in the study is listed in Table 3.1.

Table 3.1. Energy Use of Appliances Used in the Dormitory Rooms.

Equipment	**Energy use (watts)**
Laptop (male students)	125
Laptop (female students)	75
Cellphone charger	5
A personal electrical device charger (e.g., Tablet, Ebook reader, Bluetooth headphones)	15
Lighting bulbs	50
Coffee maker (or electric kettle)	1200
Electric cooker	1500
Beard trimmer (or shaver)	15
Hairdryer	1250

It should be noted that different values are considered for male and female students' laptop power load. Using a laptop for studying and doing course assignments is similar for both groups. However, based on experience, male students spend long hours playing computer games in their free time. Although no question about this behavior was asked in the questionnaire, this assumption seemed reliable and sound after a friendly chat with some random students. Female students, however, spend time on their laptops for other purposes such as browsing or watching movies. The difference had to be noted in the modeling process since playing video games, especially on laptops with good graphic cards, demands more energy. The power demand of laptops depends entirely on their model and hardware configuration, yet laptops for daily use consume between 60-80W on average. However, most gaming laptops consume more than 100W and even up to 200W while overclocking

[93]. Not all male students have gaming laptops, but every laptop changes its power load depending on the ongoing process. Gaming is always a power-consuming process; therefore, considering a higher wattage for the laptop use of all male students is rational.

3.2.3. Building the Simulation

In general, almost all NetLogo simulations have two major procedures: "to setup" and "to go", although both can consist of several minor procedures [61]. In the first procedure, agents and the environment are created, and it can be regarded as an initialization step that prepares the simulation. The "to go" procedure includes all the codes and functions that tell agents what to do in each time step. Time in NetLogo is divided into discrete steps called "ticks". NetLogo has a built-in tick counter and records every action taken in each tick (step). It is up to the model builder to specify what each tick represents. In our model, each tick represents one hour in real life. If the measured electricity consumption had covered a full academic year, assigning each tick to a day would also be possible. On the other hand, if ticks were linked to minutes in real life, more computation power would be required. Besides making the process time-consuming, the detailed simulated data would not be beneficial, and it can even result in noisy output data. Our data covers about three months; therefore, choosing ticks as hours seems sufficient for simulating the necessary behaviors and simulating daily actions.

The general structure of a NetLogo model is shown in Figure 3.6. It should be noted that the tick command must be inside the "to go" procedure. This command alerts NetLogo that one timestep in a simulation is finished and prepares the program for the next tick. NetLogo runs all procedures one by one by referring to their functions, and when no procedure is left, it runs the tick command and adds one unit to it. In minor procedures, the process is repeated depending on the number of agents if the function contains the command "ask turtles". In NetLogo, we refer to agents as turtles, and each turtle represents a distinct agent. So, if the model includes 100 turtles, the procedure with "ask turtles" will run 100 times, and it will end when all turtles complete their actions.

```
define variables []
to setup
  create/configure environment
  create/configure angents
  additional procedures for initialization
end
to go
  procdeure 1
  procedure 2
  ...
  tick
end
to procedure_name
  ask turles[
    if condition = true
      [do something]
  ]
end
```

Figure 3.6. General Structure of a NetLogo Code.

The "to setup" procedure starts with a "clear-all" function to reset everything from the previous run and prepares the simulation for a fresh start. The next three sub-procedures create the environment, agents, and electrical equipment. The spatial environment in NetLogo is a two-dimensional world made of patches. Patches are square pieces, like pixels, in a blank plane, and each patch is positioned in a Cartesian coordinate system. Therefore, the middle patch is located at (0, 0). Patches have built-in attributes such as coordinates and colors. In our model, patches with an X-coordinate of less than zero are given blue color to represent the male dormitory, and the ones on the right of the Y-axis are turned to pink to represent female students' rooms. All patches with a Y-coordinate of less than zero are grouped to represent the outdoor area. The "setup-turtle" procedure simply creates male and female agents and gives them different colors to be distinguishable in the validation process. The simulation user specifies the number of agents as inputs. Finally, the third sub-procedure ("setup-appliances") assigns the wattage demand values to each device based on Table 3.1.

Our model's "to go" procedure consists of four primary sub-procedures. The first procedure ("check-sleep") tells agents to go to bed after a specific hour. In the second procedure ("check-location"), each agent picks up a time value and, based on it, decides whether to go out or stay in the room. The following procedure ("move-turtles") gives orders to agents to change their location depending on their decision in the previous step. The last important sub-procedure ("consume-energy") informs agents to start using electrical devices if they have decided to stay indoors. The other sub-procedures in "to setup" and "to go" procedures are added only for control and validation purposes and do not affect the simulation process. The codes for the whole process can be found in Appendix B.

Generally, it has been recommended to put the "tick" as the last command in the "to go" procedure. This command ends one round of simulations, saves the produced data, and tells the program to prepare for the next round. However, in our model, "tick" is not the final command; a simple command and two procedures come after it. The command creates a variable for simplifying the coding process. The "show-time" procedure reports the current time in each step and is designed to control the model's reliability. The remaining procedure, "check-day", is an important section in the model since it tells the model to distinguish between days and weeks.

Days are divided into weekdays and weekends in the model. Here, Saturdays and Sundays are considered as weekends. The amount of time that students spend in their rooms changes on weekends. Generally, students spend more time in their rooms on weekends if they decide to stay in the dormitory. However, according to dormitory management logs and conversations with random students, some prefer not to stay in the dormitory on weekends. Usually, one in five students go back to their family houses or plan to stay at a friend's flat. Students who plan to spend weekends outside the dormitory usually go out on Friday evenings and return on Sunday evenings. In the model, for simplicity, Sunday nights substitute the Friday nights. Therefore, these students were assumed to spend Saturday and Sunday outside their rooms, resulting in zero electricity consumption on weekends. In the model, a variable called "home-sick" is introduced, and each weekend, 20% of students are randomly assigned to this variable. Agents included in this variable are considered to be outside; therefore, no energy consumption is recorded for them.

The measured data starts from Monday, the 19th of September. When five days pass, the first weekend starts; therefore, when ticks reach the number 120 (5 × 24 hours), the model automatically considers the date as Saturday. Similarly, after another 24 ticks, the model changes the current date to Sunday. Modulo function (mod) is used in the whole process to differentiate hours and days. Modulo is a mathematical operator that returns the remainder of a division. For example, when the ticks reporter reaches the value 241, the model understands that it is again weekend (241 mod 120 = 1) and the time reporter shows

Saturday, 1 A.M. The same goes with hours; the model understands each hour with the remainder of a tick's division by 24 (ticks mod 24). For example, if the tick counter reaches 48, the time reporter will show 00:00 (48 mod 24 = 0), meaning two days have passed.

Agents are coded to use the mentioned electrical devices only when they are indoors and awake. Between 2 A.M. and 8 A.M., all agents' status turns to "sleeping", and they stop consuming energy. Each day at 8 o'clock, agents wake up but do nothing until 9 o'clock. This one-hour pause in simulation is considered to mimic various actions students may do in real life. Some students go out to have breakfast in the dining hall, and others may take a shower or even stay in bed. During this time, they decide their daily activities by choosing a random value from a weighted distribution of numbers and setting it as their "M-in-hour" attribute. Agents start to act after 9 o'clock. If an agent chooses zero hours for its time indoors, it will go outside and stay there until evening. In reality, it means that a student has lessons that day or decides to spend time on campus. If the value is greater than zero, agents stay inside their rooms and start to consume electricity depending on the value they have chosen as their "M-in-hour" attribute. The exact process occurs again at 4 P.M., and agents choose the hours for spending time inside rooms during nighttime. Some activities occur only in the morning and others at night, although it does not really matter as the final consumption results are saved for days, not hours. For example lighting system only activates during nighttime. On the other hand, laptops use electricity according to hours spent indoors during both daytime (M-in-hour) and nighttime (N-in-hour).

As mentioned before, the energy consumption function in the model only triggers when an agent's status changes to "awake" and "indoor". The function works on the concept of kilowatt per hour, meaning the demand wattage of an electrical device multiplies by the hours an agent spends in their room. It is assumed that students need only two hours each day to charge their mobiles and other personal devices. For laptops, however, a usage probability is taken into account, meaning that students only spend a specific portion of their time using these devices each day. Accordingly, the multiplication consists of three elements: the energy load of the device, the spent hours in rooms, and a randomly chosen value from the pool of previously generated device use probability. Like hours, the probabilities are also generated with Python. The python codes for assigning new values to the original survey results are similar to the codes used for generating new hours only with minor modifications for assumptions and visualization methods. The Python codes are presented in Appendix C. After using all electrical equipment, the total daily consumption of all agents is summed and reported for plotting. NetLogo lets us export the plots and their associated data as a CSV file for further analysis.

3.3. Model Calibration and Verification

3.3.1. Examining the Simulation

Model verification is essential to ensure the reliability of the model. For this reason, some extra functions are coded into the model to report the current status of the simulation. Several tests were performed as well before finalizing the model. Another benefit of using NetLogo is its graphical demonstration of the simulation. NetLogo updates the simulation graphics in each step. It is also possible to decrease the simulation speed and observe how agents perform tasks one by one in slow motion. The graphical user interface of NetLogo is shown in Figure3.7. Two boxes are planted to record and plot daily electricity consumption values; “plot 1” draws a line chart for male students and “plot 2” for females. Another reporter box, on the upper right side of the NetLogo environment, translates the ticks into standard date and time format. This reporter has a vital role in simulation verification. Controlling agent behavior is extremely confusing in terms of ticks, but the time reporter helps to compare and match every action to its corresponding hours. Without knowing time and date, it is impossible to determine whether agents are acting properly or not. If an agent’s behavior and movements do not match the time, we would realize that there is a logical mistake in the codes. The reporter also shows “M-in-hour” and “N-in-hour” for the first four agents. In the initial steps of developing the model, only four agents were created to make the simulation easier to control. The values each of these agents choose are displayed in the reporter to check whether they really act upon these values or not. Together, the reporter and the graphical agents on the environment act as a control room for the simulation.

