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Development of Synthetic Load Profiles for University Buildings: A Case Study of Nordhausen University of Applied Sciences

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Abstract

The increasing need for sustainable and efficient energy management within educational institutions has emphasised the importance of accurately understanding electricity consumption patterns. This thesis presents a comprehensive methodology for developing synthetic load profiles specifically tailored to university buildings, using Nordhausen University of Applied Sciences as a detailed case study. The research meticulously analyses electricity demand by categorising buildings based on functionalities, room types, occupancy patterns, and the usage behavior of electrical equipment under varying weather conditions.

To ensure precision, extensive data collection and categorisation were conducted, coupled with simulation-based modeling using the RAMP tool. Synthetic load profiles were generated and calibrated against historical electricity consumption data averaged over three years (2021–2023). This approach led to an accurate monthly scaling, significantly aligning the synthetic profiles with measured consumption. Notably, the analysis of Building 34 demonstrated identifiable peak consumption variations, such as a substantial increase in April due to semester initiation activities and a notably higher consumption in December resulting from continuous heating demands.

The derived load profiles provide valuable insights into energy consumption dynamics, highlighting critical periods of peak demand and identifying substantial energy-saving potentials. This detailed characterisation facilitates the development of targeted strategies for energy efficiency, cost reduction, and optimised integration of renewable energy resources within campus infrastructures. Ultimately, the outcomes of this research not only support enhanced energy management practices at Nordhausen University but also serve as a foundational framework for similar sustainability projects across educational institutions.

Kurzfassung

Der zunehmende Bedarf an nachhaltigem und effizientem Energiemanagement in Bildungseinrichtungen macht es notwendig, den Stromverbrauch genau zu verstehen. Diese Masterarbeit stellt eine umfassende Methodik vor, um synthetische Lastprofile speziell für Hochschulgebäude zu entwickeln, wobei die Hochschule Nordhausen als detaillierte Fallstudie dient. Die Untersuchung analysiert den Strombedarf sorgfältig, indem Gebäude nach ihrer Nutzung, Raummodellen, Belegungsmustern und dem Einsatz elektrischer Geräte bei unterschiedlichen Wetterbedingungen kategorisiert wurden.

Für genaue Ergebnisse erfolgte eine umfangreiche Datensammlung und -klassifizierung sowie eine simulationsbasierte Modellierung mit dem RAMP-Werkzeug. Die synthetischen Lastprofile wurden erstellt und mithilfe historischer Stromverbrauchsdaten, gemittelt über drei Jahre (2021–2023), kalibriert. Dieses Verfahren ermöglichte eine genaue monatliche Skalierung, wodurch die synthetischen Profile sehr gut mit dem gemessenen Verbrauch übereinstimmen. Besonders bei Gebäude 34 wurden deutliche Verbrauchsspitzen festgestellt, etwa eine erhebliche Steigerung im April aufgrund des Semesterstarts sowie ein spürbar höherer Verbrauch im Dezember durch durchgehenden Heizbedarf.

Die entwickelten Lastprofile liefern wertvolle Informationen über den Energieverbrauch und zeigen Zeiten hoher Spitzenlasten sowie großes Potenzial für Energieeinsparungen. Diese detaillierte Charakterisierung hilft dabei, gezielte Maßnahmen für mehr Energieeffizienz, Kostensenkung, und eine optimierte Einbindung erneuerbarer Energien in die Infrastruktur des Campus zu entwickeln. Die Ergebnisse dieser Arbeit unterstützen nicht nur das Energiemanagement an der Hochschule Nordhausen, sondern bilden auch eine Grundlage für ähnliche Nachhaltigkeitsprojekte an anderen Bildungseinrichtungen.

Acknowledgment

I would like to express my sincere gratitude to my academic supervisors, Mr. Gokarna Dhungel and Mr. Rohith Krishnan Bala Krishnan, for their invaluable guidance, constructive feedback, and continuous support throughout this thesis. Their expertise and encouragement have been instrumental in shaping this research and helping me overcome challenges along the way.

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Contents

List of Symbols

Symbol	Unit	Meaning
COP	-	Coefficient of performance
COP_{base}	-	Baseline coefficient of performance
E	kWh	Electrical energy consumption
N	-	Number of rooms considered for a room type
P	kW	Electrical power consumption
T	$^\circ$C	Temperature
T_{amb}	$^\circ$C	Ambient temperature
T_{max}	$^\circ$C	Maximum temperature
T_{min}	$^\circ$C	Minimum temperature
t	mins	Time
α	-	COP reduction factor per degree temperature increase

List of abbreviations

ALPG Appliance Load Profile Generator

AP Active Power

APT Active Power Time

COP Coefficient of Performance

DSM Demand Side Management

FT Functioning Time

HSN Hochschule Nordhausen (Nordhausen University of Applied Sciences)

HVAC Heating, Ventilation, and Air Conditioning

kW Kilowatt

kWh Kilowatt-hour

MT Minimum Time

OFF Office

RAMP Room Appliance Model for Python

SLP Synthetic Load Profile

SP Stand-by Power

SPT Stand-by Power Time

SS Summer Semester

W Watt

WD Weekday

WE Weekend

WS Winter Semester

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Chapter 1

Introduction

1.1 Introduction to the studies

The global shift towards sustainable energy systems has underscored the necessity for efficient energy management across all sectors, including higher education institutions. In Germany, buildings accounted for approximately 27.6% of the total final energy consumption in 2021, with heating alone constituting a significant portion of this usage [1]. This substantial energy demand highlights the critical role that universities play in the nation's energy landscape.

Several factors influence the energy consumption patterns of university buildings. Building characteristics, such as architectural design and construction materials, significantly impact energy efficiency [2]. A higher occupancy rate increases interactions between individuals and building systems, creating more opportunities for energy optimisation. Intuitive control mechanisms and real-time energy feedback can enhance user awareness, promoting energy-efficient behavior. When occupants engage effectively with these systems, energy consumption tends to decrease. However, if behavioral efficiency remains low, high occupancy levels may lead to increased energy usage [3], as illustrated in Figure 1.1.

The global transition towards sustainable energy systems has heightened the importance of efficient energy management across various sectors. Universities, as centres of education and innovation, play a critical role in adopting and showcasing sustainable practices. The energy consumption patterns of university buildings are highly complex and are influenced by factors such as building characteristics, occupancy schedules, equipment usage, and local climatic conditions. Understanding and accurately forecasting these patterns is essential for identifying inefficiencies and implementing energy optimisation strategies. Several studies have explored predictive models for energy consumption in academic settings, each contributing valuable insights into improving campus energy management. For example, a forecasting model developed using multiple regression analysis, based on five years of data, incorporated factors such as ambient temperature, solar radiation, and building type to predict electricity consumption in university buildings [4].

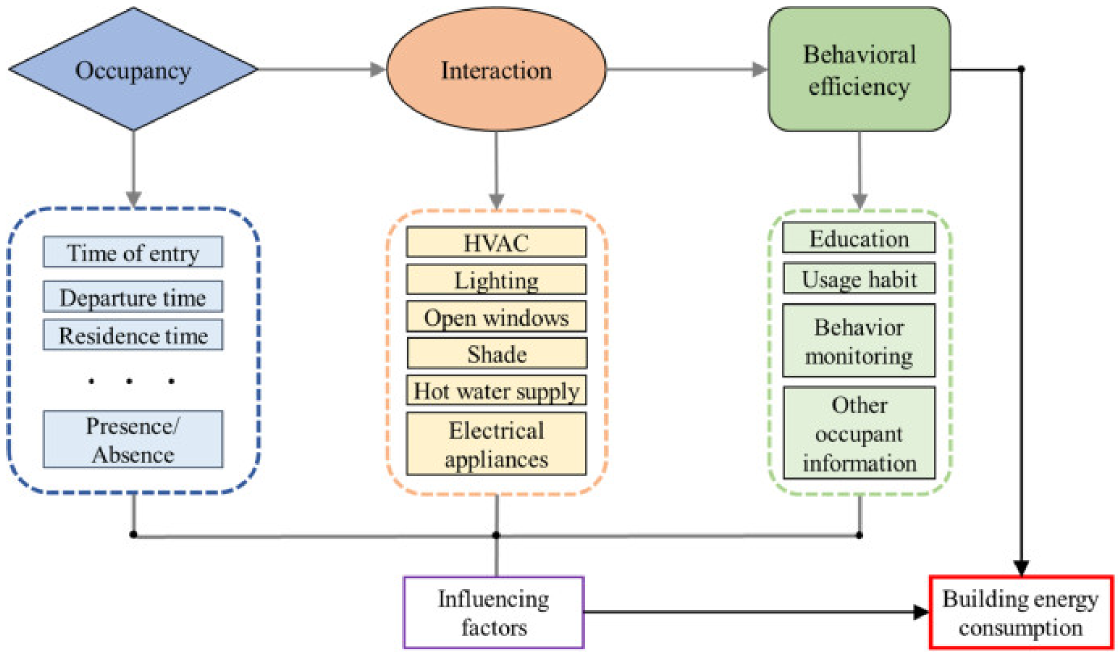

Figure 1.1: The impact of the occupants on the building's energy consumption

Recent technological advancements, including the application of machine learning techniques, have increasingly influenced the field of electricity demand forecasting. These modern approaches enable more accurate predictions by capturing complex usage behaviours, highlighting the growing importance of integrating advanced methods into energy modelling for university campuses, as explained in detail in Chapter 2.

1.2 Rationale for the Study

The rising demand for sustainable energy solutions has intensified the need for efficient electricity management in institutional buildings. Nordhausen University of Applied Sciences, like many academic institutions, operates a diverse range of facilities, including lecture halls, laboratories, administrative offices, and student accommodations. These buildings exhibit highly variable energy consumption patterns due to differences in usage schedules, equipment types, and seasonal influences. Unlike residential or commercial buildings, the electricity demand at universities fluctuates dynamically throughout the day and across academic terms, making it challenging to establish accurate load profiles. Without precise modelling, inefficiencies in energy distribution may lead to unnecessary energy costs, increased carbon footprints, and suboptimal resource allocation on campus.

To address this challenge, developing synthetic load profiles tailored to Nordhausen University is essential for effective energy planning and management. Although a variety of electricity demand forecasting methods have been developed, many existing models are primarily tailored to standard commercial or residential buildings. These approaches often oversimplify the complex and dynamic usage patterns characteristic of academic institutions. University buildings, however, experience unique variations due to academic calendars, irregular occupancy trends, and specialised equipment usage, which conventional models frequently fail to represent accurately [5]. Therefore, it becomes essential to develop tailored modelling techniques that integrate these distinctive features to improve the reliability of synthetic load profiles. By utilising the simulation tool RAMP [6], this study aims to improve the accuracy of electricity demand predictions for the university's infrastructure. The insights gained from this research will support energy efficiency measures, cost reduction strategies, and the university's broader sustainability objectives, ultimately contributing to a more sustainable and optimised campus energy system.

1.3 Research Problem and Objectives

1.3.1 Research Problem

Universities are complex environments with highly variable energy consumption patterns due to diverse building functions and occupancy schedules. Traditional forecasting methods often fail to capture these variations accurately, leading to inefficient energy management. At Nordhausen University of Applied Sciences, the lack of tailored synthetic load profiles limits the ability to optimise electricity usage across campus buildings. Recent advancements in simulation tools, such as RAMP, which is an open-source software suite based on Python that allows for the stochastic simulation of any energy demand time series driven by user input, using only a few simple parameters [7]. And Oemof, which is an indispensable tool for planning future energy systems, by providing insights into different development trajectories [8]. These tools offer good solutions for generating accurate load profiles; however, these methods have not been widely applied to university settings. This study addresses this gap by developing synthetic load profiles specifically for Nordhausen University, contributing to improved energy management strategies.

1.3.2 Research Objectives and Questions

This study aims to develop accurate synthetic load profiles for buildings at Nordhausen University of Applied Sciences. Key objectives include:

1. Developing synthetic load profiles using RAMP.
2. Analysing key factors affecting electricity consumption, including building characteristics and occupancy [9].
3. Validating the generated profiles against historical consumption data.
4. Proposing energy management strategies based on the results to improve sustainability on campus.

To guide the research, the following questions will be addressed:

- How do energy consumption patterns vary across different building types at Nordhausen University?
- How can synthetic load profiles be developed and calibrated to accurately reflect the electricity consumption of university buildings?
- What improvements can be made to optimise electricity management on campus?

1.4 Scope and Limitations

This study focuses on analysing and modelling electricity demand at Nordhausen University of Applied Sciences, with a particular emphasis on developing synthetic load profiles for various campus buildings. Given the diverse nature of university infrastructure including academic buildings, laboratories, administrative offices, and student residences, energy consumption patterns vary significantly. This research aims to capture these variations by examining key influencing factors such as building characteristics, room characteristics, occupancy patterns, equipment usage, and seasonal fluctuations.

To achieve this, the study will utilise RAMP, a stochastic simulation tool that enables the generation of realistic load profiles based on available data. By incorporating relevant variables and simulating demand patterns, this research seeks to enhance the accuracy of electricity consumption forecasts. The insights gained from this study will contribute to optimising energy management strategies, reducing inefficiencies, and supporting the university's broader sustainability goals. Additionally, the methodology developed in this research may serve as a framework for similar institutions aiming to improve their energy planning and demand modelling approaches.

However, certain limitations define the study's boundaries. The research is limited to electricity consumption only, excluding other energy-related aspects such as heating, cooling, and water usage. The study focuses on synthetic modelling rather than real-time energy monitoring, meaning that results will be based on simulations rather than live measurements. Additionally, the research is constrained by data availability, meaning that assumptions may be required for missing or incomplete datasets. While the findings are specific to Nordhausen University, the methodology could be adapted for similar institutional settings.

Chapter 2

Synthetic Load Profile Development

2.1 Understanding Load Profiles and Electricity Demand

2.1.1 Synthetic Load Profile

Electricity demand varies significantly based on several factors, such as building type, user behavior, and external influences like climate conditions. Understanding and forecasting these demand patterns is crucial for optimising energy management strategies. A synthetic load profile (SLP) is a statistical or simulation-based representation of electricity consumption patterns over a given period. These profiles are typically generated using historical data, stochastic modeling, and machine learning techniques to reflect realistic energy demand variations [10]. Unlike real-time measurements, synthetic load profiles allow researchers and energy planners to analyse and predict electricity consumption in scenarios where actual data may be missing or incomplete.

One methodology for generating synthetic load profiles involves classifying industry types and quantifying electricity consumption for various end-use applications. In their study, Sandhaas et al. applied this approach to 11 different industry types, creating high-resolution load profiles that capture the unique consumption patterns of each sector. [10]

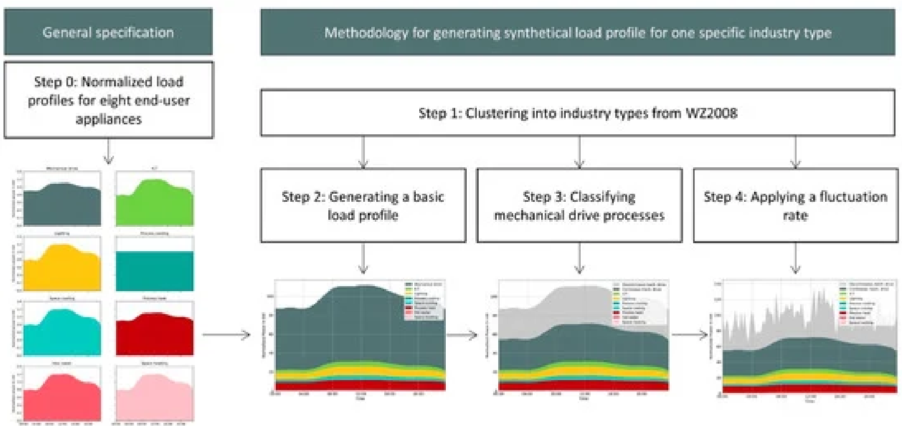

Figure 2.1: One methodology for generating synthetic load profiles

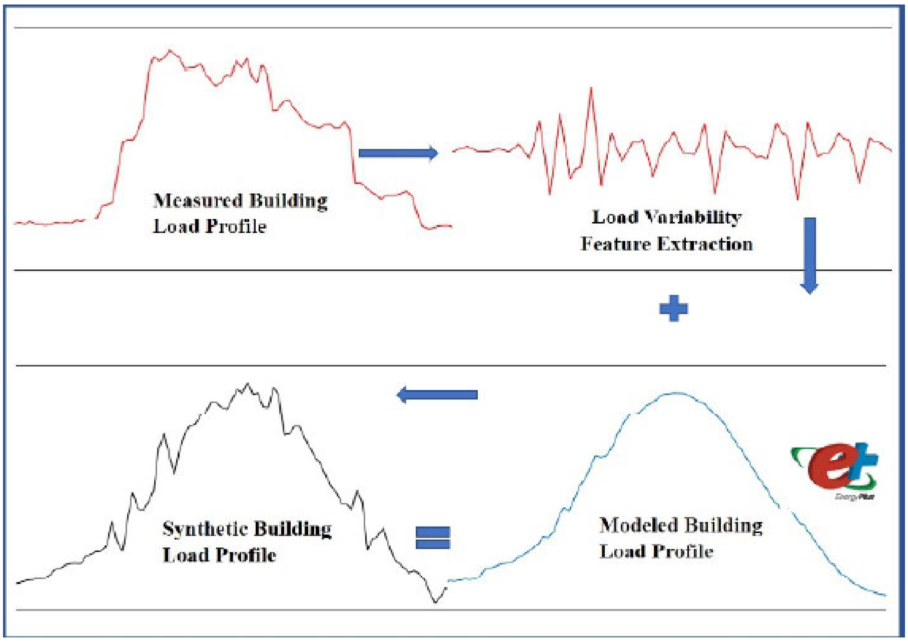

Figure 2.2: Graphical representation of the synthetic building load profile generation process

Figure 2.1 from Sandhaas et al.'s study provides a graphical representation of the synthetic load profile generation process. This figure illustrates the step-by-step methodology, including the classification of end-use applications, statistical adjustments, and stochastic variations applied to reflect daily and seasonal fluctuations. This approach ensures that synthetic load profiles closely resemble actual consumption patterns, making them an essential tool for energy planners and policymakers in designing efficient demand-side management strategies.

In the residential sector, Schlemminger et al. developed a model that predicts household electricity consumption on regional and national scales. This model utilises neural networks to correlate measured consumption data with weather information and daily activity profiles, resulting in end-use-specific load profiles that can be applied across different countries. [11]

One of the primary motivations for developing synthetic load profiles is to support energy system modeling and planning. These profiles are widely used in research and policy-making to simulate the impact of demand-side management strategies, renewable energy integration, and grid stability analysis. A study by Parker et al. [12] introduced a framework for generating synthetic load profiles by integrating measured building load data with high-frequency variability extracted through discrete wavelet transform techniques. This method enhances the realism of synthetic profiles, making them valuable for applications sensitive to short-term power fluctuations.

As shown in Figure 2.2, the synthetic building load profile generation process follows a structured approach that aligns modeled energy consumption patterns with measured building load profiles. The figure illustrates the step-by-step methodology used to create synthetic load profiles, where data is processed either on a day-by-day or year-by-year basis. For long-term analysis, the year-by-year approach is preferred, as it ensures that modeled load profiles are matched with real-world measured profiles, allowing for a more accurate representation of annual energy consumption trends. This process is essential in refining load profile accuracy, particularly in cases where high-resolution metered data is unavailable. By systematically mapping modeled profiles to measured datasets, Figure 2.2 provides a visual overview of how synthetic load profiles are generated and validated, reinforcing their role in energy forecasting and system optimisation.

To improve the accuracy of synthetic load profiles, researchers utilise different modeling approaches. These include top-down methods, which aggregate national or regional energy consumption data, and bottom-up approaches, which use detailed consumption patterns from individual buildings or appliances. Additionally, machine learning-based SLP models have gained traction due to their ability to adapt to changing user behaviors and environmental factors, specifically for building consumption [13].

2.1.2 Factors Influencing Electricity Consumption in University Buildings

Understanding the factors influencing electricity consumption is essential for effective energy management and the development of accurate synthetic load profiles.

One primary determinant is the academic calendar, which dictates occupancy levels and operational hours. Periods such as semester commencements and vacations significantly impact energy usage. For instance, studies have shown that electricity consumption peaks during the start of academic terms due to increased student presence and activities, while it diminishes during vacation periods when occupancy is low. [14]

Another critical factor is the building's physical characteristics, including its total gross floor area and the specific functions of its spaces. Larger buildings or those housing energy-intensive facilities, such as laboratories and data centers, tend to have higher electricity demands. [15]

In summary, both operational schedules and physical attributes of university buildings play pivotal roles in shaping their electricity consumption patterns. Recognising and analysing these factors are vital steps toward implementing effective energy-saving measures and optimising overall energy efficiency in higher education institutions.