Figure 3.7. Graphical User Interface of NetLogo.

Three additional factors related to the location and status of agents are considered in building the model. First, for unknown reasons, the consumption values of male students in the actual measurements were less than the anticipated amount in the first twelve days. By comparing the actual electricity consumption of the two groups, it was apparent that the growing consumption trend was not logical for the male dormitory. Some students might have moved into their rooms later than others. Another guess is that some of the monitored rooms were completely or partially empty on the first days. It is also usual for students to ask the management to change their rooms on the first days of the semester. By considering these possibilities, it was assumed that around 20% of students moved into the monitored rooms after two weeks to calibrate the model. Although, in reality, these students may have arrived on various days, the mentioned assumption greatly improved the model and reduced errors.

The other modification decreases the consumption rate on the last days of the academic semester. As students had different lessons and final exams, they started to leave the dormitory one by one for the semester break after finishing their exams. For this reason, a set of functions are added to the “check-location” procedure, which chooses some students randomly and adds them to a new variable called “holiday”. The number of students added to the variable increases cumulatively during exam days, lasting about ten days. This added function also improved the model’s output in predicting the energy consumption rate in the final days of the fall semester.

The model includes another assumption, which is more generic. In the first two weeks, it is assumed that students spend less time in their rooms. As supported by actual consumption values, the reason behind this decision is that students usually spend more time hanging out outside and exploring the campus as the university workload is still low.

3.3.2. Error Statistics

Moreover, the whole model needs to be validated by comparing the simulation outputs with the actual electricity consumption data. The results of this comparison are shared and explained in Chapter 4. In addition, two error metrics are utilized to test the accuracy of the energy consumption predictions and see how far they deviate from actual measurements. Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are selected as error metrics to evaluate the simulation results. MAPE measures the average absolute deviation between actual and simulation values and reports the results in percentage. MAPE is scale-independent; therefore, it is easier to understand and interpret the results. The formula for MAPE can be calculated as

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - P_t}{A_t}\right| \times 100 \qquad (3.1)$$

where A_t is the actual monitored value, P_t is the predicted value from the simulation output, and N is the number of measurements (days).

RMSE is another standard metric that has been used in many studies to evaluate the performance of a forecasting model. It calculates the standard deviation of residuals and reports the average distance between actual and predicted values. To put it simply, RMSE measures how spread-out simulation outputs are from the monitored consumption values. It should be noted that RMSE has the same unit as predictions, and errors can be used to compare different proposed forecasting models for a specific dataset; lower RMSE values indicate higher accuracy and better fit. RMSE can be expressed as

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(P_t - A_t)^2}{N}}. \tag{3.2}$$

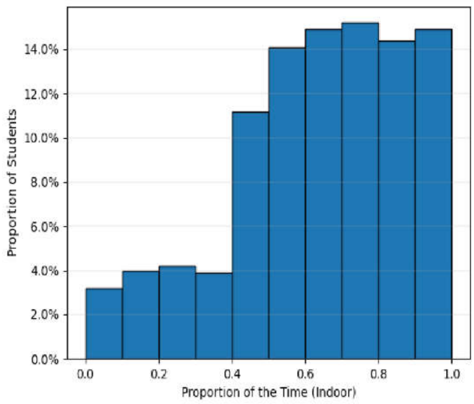
4. RESULTS

4.1. Survey Results

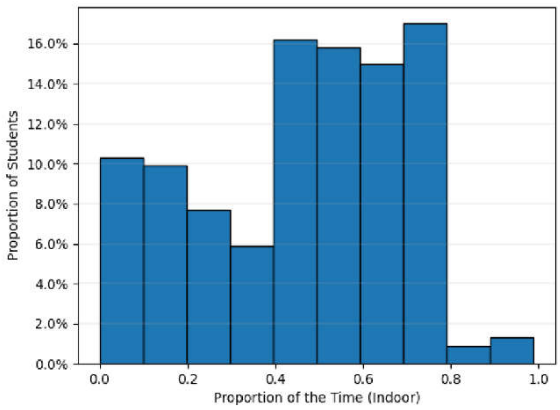
Information about students' lifestyles and energy consumption was gathered by randomly choosing 100 students residing in the 3rd Kilyos. The participation rate of the survey was 94% because 94 of the received questionnaires were effective and had complete information. The participation rate is higher than the rates usually reported in the literature because the data was gathered in person by going to the dormitory. Respondents were all enrolled in the English preparatory lessons, and their class schedules varied depending on their English language level. All students were 18 to 20 years old and shared their rooms with at least one other person. Out of the 94 accepted questionnaires, 45 belonged to male and 49 to female students. Results also show that answers came from 23 different rooms, providing various lifestyles. As stated in Section 3.2, answer choices of questionnaires are similar to a 5-point Likert Scale, but they are turned into hours or probabilities depending on the question. The generated values, especially for hours spent in rooms, are based on values from the survey and assumptions based on the researcher's experience. The original values cannot be neglected because students decided their answers by looking at the hour ranges written in the original questionnaire. Modified hours are generated in a way to have the same distribution as the original values. According to the results, both male and female students spend relatively equal hours in their rooms. Generally, the majority of the students spend between two to five hours indoors. However, the situation is a bit different during the daytime on weekdays, when students have lessons. More than 60% of students are reported to spend three hours or less in their rooms. Besides, less than 10% of females spent more than seven hours in their rooms, but none of the males spent this much time inside rooms. The plots for more detailed hour distributions can be found in Appendix D.

In the original survey, the question regarding computer use behavior is asked with "How often", and answer choices are in terms of adverbs of time. To make the answers adaptable for the model, they are turned into probabilities. Thus, each answer covers a 20% probability range, adding to 100%. The associated probabilities are presented in Appendix E.

Probability values are weighted random numbers generated based on the distribution of answer choices, using the distribution percentages as weights. Figure 4.1 shows the distributions of computer use probability for both group of students when they decide to stay in their rooms. It is evident that students in male dormitories spend more time using laptops than female dormitories. Most spend more than half of their time indoors working their laptops, and one in four even spend more than 80% of their time behind laptops. The situation is different with female students as less than 3% spend more than 80% of their indoor time working with laptops. The majority of females spend between 40% to 80% of their time with laptops.



(a)



(b)

Figure 4.1. Distribution of Laptop Use Probabilities for (a) Male and (b) Female Students.

The format of answer choices changes again for the questions related to using other electrical devices. There are five different choices, but the intervals are not consistent and do not have units; therefore, they cannot be imported directly into the model. Since answer choices were in terms such as “once a week” or “twice a day”, they had to be converted into a standard time unit. Students spend significantly lesser time using electric cookers, coffee makers or kettles, hairdryers, and personal beard trimmers; therefore, units are not in hours but minutes. Some assumptions were required to transform the survey results. Tables presented in Appendix E clarify the considered assumptions for changing survey results into minute-based values. According to the resulting data shown in Figure 4.2, most students use electric kettles for less than 10 minutes each day. The majority of students in male dormitory use kettles or coffee-makers for less than three minutes; thus, maybe once a day, but female students use them slightly more. Regarding the electric cooker, it seems that students do not prefer to prepare meals themselves. Both group of students have shown similar behaviors here, and more than 70% of both groups use the devices less than 10 minutes per day. Hairdryer or shaver use behaviors are also similar between both groups. More than 90% of students use these devices for less than 15 minutes each day. It is known that females use hairdryers for a longer time in reality, and not all males use them. Therefore, it is assumed that female students choose the generated minutes only for the hairdryer in the model. Male students, however, use both hairdryers and beard trimmers, but the usage time is divided in half for each device.

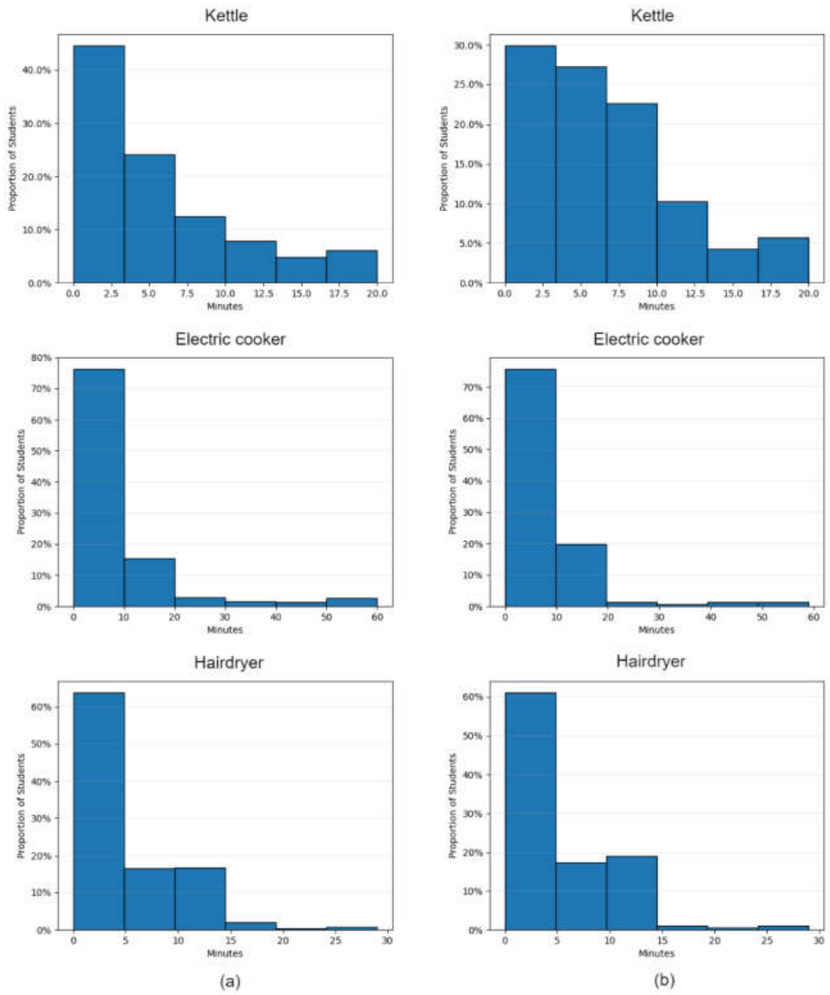


Figure 4.2. Distribution of the Time Spent Using Appliances in (a) Male and (b) Female Dormitories.

4.2. Model Output and Validation

After building the model and entering all the modified data from the survey, it is possible to run some simulations and analyze their outputs. The actual electricity consumption came from 20 different rooms. Half of the selected rooms are on the first floor, and the other half are on the second floor. The monitored rooms on the first floor housed 54 male students, and the ones on the second floor were occupied by 58 female students. The number of students in rooms was not equal; some rooms were shared by only two students, others up to eight people.

The total electricity consumption was around 8708 kWh, according to the measurements during the fall semester of 2016-2017. Male students consumed 4364 kWh and the consumption was 4344 kWh for female students. Even though the number of female residents was slightly higher than males, they consumed lesser energy. However, both groups have relatively similar consumption values, and there are no significant differences. It must be highlighted that the consumption values came only from the selected rooms, not the whole building. Therefore, the electricity consumption was neglected in all public areas inside the dormitory building, including hallways, bathrooms, study rooms, as well as all the remaining rooms without measurement devices.

When the exact number of monitored male and female students (in monitored rooms) were entered into the simulation, the initial model's results seemed satisfactory. Figure 4.3 shows a sample result from initial runs before the model was improved and verified. There are gaps in the plot since monitoring devices stopped working and did not collect data for some periods. The simulation outputs for those days are deleted to achieve a better comparison.

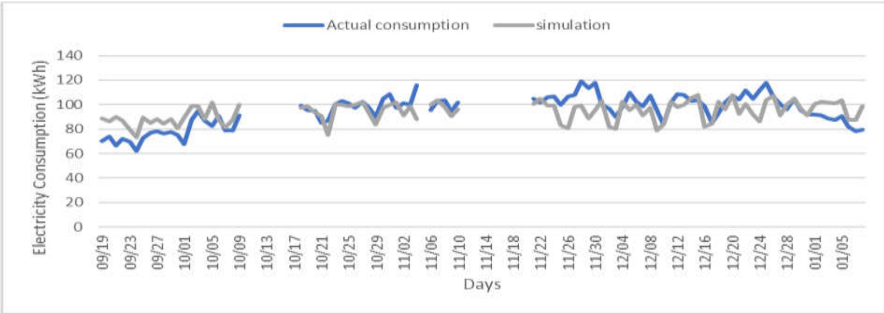


Figure 4.3. Comparison of Monitored and Simulated Electricity Consumptions.

Although the output is acceptable, it is somehow deceptive. If only daily energy use in male dormitory is plotted, the values will not be as satisfying as the previous one. The results are more acceptable for females and only need minor modifications. Figure 4.4 illustrates male students' energy consumption, and the differences between real and predicted values, especially on the first day, can be noticed better. In Figure 4.3, values are the total energy consumption of both groups. At some points, extreme deviations of each group are canceled out by the other group due to the summation (negative errors canceling positive errors, and vice versa), resulting in lesser deviations from the actual readings. Also, comparing energy use between male and female students is one of the study's aims, and each group's results need to be analyzed separately.

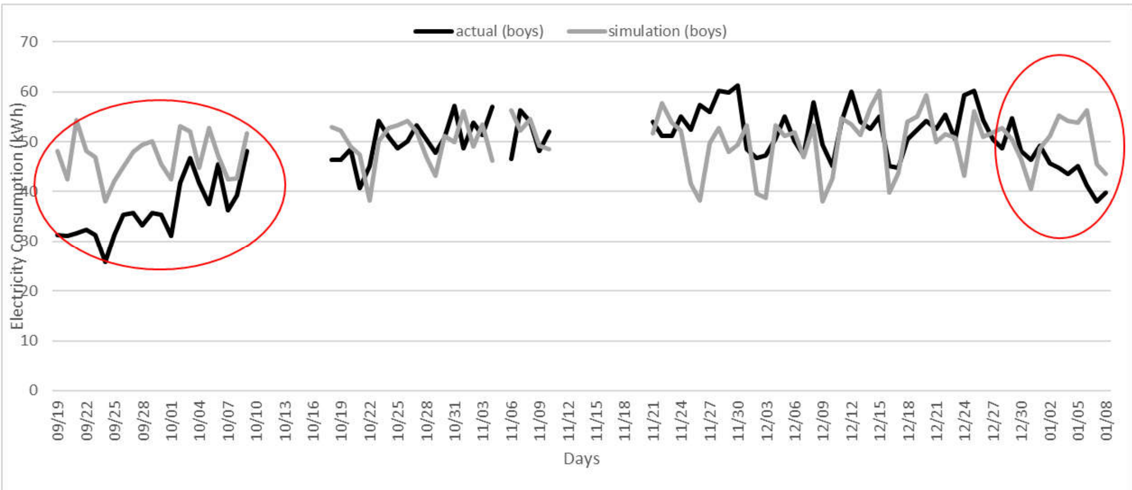


Figure 4.4. Comparison of Monitored and Simulated Electricity Consumptions (Only Male Students).

Figure 4.4 shows that there are noticeable errors on the first and last days. After considering the necessary factors mentioned in Chapter 3 (Section 3.3.1) and calibrating the model, results become more accurate. Figure 4.5 and Figure 4.6 show a sample run for male and female students, respectively. The modified model has a MAPE of 9.5% and RMSE of 0.55 for male students. The MAPE of the previous plot (Figure 4.4) was 15.2% and had RMSE equal to 0.83. Reducing the number of students in the last days and excluding the students who checked in late in the first days have had noticeable effects. The modified model shows increased accuracy, especially for the male students, resulting in a 5.7% reduction in MAPE and 0.28 in RMSE values. Unfortunately, the modified model cannot represent female dormitory's energy use behaviors as good as the male dormitory. The current model's outputs for female rooms have a MAPE of around 11.5% and an RMSE of 0.72. Although these error rates are for a single simulation run, different simulations also resulted in relatively similar errors as the mean values are considered.

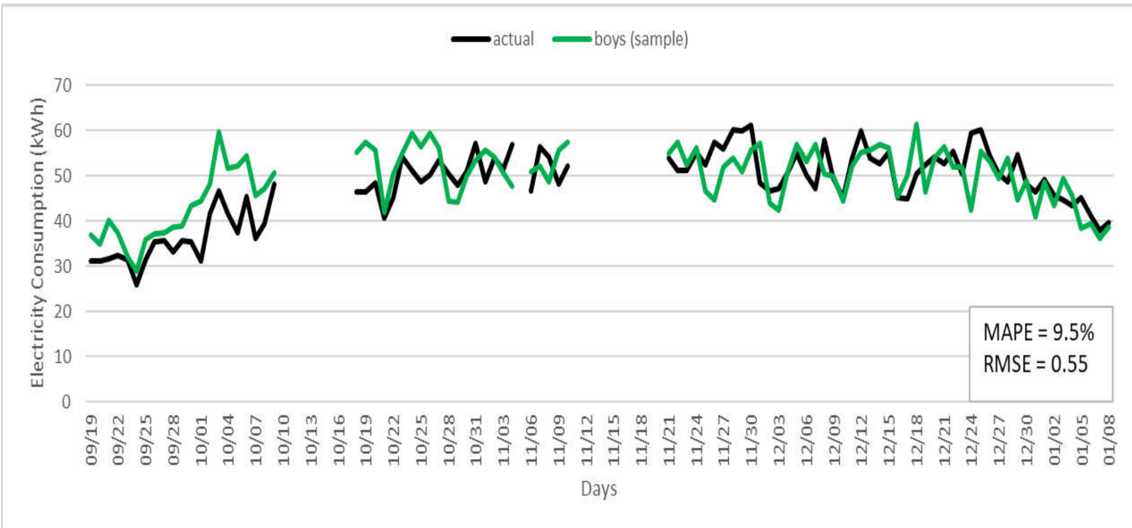


Figure 4.5. Comparison Between a Sample Simulation Run and Actual Measurements (Only Male Students).

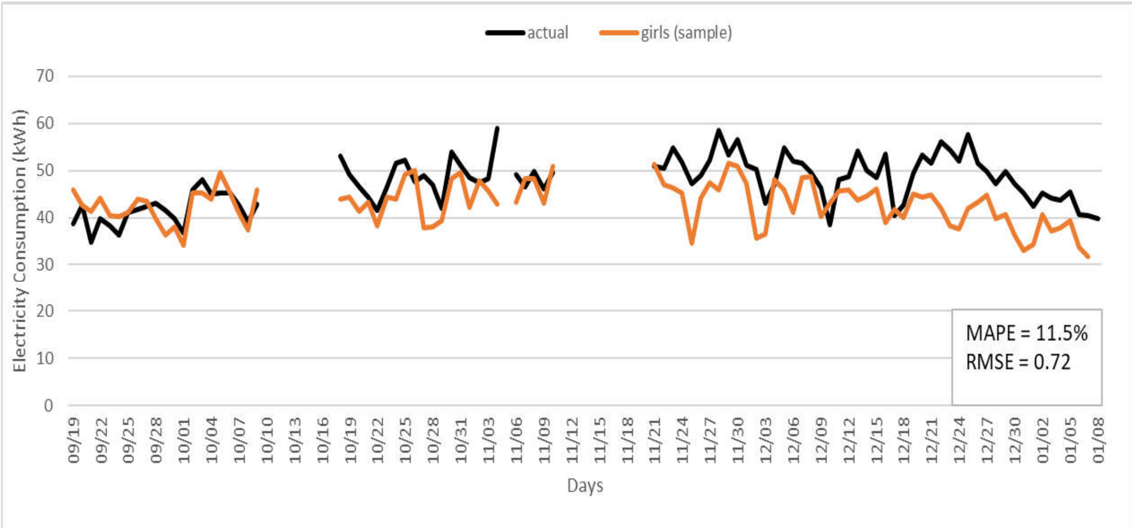


Figure 4.6. Comparison Between a Sample Simulation Run and Actual Measurements (Only Female Students).