2.1.3 Advancements in Electricity Demand Forecasting Methods

In response to the limitations of traditional forecasting models, recent research has increasingly adopted machine learning-based approaches to improve electricity demand predictions. These advanced methods are capable of capturing complex and non-linear consumption patterns that simpler statistical models often overlook.

For example, Akbar [16] demonstrated that deep neural networks can effectively model demand fluctuations, achieving better accuracy than classical time-series forecasting techniques. Similarly, Lee [17] highlighted the benefits of ensemble learning methods combined with diverse data sources to enhance forecast precision. Furthermore, Ferrari [18] introduced hybrid modelling strategies that integrate machine learning with domain-specific knowledge, reinforcing the robustness of electricity consumption predictions.

Collectively, these advancements indicate a major shift in the literature towards embracing data-driven methodologies to address the increasing complexity of electricity consumption behaviours.

2.2 Techniques for Developing Synthetic Load Profiles

Developing accurate synthetic load profiles is essential for modeling and analysing energy consumption patterns, especially in scenarios where real-world data is limited or unavailable. Two primary methodologies are employed in this endeavor: data-driven approaches and simulation-based approaches.

2.2.1 Data-Driven Approaches (Statistical & Machine Learning Models)

Data-driven approaches utilise historical consumption data to identify patterns and relationships, enabling the creation of synthetic load profiles that reflect real-world usage. These methods often employ statistical analyses and machine learning algorithms to capture the nuances of energy consumption behaviors.

A notable example is the work by Sandhaas et al., who developed a methodology for generating synthetic electricity load profiles tailored to various industry types. Their approach involved:

1. **Classification of Electrical End-Use Applications**: Identifying and categorising the different applications consuming electricity within an industry.

2. **Development of Normalised Daily Load Profiles**: Creating standard load profiles for each identified application to serve as foundational templates.

3. **Integration of Mechanical Process Data**: Incorporating specific mechanical processes unique to different industry branches to enhance the accuracy of the profiles.

4. **Application of Stochastic Fluctuations**: Introducing random variations to account for unpredictable changes in consumption patterns.

This comprehensive method ensures that the generated synthetic profiles closely mirror actual consumption behaviors, making them valuable for energy system modeling and planning [10].

2.2.2 Simulation-Based Approaches (Including RAMP and Other Tools)

Simulation-based approaches are pivotal in generating synthetic load profiles, especially when real-world data is scarce or incomplete. These methods model the underlying factors influencing energy consumption, such as user behavior, appliance usage, and environmental conditions, to create realistic demand patterns.

RAMP

RAMP is an open-source software suite designed for the stochastic simulation of user-driven energy demand time series based on minimal input data [6]. Developed to address scenarios lacking detailed consumption data, RAMP offers:

- **User-Centric Modeling**: Simulates energy consumption by considering appliance ownership and usage behaviors.
- **Stochastic Variability**: Introduces randomness to account for the unpredictability of human behavior and other influencing factors.
- **Flexibility**: Allows users to define specific scenarios, such as designing systems for remote areas where metered data is scarce.

By leveraging these features, RAMP generates realistic synthetic data, facilitating the analysis and planning of energy systems in diverse contexts.

Load Profile Generator (LoadProGen):

The Load Profile Generator is a tool designed for Microsoft Windows that creates load profiles for households, covering electricity, gas, hot water, and cold water consumption [19],[20]. It is particularly useful for simulating energy systems of various kinds, offering:

- **Comprehensive Behavior Simulation**: Provides a full behavior simulation that is completely customisable.
- **High Time Resolution**: Offers time resolutions ranging from one hour to one minute, allowing for detailed analysis.

This tool is beneficial for researchers and planners aiming to understand and predict household energy consumption patterns.

nPro:

nPro generates consistent synthetic demand profile sets for various energy demands, including space heating, domestic hot water, cooling, and e-mobility [21]. It is particularly suited for:

- **District and neighbourhood planning**: Facilitates detailed load simulations at larger community scales.
- **Integrated simulations**: Provides comprehensive profiles, essential for district-level energy system optimisation.

HOMER:

HOMER (Hybrid Optimisation Model for Electric Renewables) is a robust simulation and optimisation tool widely used for microgrid and renewable energy system planning [22]. It is primarily suitable for:

- **Energy system optimisation**: Analysing renewable resource integration, economic feasibility, and system reliability.
- **Hybrid systems analysis**: Effectively simulates combinations of conventional and renewable energy technologies.

However, its appliance-level detail and stochastic user behaviour modelling capabilities are limited, as HOMER focuses primarily on system-level energy management.

EnergyPlus:

EnergyPlus is a comprehensive building energy simulation tool widely used to model heating, ventilation, air conditioning (HVAC), and overall energy performance in buildings [23]. Key features include:

- **Detailed physical modelling**: Offers accurate simulations of building envelope performance, HVAC systems, and thermal dynamics.
- **System integration analysis**: Suitable for detailed energy balance studies and energy efficiency optimisations at the building scale.

While powerful, EnergyPlus is less focused on detailed, stochastic appliance-level consumption modelling, making it less suitable for studies prioritising explicit user behaviour analysis.

Each simulation tool offers unique capabilities tailored to specific energy consumption modelling and scenario analysis needs. Selecting the appropriate tool depends largely on the goals and scope of the research whether emphasising detailed appliance-level behaviour, demand-side management (DSM), comprehensive system-level simulations, or district-level energy planning. For example, tools such as RAMP and Load Profile Generator excel at simulating granular, stochastic appliance usage patterns and occupant behaviour, making them highly suitable for studies involving residential buildings or detailed consumption analyses in smaller-scale commercial and institutional environments [19]. Conversely, tools like HOMER and EnergyPlus are geared towards broader energy system analyses; HOMER supports renewable energy system integration and microgrid simulations, while EnergyPlus focuses on building-level energy performance, primarily involving heating, ventilation, and air-conditioning (HVAC) systems. For district- and neighbourhood-level simulations, particularly those involving heating, cooling, and e-mobility scenarios, nPro offers detailed and consistent demand profile sets.

By strategically leveraging these simulation-based approaches, researchers and practitioners can generate highly realistic synthetic load profiles specifically tailored to the requirements of their particular studies. These profiles are vital for evaluating the effectiveness of energy efficiency interventions, implementing demand-response strategies, integrating renewable energy resources, and supporting comprehensive grid planning and stability analyses. Furthermore, employing multiple complementary simulation tools in conjunction, for instance, integrating a stochastic model such as RAMP with a district-scale model like nPro, can significantly enhance the depth and accuracy of analyses. Such combined approaches offer a robust and detailed insight into interactions between user behaviour, appliance usage, and broader energy system dynamics [21].

As energy systems increasingly transition towards decentralised generation and smart-grid technologies, the importance of accurate synthetic load profiles continues to grow. These profiles are critical for predictive modelling, optimal energy system design, and effective demand-side management. Emerging advancements in artificial intelligence, machine learning techniques, and enhanced high-resolution energy data collection are expected to further refine and improve these simulation tools, enabling them to more accurately replicate complex, real-world consumption patterns. Consequently, carefully selecting the appropriate simulation tool or integrating multiple methodologies is crucial for ensuring robust, reliable, and applicable synthetic load profiles capable of addressing the challenges of modern energy systems.

2.3 Applications and Case Studies of Synthetic Load Profiles

Synthetic load profiles (SLPs) are instrumental in modeling and analysing energy consumption patterns, particularly when real-world data is scarce or incomplete. This section delves into various applications and case studies of SLPs, with a focus on university campuses and industrial settings.

2.3.1 Applications of Synthetic Load Profiles

In energy system modeling, SLPs allow researchers and planners to simulate electricity consumption patterns in the absence of detailed real-world data. This capability is crucial for designing and optimising energy systems, facilitating the assessment of different scenarios, and understanding potential impacts on the grid. For instance, a study developed a methodology to generate synthetic electricity load profiles for eleven industry types, aiding in analysing the transformation of the German industry towards renewable energies. [10]

Demand response strategies benefit significantly from synthetic load profiles (SLPs) by predicting periods of peak demand and enabling the implementation of measures to balance supply

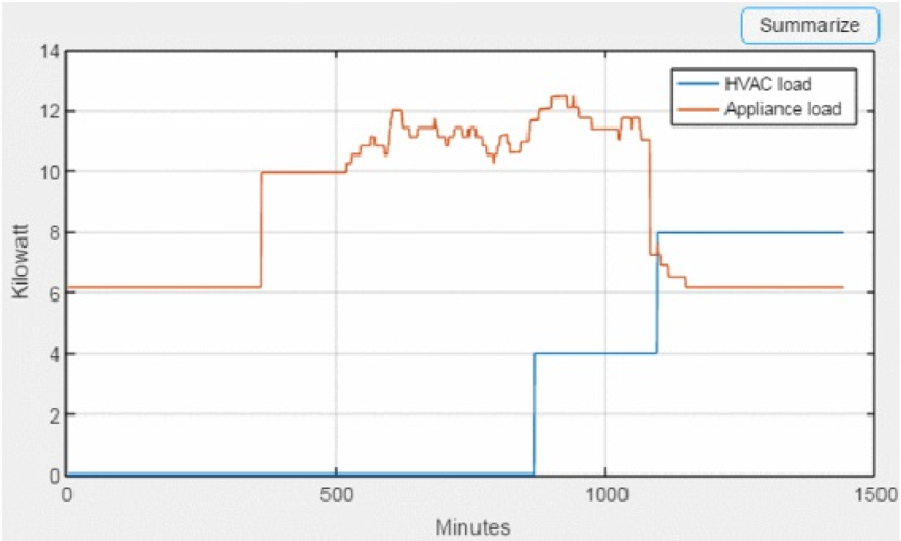

Figure 2.3: Load Profile of a Two-Floor office building with HVAC and appliance load breakdown

and demand efficiently. By anticipating consumption patterns, utilities can design programs that incentivize consumers to adjust their energy use during peak times, enhancing grid stability. A study utilising MATLAB applications generated synthetic electricity load profiles for office buildings and detached houses with high temporal resolution, demonstrating their potential in designing effective demand response strategies [24].

Figure 2.3 illustrates an example of a synthetic load profile for a two-floor office building, showcasing the breakdown of appliance and HVAC loads over the day. The appliance load varies significantly during work hours (7:00–18:00), reflecting increased equipment usage, while HVAC consumption activates in response to temperature fluctuations. In university buildings, office spaces exhibit similar patterns, with appliance loads modeled individually and HVAC demand assessed at the building level for a more holistic energy analysis. Such insights are crucial for optimising heating and cooling schedules, implementing energy efficiency strategies, and improving demand-side management in university energy systems.

The integration of renewable energy sources into the power grid poses challenges due to the intermittent nature of resources like solar and wind power [25]. SLPs assist in modeling these fluctuations by providing detailed consumption patterns that can be matched against variable generation profiles. This alignment is crucial for designing systems that can accommodate renewable energy variability, ensuring reliability and efficiency. For instance, the synGHD project aims to develop individualized high-resolution load profiles to improve the planning of building supply technology, thus enhancing the integration of renewable energy. [26]

2.3.2 Case Studies in University Campuses

University campuses present unique challenges for energy management due to their diverse activities, varying occupancy levels, and complex infrastructure. Several studies have explored the application of SLPs in such settings:

At the Democritus University of Thrace in Greece, researchers investigated the real and reactive power consumption across nine campuses to analyse load shape factors and improve forecasting accuracy. This study highlighted the variability in consumption patterns due to factors such as academic schedules and seasonal changes, emphasising the need for tailored SLPs to enhance energy management strategies. [27]

In the United States, a study collected high-resolution data from two university buildings in the Midwest to analyse load variability. The researchers developed a framework to quantify this variability, providing insights into the factors influencing energy consumption in educational facilities. The findings underscored the importance of considering specific building usage patterns when developing SLPs for university campuses. [9]

2.3.3 Challenges and Future Directions

Data quality is a significant concern, as the accuracy of SLPs heavily depends on the availability and precision of input data. In many cases, especially in residential settings, detailed consumption data is limited due to privacy concerns and the high cost of data collection. This scarcity can lead to less accurate profiles, affecting the effectiveness of energy management strategies. To address this, researchers have explored the use of publicly available data and advanced modeling techniques to generate synthetic benchmark electrical load profiles, aiming to overcome data limitations. [28]

Representing the inherent variability in energy consumption patterns is another challenge. Factors such as human behavior, weather conditions, and occupancy rates can cause significant fluctuations in load profiles. Capturing this variability requires sophisticated modeling approaches that can account for both predictable patterns and random events. Recent advancements in machine learning and data analytics offer promising avenues to enhance the realism of SLPs. For instance, a study proposed a novel method for generating synthetic residential load data using conditional diffusion models, aiming to represent actual electricity consumption patterns accurately. [29]

Looking ahead, integrating advanced technologies such as artificial intelligence and high-resolution data analytics holds the potential to improve the precision of SLPs. These advancements could lead to more adaptive and responsive energy management systems capable of optimising consumption in real-time. Moreover, as smart grids become more prevalent, the role of SLPs in facilitating demand response and integrating renewable energy sources is expected to grow, necessitating ongoing research and development in this field. For example, a study explored the use of transfer learning techniques with open-access synthetic load profiles to improve load forecasting in energy communities, highlighting the potential of advanced data analytics in this domain. [30]

In conclusion, synthetic load profiles are invaluable tools in modern energy management, offering insights that drive efficiency and sustainability. By addressing current challenges and embracing future technological advancements, the development and application of SLPs can significantly contribute to the optimisation of energy systems across various sectors.

Chapter 3

Methodology

Developing accurate synthetic load profiles for university buildings requires a structured and multi-faceted methodology that accounts for the diverse usage patterns of different building types. This study adopts a hybrid approach, integrating data-driven analysis, assumption-based modeling, and simulation-based techniques to estimate the electricity demand of various campus buildings. By combining empirical data collection, logical extrapolation, and stochastic simulations, this methodology ensures that the developed load profiles are both realistic and adaptable to different building conditions.

The overall methodological framework is visually represented in Figure 3.1, illustrating the structured approach followed in this study. The methodology begins with data collection on building classification, room categorisation, and electrical equipment usage. This is followed by the analysis of occupancy patterns and usage behaviors, primarily using Building 34 as a reference model. Based on the collected data, RAMP is employed to generate synthetic load profiles, incorporating stochastic variations in electricity demand. The methodology also includes a validation step to refine the generated profiles, ensuring accuracy and applicability. This structured approach ensures that the synthetic load profiles developed in this study accurately reflect the real-world electricity consumption patterns of university buildings.

The methodological framework consists of three key phases:

Data Collection and Empirical Analysis:

The first step involved on-site observations and equipment surveys to gather information on electrical appliances, power ratings, and user behavior within university buildings. Building 34 was selected as the primary reference building due to its accessibility and availability of detailed data. A comprehensive survey of electrical equipment was conducted, documenting the types, quantities, and power consumption characteristics of various devices, such as computers, lighting systems, laboratory instruments, and office appliances. Additionally, interviews with students, faculty, and staff were conducted to understand occupancy schedules and typical device usage patterns in different room types. These empirical observations formed the basis for the analysis of trends in electricity consumption.

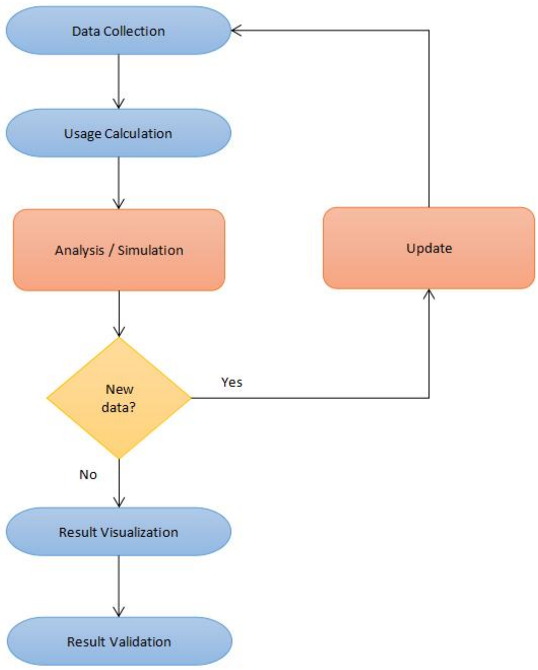

Figure 3.1: Flowchart of methodological approach

Assumption-Based Load Estimation for Other Buildings:

Since Building 34 served as the baseline model, precise data for other university buildings was not available due to lack of metering or detailed records. Therefore, an assumption-based modeling approach was adopted to estimate energy consumption across the campus. The methodology involved extrapolating usage patterns from Building 34 and applying them to similar room types in other buildings. For example, seminar halls across different buildings were assumed to follow comparable usage schedules and equipment behavior, with necessary adjustments based on building function and occupancy levels. These assumptions were structured logically to ensure that the estimated load profiles accurately represented realistic energy usage across campus while acknowledging inherent uncertainties.

Simulation-Based Modeling Using RAMP:

To refine the load profiles further and introduce stochastic variability, the RAMP (Random Appliance Model of Demand) simulation tool was utilised. RAMP provides a probabilistic approach to energy modeling by simulating time-dependent appliance usage patterns based on typical user behaviors. The software was used to generate synthetic load profiles, reflecting daily and seasonal fluctuations in electricity consumption. By incorporating both empirical data and assumption-based estimates, RAMP produced detailed and adaptable load profiles for various university buildings. The integration of simulation-based modeling ensures that the final synthetic load profiles are not only data-informed but also capable of capturing realistic consumption variations.

By employing this three-phase methodology, the study balances real-world observations with simulation techniques, enabling a reliable estimation of electricity demand in university buildings despite data limitations. The combination of empirical analysis, structured assumptions, and stochastic modeling ensures that the resulting synthetic load profiles are robust, reliable, and applicable for future energy planning and management within academic institutions.

3.1 Classification of Buildings at Nordhausen University of Applied Sciences

The development of accurate synthetic load profiles begins with a clear classification of university buildings based on their functional characteristics and usage patterns. Nordhausen University of Applied Sciences consists of multiple buildings serving distinct purposes, including academic teaching, administrative services, student accommodations, specialized facilities, and recreational amenities. Due to significant differences in energy consumption patterns, a structured classification was developed to facilitate targeted data collection and precise electricity demand analysis. The detailed classification provides clarity for subsequent steps involving room classification, equipment analysis, and behavioural assessments.

The campus layout of Nordhausen University of Applied Sciences is presented in Figure 3.2,

Figure 3.2: Campus map

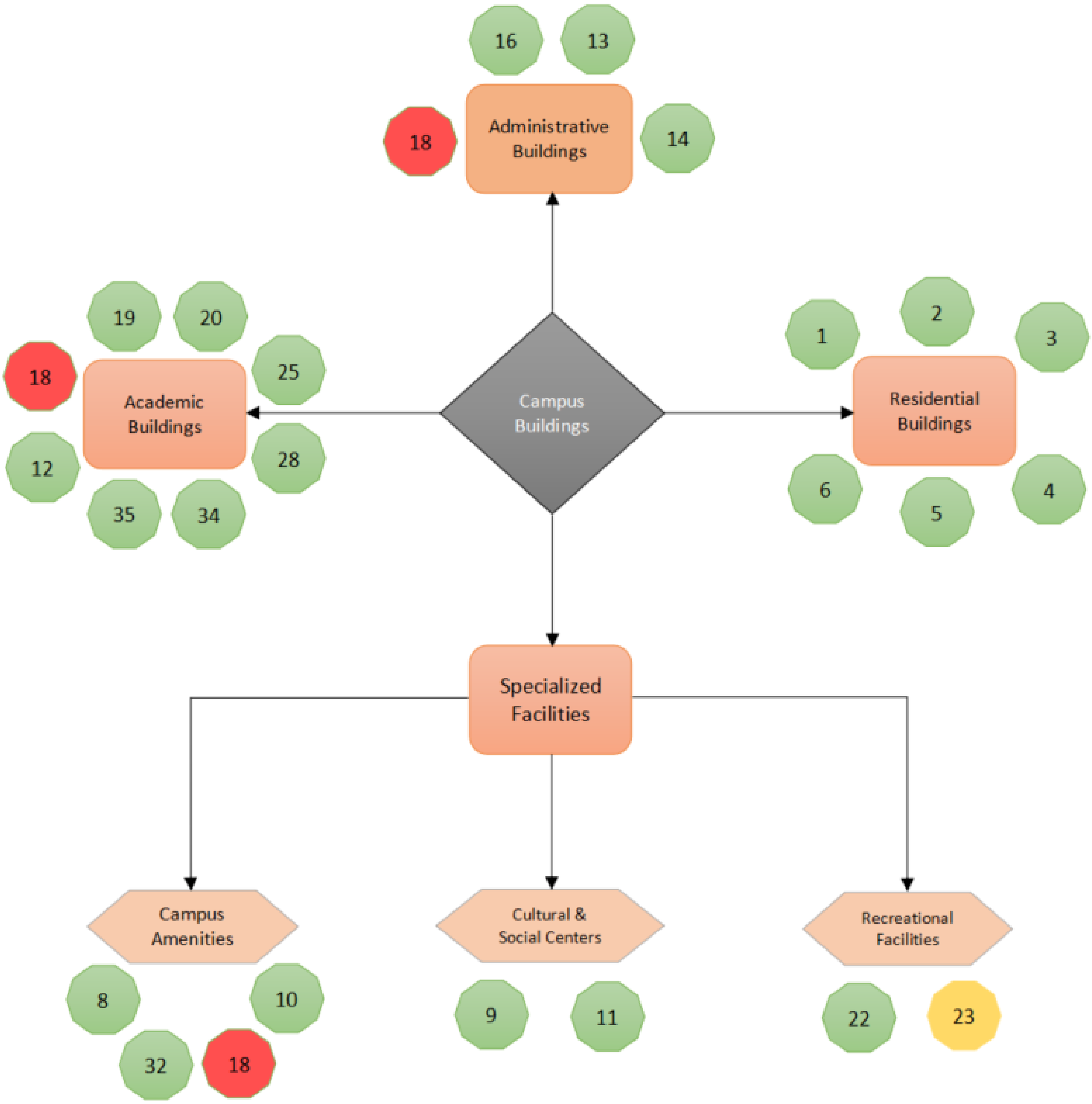

Figure 3.3: Graphical representation of building classification at Nordhausen University of Applied Sciences, highlighting building groups based on functionality and typical usage characteristics

clearly indicating the locations and numbering of individual buildings. This visual representation allows easy identification and enumeration of all buildings across the campus [31].

The buildings at the university campus were Categorised into five main groups, as shown in Figure 3.3. These groups include Academic Buildings, Administrative Buildings, Residential Buildings, and Specialized Facilities, the latter further subdivided into Campus Amenities, Cultural and Social Centres, and Recreational Facilities. Each building category includes structures with similar usage characteristics, occupancy patterns, and energy consumption behaviours. For instance, academic buildings predominantly contain seminar halls, lecture halls, laboratories, and office spaces, each with its specific energy-use profile. In contrast, residential buildings mainly reflect stable daily occupancy patterns with predictable electricity usage for lighting, heating, and personal appliances.

A notable exception is Building 18, which is classified as a mixed-use building. It accommodates administrative offices, student support services, and notably, the campus library. Due to the multifunctional nature of Building 18, its energy profile is particularly complex and unique, demanding specific attention within the analysis. Moreover, building 23 is an abandoned facility that is not in use and is also excluded as a part of this thesis.

The Categorisation depicted in Figure 3.3 serves as a foundation for subsequent methodological steps, ensuring that the variations in electricity consumption between different types of buildings are accurately captured and represented. This structured classification allows targeted data collection and facilitates precise and effective application of the synthetic load profiling process, significantly enhancing the quality of the resulting energy demand analysis.

3.2 Categorisation of Room Types and Electrical Equipment

Following the classification of campus buildings, the next crucial step was the detailed classification of different room types within the university buildings. Accurately identifying these room categories was essential due to their distinct functions, usage patterns, and resulting differences in electricity consumption profiles. As part of this research, Building 34 was selected as the primary reference, as comprehensive data was readily available. An extensive survey and systematic classification of room types were undertaken, encompassing seminar halls, lecture halls, laboratories (electronics and thermal), offices (single-person, two-person, and five-person offices), toilets, corridors, and staircases. This categorisation facilitated an accurate representa-

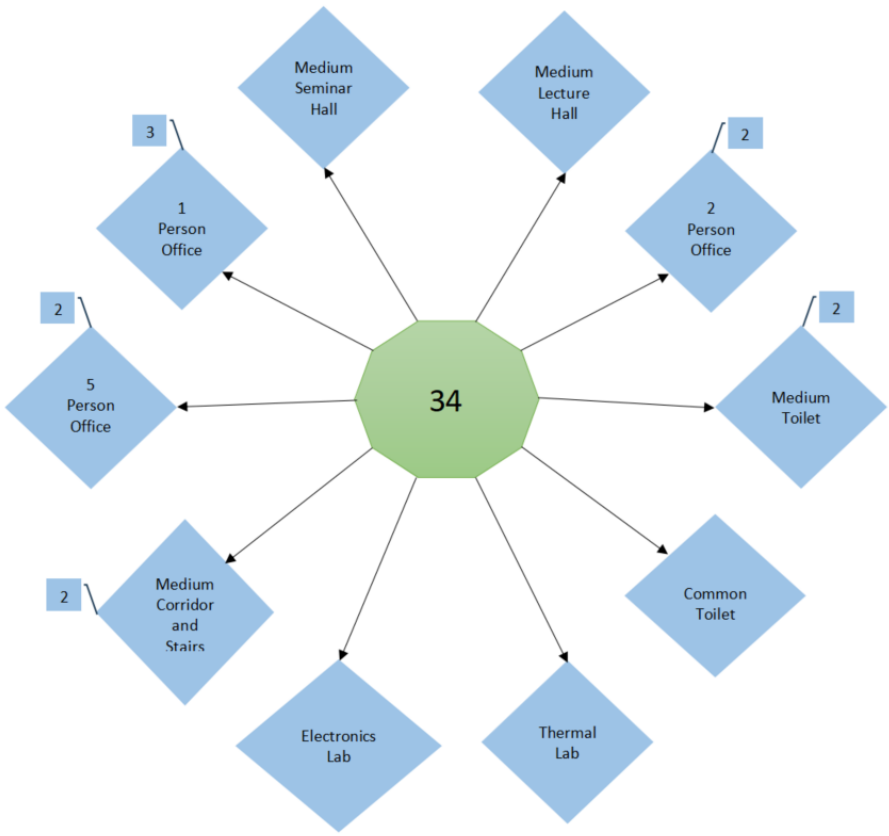

Figure 3.4: Categorisation of room types within Building 34

tion of realistic load profiles, reflecting the specific usage characteristics of each room type.

Figure 3.4 illustrates the categorisation of room types and their counts, specifically within Building 34, highlighting how rooms were organised based on their usage characteristics and typical occupancy. As depicted, the rooms were categorised into clearly defined types, such as medium-sized seminar and lecture halls, offices for one, two, or five persons, thermal and electronics laboratories, and common areas, including toilets and corridors. Such categorisation facilitated a structured approach to collecting equipment data, enabling systematic analyses and ensuring consistency in subsequent calculations and simulations.

Following this classification, detailed data collection on electrical equipment installed in each room type was conducted. This involved careful on-site inspections, surveys, and consultations with facility management personnel. Equipment details such as type (e.g., lighting systems, desktop computers, laptops, projectors, laboratory equipment), quantity, and power ratings were meticulously documented for each room type. The detailed data collected in Build-

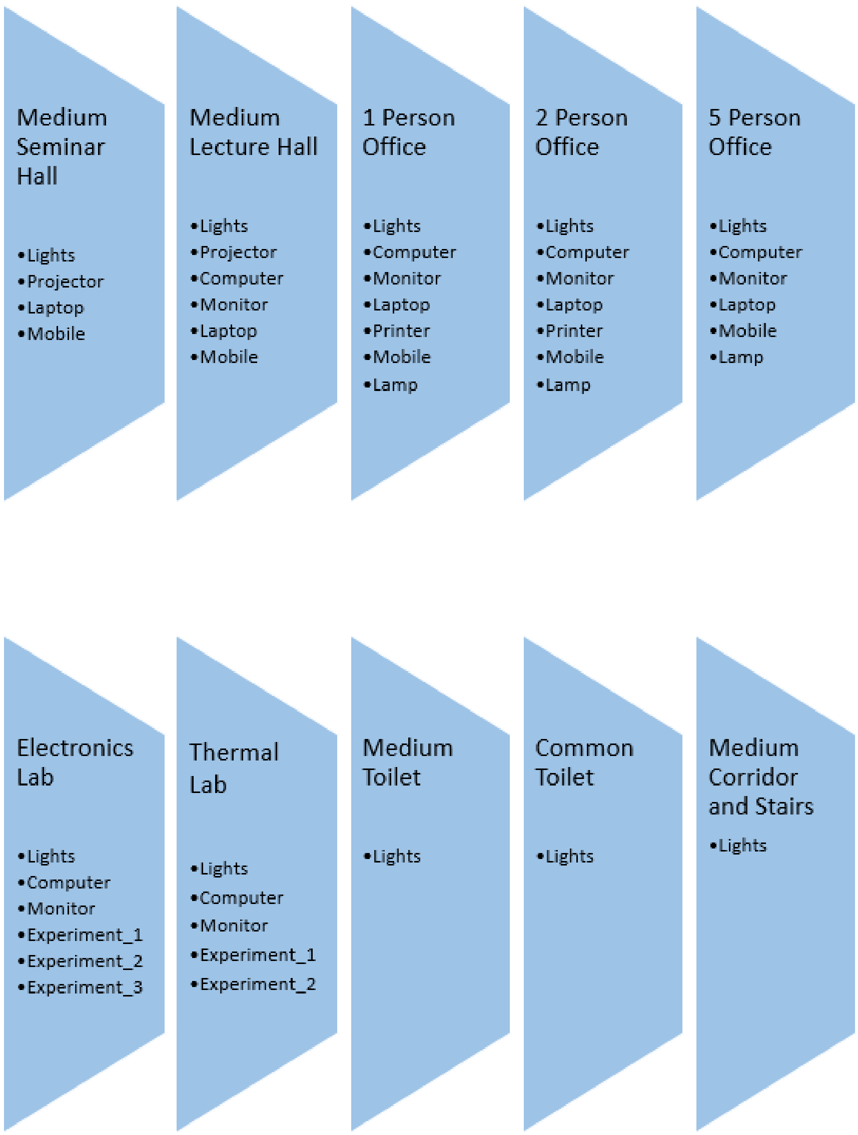

Figure 3.5: Electrical equipment classification within different room types in Building 34

ing 34 served as the basis for subsequent analyses and modelling procedures.

The types of electrical equipment identified within each room category in Building 34 are illustrated in Figure 3.5. This representation clearly depicts the primary electrical devices and appliances typically found in each room type, including seminar halls, lecture halls, laboratories, offices, and common areas. Seminar and lecture halls predominantly include lighting, computers, laptops, and projectors, whereas offices generally feature common workplace equipment such as computers, monitors, and printers, with slight variations based on occupancy.

In the case of laboratory rooms, additional considerations were necessary due to their specialised experimental setups. The laboratories typically contained standard equipment along with experiment-specific apparatus. To simplify data collection and enhance accuracy, electrical consumption in laboratories was categorised according to specific experiments conducted within them. In the electronics laboratory, three distinct experiments were identified, with Experiment 1 predominantly involving a high-consumption device, the "sun simulator," and two additional smaller experiments contributing to overall lab usage. Similarly, in the thermal laboratory, two main experiments were considered, where Experiment 1 primarily utilised the significant energy-demanding equipment "solar thermal system," supplemented by one smaller experiment. By explicitly including these experiments and their associated major electrical devices, the developed profiles more accurately reflect realistic and experiment-specific energy demands within laboratory settings.

This refined graphical overview, combined with the experimental details, ensures clarity and aids in the systematic interpretation of equipment-related data, significantly enhancing the accuracy and robustness of synthetic load profiles.

3.2.1 Scope and Assumptions for Equipment Selection

For practicality and clarity in developing synthetic load profiles, this study focused primarily on the major and most commonly used electrical devices within each room type. Small consumers, such as sensors, continuous operational emergency lighting systems (directional signs), and similar low-consumption devices although essential for building operations were excluded from the detailed individual analysis. These devices, while numerous, typically contribute minimally to the overall electricity consumption and would overly complicate the analysis without significantly improving accuracy.

3.3 Analysis of Equipment Usage Patterns and Seasonal Demand Variations

Developing synthetic load profiles requires detailed consideration of how equipment usage and electricity demand vary across different room types, periods, and seasonal conditions within the university campus. This section outlines the systematic approach adopted to analyse usage behaviour, examine the impacts of seasonal and academic schedules on consumption patterns, and address data limitations through carefully structured assumptions. These analyses ensure that the generated profiles realistically represent the dynamic electricity demands throughout the academic year.

3.3.1 Equipment Usage and Behavioural Patterns

The realistic representation of electricity usage in university buildings requires an in-depth understanding of occupants' interactions with electrical equipment. Therefore, a thorough analysis was carried out in Building 34 to collect detailed data concerning the operational patterns of electrical appliances. This data collection involved on-site observations, short interviews with room users, and direct assessments of equipment usage during typical university hours. Specific attention was given to variations in equipment operation, such as device activation frequency, duration of use, and typical standby periods. The resulting parameters provided essential inputs for generating precise synthetic load profiles using the RAMP tool.

3.3.2 Influence of Academic Schedule and Seasonal Changes

Nordhausen University of Applied Sciences follows a structured academic calendar divided into two primary semesters: Winter and Summer. Each semester comprises distinct periods, including lectures, breaks, and examination phases, which significantly impacting the occupancy and consequent electrical usage within campus buildings. To accurately reflect these variations, eight specific academic periods were defined. These periods directly affect daily occupancy patterns, influencing the frequency and duration of equipment usage.

To illustrate, seminar halls and lecture rooms experience intensive usage during regular lecture periods (e.g., WS_Winter and SS_Summer), but significantly lower activity during examination or break periods, resulting in notable differences in electricity demand. Additionally, seasonal factors, such as shorter daylight hours in winter, necessitate prolonged artificial lighting usage, whereas warmer summer months increase demand for cooling appliances. A concise summary of these defined academic periods is provided in Table 3.1 below, whereas comprehensive details regarding specific assumptions, device usage durations, and operational parameters per academic period are elaborated in Appendix A.

Table 3.1: Academic periods considered for seasonal analysis.

Winter Semester (WS)			**Summer Semester (SS)**		
Lecture Periods	**Break Period**	**Exam Period**	**Lecture Periods**	**Break Period**	**Exam Period**
WS_Winter WS_Autumn	WS_Break	WS_Exam	SS_Summer SS_Spring	SS_Break	SS_Exam

The specific durations and exact timings associated with each academic period outlined in Table 3.1 were determined based on the university's annual academic calendar. To understand how these durations are explicitly applied within the RAMP simulation tool, readers are referred to Appendix B, where detailed explanations of period durations, their implementation, and their role in the simulation process are provided.

3.3.3 Profile Generation for Buildings with Limited Data

Due to the absence of detailed electrical appliance information and comprehensive usage patterns for buildings other than Building 34, an assumption-based approach was adopted to create their synthetic load profiles. These profiles were initially developed using data extrapolated from Building 34, with adjustments based on observable differences in room size, occupancy capacity, and intended functionality. Laboratories with incomplete data posed a particular challenge; thus, profiles for these spaces were based on available standard device usage assumptions and scaled appropriately. A more detailed explanation of these assumptions and their justification can be found explicitly documented in Appendix B.

3.3.4 Calibration with Measured Consumption Data

To ensure realism and accuracy, preliminary synthetic profiles generated for buildings lacking detailed equipment data underwent calibration against measured monthly electricity consumption data provided by the university. This step involved scaling the initially developed synthetic profiles up or down to closely match actual historical energy use, enhancing their validity and reliability. Detailed explanations, assumptions, and scaling methodologies applied during calibration are documented explicitly in Appendix B.

3.4 Adaptation and Application of the RAMP Tool

3.4.1 Brief Introduction to RAMP

The RAMP is a stochastic simulation tool designed to generate detailed synthetic electricity load profiles, initially targeted towards residential households [6]. The fundamental principle behind RAMP is the realistic reproduction of user behaviour and electricity consumption patterns through probabilistic methods and detailed statistical modelling. Specifically, RAMP simulates appliance-level usage, capturing the variability and temporal characteristics of electrical appliance operations across defined time intervals [32],[33].

Key input parameters required by RAMP include the appliance's maximum power ratings, standby power, typical usage durations, frequency of activations, and the probabilities associated with the operation of each device at different times of the day [32]. Using these detailed inputs, RAMP generates high-resolution synthetic load profiles, reflecting realistic variations in demand that arise from diverse occupant behaviour and appliance interaction. These profiles are particularly valuable for energy planners and researchers aiming to analyse household electricity consumption dynamics, evaluate energy management strategies, or assess the impacts of demand-side management interventions [33].

Moreover, a notable feature of RAMP is its flexibility, allowing adaptation beyond its initial residential scope. Its parameter-driven structure can be adjusted to replicate consumption patterns in diverse settings, including institutional and commercial environments, provided that the model parameters are appropriately defined and adjusted according to the specific context [20]. Although primarily created to model residential scenarios, this adaptability has enabled its successful application in broader research contexts, offering a robust and scalable approach for the development of synthetic load profiles across various building types and usage conditions [33],[20].

For this study, RAMP was specifically adapted and customised to model the electricity consumption patterns of university buildings, reflecting their unique occupancy schedules, diverse room types, and varying equipment usage behaviours. A detailed explanation of these specific modifications and the adaptation process undertaken for university buildings is provided explicitly in subsection 3.4.3.

3.4.2 Rationale for Selecting and Modifying RAMP

The selection of RAMP for this study was guided by a comprehensive evaluation of available simulation tools described previously in subsection 2.2.2, including Load Profile Generator, nPro, HOMER, and EnergyPlus. Load Profile Generator, while detailed and capable of representing household-level appliance behaviours, is specifically tailored for residential contexts, thus limiting its direct application to institutional buildings. Similarly, nPro excels at generating demand profiles for heating, cooling, and e-mobility systems at neighbourhood scales, but it lacks the explicit flexibility needed for detailed appliance-level behavioural modelling within university settings.

Table 3.2: Comparison of simulation tools for synthetic load profile generation

Tool	**Appliance-level Detail**	**Institutional Building Flexibility**	**System-level Modelling**	**Stochastic Behavioural Modelling**
Load Profile Generator	High	Low (household-focused)	Moderate	High
nPro	Moderate	Moderate	High	Moderate
HOMER	Low	Moderate	High	Low
EnergyPlus	Moderate (HVAC-focus)	Moderate	High	Low
RAMP (Selected)	**High**	**High (after modification)**	Moderate	**High**

Table 3.2 provides a concise comparison of selected simulation tools evaluated for generating synthetic load profiles. The comparison considers critical aspects such as appliance-level detail, flexibility for institutional building contexts, capability for system-level modelling, and the ability to simulate stochastic behavioural patterns. RAMP emerged as the most suitable tool for this study, given its superior flexibility and capability after necessary modifications.

Conversely, tools such as HOMER and EnergyPlus offer strengths in system-level and building-level modelling, respectively. HOMER primarily supports renewable energy system optimisation and microgrid analyses, with limited attention given to detailed, stochastic appliance-level user behaviours. EnergyPlus focuses on detailed HVAC and thermal energy modelling within buildings, but it is less effective for simulating granular occupant behaviour and detailed appliance interactions, which are essential aspects of this study.

In contrast, RAMP's detailed stochastic appliance-level simulation, extensive flexibility, and explicit user-behaviour modelling capabilities made it particularly suitable for adapting to the context of university buildings. Its probabilistic structure effectively addresses the variability and complexity inherent to diverse room usage patterns and occupant interactions within academic environments.

However, due to RAMP's original focus on household scenarios, targeted modifications were required to address the specific characteristics and usage patterns of institutional buildings. These modifications and their implementation details are elaborated explicitly in subsection 3.4.3.

3.4.3 RAMP Simulation Setup and Adaptation for University Buildings

To accurately represent electricity consumption within university buildings, the original RAMP (version 0.3.1) tool required careful adaptation. Initially developed for simulating household energy use, RAMP's original structure was adjusted by introducing and modifying several

Python scripts to reflect the unique characteristics and usage patterns of university environments. The adapted framework consists of a combination of original RAMP scripts and newly created scripts, each serving a specific role in generating realistic synthetic load profiles tailored to the Nordhausen University of Applied Sciences.

Table 3.3: Python scripts used in the adapted RAMP framework

Original RAMP Scripts	**Newly Created Scripts**
core.py	Room_Profile.py
ramp_run.py	Building_Profile.py
initialise_mod.py	Ventilation_Profile.py
stochastic_process_mod.py	
post_process.py	

Table 3.3 summarises the Python scripts utilised in the adapted RAMP framework. It categorises scripts based on their origin, either adapted from the original RAMP implementation or newly developed specifically for this thesis.

core.py

The file core.py serves as the foundational component within the adapted RAMP framework. It consists primarily of two interconnected Python classes: "Room" and "Appliance". The original class named "User", initially intended for modelling household energy consumption, has been renamed "Room" to align more clearly with university building applications. This class provides the structure to categorise each room type and manage associated appliances. The "Appliance" class within this script defines each electrical appliance's operational characteristics, usage windows, and duty cycles. Modifications included the addition of an extra usage window and specific duty cycle parameters to improve the representation of appliance usage patterns in university rooms.

ramp_run.py

The script ramp_run.py serves as the central executable within the adapted RAMP framework, coordinating the overall simulation process. It initiates the workflow by prompting users to specify key parameters such as the simulation year, desired room type (identified through numerical codes), academic semester, specific academic periods, simulation intervals (defined by start and end months), and the number of simulation days. Based on these inputs, the script subsequently manages the internal calls to associated Python modules, executes stochastic simulations to generate detailed synthetic load profiles, and performs post-processing tasks, including graphical visualisation and structured data export. Detailed instructions for entering these inputs, as well as the definitions and durations of the academic periods used, are explicitly provided in Appendix B.

initialise_mod.py

This script is responsible for the initialisation of input parameters and data structures necessary for running the simulation in RAMP. It defines key components used throughout the simulation process, including identifying specific room types based on user inputs and determining behavioural patterns over a selected year.