Generally, a single simulation run is not very dependable. Stochasticity is inherent in ABM, and our model also utilizes several probabilistic elements; therefore, each simulation results in different outputs. Focusing on a single simulation run may lead to extreme outputs. In order to have well-grounded results, it is recommended to perform multiple simulation runs and take the mean values [39, 78]. It is possible to run hundreds of simulations for each scenario, but 20 to 50 would usually be enough in occupancy studies. Our model converges to the calculated mean values after the 25th run, and running more simulations does not result in noticeable changes. Figure 4.7 demonstrates the daily electricity consumption of all the monitored rooms for male students if mean values from 25 runs are considered for comparison.

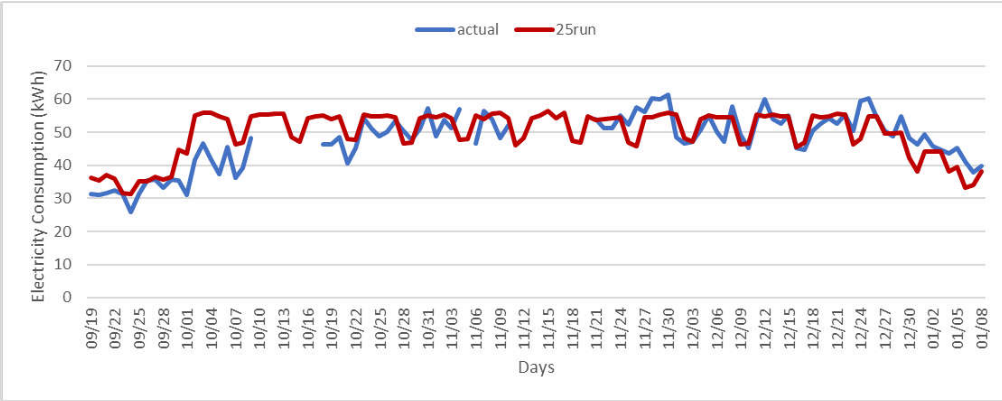


Figure 4.7. Comparison of Actual Consumption Values and Average Values of 25 Simulation Runs (Only Male Students).

Although highlighting a single simulation is not recommended, utilizing average daily consumptions for comparison is not helpful either. As shown in Figure 4.7, consumption rates during weekdays are very similar. Consumption values are lower only on weekends, but they also have similar values. Choosing average values neutralizes all extreme consumption behaviors and reduces the model's randomness. For this reason, cumulative consumption values are taken into consideration. The model can be regarded as stable if all simulation runs have a similar rising trend and end in relatively close values on the last day. The results of 25 simulations for male students are illustrated in Figure 4.8. The total consumption average is 5337.62 kWh, the standard deviation is 27.8 kWh, and the coefficient of variation is 0.52%, indicating an acceptable and stable model. The proposed model for the female dormitory is the same as male dormitory, only with different inputs and variables; hence its stability is also validated.

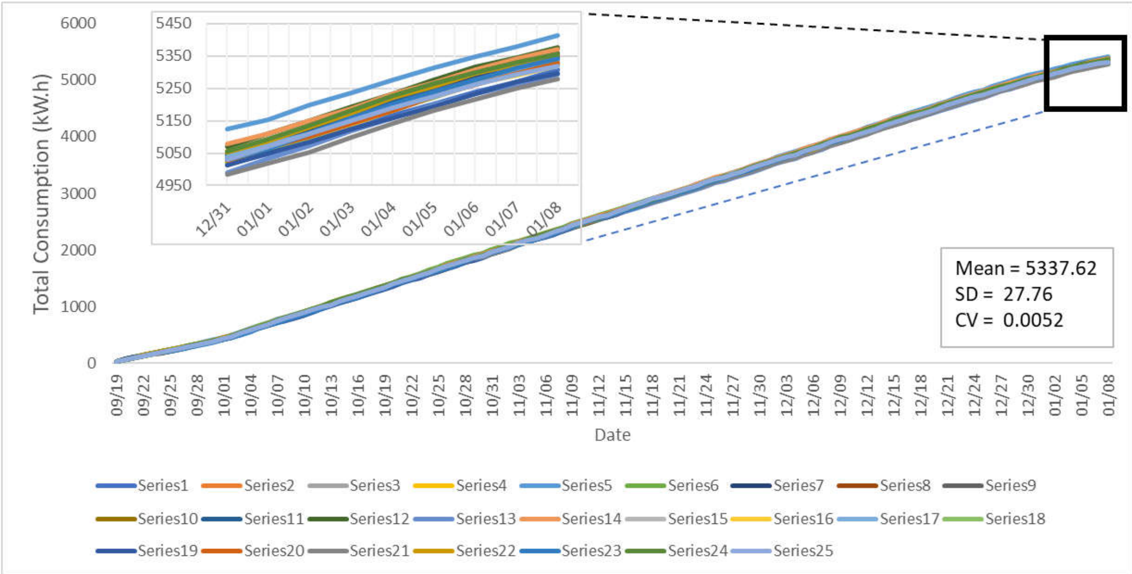


Figure 4.8. Comparison of 25 Simulation Runs' Total Electricity Consumption (Only Male Students).

4.3. Energy-saving Scenarios

After the model is validated, it can be utilized to analyze different scenarios regarding energy-saving behaviors. It is possible to modify several variables such as the number of students, indoor hours, as well as the electrical devices' power demand to observe the resulting variations. Here, two strategies are tested to analyze the energy-saving potentials.

In the first case, the probability of laptop use for the male students is reduced by 20% and then by 25% to check whether these modifications will result in noticeable energy savings or not. Each student will choose a reduced probability to spend time behind his laptop. Only male students are selected for this experiment because of their long gaming hours, which results in high electricity consumption. Two factors influence energy consumption; usage time and electric power necessary for a device to function. The proposed model calculates the electricity consumption by simply multiplying these two elements; therefore, this scenario can also be interpreted as decreasing the power demand of laptops by 20%. Laptop power load is only an example, but some electronic devices' power consumption can cause unwanted costs. However, a simple way to reduce unnecessary costs and save money in the long term is to change old devices with new energy-friendly ones on the market. The scenario can also be tested for lighting bulbs, kitchen appliances, and any energy-hungry electrical device. Table 4.1 shows the energy-saving scenarios for male students' electricity consumption and compares the results with the initial model.

Table 4.1. Experiments Results for the First Energy-Saving Strategy.

Agent type	Original model (base case)	Scenario 1: 20% reduction		Scenario 2: 25% reduction	
	Consumption value (kWh)	Consumption value (kWh)	Change (%)	Consumption value (kWh)	Change (%)
Male	5337.62	5061.55	-5.17	4983.14	-6.64

According to scenario results, when the probability of working with laptops is reduced by 20%, total consumption for decreases by 5.17%. If male students decide to spend even less time behind laptops (25% reduction in probabilities), they can save energy by 6.64%. The changes are not significant, and there may be better alternatives for energy-saving.

The second case aims to check how much energy can be saved if all students spend less time in their rooms. This strategy encourages students to spend more time in public facilities rather than staying in their rooms. Students can study in the library, use the gym, watch movies together, or participate in whatever group activity they prefer. The scenarios include testing 25% and 33% less time in rooms at nighttime (evenings and nights).

Table 4.2. Experiment Results for the Second Energy-Saving Strategy.

Agent type	Original model (base case)	Scenario 1: 25% less indoor time		Scenario 2: 33% less indoor time	
	Consumption value (kWh)	Consumption value (kWh)	Change (%)	Consumption value (kWh)	Change (%)
Male	5337.62	5052.86	-5.33	4853.64	-9.1
Female	4937.36	4476.16	-9.34	4333.23	-12.24

As shown in Table 4.2, spending fewer hours in rooms results in noticeable energy savings, especially for females. It should be noted again that only nighttime values are reduced, and agents are assumed to spend the same hours as before during daytime. Energy-saving potential nearly doubles if male students try to increase their out-of-room activities a little bit more. For female students, however, the energy consumption does not significantly reduce even if they spend more hours than the first scenario. Therefore, spending only 25% fewer hours in rooms would be enough to achieve satisfying saving potentials.

5. DISCUSSION

5.1. Collected Data

The study's primary goal is to develop a model to predict student occupancy and calculate their electricity consumption based on it. Data from a questionnaire survey was utilized to gain an overall knowledge of the situation in the 3rd Kilyos Dormitory. Although conducting a survey is a standard and commonly used method, it may not be the best method to acquire information about occupancy schedules. Using smart sensors or cameras can be another alternative; however, implementing advanced monitoring tools may not always be feasible due to several limiting factors. Limited budget, privacy concerns, and problems in installation, operation, and maintenance of devices are some examples that can hinder the data gathering process and even lead to its termination. The initial plan was to gather updated data from the academic year 2020-2021. Unfortunately, due to the emergence of the Covid-19 pandemic, dormitories were evacuated, and all rooms' energy consumption stopped. Hence, earlier surveys conducted in previous years were utilized to acquire information about students' daily schedules and energy behaviors. Although related to the same building, the survey conducted earlier for a different study did not fully provide all the necessary information needed to construct a computerized model.