Specifically, this script performs two primary functions:

- **Yearly Behaviour Pattern Definition**: A dedicated function, yearly_pattern, calculates the behavioural pattern over a defined simulation period by distinguishing weekdays, weekends, and public holidays specific to Germany (subdivision Thuringia). This functionality incorporates variations such as leap years and adjusts dynamically based on the calendar of the simulation year. This ensures the simulation accurately reflects seasonal and daily variations in electricity demand.

- **Room Input Initialisation**: This script associates numerical room codes, provided by the user in the ramp_run.py script, with corresponding room-type modules. Each numerical room code corresponds to a specific input file containing detailed appliance and occupancy data required for the simulation of individual room types. For instance, the numerical code 3 refers to "Room inputfiles. Office 1P.OFF_1P", where "OFF_1P" represents the specific room code for a one-person office. A complete description of these numerical room codes, their respective room codes, and the structure of the input files is provided in Appendix B.

Additionally, the script defines adjustable calibration parameters, such as peak window enlargement and coincidence factors, allowing customisation for different rooms or specific modelling requirements.

stochastic_process_mod.py

The stochastic_process_mod.py script implements the core stochastic simulation algorithm within the modified RAMP tool. This script calculates the peak time range, distinguishing between peak and off-peak periods, to determine appliance usage probabilities more realistically. The simulation first identifies a general "peak window," which represents a period of higher simultaneous appliance activation probability. Within this peak window, a specific "peak time" is randomly selected and then expanded using stochastic methods to create a realistic representation of energy demand peaks.

In the modified approach adopted for this study, the script generates multiple (N) stochastic load profiles for each selected room type. Each individual profile captures daily variability based on appliance behaviour, occupancy patterns, and randomised usage within defined operating windows. After generating these profiles, the script computes an average profile from all simulated profiles (N profiles) to produce a representative energy consumption profile for the particular room. The number of profiles (N) to generate for each room type is specified within the respective seasonal input files, as detailed in Section 3.3.2 and Appendix B.

This averaging approach improves the robustness and reliability of the final synthetic load profiles, accounting effectively for random variations in equipment usage behaviour, occupancy patterns, and peak-time fluctuations throughout different academic periods.

Input Files and Seasonal Profiles

The synthetic load profiles generated by RAMP rely heavily on carefully structured input files, which contain specific information about appliance types, their usage patterns, and power ratings for different rooms. Each room type defined in this study has separate input files corresponding to eight distinct academic periods throughout the year. These periods, as previously explained in Table 3.1, represent the university's academic calendar and associated seasonal occupancy patterns.

Each input file specifies detailed parameters required by the RAMP model, including the number of electrical devices, their active and standby power ratings, typical usage duration, and minimum operating times. A practical example of such a file for a five-person office(Office 5P) during the winter semester break (WS_Break) can be seen in detail in Appendix B. Similar input file structures apply to all other defined periods.

When running the main simulation script (ramp_run.py), the user selects the room type, the specific academic semester, and its associated sub-period (e.g., winter break, summer exam period). Based on these inputs, RAMP automatically reads the corresponding file containing all necessary parameters and performs stochastic simulations to generate multiple synthetic daily profiles. These daily profiles are then averaged, creating a representative profile for each selected period.

Annual Load Profile Generation

After generating synthetic load profiles separately for each academic period, it is crucial to compile them to represent a realistic, continuous annual profile for the selected room. This compilation process utilises an additional Python script named Room_Profile.py. This script collects all individually generated seasonal profiles from their corresponding directories, rearranging and concatenating them according to the chronological order defined by the university's academic calendar.

More specifically, the script:

- Loads the synthetic profiles for all eight academic periods.
- Extracts the exact time durations defined for each period based on user inputs, which contains precise start and end dates for each period).
- Concatenates these extracted profiles sequentially, resulting in a complete year-long synthetic load profile.

Finally, this concatenated annual profile is exported and stored as an Excel file for each specific room type, simplifying further analysis and visualisation. To provide a clear visual understanding, the final annual load profile generated through this process is graphically represented at both monthly and hourly resolution. This visualisation aids significantly in identifying seasonal variations, peak consumption periods, and specific energy consumption patterns tied directly to the academic schedule and occupancy behaviours.

The detailed procedures, along with explicit Python codes (ramp_run.py, seasonal input file, and Room_Profile.py), and data used in each step of the simulation process, can be reviewed comprehensively in Appendix B.

Building-Level Load Profile Aggregation

Following the creation of annual load profiles for individual room types, the next crucial step involves synthesising these room-specific profiles to generate comprehensive load profiles for entire university buildings. This aggregation process is executed through the custom-developed Python script Building_Profile.py, which systematically combines individual room profiles into consolidated load profiles at the building level.

The script initiates by importing annual load profile dataframes for each relevant room type, generated previously via the Room_Profile.py script. Each of these dataframes contains hourly electricity consumption data tailored to specific room characteristics and their corresponding occupancy and appliance use patterns.

Subsequently, the script prompts the user to select a building for analysis. For each selected building, the corresponding room profiles are adjusted by applying appropriate scaling multipliers that reflect the actual count and distribution of each room type within the building. Plus, electrical loads due to building-specific ventilation systems are incorporated (further explained in Section 3.4.3 - Ventilation load profile integration).

A unique feature of this script is the integration of measured historical electricity consumption data (provided for the years 2021, 2022, and 2023). This data serves as a benchmark to calibrate the aggregated synthetic load profiles. The script achieves calibration by calculating a monthly scaling factor, based on the ratio between the average measured monthly consumption and the aggregated monthly synthetic consumption to align the synthetic profiles more closely with observed data. After scaling, the script adds a building-specific base load, representing continuous electricity demand independent of room-specific activity. The base load calculation methodology is explained in detail in Appendix B.

Lastly, the script outputs a refined building-level load profile, exported as an Excel file for further analysis or integration with other building models. It also generates clear visual plots to enable intuitive comparison between simulated and actual historical energy consumption patterns, thereby validating the accuracy and applicability of the synthetic load profiles.

Ventilation Profile Generation

The final stage of building-level load profile generation involves creating a ventilation load profile, which significantly contributes to total energy consumption in university buildings. The script Ventilation_Profile.py calculates the hourly electrical consumption for the ventilation system based on external temperature variations throughout the year, considering different seasonal periods. The calculation relies on the hourly ambient temperature and the operational status of the ventilation system, influenced by weekends and holidays determined through a yearly behavioural pattern.

The simulation begins by importing hourly ambient temperature data from the Excel file, which is the average profile of 10 years of Nordhausen. The temperature data is then segmented into four distinct seasonal periods, Winter, Spring, Summer, and Autumn, aligned with the academic calendar of Nordhausen University of Applied Sciences. The specific date ranges assigned to each season mirror the simulation periods used for room-level profile generation. For each season, the script calculates hourly mean temperature values using the function average_hourly_values() and exports both raw and averaged data into the seasonal dataframes.

To model realistic usage behaviour, the script employs a function named yearly_pattern(), which accounts for weekdays, weekends, and public holidays (using the German holidays package with the TH region for Thuringia). This generates a behavioural vector that flags non-working days, ensuring the operational logic of the ventilation system reflects actual campus activity patterns.

The actual power consumption is computed through the function calculate_power_consumption(), which evaluates each hour based on both ambient temperature and behavioural flags. During winter, autumn, and spring, when temperatures drop below 15°C and the day is not a public holiday, the system assumes heating demand and applies a base consumption of approximately 2 kW. On other days, a base load of around 0.5 kW is simulated to represent minimal system activity.

For the summer period, where cooling becomes relevant, the script introduces a dynamic calculation of the Coefficient of Performance (COP). The formula used is:

$$\mathrm{COP} = COP_{\mathrm{base}} - \alpha \times (T_{\mathrm{ambient}} - T_{\mathrm{min}}) \tag{3.1}$$

where:

- COP_{base} the baseline COP at the reference ambient temperature (20°C in this study).
- α is the COP decrease rate per degree Celsius, set at 0.2.
- T_{ambient} is the current ambient temperature.
- T_{min} represents the reference temperature (20°C).

When ambient temperatures exceed this threshold and the hour falls within defined daytime working periods (typically 08:00 to 18:00), the script calculates power demand using this COP value by inverting the cooling efficiency (i.e., dividing a constant cooling load of 10 kW by the COP). On holidays or outside operational hours, only minimal consumption is recorded to reflect standby conditions. The hourly results are stored in a DataFrame. Additionally, a plot of the hourly load profile is generated and saved as an image.

This comprehensive modelling approach ensures that the ventilation energy demand, both heating and cooling, is accounted for in a seasonally responsive and operationally accurate manner. By using real world behavioural data and dynamic temperature-dependent COP logic, the script produces realistic, high-resolution ventilation load profiles.

The systematic approach included defining room-specific input parameters, generating seasonal load profiles, and consolidating these into annual profiles to reflect realistic electricity consumption scenarios. The customised Python scripts, additional modules, and specific configurations were introduced and explained to facilitate reproducibility and clarity. Consequently, the adapted RAMP model provides a robust foundation for accurately analysing and simulating electricity demand patterns.

Chapter 4

Results and Discussion

4.1 Overview

This chapter discusses the outcomes of the electricity load profile simulations conducted for the buildings at the Nordhausen University of Applied Sciences, highlighting Building 34 as the core case study. The main objective is to evaluate and validate detailed synthetic electricity profiles tailored specifically to the distinctive usage patterns found within university buildings.

Building 34 was chosen for its representative diversity of room types, variety of electrical equipment, and available measured consumption data, enabling effective validation of the simulation approach outlined in Chapter 3. By examining individual room profiles, aggregating these results, and integrating additional energy demands such as ventilation, this case provides a practical illustration of the accuracy and reliability of the adapted RAMP simulation methodology.

Subsequent sections offer a thorough analysis of simulated profiles, comparisons with actual energy consumption data, and discussion of seasonal and operational factors influencing electricity demand. This targeted investigation sets a foundation for extending similar methodologies to other buildings, supporting strategic decisions aimed at enhancing energy efficiency and sustainability across the campus.

4.2 Load Profiles of Selected Room Types

Accurately representing electricity consumption patterns for individual room types is crucial to the development of precise synthetic load profiles for buildings. To illustrate this effectively, specific room types primarily located in Building 34 are presented here. These include the Medium Seminar Hall, 5-Person Office, Electronics Laboratory, and Thermal Laboratory.

It should be noted that the load profiles of Medium Seminar Hall and Medium Lecture Hall are largely similar due to comparable occupancy and device usage patterns. The only distinction is the inclusion of computers in Lecture Halls, resulting in slightly higher overall electricity consumption. For this particular reason, only the load profile of Medium Seminar

Hall is represented.

Similarly, the electricity consumption patterns of various office types (e.g., 1-Person and 2-Person Offices) are comparable to that of the 5-Person Office presented here. While device types remain consistent across these offices, variations occur in the number of devices and occupancy patterns, influencing the total electricity consumption.

Other room types within the university, though essential for comprehensive campus load characterization, are not individually detailed in this section. This approach avoids unnecessary repetition and maintains focus, as the primary objective is the representation of the overall building profile.

Moreover, it is important to note that the base load was not individually accounted for in each room type's load profile. Instead, only the major electrical equipment's consumption was considered. This decision was made to avoid complexity since a building-specific base load calculation has been applied separately at the aggregated building level rather than at the individual room level.

Medium Seminar Hall

The monthly electricity consumption profile of the Medium Seminar Hall exhibits clear seasonal fluctuations aligned closely with the academic schedule, as depicted in Figure 4.1. Peak monthly consumption occurs during January (75 kWh) and December (74 kWh), reflecting high utilisation during active academic months. Conversely, the lowest consumption is observed during the semester breaks, particularly in March (18 kWh) and August/September (10 kWh), indicating significantly reduced room usage.

The hourly load profile presented in Figure 4.2 further illustrates these usage patterns, showing consistent daily electricity demand peaks around 0.4 kW, corresponding to seminar and

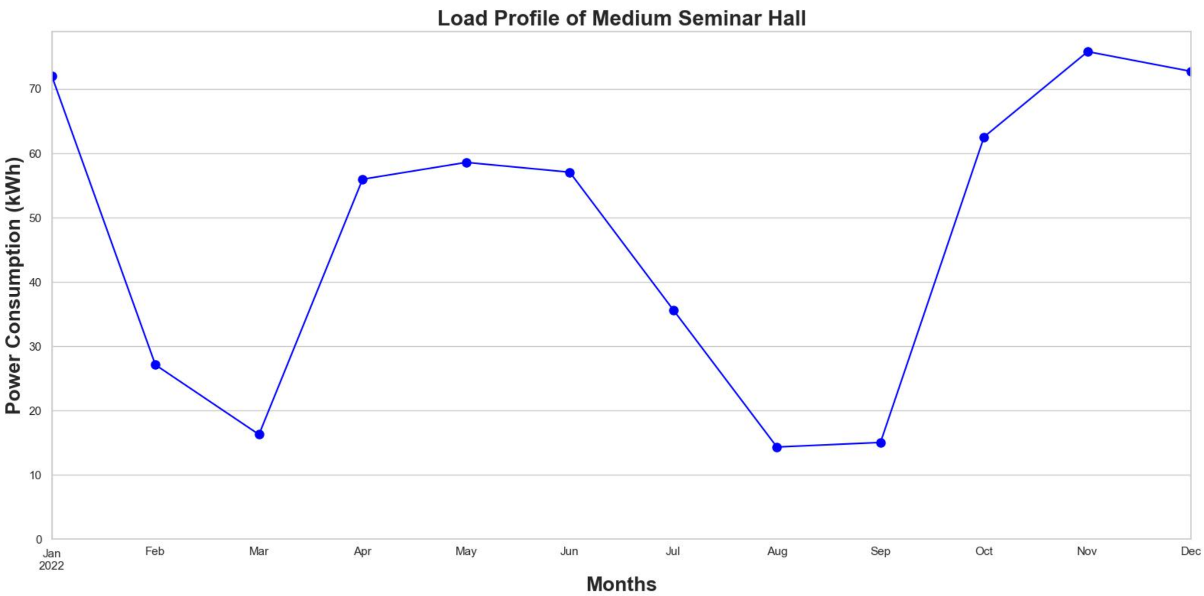

Figure 4.1: Monthly consumption of Medium Seminar Hall

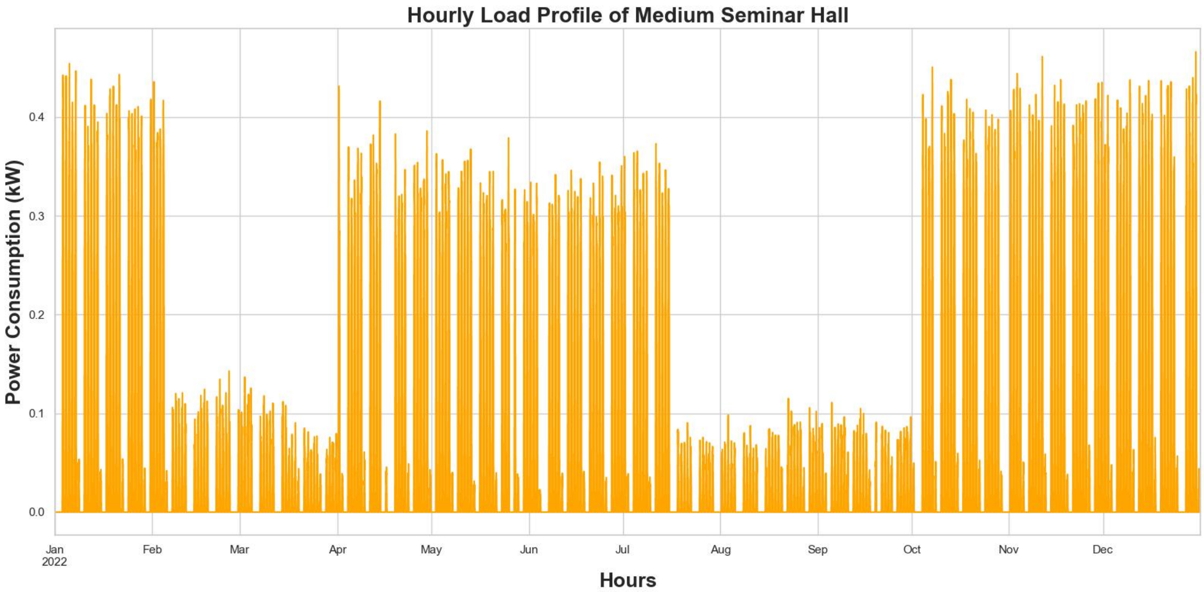

Figure 4.2: Hourly consumption of Medium Seminar Hall

lecture timings, predominantly on weekdays. Outside these operational hours, power demand drastically reduces, approaching near-zero values, particularly during weekends, nights, and extended semester breaks. This distinct hourly usage pattern emphasises the predictable nature of electricity consumption within seminar halls, providing a reliable basis for accurate synthetic load profile generation and effective energy planning.

5-Person Office

The monthly electricity consumption for the 5-Person Office is depicted in Figure 4.3, indicating a relatively consistent consumption pattern throughout the year 2022. Monthly values range narrowly between approximately 300 kWh to 350 kWh, demonstrating stable usage regardless of seasonal variations. Peak consumption occurs in June at around 355 kWh, while the lowest consumption is observed in July, around 295 kWh. The consistency throughout the year reflects typical office usage patterns driven by routine operation schedules and standard equipment utilisation.

In terms of hourly electricity demand (see Figure 4.4), the 5-Person Office exhibits a consistent pattern primarily during working hours, from approximately 08:00 to 18:00, indicating a typical office operation profile. The peak hourly power demand frequently approaches approximately 2 kW, whereas outside of working hours and during weekends, consumption significantly decreases, approaching minimal levels. This hourly distribution aligns with expected office usage, clearly reflecting regular occupancy schedules and working routines.

Electronics Laboratory of Building 34

The monthly electricity consumption profile of the Electronics Laboratory (see Figure 4.5) illustrates a distinct pattern with significant fluctuations throughout the year. Notably, electricity

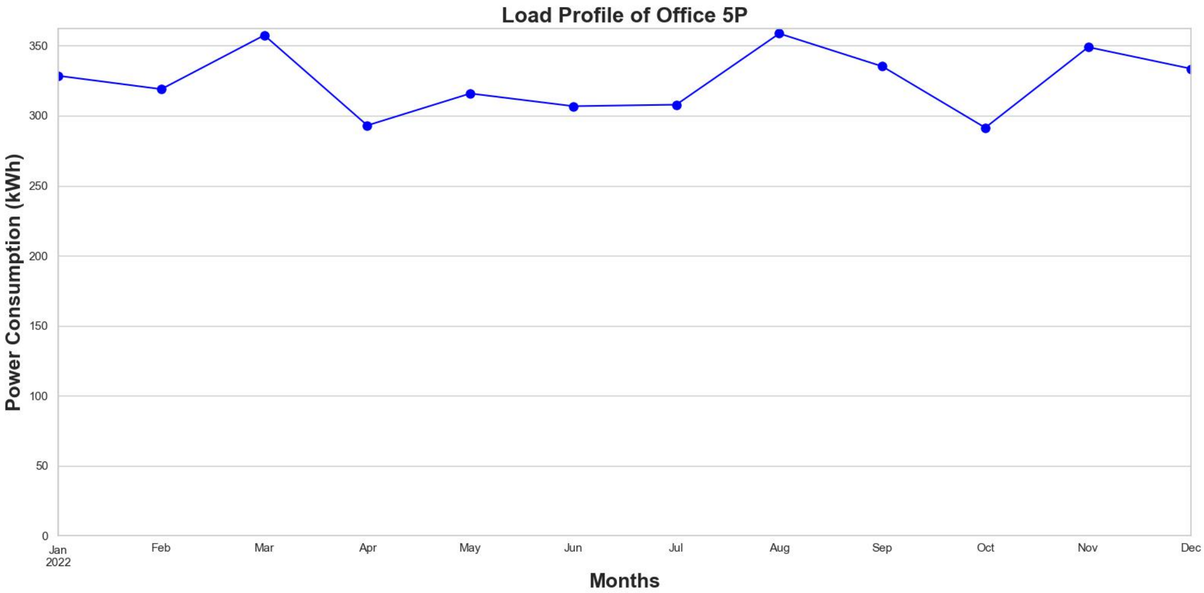

Figure 4.3: Monthly consumption of 5-Person Office

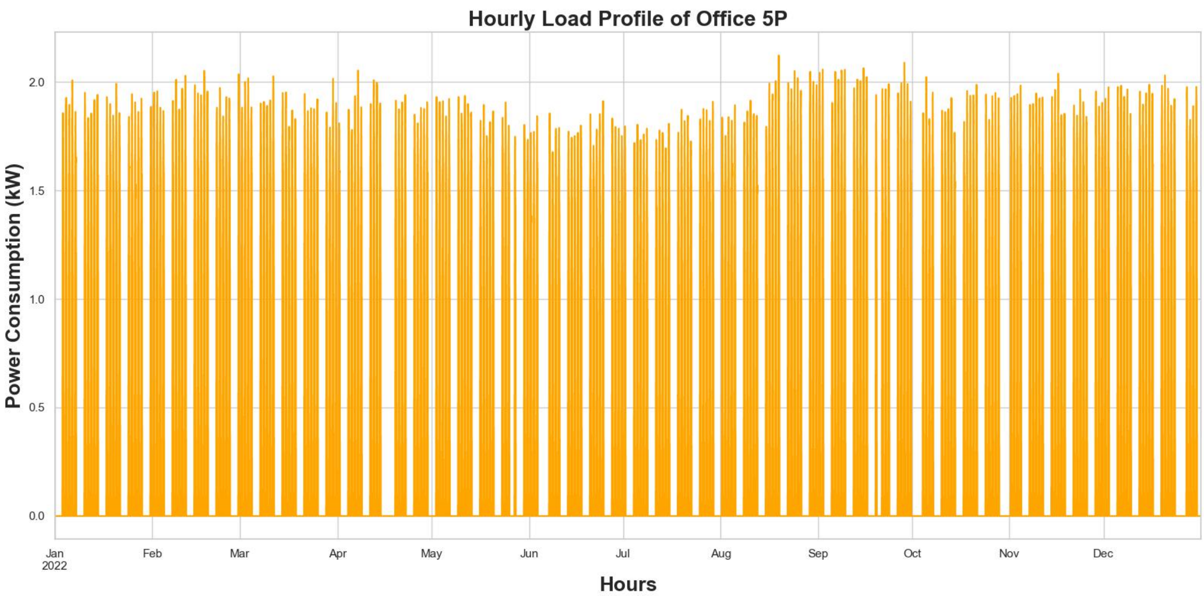

Figure 4.4: Hourly consumption of 5-Person Office

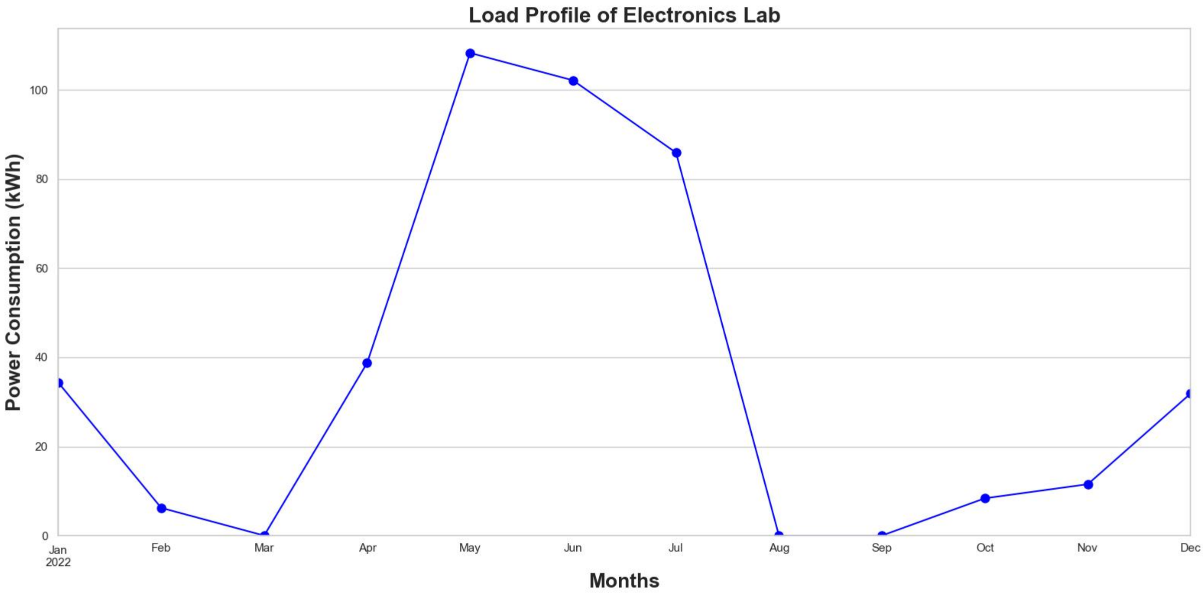

Figure 4.5: Monthly consumption of Electronics Laboratory

consumption peaks sharply between April and July, exceeding 100 kWh monthly, as intensive experimental activities occur during these periods. This aligns with the previously mentioned experimental setups involving high-power devices such as Sun Simulator, as described in the methodology chapter. Conversely, from August to September, minimal to no electricity usage is observed, reflecting semester breaks and reduced laboratory activity.

The hourly profile (Figure 4.6) reveals sporadic peaks in power demand, occasionally surpassing 10 kW, highlighting the nature of laboratory operations where short but intense power usage occurs due to equipment startup, testing cycles, or demonstration sessions. Outside these high-usage intervals, the laboratory maintains a relatively low electricity demand, underscoring the intermittent and experiment-dependent characteristic of electricity consumption in the Electronics Laboratory.

Thermal Laboratory of Building 34

The monthly load profile for the Thermal Laboratory, shown in Figure 4.7, clearly highlights distinct consumption peaks and troughs that correlate with academic and experimental activities. The peak load, reaching approximately 72 kWh in June, corresponds to the active use of the primary electrical device in the laboratory, the Solar Thermal experimental setup, indicating heightened experimental operations during this period. Conversely, significantly lower energy use (below 10 kWh) is evident from July to September, reflecting minimal or no academic activity during summer vacations.

In terms of the hourly load distribution presented in Figure 4.8, consumption predominantly remains low, punctuated by occasional spikes reaching up to 8 kW during specific experimental sessions. This is consistent with the operational characteristics of the Solar Thermal system, which is utilised intermittently for structured laboratory sessions and student practical exercises.

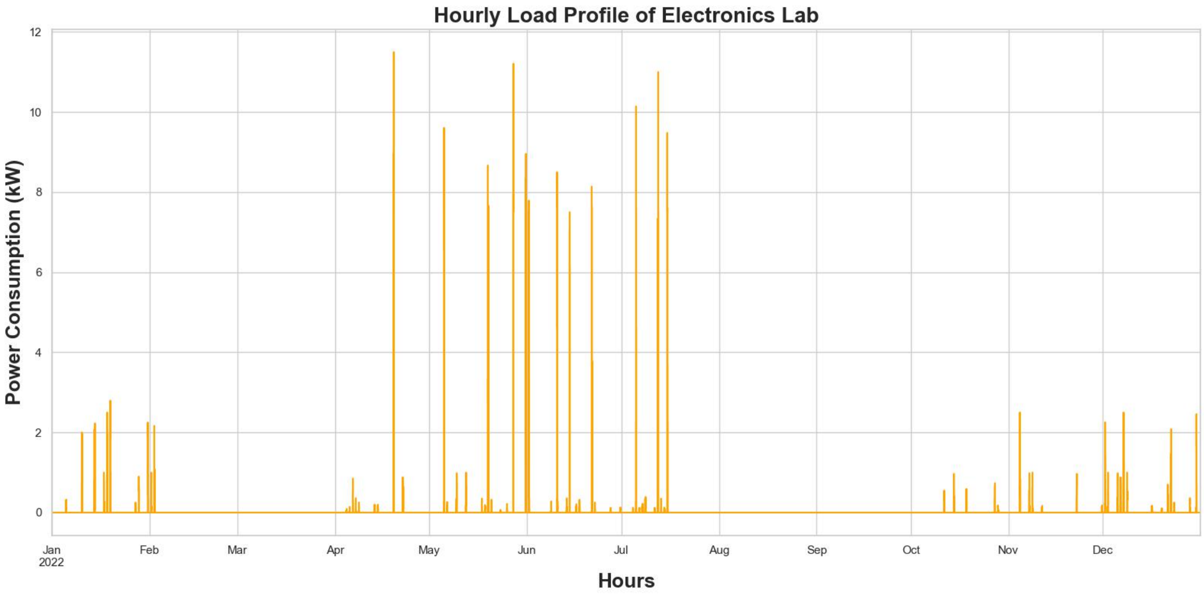

Figure 4.6: Hourly consumption of Electronics Laboratory

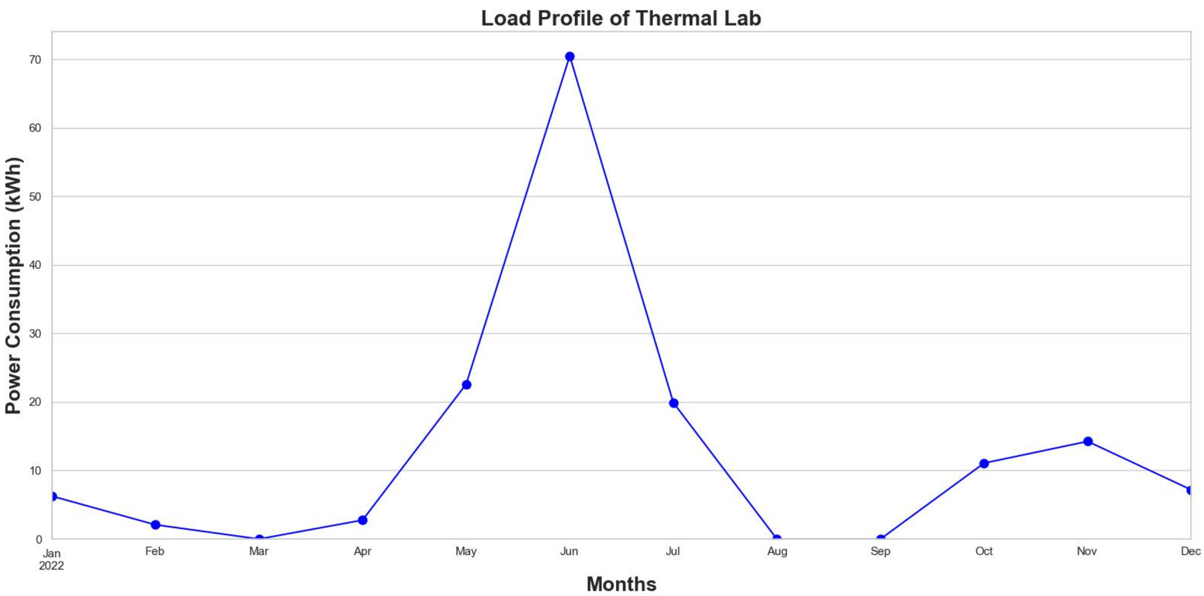

Figure 4.7: Monthly consumption of Thermal Laboratory

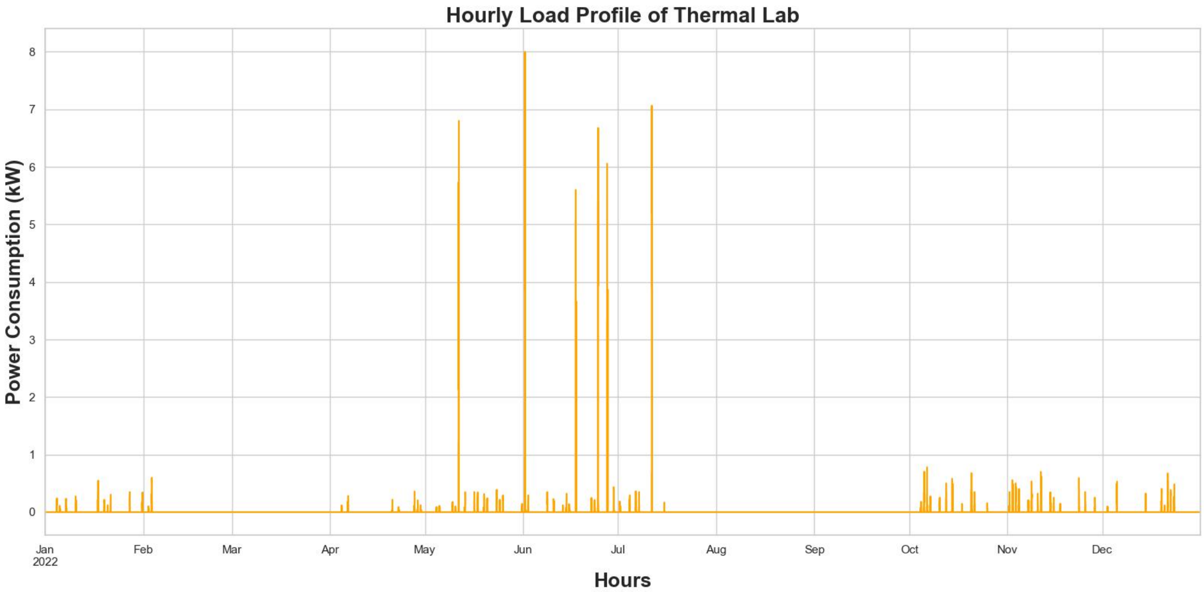

Figure 4.8: Hourly consumption of Thermal Laboratory

Such pronounced fluctuations underscore the necessity of accounting for laboratory-specific experimental schedules when synthesizing detailed electricity load profiles for academic buildings.

The distinct peaks observed for both the Electronics and Thermal laboratories predominantly occur during the summer semester, reflecting the dependence of their primary experiments on favourable sunlight conditions. As these experiments require substantial solar irradiance for accurate results, laboratory activities, and consequently electricity consumption increase significantly during this period.

4.3 Ventilation Electricity Consumption

The electricity consumption profile of the ventilation system in Building 34 is presented in Figure 4.9. The hourly load profile reveals distinctive seasonal variations influenced primarily by heating and cooling requirements. During winter months (October to March), the ventilation system exhibits a relatively constant consumption level of approximately 2 kW, which corresponds to the base load for heating purposes. In contrast, significant fluctuations are observed during the summer period (May to September). This higher variability results from the operation of an additional cooling machine. The cooling unit activates according to the ambient temperature thresholds, causing consumption peaks reaching up to approximately 14 kW, as demonstrated clearly in Figure 4.9. A comprehensive explanation of the ventilation system's temperature-based operation, including detailed equipment parameters and settings, is provided in Chapter 3.

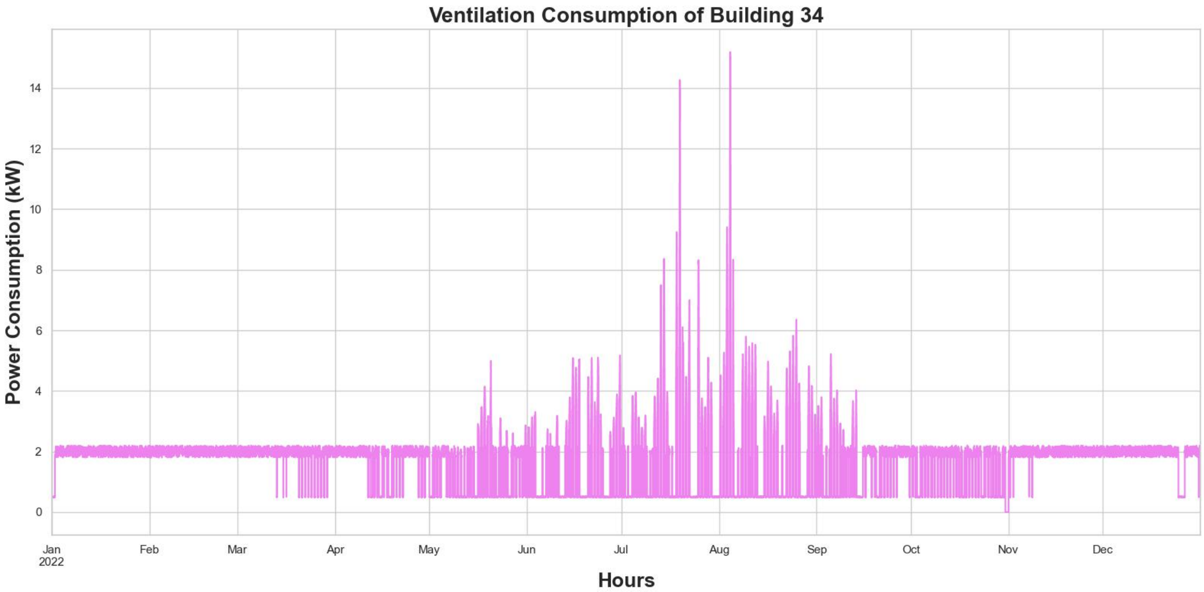

Figure 4.9: Ventilation consumption of Building 34

4.4 Load Profiles of Buildings

Building 34

The monthly and hourly electricity consumption profiles for Building 34 are presented in Figures 4.10 and 4.11, respectively. The monthly profile includes both the scaled synthetic load profile (Scaled Power) and the calculated synthetic load profile (Calculated Power), offering a comparative view with historical measured data from the years 2021 to 2023. It can be observed that the scaled synthetic profile aligns closely with the average historical data, while noticeable deviations are present in specific months for the calculated synthetic load.

Particularly significant differences can be observed in the months of April, September, and December. April typically marks the beginning of the semester, resulting in higher building utilisation due to increased seminars and classes. Conversely, despite September being a semester break period, consumption has historically been unexpectedly high, possibly attributed to major laboratory-based projects occurring during this time. Such anomalies highlight the challenges posed by unpredictable utilisation patterns. The simulation allocates usage durations based on predefined periods detailed in Table B.1 (Appendix B), assuming consistent usage behaviour within each period. Consequently, the months within the 'Lecture Period,' April, May, June, and July, display relatively uniform consumption levels, although lower than those during the winter semester months of October, November, December, and January. This seasonal increase is attributable to greater lighting demands and continuous heating requirements.

The consistently higher calculated consumption compared to measured values observed in December arises due to the exclusion of the end-of-year holiday period, approximately 15 days typically spanning from mid-December to early January, in the simulation. Addressing such discrepancies requires incorporating more detailed temporal resolution or additional context-specific adjustments to the synthetic profile generation methodology.