It was not possible to directly employ them as they were in the model. The choices had no meaning for the NetLogo model by themselves; therefore, the distribution of answer choices is used as primary information about student lifestyles. Some answer choices had to be converted into probabilities and others into a range of numbers with specific units. The main attempt was to preserve the original data and create new values without neglecting original answers. This objective was fulfilled by keeping the distribution of answer choices equal in both old and new datasets. The process is explained in Chapter 3, Section 3.2. Each assumption, though realistic, results in minor changes and deviations from the original data. When these deviations come together with the problems inherent in the original questionnaire, the two factors result in errors and reduce the chance of correctly understanding what goes on in students' daily lives in reality. In this study, the assumptions included the reality of dormitory life based on the researcher and other random students' experiences to compensate for the mentioned errors.

Nevertheless, assumptions had to be made to obtain values with consistent intervals and proper units. Some studies had fixed assumptions about movement times, with small variations to add randomness, or considered probabilities for occupying various spaces within the buildings [39, 94]. Ding et al. [39] also studied a student residence building, and they asked about the probabilities of staying in the dormitory after classes and on weekends in their survey. They utilized the triangular distribution method for their model to generate random probability values for each agent based on the survey data.

Another obstacle faced during the validation process was the limited amount of data available for comparing simulation outputs with actual data. The monitored data are precise and beneficial; however, measurements covered less than four months and contained gaps due to disruptions in the reading or uploading process. Therefore, only 93 (out of 112 total) daily measurement points were available to test the simulation outputs. The simulation has no timestep limits, and it can easily predict daily electricity consumption for many months and years. In contrast, collecting detailed actual consumption data is challenging and costly. However, having a one-year data would have significantly improved the validations. The amount of real-life data depends on the scale of the study. If the evaluated space were smaller and contained fewer people (e.g., a single floor of an office building), gathering consumption measurements for a few months or even weeks would be sufficient. The consumption behaviors that are studied also influence the required period for data collection. If the study focuses on a single or two behaviors, then the monitoring period can be shorter, but a comprehensive dataset covering a more extended period may be needed if many energy behaviors are considered simultaneously. Generally, energy behaviors consist of but are not limited to laptop use, kitchen appliances use, turning on/off the lights, and adjusting heaters, fans, and air conditioners to control the temperature. For example, Langevin et al. [81] validated their office building model by comparing the simulation results with thermal comfort and behavior data collected during a one-year field study. Ding et al. [39] also utilized data collected over an entire year from a university dormitory to construct and validate their model.

For this study, having electricity consumption measurements for an entire year would have helped achieve more accurate and valid prediction results for a longer period. Although the model predicts electricity consumption with acceptable accuracy, it is better not to be used for the spring semester until related data is available for necessary modifications and final validation. The forecasted consumption rates for the second academic half-year will contain more errors since students' schedules and energy behaviors are expected to change in the spring semester due to more satisfying outdoor conditions.

In general, the quality of the data at hand is vital for developing a proper model as it directly affects the research results; however, having more data is also beneficial. In an exhaustive survey, differences among individuals are more apparent. In addition, it can also provide a chance to perform statistical analysis and even create clusters for a more detailed analysis. If the monitored (observed) data do not cover an extended period, reliable validation will not be possible.

5.2. Model Clarification

As mentioned earlier, the model uses different lists of generated values to predict the time of being inside rooms and then the time for using electrical devices. Each list represents possible answer choices for a single question from the questionnaire. Lists contain 1000 random values, which are closely connected with the original survey results. There is no specific reason for choosing "1000" as the quantity; however, it had to be larger than 200. Each NetLogo agent requires a distinct value from a given list of values for its attributes. The answers of the 94 survey respondents had to be broadened, and since the dormitory building has the capacity to house 400 students, at least 200 values for males and 200 values for females are needed. As the numbers are generated by weighted probability, there is no difference in having 200 or 1000 values. However, if someone wants to analyze the consumption behavior based on entirely random hours or probabilities (or based on any form of distribution), then having 1000 values will better represent the diversity in hours than having only 200 distinct values. In addition, if the model is used for a building with a larger housing capacity, then already having a large pool of values will satisfy all agents.

As for the simulation results, the model predicts daily electricity consumption with acceptable accuracy, as shown in Figure 4.5 and Figure 4.6. On average, the model has a MAPE of 10% for all students. Some proposed models in the literature have lower error rates and predict more accurately. As an example, Azar et al.'s [82] model was reported to have a MAPE of around 2%; however, it should be noted that they did not have field data. In their study, occupancy and consumption data were generated and then divided into two parts: training surrogate models (80%) and validating the results (20%). Therefore, their validation is rather technical than predictive. Also, the complexity of the environment and its occupants' behaviors influence the precision of the model. As mentioned before, offices have a relatively fixed occupancy schedule, especially regarding arrival and departure times. The number of employees who work on weekends does not change a lot, leading to a more static occupancy. Therefore, proposed models for office buildings in the literature have less stochasticity, and they simulated occupancy movements with more confidence [79, 94]. In studies about energy consumption in offices, there are usually fewer occupants, thus making it easier to gather relevant data and analyze behaviors in greater detail. However, it should be highlighted that researchers studied more complex behaviors in office buildings, including window opening, thermostat control, and occupant comfort levels.

In some cases, where a single office was studied, graphical simulations representing movements and energy behaviors were more detailed [94]. It is unlikely to graphically represent all rooms in buildings such as student residents, especially when no information about movements between spaces within a building is known. Considering extra details would not always result in a better model. For example, if a student gets out of a dormitory room where several students stay together, others will continue to use lighting, air conditioning, and heating systems; hence, no specific energy-saving measures can be considered. Therefore, movement information between different spaces in a dormitory should only be analyzed when each student stays in a separate room.

In our case study building, consumption values usually drop on weekends, and the model perfectly simulated the drops on weekends. Nevertheless, for unknown reasons, the consumption rate increased on some weekends in reality. Various reasons could have caused these irregularities, such as midterms or harsh weather conditions preventing students from going out. Also, for females, the model could not accurately capture variations in the last days of the semester; for male students, results were more acceptable. The model includes another assumption, which is somehow generic. In the first two weeks, it is assumed that students spend less time in their rooms. As supported by actual consumption values, the reason behind this decision is that students usually spend more time hanging out outside and exploring the campus as the university workload is still low. Although the simulation result changes with each run, the overall accuracy stays relatively the same. Usually, there are no consecutive noticeable deviations from the actual measurements. Comparing the average of the multiple runs would give a better insight into the accuracy. However, variations in daily consumptions cannot be captured by taking average values from multiple runs, as illustrated in Figure 4.7.

For a more solid validation, the average values of cumulative daily consumptions (Figure 4.8) were compared instead. The result shows an average electricity consumption value of 5337.62 kWh, with a standard deviation is 27.8 kWh. At first look, it might seem the final result is not very accurate as the actual measurements for male students show a total of 4424 kWh. It should be noted that simulation predicts daily energy consumption for every single day without any disruptions, but 19 days were missing in the monitored consumption data. When those 19 days are taken out from the simulation outputs and equal days are considered for the comparison, the net result will decrease to 4432.13 kWh (5337.62 × 93 / 112). The exact result is slightly different from how it has been calculated here, but the difference is very small because average values are used. This comparison considered the 54 males whose electricity consumption was monitored, resulting in less than 2% error. When a similar comparison is made for the female student’s total energy consumption, average simulation results show a 6.6% error. All the calculated values in this study considered 54 males and 58 females. The proposed model can also predict the energy consumption for all the students residing in the dormitory; however, the results are expected to have slightly more errors.

5.3. Limitations and Future Research

The obstacles faced in the study regarding the collected data are thoroughly discussed in the previous section (Section 5.1). Another limitation is the unavailability of reliable data for the whole building’s energy consumption. The university does not have any electricity bills for the dormitory building as there is a single bill for the whole campus. Therefore, it would not be possible to test how accurately the model predicts the energy consumption if all students are considered. Moreover, this study only analyzed electricity consumption behaviors and did not consider any behavior related to heating and cooling. As the study covered the fall semester, no cooling device was included; however, heating plays a significant role during cold days of the year. Unfortunately, no detailed data were available for heating. In addition, the proposed model can forecast electricity consumption with a satisfying accuracy in daily intervals; however, the model is not practical for hourly forecasts. Information about students' hourly schedules was not adequate to build a model that can simulate behaviors for every hour. This detail is also unnecessary for the whole building, especially if long periods are of interest. Finally, regarding the male students who were assumed to arrive late, the assumption is specific to the dorm under observation in that year. There are always fluctuations in the first days, but, in this study, it was only considered for male students and not females. It is better to cancel out the included factors if the model is used for other dormitories unless registration logs suggest a similar situation.

Future studies can collect information for the spring semester and improve the proposed model in order to predict the building's electricity consumption for an entire year. Also, this model did not consider holidays. In the fall semester, holidays are limited, and they will not noticeably change the final results. However, if the model is extended for the whole year, all holidays and semester breaks should be included to achieve acceptable results. Analyzing an automatic lighting system (instead of manually turning lights on and off) and its potential savings is another intriguing study, only if more accurate occupancy detection information is gathered for the whole building. As mentioned earlier, this study does not include heating and temperature values; therefore, researchers can also use this model for occupancy prediction and modify it to analyze heating consumption behaviors. If heating is considered, studying occupants' thermal comfort level is also recommended as every individual judges the temperature differently. One student may feel cold, and the other feels warm on a specific day. Each room houses several students, and adjusting the heaters to satisfy all occupants is a challenge that can be analyzed with ABM. Also, the energy awareness and influence each person can have on another person can be studied with ABM. In such a scenario, agents share information with each other, and the goal is to decrease energy consumption by increasing awareness. This can be achieved by benefitting from the network environment capability of NetLogo and constructing links between agents in future works. In addition, the occupancy prediction part of the model can be coupled with more advanced energy analysis tools such as eQuest or EnergyPlus to calculate energy consumption more accurately.