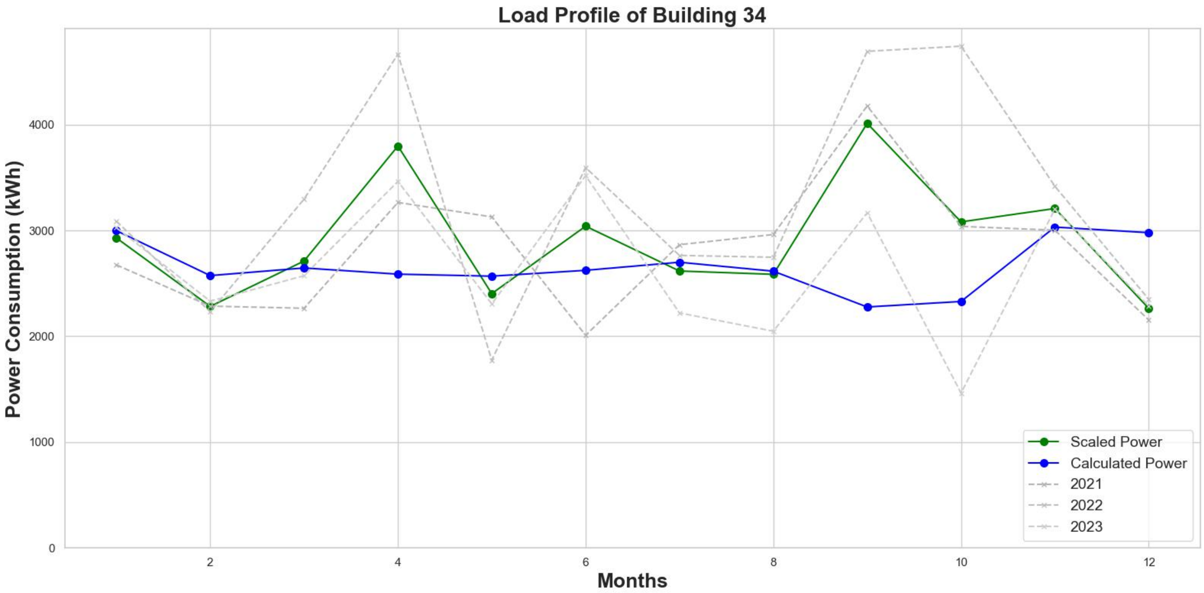

Figure 4.10: Monthly consumption of Building 34

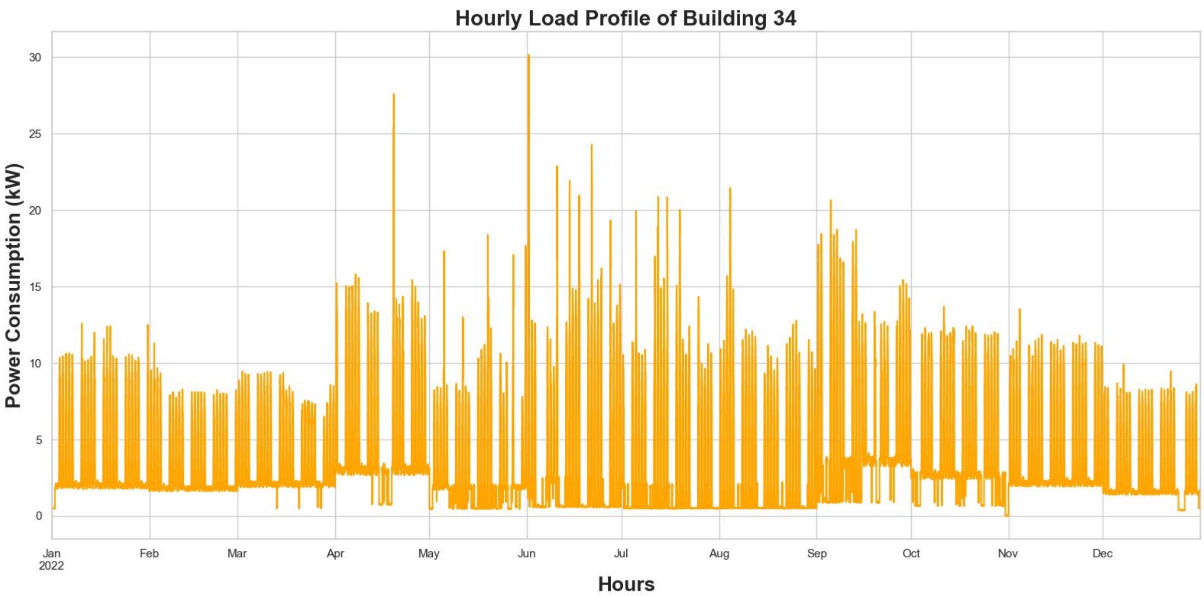

Figure 4.11: Hourly consumption of Building 34

The allocation of the base load for each building in the simulation was supported by historical electricity consumption data available from a prior study conducted at Hochschule Nordhausen in 2015 [34]. According to this report, Building 34 accounted for approximately **17%** of the university's south campus electricity consumption at the time. Although the study is dated, the proportional values were adopted as a reference for estimating current consumption shares.

Building 35

The monthly and hourly electricity consumption profiles for Building 35 are presented in Figures 4.12 and 4.13, respectively. The monthly profile (Figure 4.12) compares the scaled synthetic load profile (Scaled Power) and the calculated synthetic load profile (Calculated Power) against the historical measured electricity consumption from the years 2021 to 2023. As observed, the calculated profile follows a relatively consistent consumption pattern across all months, while the scaled profile exhibits fluctuations that align with seasonal variations and operational phases.

In particular, lower scaled consumption is noted in February (612.4 kWh) and June (567.9 kWh), which corresponds to semester break periods, whereas October (822.1 kWh) and November (923.5 kWh) reflect higher utilisation—likely due to intensified academic activities during the peak of the winter semester. The synthetic model captures these patterns, but minor mismatches still occur, notably in January and December, where the measured data is slightly higher than both calculated and scaled profiles. These deviations may be attributed to underrepresented base loads or special events not accounted for in the current model configuration.

The hourly profile (Figure 4.13) provides a detailed representation of daily consumption dynamics throughout the year. The load profile indicates stable weekday activity with peak power values reaching approximately 4.2 kW, while weekends and break periods show a noticeable

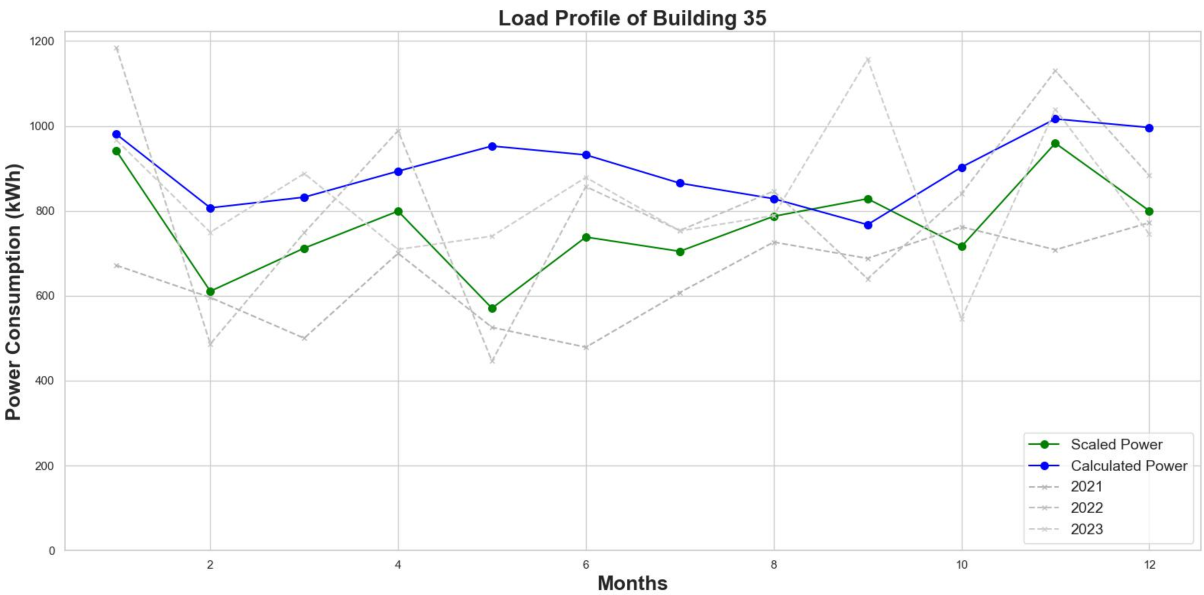

Figure 4.12: Monthly consumption of Building 35

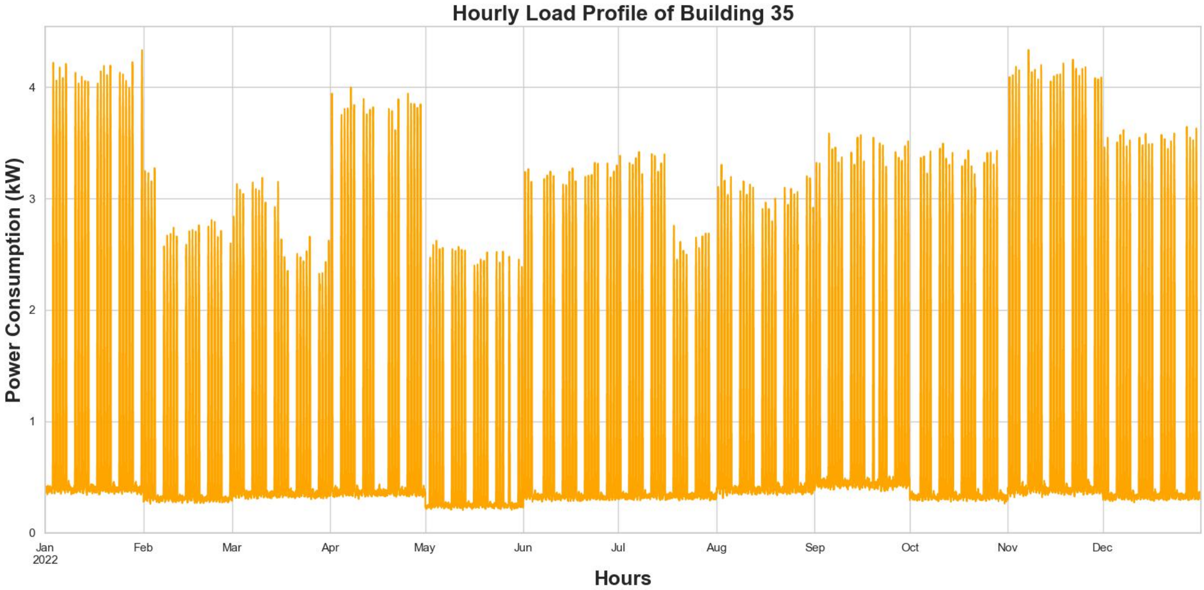

Figure 4.13: Hourly consumption of Building 35

drop in consumption to values closer to 0.5 kW, representing standby loads. Summer periods, such as July and August, show a slight dip in load intensity due to reduced academic activity.

Building 28

The monthly and hourly electricity consumption profiles for Building 28 are illustrated in Figures 4.14 and 4.15, respectively. The monthly load profile includes both the scaled synthetic profile and the calculated synthetic profile, alongside historical consumption data from 2021 to 2023. The scaled synthetic profile closely follows the average trend of historical data, while the calculated synthetic profile shows a consistently lower consumption throughout the year. This

Figure 4.14: Monthly consumption of Building 28

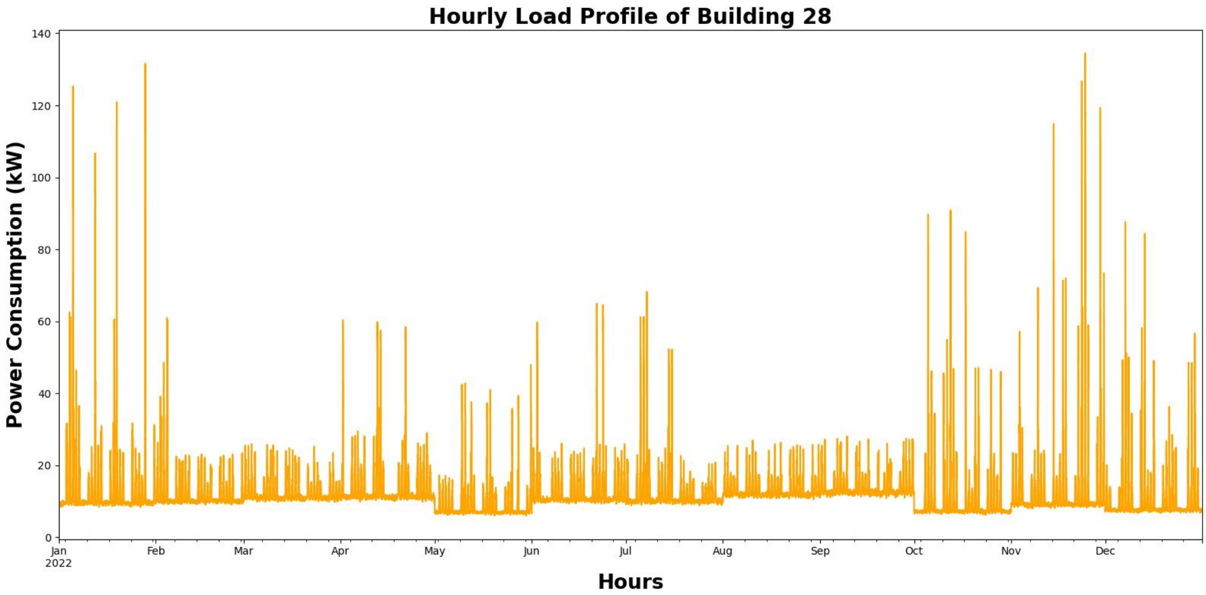

Figure 4.15: Hourly consumption of Building 28

discrepancy can be attributed to the nature of Building 28, which primarily consists of multiple laboratories. Due to the unavailability of accurate laboratory appliance data and ventilation parameters, the calculated profile underestimates the total energy demand. Laboratories are known to house energy-intensive equipment, and without precise usage patterns, their contribution is difficult to simulate effectively.

The hourly profile (Figure 4.15) displays significant power consumption spikes during specific months, most notably in January, November, and December. These peaks correspond to periods of intense laboratory activity or heating demands. The consistently low baseline between spikes indicates intermittent usage patterns, typical of lab-based buildings.

Overall, while the scaled profile presents a reasonable approximation, the calculated results highlight the need for enhanced data collection, especially for specialised rooms like laboratories, to improve simulation accuracy for such complex buildings.

Building 25

The monthly and hourly electricity consumption profiles for Building 25 are illustrated in Figures 4.16 and 4.17, respectively. The hourly profile highlights the building's regular usage patterns across the year, with significant peaks during academic periods and lower consumption during breaks. Building 25 exhibits relatively stable weekday activity with pronounced weekday-weekend variation, consistent with typical teaching and office use.

The monthly load profile (Figure 4.16) shows both the calculated synthetic profile and the scaled power curve. It is important to note that, for this building, measured consumption data were only available for the year 2021. Consequently, the calculated synthetic load was compared against the 2021 measured values and scaled accordingly to align with the real consumption levels.

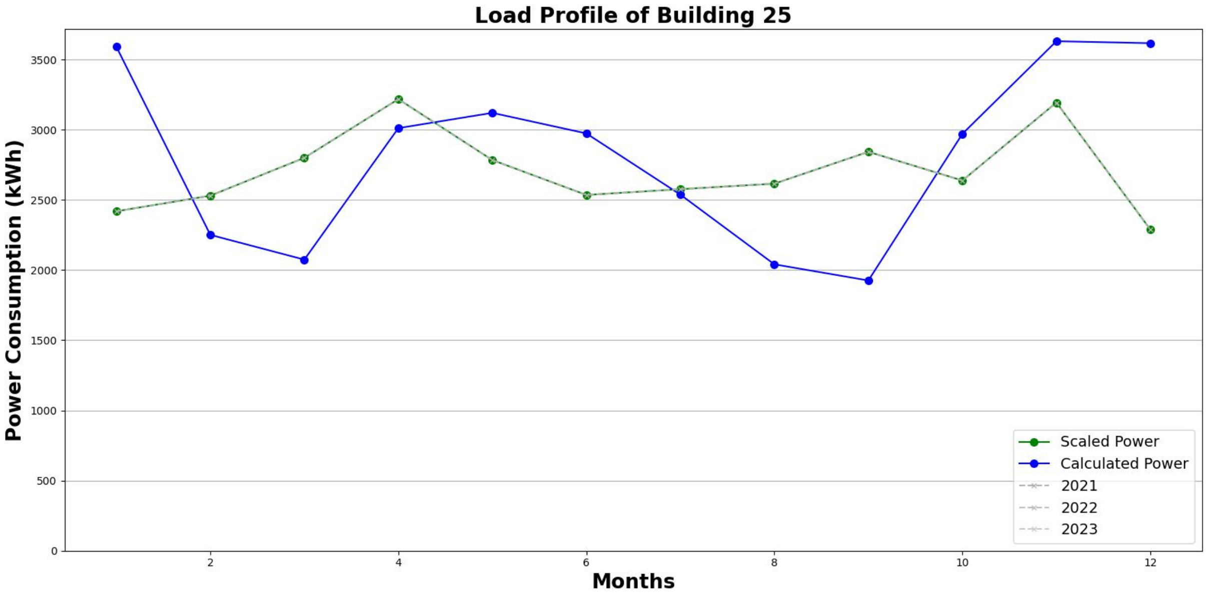

Figure 4.16: Monthly consumption of Building 25

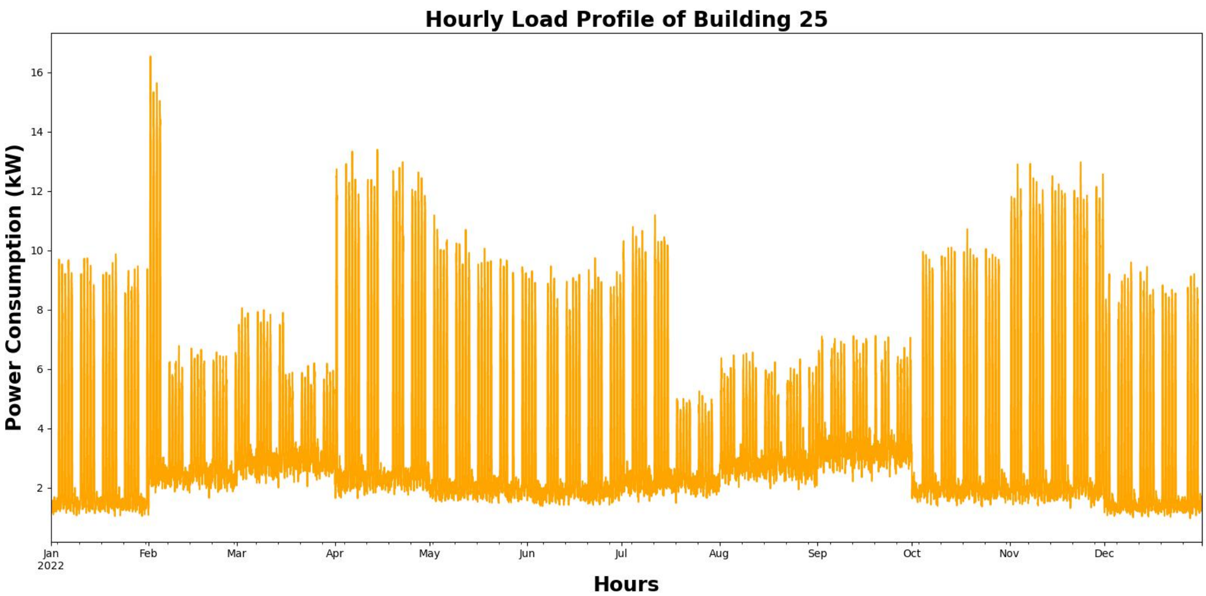

Figure 4.17: Hourly consumption of Building 25

The comparison shows a reasonably close alignment between the synthetic and historical values in most months. Some discrepancies occur in April and December, where the calculated power is slightly lower. These deviations may result from specific activities not fully captured in the appliance-level modelling, such as extended project work in laboratories or irregular classroom bookings.

Building 20

The electricity consumption patterns for Building 20 are illustrated through the monthly and hourly load profiles shown in Figures 4.18 and 4.19, respectively. The hourly plot provides a high-resolution view of the load distribution over the year 2022, capturing seasonal and operational fluctuations. The monthly profile presents the comparison between the calculated synthetic load (Calculated Power), the scaled synthetic profile (Scaled Power), and the historical measured consumption data from the years 2021 to 2023.

From the comparison, it can be observed that the scaled synthetic profile closely aligns with the historical trends, while the calculated synthetic values show some underestimations in specific months. Particularly in February and July, the measured data shows relatively high consumption spikes, likely reflecting high-occupancy usage periods or events not fully captured in the simulation inputs. Conversely, during spring and autumn, the alignment between synthetic and measured values is more consistent.