6. CONCLUSION

Buildings have a significant role in energy consumption, and the operation phase of a building produces a large amount of carbon emissions. It is crucial to analyze buildings' energy performance and employ energy-saving strategies. Until recent years, buildings' energy performance was analyzed without considering their residents. Occupants' role in a building's energy consumption cannot be neglected as all the lighting and HVAC systems are adjusted depending on their presence and comfort. Besides, occupants use many electrical devices inside building spaces, increasing the overall electricity consumption. Therefore, considering the occupancy schedule would result in a more detailed analysis and more feasible strategies to reduce energy consumption. People have regular arrival and departure times in many academic or office buildings, and their energy consumption behaviors are relatively fixed. The situation, however, gets more complex when residents are individuals without a fixed schedule and have erratic daily activities inside a building. Student residents and university dormitories are examples of buildings with this kind of occupants. It is not possible to consider a fixed schedule for these buildings, and proper methods are needed to predict occupancy and the resulting energy consumption.

In this study, an agent-based model was proposed to predict electricity consumption in a university dormitory. Several methods can be found in the literature for building energy simulation. Occupancy schedules and their resident's energy-related behaviors should also be included and analyzed, considering their role in the energy consumption of buildings. As mentioned earlier in the methodology section, ABM is a well-grounded method for predicting occupancy schedules and studying human-building interactions. Although ABM is used in various studies regarding occupancy predictions in buildings and occupants' energy consumption, this study tries to fill the literature gap about anazlying a dormitory building's energy performance and occupants' role in it as the number of studies that have dealt with such a building is still limited. Many students who have different lifestyles reside in a single dormitory building, and generally, there are no restrictions regarding their movement schedules. Students have more freedom than people working in office buildings, where they have to arrive, have lunch, work again, and leave on specific hours. This freedom in movements and behaviors results in greater complexity in analyzing and predicting their actions and cannot be compared with the conditions in office buildings.

In order to construct the model, general information about students' occupancy schedules and energy behavior was needed. The required data were collected from a previously conducted survey. Also, 20 rooms were monitored to collect actual consumption data. The monitored data is used to calibrate the primary models and validate the final model. Unfortunately, the survey data had some minor problems as it was designed for another study but related to the same building. Several modifications had to be made to achieve useable data for the model. Section 3.2.2 thoroughly explains the steps for preparing the data without losing the original survey results.

Moreover, some assumptions had to be made for preparing the model, for example, the hours when students go to sleep and wake up. The final model predicts daily electricity consumption with acceptable accuracy. The model also separately analyzes the energy consumption for male and female students. Therefore, their consumption can be compared, and different energy-saving measures can be recommended for each group. For example, if students are encouraged to spend 25% less time in their rooms, the total electricity consumption will be reduced by about 5% for male students and 9% for female students. The final models of both groups have an average MAPE of around 10%, and the cumulative consumption prediction for the whole semester has an error of 2% compared to the actual measurements. Due to limited monitored data, the model's performance is validated for prediction of about four months. Specifically speaking, these four months in the monitored data covered September to January. Therefore, the model should be utilized for the fall semester of an academic year. Although the model is capable of forecasting more extended periods, further predictions may include more errors.

In general, researchers can benefit from this study to learn how an agent-based model works and how it can be used in energy analysis and building-related studies. Most of the buildings studied in the literature are commercial and office buildings. In the case of university buildings, studies mainly cover classrooms and research offices, and very few studies can be found about student residences. This study analyzes the electricity consumption of rooms in a dormitory building. The model also demonstrates that it is possible to achieve a satisfying energy consumption prediction model in buildings without the need to create a 3D model of the building as well as using complex methods and coupling techniques that utilize building energy simulation engines such as EnergyPlus as they are chiefly used for simulating HVAC system consumption. A reliable model has been achieved, primarily based on actual data and limited assumptions, by formulating occupants' stochastic movement decisions and their electricity use behaviors. It must be noted that Kilyos dormitory does not utilize electricity for heating, and rooms do not have air conditioners. Therefore, this model is applicable for other buildings with similar characteristics. In this study, the comparison of the model's predictions and the actual data show that ABM is indeed a capable method for modeling occupancy prediction and human-building interaction.

Regarding practical contribution, the model is reproducible and can be modified for other student resident buildings and improved with newly gathered data. The proposed model is more suitable for dormitories located in regions where weather is not mild, and students prefer to spend more time indoors. The study can provide quantitative insight into how promoting energy awareness and energy-saving measures can reduce electricity consumption. Dormitory managers can also utilize the model to do experiments and test energy-efficiency strategies, like the sample scenarios proposed in this study, and choose the most appropriate methods for reducing electricity consumption. Also, the energy consumption simulation results from various dormitory buildings and student bodies can be used for analyzing and understanding possible energy use in future buildings.

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APPENDIX A: SURVEY FORM

#	QUESTIONS					
#	**Section 1 : Respondent Profile**					
1	Dormitory No.	1st Dorm	2nd Dorm	3rd Dorm		
2	Gender	Female	Male			
3	Age	17	18	19<		
4	Your High School					
5	Faculty	Faculty of Science and Literature	Faculty of Economics and Administrative Sciences	Faculty of Education	Faculty of Engineering	School of Applied Sciences
6	Prep Class Level	Advanced	Intermediate	Pre-Intermediate	Beginner	
7	Apartment/Room Number		Your room number in last semester and the number of students staying together in the room			
8	How many students stay together in your dorm room? (**Room: The area where you share the kitchen, bathroom and toilet**)	2 / 3	4	5	6	7 / 8
9	Which electrical appliances are available in your room?	Electric Kettle	Stove/Toaster	Hair dryer	Hair Styling Tools	Shaving Machine
	Section 2: While Staying Inside the Student Rooms	**Never**	**Rarely**	**Sometimes**	**Usually**	**Always**
10	How often do you spend time in your room during the daytime (Weekdays only)					
11	How often do you spend time in your room during the daytime (Weekends only)					
12	How often do you spend time in your room during Evening/Nighttime (Weekdays only)					
13	How often do you spens time in your room during Evening/Night time (Weekends only)					
	Section 3: Energy Consumption Behaviors of Students	**Never**	**Rarely**	**Sometimes**	**Usually**	**Always**
	Electricity Consumption Behaviors					
14	How often do you turn off your lights when your room is empty?					
15	How often do you use your lights during the daytime?					
16	Do you keep the curtains in your room open during the day?					
17	How often do you use a computer in your room?					
18	How often do you turn off your electrical appliances when they are not in use?					
	Personal Electricity Consumption Behaviors (1)	**Never**	**Once a week**	**Twice a week or more**	**Every day**	**Twice a day or more**
19	How often do you cook and use electrical kitchen appliances? (for example: electric oven, toaster etc.)					
20	How often do you use an electric kettle?					
21	How often do you use a hair styler or shaver?					
22	How often do you use water/coffee/soft drink vending machines?					