Building 20 exhibits relatively high and stable usage throughout the year, indicating the presence of consistent activities, possibly including administrative operations, lab-based sessions, or office functions. However, despite the reasonable overall agreement, some deviations remain between the calculated profile and the actual values, possibly due to unmodelled appliance usage patterns or missing equipment data. These differences could be further refined by

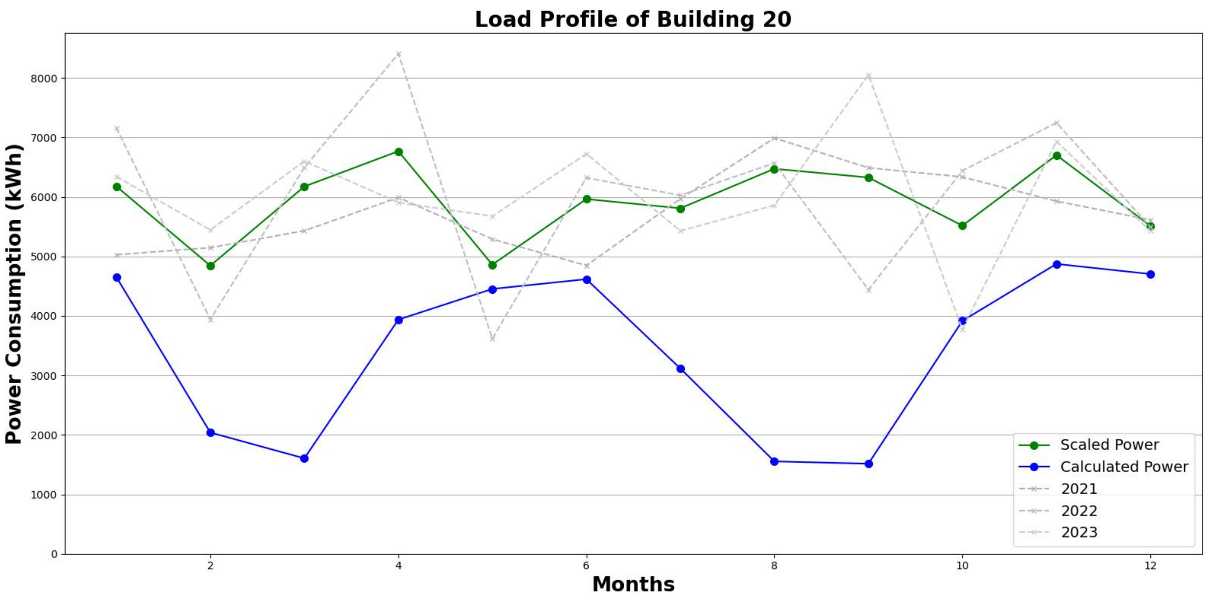

Figure 4.18: Monthly consumption of Building 20

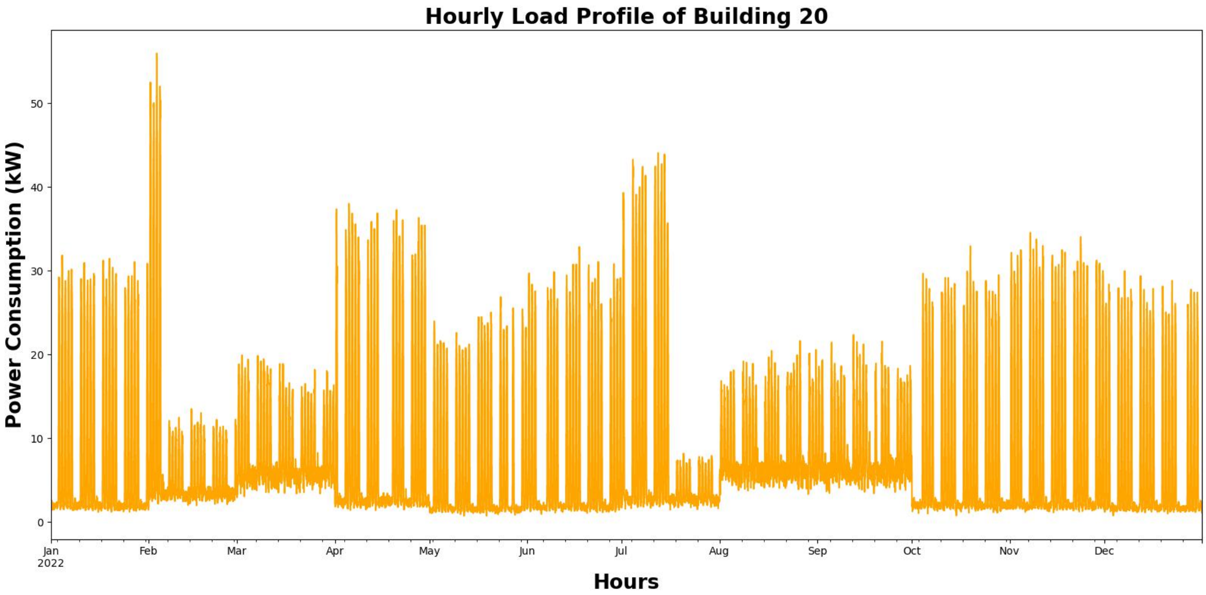

Figure 4.19: Hourly consumption of Building 20

introducing more accurate device-level inputs and behavioural patterns in future simulations.

Building 19

The monthly and hourly electricity consumption profiles for Building 19 are presented in Figures 4.20 and 4.21, respectively. As this building was under construction during 2021 and 2022, it only became operational in early 2023. Consequently, the validation and scaling of the simulated synthetic profiles have been carried out using measured data exclusively from the year 2023.

It is important to note that the calculated synthetic load profile exhibits significantly higher consumption than the measured data. This is primarily because the usage behaviour and functional assumptions for each room type, such as offices, seminar rooms, and computer labs, were uniformly applied based on the parameter set used for the reference Building 34. In other words, the individual behavioural patterns or utilisation schedules specific to the rooms in Building 19 were not uniquely defined due to the unavailability of detailed data.

Moreover, Building 19 contains a large number of seminar halls and two major lecture halls, which could lead to diverse usage dynamics and irregular operational hours. Since these factors were not distinctly considered in the simulation, the profile tends to overestimate electricity usage when compared with the measured values.

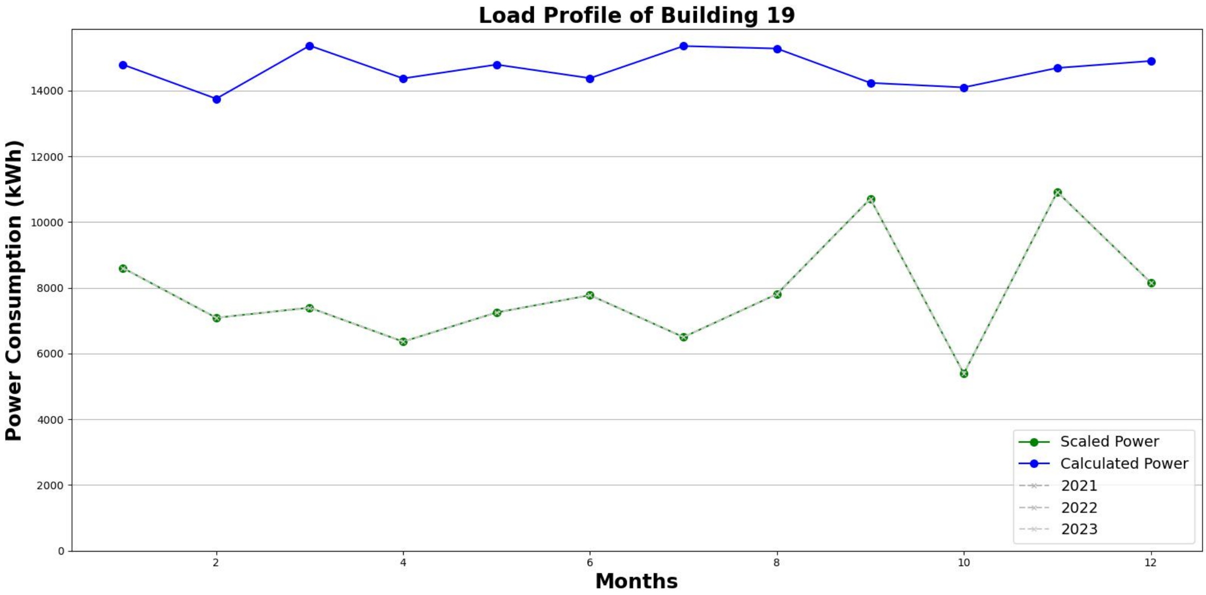

Figure 4.20: Monthly consumption of Building 19

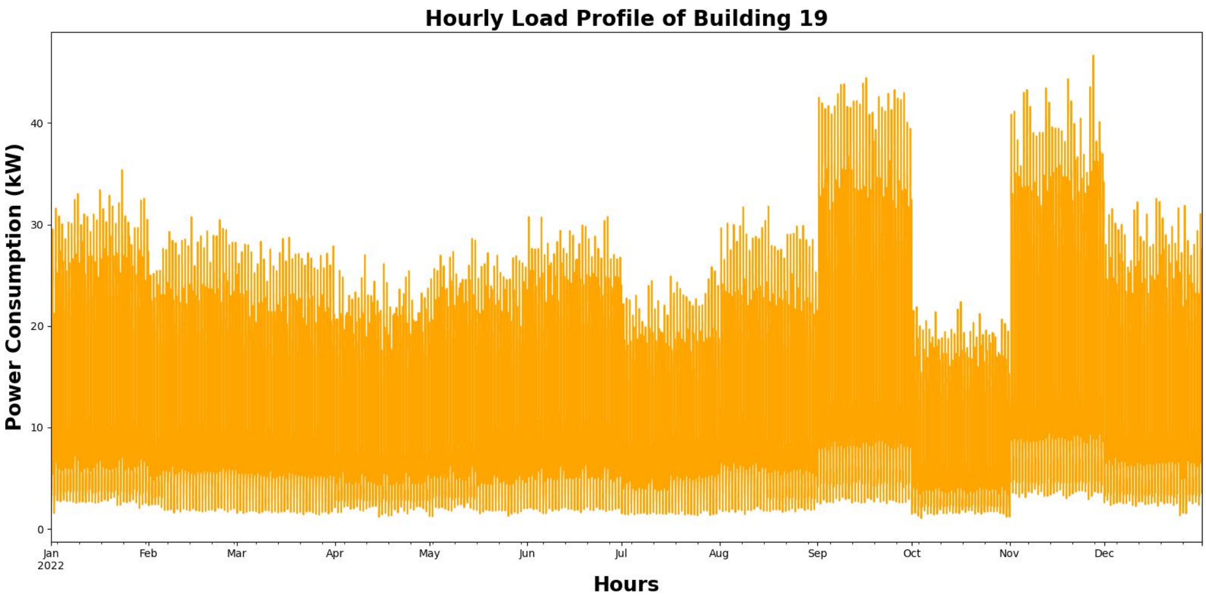

Figure 4.21: Hourly consumption of Building 19

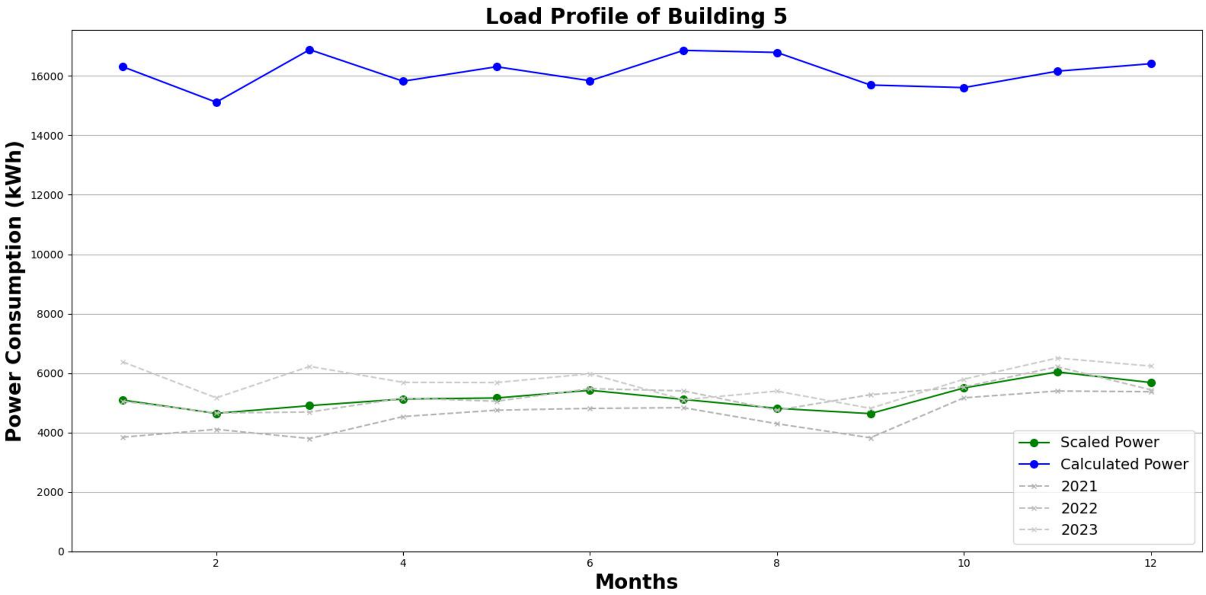

Figure 4.22: Monthly consumption of Building 5

Building 5 - Student Dormitory

The electricity consumption profile of Building 5, shown in Figures 4.22 and 4.23, corresponds to one of the student dormitory buildings on the university campus. These figures display the monthly and hourly load profiles, respectively.

The hourly profile (Figure 4.23) indicates relatively stable and continuous usage patterns throughout the year, with slight increases during winter months due to lighting and heating appliance usage. Monthly results in Figure 4.22 illustrate both calculated and scaled synthetic load profiles, along with historical measurements for reference.

Building 5 is primarily composed of student apartments with varying layouts. However, in

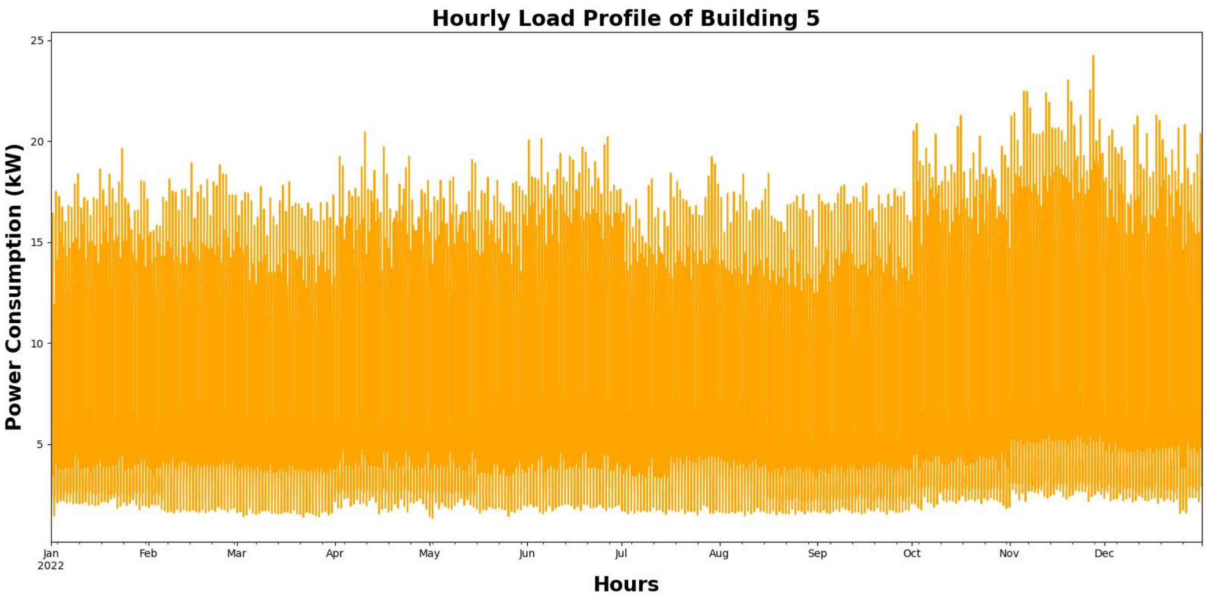

Figure 4.23: Hourly consumption of Building 5

this study, a uniform usage behaviour was assumed across all apartment types to simplify the simulation model. While the number of devices changes based on apartment size, the assumed appliance usage pattern remains constant for all rooms. This decision was made due to the highly unpredictable and diverse nature of individual student behaviour, which would otherwise introduce considerable complexity into the modelling process.

A significant factor contributing to the elevated electricity consumption in the calculated profile is the presence of numerous kitchens and kitchen appliances, such as refrigerators, microwaves, induction cookers, and electric kettles, which are extensively used in residential settings. This elevated load is expected for student housing, particularly where students prepare their own meals at varying hours.

Importantly, Building 5 is selected to represent all student dormitories on campus. Since similar layouts, appliance distributions, and usage intentions apply across dormitory buildings, results for other dormitories are not separately shown. Instead, Building 5 serves as a reference for their collective consumption patterns.

Chapter 5

Conclusion and Recommendations for Future Work

5.1 Conclusion

The aim of this thesis was to develop a methodology for generating synthetic electricity load profiles tailored to the operational behaviour and room categorisation of university buildings, using the Nordhausen University of Applied Sciences as a case study. This objective was achieved through a structured approach involving detailed classification of buildings and room types, collection of appliance-specific data, period-based simulation using the RAMP tool, and validation using historical consumption data.

The study began with the identification and categorisation of rooms based on their functions and typical usage characteristics. Over 30 distinct room types were considered and grouped into categories such as educational, residential, laboratory, administrative, and auxiliary spaces. These classifications were then used to prepare simulation input files for eight academic periods across a year, each reflecting different occupancy and operational patterns.

To generate realistic load profiles, the RAMP simulation tool was extensively modified and implemented. The stochastic nature of RAMP allowed the modelling of daily electricity consumption patterns by considering not only the number and rating of appliances but also their usage frequencies, durations, and behaviour during weekdays and weekends. A key contribution of this study was the creation of structured input datasets, based on both literature values and on-site observations, compiled into a reusable OneNote documentation framework.

A unique aspect of this work was the incorporation of building-level base load estimations using historical campus-wide electricity data (from 2011 to 2013). This enabled the modelling of non-appliance-related continuous electricity consumption, such as that from networking equipment, security systems, or standby loads. By integrating these base loads into the final profiles, a more comprehensive representation of each building's total electricity demand was achieved.

The ventilation system was also considered, with a dedicated model built to simulate the heating and cooling loads of mechanical ventilation systems across seasons. This was based on external ambient temperatures and behavioural schedules, ensuring accurate representation of heating and cooling demands, especially during winter and summer periods.

Among all buildings, Building 34 and Building 35 were selected for detailed simulation and validation due to the availability of higher-quality measured data. Their synthetic profiles were scaled using monthly averages from three years (2021–2023) or the available year and compared against actual electricity usage, demonstrating a reasonable alignment. In addition to these two buildings, several other buildings, including Building 5, Building 19, Building 20, Building 25, and Building 28, were also simulated and analysed in the results chapter. While the synthetic profiles for these additional buildings could not be validated in the same way due to limited or incomplete measured data, the results still provided important insights into seasonal consumption behaviours, operational patterns, and assumptions required for campus-wide load modelling.

The developed framework provides a strong foundation for understanding energy consumption behaviour within academic institutions and can support campus energy planning, demand-side management, and the integration of renewable energy sources. Furthermore, the modular nature of the methodology ensures that it can be adapted or expanded for other buildings or institutions with minimal effort.

The three main research questions formulated at the beginning of this thesis were successfully addressed:

- **How do energy consumption patterns vary across different building types at Nordhausen University?**
  This was explored through room categorisation, building-specific simulations, and comparative analysis of seasonal and annual load profiles.

- **How can synthetic load profiles be developed and calibrated to accurately reflect the electricity consumption of university buildings?**
  This was demonstrated by the generation, scaling, and validation of synthetic profiles, using the adapted RAMP framework.

- **What improvements can be made to optimise electricity management on campus?**
  Opportunities were identified through the analysis of peak load periods, efficiency potentials, and recommendations for enhanced data collection and modelling strategies.

5.2 Study Constraints and Considerations

As already mentioned in the methodology chapter, the availability of measured data was limited. This constraint is further discussed below as a key limitation of the study. Firstly, complete appliance inventories and usage data were not available for all buildings and room types. This led to reliance on assumptions, external standards, or analogical reasoning based on similar rooms where direct data were missing.

Only most of the south campus buildings were included in the validation results, as their simulations were supported by sufficient and reliable data. Other north campus buildings were tried to simulate within the model framework, but were not included due to missing, inconsistent, or incomplete input data, except the dormitories. Although these buildings were part of the simulation scripts, their results are considered preliminary and should be interpreted with caution.

The base load estimation, although grounded in a previously validated university study [34], was derived from relatively dated data (2015). While the proportional allocation method ensures practical applicability, newer measurements would further enhance accuracy. Nevertheless, this approach remains useful for approximating realistic baselines where updated measurements are unavailable.

Another limitation was the lack of granular real-time validation for all buildings beyond Building 34. Moreover, the RAMP tool, while powerful in its stochastic modelling, inherently cannot capture every behavioural variation, especially in buildings with irregular or dynamic schedules. Additionally, due to time constraints and data limitations, full campus-wide simulation and validation were beyond the scope of this thesis.

5.3 Recommendations for Future Work

This research opens the door for several promising extensions. Firstly, the inclusion of additional building profiles using the same simulation framework would increase the comprehensiveness of the synthetic profile library. Efforts should be made to collect real-time or recent annual energy data, particularly for the purpose of refining base load estimations and improving model accuracy.

The results of other buildings can be generated in future work by collecting proper and complete data. Although these buildings were already integrated into the simulation scripts, presenting them reliably requires validation with newer or complete input datasets. Similarly, additional room types can be added or existing ones modified as needed, since the system is designed with a flexible and robust structure.

Expanding the appliance library through detailed energy audits and measurements could further reduce the reliance on assumptions and generic values. Introducing smart meter integration or IoT-based monitoring within university buildings could significantly enhance data granularity and support more dynamic simulations.

The methodology could also be adapted into a more user-friendly format by developing a graphical user interface (GUI) that allows facility managers to generate load profiles without deep programming knowledge. Integration with building automation or energy management systems could make this tool applicable in real-time operations and demand-side management.

In terms of modelling, future work could incorporate behavioural changes over time (e.g., shifts in remote learning, adoption of new technologies), link weather datasets dynamically, or simulate seasonal ventilation and lighting responses with finer resolution.

Lastly, this framework can be scaled to other academic or institutional campuses. As the tool becomes more robust and adaptable, it can support energy policy development, campus sustainability strategies, and simulation-based design of future-ready infrastructure.