APPENDIX B: NETLOGO CODES

```
extensions [time]

breed [boys boy]
breed [girls girl]

boys-own [
  e-cons
  room-id
  status
  M-in-hour
  N-in-hour]

girls-own [
  e-cons
  room-id
  status
  M-in-hour
  N-in-hour]

globals [
 Start-time
 Current-time
 Weekend-name
 in-out-rand
 v-tick
 x-tick
 Outside
 B-dorm
 G-dorm
 Laptop-B
 Laptop-G
 Phone-charger
 Tablet-charger
 Coffee-maker-Kettle
 Light-bulb
 Shaver
 Hair_Dryer
 Electric_Cooker
 Morning-List-B
 Morning-List-G
 Night-List-B
 Night-List-G
 Morning-W-List-B
 Morning-W-List-G
 Night-W-List-B
 Night-W-List-G
 Laptop-Use-B
 Kitchen-Use-B
 Kettle-Use-B
 Hair-Use-B
 Laptop-Use-G
 Kitchen-Use-G
 Kettle-Use-G
```

```
 Hair-Use-G
 home-sick-B
 home-sick-G
 ar-late-B
 Holiday-B
 Holiday-G
]

to setup
  clear-all
  setup-patches
  setup-turtles
  setup-appliances
  setup-time
  initialize-time
  reset-ticks
end

to setup-patches
  set B-dorm patches with [pycor > 0 AND pxcor < 0]
  ask B-dorm [set pcolor 99]
  set G-dorm patches with [pycor > 0 AND pxcor > 0]
  ask G-dorm [set pcolor 139]
  set Outside patches with [pycor < 0]
  ask Outside  [set pcolor white]
end

to setup-turtles
  create-boys b-number
  ask boys [
    set color blue
    set e-cons 0
  ]
  create-girls g-number
    ask girls [
     set color pink
     set e-cons 0
  ]
  ask turtles [move-to one-of Outside]
end

to setup-appliances
  set Laptop-B 125
  set Laptop-G 75
  set Phone-charger 5
  set Tablet-charger 15
  set Coffee-maker-Kettle 1200
  set Light-bulb 50
  set Shaver 15
  set Hair_Dryer 1250
  set Electric_Cooker 1500
end

to setup-time
  set Start-time time:create "2016-09-19 00:00:00"
  set Current-time time:anchor-to-ticks Start-time 1 "hour"
  file-open "Hours-B.txt"
  set Morning-List-B file-read
  set Night-List-B file-read
```

```
  set Morning-W-List-B file-read
  set Night-W-List-B file-read
  file-close
  file-open "Hours-G.txt"
  set Morning-List-G file-read
  set Night-List-G file-read
  set Morning-W-List-G file-read
  set Night-W-List-G file-read
  file-close
  file-open "E_D-B.txt"
  set Laptop-Use-B file-read
  set Kitchen-Use-B file-read
  set Kettle-Use-B file-read
  set Hair-Use-B file-read
  file-close
  file-open "E_D-G.txt"
  set Laptop-Use-G file-read
  set Kitchen-Use-G file-read
  set Kettle-Use-G file-read
  set Hair-Use-G file-read
  file-close
  ;;Lines: 1: Computer, 2: Kitchen, 3: Kettle, 4:Hair_Dryer;;
end

to go
  check-sleep
  check-location
  move-turtles
  consume-energy
  tick
  set x-tick ticks mod 24
  check-day
  show-time
end

to check-day
  if (ticks < 169) [set v-tick ticks]
  ifelse (ticks mod 168 = 0) [set v-tick 0] [set v-tick ticks mod 168]
  ifelse (v-tick > 120) AND (v-tick mod 120 > 0) AND (v-tick mod 120 < 25) [set Weekend-name
"SATURDAY"] [set Weekend-name "WEEKDAY"]
  if (v-tick > 120) AND (v-tick mod 120 >= 25) AND (v-tick mod 120 < 49) [set Weekend-name
"SUNDAY"]
end

to check-sleep
  ask turtles [
    ifelse (x-tick >= 1) and (x-tick < 9) [set status "sleeping"] [set status "awake"]
  ]
end

to check-location
  ask boys [
    if (x-tick >= 8) and (x-tick < 16) [
      if (x-tick = 8) [set M-in-hour one-of Morning-List-B]
      let until-m 9 + M-in-hour
      ifelse (x-tick >= until-m) [set room-id "outdoor"] [set room-id "indoor"]
    ]
    if (x-tick >= 16) or (x-tick = 1 ) [
      if (x-tick = 16) [set N-in-hour one-of Night-List-B]
```

```
    if (ticks < 336) and (x-tick = 16) [set N-in-hour (N-in-hour * 0.8)] ;assumed that on the first weeks
students spend more time outside;
    let until-n 16 + N-in-hour
    ifelse (x-tick >= until-n) [set room-id "outdoor"] [set room-id "indoor"]
   ]
  ]

  if (Weekend-name = "SATURDAY") or (Weekend-name = "SUNDAY") [
   ask boys [
    if (x-tick >= 8) and (x-tick < 16) [
     if (x-tick = 8) [set M-in-hour one-of Morning-W-List-B]
     if (ticks < 336) and (x-tick = 8) [set M-in-hour (M-in-hour * 0.8)]
     let until-m 9 + M-in-hour
     ifelse (x-tick >= until-m) [set room-id "outdoor"] [set room-id "indoor"]
    ]
    if (x-tick >= 16) or (x-tick = 1 ) [
     if (x-tick = 16) [set N-in-hour one-of Night-W-List-B]
     if (ticks < 336) and (x-tick = 16) [set N-in-hour (N-in-hour * 0.8)] ;same assumption
     let until-n 16 + N-in-hour
     ifelse (x-tick >= until-n) [set room-id "outdoor"] [set room-id "indoor"]
    ]
   ]
   if (ticks mod 121 = 0) [set home-sick-B turtle-set n-of (round(count boys * 0.2)) boys]
   ask home-sick-B [
    set room-id "outdoor"
    ;set color green
   ]
  ]
  if (ticks = 0) [set ar-late-B turtle-set n-of (round(count boys * 0.2)) boys]
  if (ticks > 288) [set ar-late-B no-turtles]
  if (ticks >= 8) [ask ar-late-B [
   set room-id "outdoor"
   set color green ;only for control and verification!
  ]]

  if (ticks < 2400) [set Holiday-B no-turtles]
  if (ticks = 2400) [set Holiday-B turtle-set n-of (round(count boys * 0.1)) boys]
  if (ticks = 2500) [set Holiday-B turtle-set n-of (round(count boys * 0.15)) boys]
  if (ticks = 2600) [set Holiday-B turtle-set n-of (round(count boys * 0.2)) boys]
  ask Holiday-B [
   set room-id "outdoor"
   set color red ;only for control and verification!
  ]

  ask girls [
   if (x-tick >= 8) and (x-tick < 16) [
    if (x-tick = 8) [set M-in-hour one-of Morning-List-G]
    let until-m 9 + M-in-hour
    ifelse (x-tick >= until-m) [set room-id "outdoor"] [set room-id "indoor"]
   ]
   if (x-tick >= 16) or (x-tick = 1 ) [
    if (x-tick = 16) [set N-in-hour one-of Night-List-G]
    if (ticks < 336) and (x-tick = 16) [set N-in-hour (N-in-hour * 0.8)] ;same assumption
    let until-n 16 + N-in-hour
    ifelse (x-tick >= until-n) [set room-id "outdoor"] [set room-id "indoor"]
   ]
  ]
  if (Weekend-name = "SATURDAY") or (Weekend-name = "SUNDAY") [
   ask girls [
```

```
    if (x-tick >= 8) and (x-tick < 16) [
     if (x-tick = 8) [set M-in-hour one-of Morning-W-List-G]
     if (ticks < 288) and (x-tick = 8) [set M-in-hour (M-in-hour * 0.8)] ;same assumption
     let until-m 9 + M-in-hour
     ifelse (x-tick >= until-m) [set room-id "outdoor"] [set room-id "indoor"]
    ]
    if (x-tick >= 16) or (x-tick = 1 ) [
     if (x-tick = 16) [set N-in-hour one-of Night-W-List-G]
     if (ticks < 336) and (x-tick = 16) [set N-in-hour (N-in-hour * 0.8)] ;same assumption
     let until-n 16 + N-in-hour
     ifelse (x-tick >= until-n) [set room-id "outdoor"] [set room-id "indoor"]
    ]
   ]
   if (ticks mod 121 = 0) [set home-sick-G turtle-set n-of (round(count girls * 0.2)) girls]
   ask home-sick-G [set room-id "outdoor"]
  ]

  if (ticks < 2400) [set Holiday-G no-turtles]
  if (ticks = 2400) [set Holiday-G turtle-set n-of (round(count boys * 0.1)) girls]
  if (ticks = 2500) [set Holiday-G turtle-set n-of (round(count boys * 0.15)) girls]
  if (ticks = 2600) [set Holiday-G turtle-set n-of (round(count boys * 0.2)) girls]
  ask Holiday-G [
   set room-id "outdoor"
   set color yellow
  ]
end

to move-turtles
  ask boys [
   ifelse room-id = "outdoor" [move-to one-of Outside] [move-to one-of B-dorm]
   if status = "sleeping" [
    setxy -12 16
   ]
  ]

  ask girls [
   ifelse room-id = "outdoor" [move-to one-of Outside] [move-to one-of G-dorm]
   if status = "sleeping" [
    setxy 12 16
   ]
  ]
end

to consume-energy
  ask boys [
   if (status = "awake") and (room-id = "indoor") [daily-b-consume]
  ]
  ask girls [
   if (status = "awake") and (room-id = "indoor") [daily-g-consume]
  ]
  ask turtles [
   if (ticks mod 24 = 6)  [set e-cons 0]
  ]
end

to daily-b-consume
  if (ticks mod 24 = 9)  [
   set e-cons e-cons + (Coffee-maker-Kettle * (one-of Kettle-Use-B))
   set e-cons e-cons + (Laptop-B * (M-in-hour) * (one-of Laptop-Use-B))
```

```
    set e-cons e-cons + (Electric_Cooker * (one-of Kitchen-Use-B))
  ]
  if (ticks mod 24 = 16) [
    set e-cons e-cons + (Light-bulb * N-in-hour)
    set e-cons e-cons + (Laptop-B * (N-in-hour) * (one-of Laptop-Use-B))
    set e-cons e-cons + ((Shaver + Hair_Dryer / 2) * (one-of Hair-Use-B))
    set e-cons e-cons + ((Phone-charger + Tablet-charger) * 2)
  ]
end

to daily-g-consume
  if (ticks mod 24 = 9)  [
    set e-cons e-cons + (Coffee-maker-Kettle * (one-of Kettle-Use-G))
    set e-cons e-cons + (Laptop-G * (M-in-hour) * (one-of Laptop-Use-G))
    set e-cons e-cons + (Electric_Cooker * (one-of Kitchen-Use-G))
  ]
  if (ticks mod 24 = 16) [
    set e-cons e-cons + (Light-bulb * N-in-hour)
    set e-cons e-cons + (Laptop-G * (N-in-hour) * (one-of Laptop-Use-G))
    set e-cons e-cons + ((Shaver + Hair_Dryer) * (one-of Hair-Use-G))
    set e-cons e-cons + ((Phone-charger + Tablet-charger) * 2) ;generally it takes around 2 hours each day!
  ]
end

to-report b-consumption
  if (ticks mod 24 = 3) [
    let daily-b-cons sum [e-cons] of boys
    set daily-b-cons daily-b-cons
    report daily-b-cons
  ] ;It not necessary to make things hard like, but this function helps a lot when running multiple simulation
simultaneously in BehaviorSpace
end

to-report g-consumption
  if (ticks mod 24 = 3) [
    let daily-g-cons sum [e-cons] of girls
    set daily-g-cons daily-g-cons
    report daily-g-cons
  ]
end

to-report location
  report [room-id] of turtle 0
end

to-report condition
  report [status] of turtle 0
end

to  initialize-time
  clear-output
  output-print Start-time
end

to  show-time ; only for control and verificatoin; disable them if fewer than 4 agents are considered or it will
cause error!
  clear-output
  output-print Current-time
  output-print Weekend-name
```

```
 output-type "M-in-hour: " output-type [M-in-hour] of turtle 0 output-type " " output-type [M-in-hour] of
turtle 1 output-type " "
 output-type [M-in-hour] of turtle 2 output-type " " output-type [M-in-hour] of turtle 3 output-type " "
 output-type [M-in-hour] of turtle 4 output-type "---" output-type [e-cons] of turtle 1
 output-print " "
 output-type "N-in-hour: " output-type [N-in-hour] of turtle 0 output-type " " output-type [N-in-hour] of
turtle 1 output-type " "
 output-type [N-in-hour] of turtle 2 output-type " " output-type [N-in-hour] of turtle 3 output-type " "
 output-type [N-in-hour] of turtle 4
end
```

APPENDIX C: SAMPLE PYTHON CODES FOR INDOOR HOURS

```
import random
import matplotlib.pyplot as plt
random.seed(101) ###Random Seed: 101 for girls; 202 for boys###
numberList = [1, 2, 3, 4, 5]
a = random.choices(numberList, weights=(33, 32, 20, 5, 4), k=1000)
HourList = []
for element in a:
    if element == 1:
        HourList.append(round(random.uniform(0, 0)))
    if element == 2:
        HourList.append(round(random.uniform(1, 2)))
    if element == 3:
        HourList.append(round(random.uniform(3, 4)))
    if element == 4:
        HourList.append(round(random.uniform(5, 6)))
    if element == 5:
        HourList.append(round(random.uniform(7, 8)))
frequencyDict = dict()
visited = set()
for element in HourList:
    if element in visited:
        frequencyDict[element] = frequencyDict[element] + 1
    else:
        frequencyDict[element] = 1
        visited.add(element)
frequencyDict_sorted = {}
for i in sorted(frequencyDict):
    frequencyDict_sorted[i] = frequencyDict[i]
print("Weighted values are: ", a)
print("HourList: ", HourList)
```

```
print("Frequency of NORMAL is: ", frequencyDict_sorted)
x2 = list(frequencyDict_sorted.keys())
y2 = list(frequencyDict_sorted.values())
plt.bar(range(len(frequencyDict_sorted)), y2, tick_label=x2)
for i in range(len(frequencyDict_sorted)):
   plt.text(i,y2[i]+1,str(round(y2[i]/10))+'%', ha ='center', fontsize='small')
plt.title("Daytime_Weekday (Girls)")
plt.xlabel('Hours (indoor)')
plt.ylabel('Frequencies (Probabilities %)')
plt.show()
f = open("Daytime_Weekday-Girls.txt", "w")
f.write(str(HourList))
f.close()
```

APPENDIX D: GENEARATED VALUES FOR THE SPENT TIME IN ROOMS

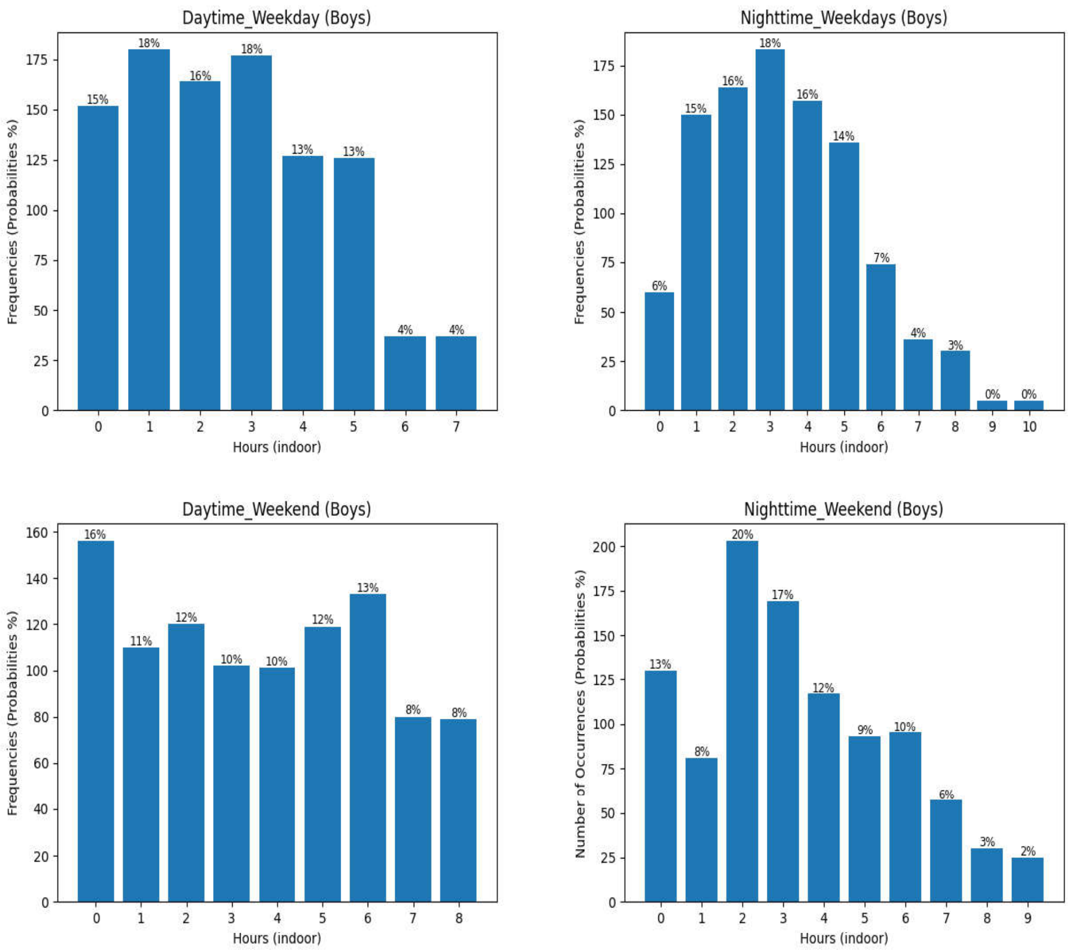

Figure D.1. Distribution of Indoor Hours for Male Students.

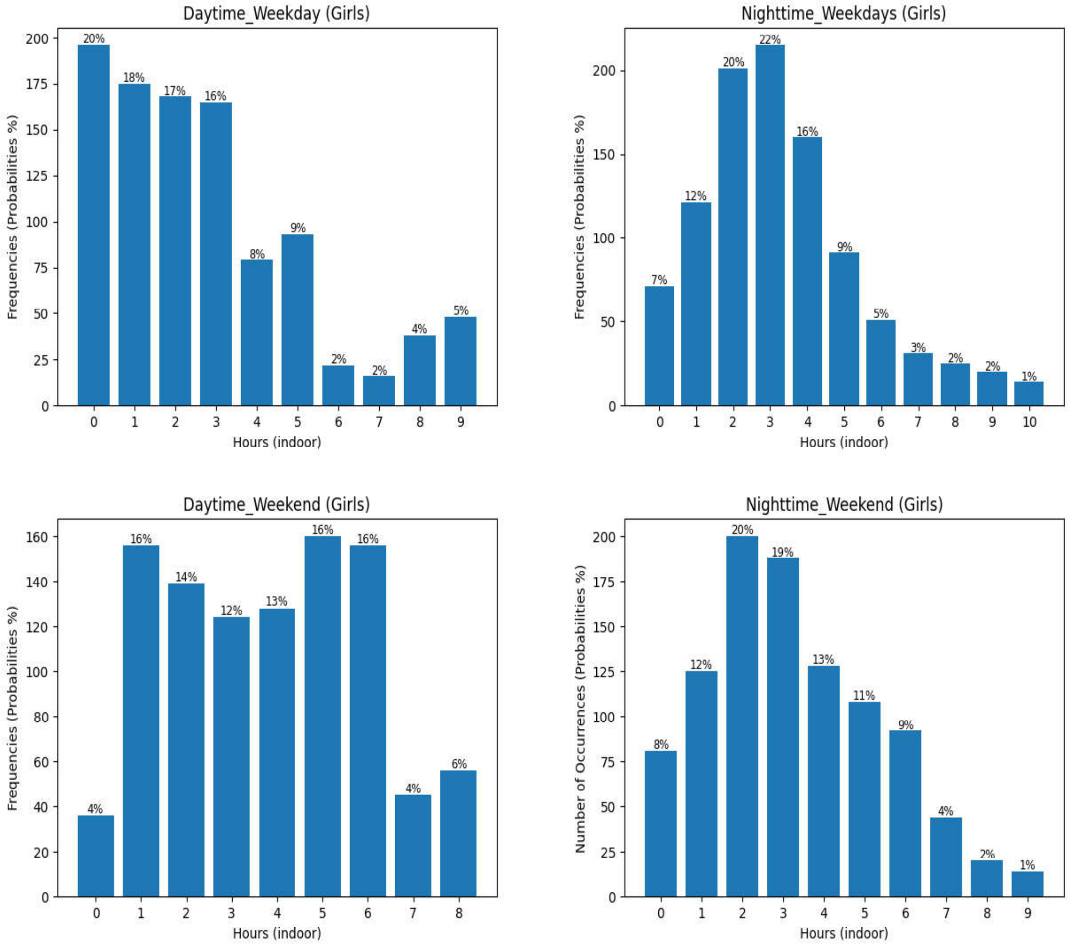

Figure D.2. Distribution of Indoor Hours for Female Students.

APPENDIX E: ASSUMPTIONS FOR HOURS AND PROBABILITIES

Table E.1. Laptop Use.

Answer choice number	Explanation	Associated probability range (%)
1	Never	0-20
2	Seldom	20-40
3	Sometimes	40-60
4	Often	60-80
5	Always	80-100

Table E.2. Kettle (Coffee Maker) Use.

Answer choice number	Explanation	Associated time range (minutes per day)
1	Never	0
2	Once a week	1-2
3	Twice a week or more	2-5
4	Every day	5-10
5	Twice a day or more	10-20

Table E.3. Electric Cooker Use.

Answer choice number	Explanation	Associated time range (minutes per day)
1	Never	0
2	Once a week	1-5
3	Twice a week or more	5-10
4	Every day	10-20
5	Twice a day or more	20-60

Table E.4. Hairdryer and Shaver Use.

Answer choice number	Explanation	Associated time range (minutes per day)
1	Never	0
2	Once a week	1-3
3	Twice a week or more	3-10
4	Every day	10-15
5	Twice a day or more	15-30

APPENDIX F: ELSEVIER LICENSE

Table F.1. Permission from Elsevier

Date	Article Title	Publication	Type Of Use	Price	Status	Expiration Date	Order Number
3-Jan-2022	Review of 10 years research on building energy performance gap: Life-cycle and stakeholder perspectives	Energy and Buildings	reuse in a thesis/dissertation	0.00 $	Completed		5221540352324