Appendix A

Other Room Types and Parameter Documentation Example

This appendix provides additional insights into room types not explicitly analysed in the main report. While these rooms may not have been individually discussed in the results, they were incorporated into the building-level profiles and played a role in the overall energy modelling framework.

A structured parameter documentation method was followed to ensure transparency and reproducibility. All relevant input parameters for each room type were recorded using a OneNote-based template. A representative example for a “5 Person Office” during the Winter Semester (WS_Winter) is shown in this appendix. This page illustrates how occupancy, device usage, and function durations were manually recorded and translated into simulation inputs. The complete OneNote documentation includes all room types and periods and is available upon request for further analysis or verification.

A.1 Overview of Additional Room Types

While detailed simulation results were presented for selected room types, such as seminar halls, offices, and laboratories, several other rooms also contributed to the comprehensive energy modelling process. These additional rooms, although not analysed individually in the results chapter to avoid redundancy and excessive length, were modelled and incorporated into the final load profile generation for each building.

To maintain clarity and focus in the thesis, room types with relatively simple or repetitive electricity usage patterns or those with a minor influence on overall demand were not discussed separately. However, they remain essential components of the complete campus-wide modelling effort. The additional room types used in the simulations are summarised as shown in Figure A.1 below, grouped according to their functional categories.

These room types are distributed across various campus buildings, with certain types occurring in multiple buildings and others limited to specific facilities. While the figure presents

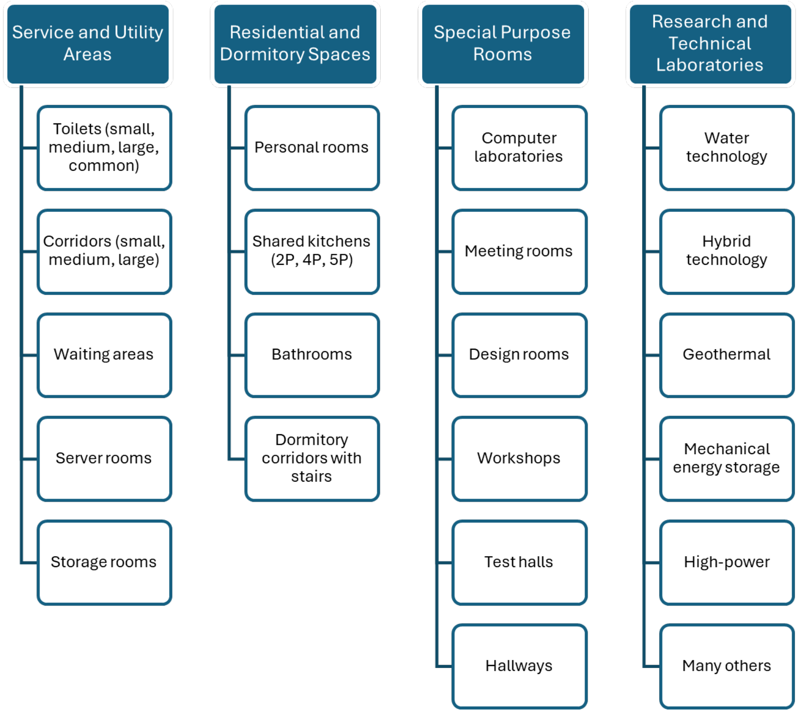

Figure A.1: Categorisation of additional room types identified across campus

the identified categories, it is important to note that additional room types may exist within the university infrastructure. However, due to limitations in available data, only the listed types have been documented in this study. Future work may involve expanding the database of room types to improve the comprehensiveness and adaptability of the synthetic load profile models. Moreover, each of these room types was documented using the same structured parameterisation approach as presented in the main chapters. Their simulation parameters- including device counts, power ratings, and usage behaviour, were defined based on either direct observations or standardised assumptions. The resulting profiles were aggregated to accurately reflect their contribution to the overall electricity demand of each building.

A.2 Example Description for Office 5P – WS_Winter Period

Due to readability constraints, the OneNote page created for the "WS_Winter" period is not inserted here directly as an image. Instead, the content of the page is reproduced below in a structured table format. This page illustrates the documentation methodology adopted for each room type, where assumptions and parameter values were detailed for all eight academic periods.

Note: The electricity usage in the 5-person office is generally steady throughout the working week, especially noticeable in the winter semester. During this time, there is frequent use of lighting, desktop computers, laptops, and additional electronic devices, which collectively form a substantial portion of the overall electricity load. Notably, the usage durations of appliances across all academic periods were derived by considering the "WS_Winter" period as the baseline. This approach was chosen because the function time t (mins) during this phase is higher than in any other period. Although weekend usage is not currently modelled for this room type, it can be incorporated following the same methodology.

1. Lights

All office ceiling lights are assumed to have a rating of 36 W.

Table A.1: Parameter assumptions for Lights

Parameter	**Value**	**Description / Justification**
Number	10	Ceiling lights based on room size and layout
Function Time WD (mins)	480	Lighting throughout the working day
Minimum Time WD (mins)	60	Partial lighting during low occupancy
Occasional use	1	Every working day

2. Computer

Desktop personal computers rated 350 W (active) and 50 W (standby) used full-time.

Table A.2: Parameter assumptions for Computers

Parameter	**Value**	**Description / Justification**
Number	5	One computer per occupant
AP Function Time WD (mins)	360	Regular working duration
SP Function Time WD (mins)	120	Standby during breaks or idle time
FT-WD (mins)	480	Total expected office occupancy time
MT-WD (mins)	480	Matches full-time operational period
Occasional use	1	Every working day

3. Monitor

Monitors rated 120 W (active) and 10 W (standby). Dual displays considered.

Table A.3: Parameter assumptions for Monitors

Parameter	Value	Description / Justification
Number	10	Dual monitors per user
AP Function Time WD (mins)	360	Synchronous with computer usage
SP Function Time WD (mins)	120	Standby during non-interaction
FT-WD (mins)	480	Full working day duration
MT-WD (mins)	480	Minimum equals maximum to ensure continuity
Occasional use	1	Every working day

4. Laptop

Laptops rated 60 W (active), 30 W (standby) for mobile/backup use.

Table A.4: Parameter assumptions for Laptops

Parameter	Value	Description / Justification
Number	5	One laptop per employee
AP Function Time WD (mins)	120	Used intermittently or for meetings
SP Function Time WD (mins)	240	Mostly idle after charging
FT-WD (mins)	360	Partial daily usage
MT-WD (mins)	360	Full span for modelling consistency
Occasional use	1	Every working day

5. Mobile

Mobile chargers assumed to draw 20 W.

Table A.5: Parameter assumptions for Mobile Charging

Parameter	Value	Description / Justification
Number	5	One per person
Function Time WD (mins)	120	Standard full charge time
Minimum Time WD (mins)	60	Partial charges also possible
Occasional use	1	Every working day

6. Desk Lamps

All office lamps are assumed to have a rating of 10 W.

Table A.6: Parameter assumptions for Desk Lamps

Parameter	**Value**	**Description / Justification**
Number	5	One per person
Function Time WD (mins)	120	Only when necessary throughout the working day
Minimum Time WD (mins)	60	Partial lighting
Occasional use	0.4	1 or 2 working days (Sometimes)

Organisation of Usage Pattern Documentation: The complete documentation for all room types and periods has been organised using a OneNote notebook titled *"Usage Pattern"*. In this notebook:

- Each building has a dedicated notebook section.
- Each section contains individual room types as sub-sections.
- Each room type includes 8 period-specific pages covering detailed parameter assumptions.

This OneNote file is saved in the project directory at: *ramp/Usage Pattern*

Due to formatting limitations, only this example is shown in the report. For comprehensive documentation of all other room types and their usage assumptions, the reader is referred to the complete OneNote document.

Appendix B

Detailed Script Descriptions and Simulation Inputs

This appendix provides detailed descriptions of all Python scripts developed and utilised within this thesis for generating synthetic load profiles of various room types and buildings at the Nordhausen University of Applied Sciences. It explains the numerical and textual codes assigned to identify and categorise room types and buildings, outlines the structure of input files, defines simulation parameters (including seasonal variations and daily operational timeframes), and details the procedures for aggregating individual room profiles into comprehensive building profiles. Additionally, it describes the methodological approach adopted for calculating the base load of buildings, drawing upon university-specific research. These comprehensive insights into script functionalities and parameterisations ensure the replicability and transparency of the modelling process.

B.1 RAMP: Simulation Process

Execution of the model: ramp_run.py and initialise_mod.py

The script ramp_run.py serves as the central interface to execute simulations for generating synthetic electricity load profiles of different room types at Nordhausen University of Applied Sciences using the RAMP simulation tool. The primary objective of this script is to facilitate user-driven simulations by allowing selections of various room types, semesters, semester-specific periods, and simulation durations.

The operational procedure of this script includes several distinct steps:

Firstly, users select the room type by providing the numerical code associated with each room category. These numerical codes correspond to predefined room types, such as "1.2" for a Medium Seminar Hall, as listed in Table B.2.

Secondly, users select the desired academic semester for the simulation, choosing either the Winter Semester (1) or Summer Semester (2). Following this, users specify the specific period within the chosen semester, such as Semester Break (WS_Break), Autumn (WS_Autumn), Winter (WS_Winter), Examination Period (WS_Exam) for the winter semester, or Semester Break (SS_Break), Spring (SS_Spring), Summer (SS_Summer), Examination Period (SS_Exam) for the summer semester.

In the next step, users input the desired duration of the simulation by specifying the start and end months along with the total number of days to be simulated. Detailed recommendations regarding these parameters are available in Table B.1.

Table B.1: User input parameters for selecting the simulation duration of room profiles

Semester	**Room File**	**Phase Name**	**Duration**		**Days to Simulate**
			Start Month	**End Month**	
Winter	'Room'_11	WS_Break	8	10	61
	'Room'_12	WS_Autumn	10	11	31
	'Room'_13	WS_Winter	11	13	61
			1	2	36
	'Room'_14	WS_Exam	11	12	43
Summer	'Room'_21	SS_Break	3	4	31
	'Room'_22	SS_Spring	4	5	45
	'Room'_23	SS_Summer	5	7	76
	'Room'_24	SS_Exam	7	8	46

The determination of simulation durations for different university semester phases, as depicted in Table B.1, was achieved by merging two primary sources. Firstly, the seasonal breakdown adopted from the literature [35] provided the foundational segmentation of periods throughout the year. Secondly, these segments were further refined by incorporating the specific academic calendar of Nordhausen University of Applied Sciences. The resulting table outlines the required inputs for users to select appropriate durations for simulation, specifying the start month, end month, and number of days to simulate for each seasonal phase.

The column titled "Room File" within Table B.1 is structured to streamline user interaction with the simulation tool. Here, the abbreviation "Room" is substituted dynamically by the script according to the selected room type, represented by specific room abbreviations listed comprehensively in Table B.2. For instance, selecting a "Medium Seminar Hall" to simulate during the "WS_Break" phase triggers the automatic loading of the input file named "MSH_11", where "MSH" is the abbreviation corresponding to "Medium Seminar Hall" and "11" signifies the WS_Break period.

After setting these input parameters, the script initiates the load profile generation process by invoking the following function:

Stochastic_Process(Semester_choice, Sub_choice, Room_code, year, start_month, end_month, num_pro)

This function executes the stochastic simulation based on user-defined settings, generating minute-level synthetic load profiles, which are then converted and resampled into hourly data.

Post-processing steps further refine these profiles into clearly structured DataFrames, facilitating subsequent analyses.

The script subsequently provides visual representation through line plots and cloud plots, offering insights into detailed electricity consumption patterns. Finally, the processed hourly load profiles are saved as CSV files within structured directories categorised by room type and semester period. These files follow a consistent naming format (e.g., *Load Profile_01-03.csv* for profiles spanning January to March). Specifically, these files are saved under the path: *ramp/Room_results*, wherein individual folders for each room type contain further subfolders corresponding to the eight academic periods, each holding their respective CSV files.

The numerical codes and abbreviations for each room type presented in Table B.2 directly correspond to the structured module paths defined in the script "initialise_mod.py". This script facilitates the automated importation of room-specific input files, thereby initializing simulation parameters according to user selection. However, it should also be noted that while Table B.2 currently provides a substantial set of room types relevant to this study, this list is inherently flexible and not exhaustive. Users can easily modify this table by adding or removing room categories according to evolving requirements or expanding scopes in future research or institutional changes.

B.2 Detailed Description of Room Input Files

The synthetic load profiles generated by RAMP significantly depend on clearly structured input files, defining essential parameters for each room type during distinct academic periods, as detailed previously (Table B.1). Each input file specifies parameters such as the number of electrical devices, active and standby power ratings, typical usage durations, and minimum operating times, which collectively characterise realistic usage behaviours for simulations.

To illustrate the detailed structure and content of these input files, an example for a five-person office during the winter semester (WS_Winter) has been provided (e.g., Office 5P.xlsx). In this Excel file, each row corresponds to a specific electrical device, while columns indicate parameters such as the quantity of devices (Number), active power (AP), standby power (SP), active power times for weekdays (APT-WD) and weekends (APT-WE), total functioning time (FT), and minimum operating times (MT). It should be noted that certain cells remain intentionally empty, as not all electrical devices are in operation during every academic period or their usage may not be significant enough for consideration during simulation. This scenario varies according to the specific academic period being simulated.

Correspondingly, parameters from this Excel file are imported and explicitly defined in individual Python scripts for each room type and period. Taking the example of the script OFF_5P_13.py for the WS_Winter period, parameters for each device type are extracted as illustrated in the Figure B.1 for lighting. The parameters for the weekend are commented out as inactive during this period. This applied to every inactive and unnecessary parameter for every

Table B.2: Numerical codes and abbreviations assigned to different room types

Numerical Code	**Room**	**Room Abbreviation**
1.1	Small Seminar Hall	SSH
1.2	Medium Seminar Hall	MSH
1.3	Large Seminar Hall	LSH
2.1	Small Lecture Hall	SLH
2.2	Medium Lecture Hall	MLH
2.3	Large Lecture Hall	LLH
3	Office 1P	OFF_1P
4	Office 2P	OFF_2P
5	Office 3P	OFF_3P
6	Office 5P	OFF_5P
7	Computer Lab	ITLAB
8.1	Small Meeting Room	SMTR
8.2	Big Meeting Room	BMTR
9.1	Small Toilet	SWC
9.2	Medium Toilet	MWC
9.3	Large Toilet	LWC
9.4	Common Toilet	CWC
10.1	Small Corridor	COS
10.2	Medium Corridor with Stairs	MCOS
10.3	Large Corridor with Stairs	LCOS
11.1	Small Waiting Area	SWA
11.2	Big Waiting Area	BWA
12	Server Room	SR
13	Storage Room	STR
14	Electronics Lab	ELAB
15	Thermal Lab	THLAB
16	Geotech Lab	GTL
17	Water Tech Lab	WTL
18	Hybrid Tech Lab	HTL
19	High Power Lab	HPL
20	Geothermal Lab	GTHL
21	Personal Room	PR
22.1	Small Kitchen	SKI
22.2	Kitchen 2P	KI2
22.3	Kitchen 4P	KI4
22.4	Kitchen 5P	KI5
23	Bathroom	BT
24	Hallway	HW
25	Dorm Corridor with Stairs	DCOS
26	Hike Lab	HKL
27	Workshop	WKS
28	Design Room	DSR
29	Test Hall	TSH

```python
# Parameters for light

nl = df.loc['Light','Number']                      # Number of the device
l_ap = df.loc['Light','AP (W)']                    # Active power of the device
l_sp = df.loc['Light','SP (W)']                    # Stand-by power of the device
l_apt_wd = df.loc['Light','APT-WD (mins)']         # Active power specific cycle time on weekdays
l_apt_we = df.loc['Light','APT-WE (mins)']         # Active power specific cycle time on weekend
l_spt_wd = df.loc['Light','SPT-WD (mins)']         # Stand-by power specific cycle time on weekdays
l_spt_we = df.loc['Light','SPT-WE (mins)']         # Stand-by power specific cycle time on weekend
l_ft_wd = df.loc['Light','FT-WD (mins)']           # Total function time of the device on weekdays
l_ft_we = df.loc['Light','FT-WE (mins)']           # Total function time of the device on weekend
l_mt_wd = df.loc['Light','MT-WD (mins)']           # Minimum function time of the device on weekdays
l_mt_we = df.loc['Light','MT-WE (mins)']           # Minimum function time of the device on weekend

# Lights - Weekdays
OFF_5P_Lights = OFF_5P.Appliance(OFF_5P,nl,l_ap,ntf,l_ft_wd,v0,l_mt_wd, wd_we_type = 0, occasional_use = 1)
OFF_5P_Lights.windows(t1,t0,v0)

# Lights - Weekend
# OFF_5P_Lights = OFF_5P.Appliance(OFF_5P,nl,ap,2,tt_we,v0,mt_we, wd_we_type = 1)
# OFF_5P_Lights.windows(t1,t0,v0)
```

Figure B.1: Excel input file defining electrical parameters for the winter semester

file of every room.

This structured procedure of importing and assigning parameters from Excel input files is consistently applied to all electrical devices listed and similarly implemented across all eight period-specific scripts for each room type.

To define the power ratings of electrical devices within this thesis, a combination of sources was used. Primarily, device ratings were referenced from the paper by Krishnan et al. [35], providing a reliable baseline for common university electrical equipment. Additionally, for certain devices unavailable in literature, ratings were collected through direct inspections of equipment in a representative office room and subsequently generalised across similar room types. Specifically, lighting fixtures were categorised based on their sizes and usage scenarios. Small circular lights typically used in toilets were rated at 18 W, whereas larger lights installed in offices, lecture halls, and seminar rooms were rated at 36 W. The quantity of these lighting fixtures in each room was determined through direct counting and validated against the lighting standards defined by the German DIN standard DIN EN 12464-1 [36].

The Room_Profile.py script aggregates the seasonal synthetic load profiles generated previously into a comprehensive annual profile for a user-selected room type. This script retrieves corresponding seasonal data files from the directory (*"Master-Thesis/ramp/Room_results"*), each representing distinct academic calendar periods, such as "WS_Break" or "SS_Summer". Each period's data is read and processed individually, converted to a consistent datetime format, and subsequently merged to form a complete annual profile. The final aggregated data is then exported to an Excel file, (saved in the directory *"Master-Thesis/ramp/Results/Room Dataframes"*) and visually represented through monthly and hourly load profiles. These plots are stored in *"ramp/Results/Room Plots"*. This provides a clear overview of the selected room's yearly electricity consumption patterns.

B.3 Base Load Calculation and Allocation Methodology

To accurately represent building electricity profiles, a percentage allocation method was utilised to calculate the base load of buildings. This methodology was adapted from a previous comprehensive study conducted at Nordhausen University of Applied Sciences, which systematically analysed the campus's electricity consumption by dividing it into North and South campuses [34].

The referenced study provided the total electricity consumption and the relative shares of individual buildings. Specifically, the study presented an annual average electricity consumption derived from data across three consecutive years: 2011, 2012, and 2013. Based on these averages, the campus's total electrical consumption was 1,173,841 kWh/a, from which the base load was identified as approximately 65 kW/h. To ensure accurate allocation, the overall campus consumption was further divided between the North and South campuses, amounting to 655,509 kWh/a (76.8%) and 197,579 kWh/a (23.2%), respectively.

The base load was subsequently allocated proportionally to each campus as follows:

$$\text{Base Load (North Campus)} = \frac{655,509\,\text{kWh/a}}{853,088\,\text{kWh/a}} \times 47.23\,\text{kW} = 36.29\,\text{kW} \tag{B.1}$$

$$\text{Base Load (South Campus)} = \frac{197,579\,\text{kWh/a}}{853,088\,\text{kWh/a}} \times 47.23\,\text{kW} = 10.93\,\text{kW} \tag{B.2}$$

Finally, these base loads were allocated individually to the buildings under study based on their percentage share determined in the referenced campus study. The calculated base load values for specific buildings have been incorporated directly into the Python script Building_Profile.py. Within this script, each building's assigned base load can be reviewed, adjusted, or expanded to include additional buildings as necessary for further studies or adjustments to reflect current scenarios. The calculated base loads are combined with the synthetic load profiles generated by the script. After processing, the resulting building load profiles are saved as Excel files within the directory *"ramp/Results/Building Dataframes"*. Additionally, visual representations in the form of plots are generated and stored in *"ramp/Results/Building Plots"*

This approach, based on validated previous research, offers a practical method to include essential base load considerations within the synthetic load profile simulations. Although the reference data dates back to 2015, making it somewhat outdated, the general method and proportional calculations remain applicable and valid for present usage, especially in scenarios where recent data is not readily available. Nevertheless, future studies may benefit from updated consumption data to enhance accuracy and reliability.

Bibliography

[1] Umweltbundesamt, "Energy consumption for buildings," https://www.umweltbundesamt.de/en/data/environmental-indicators/indicator-energy-consumption-for-buildings, 2021, german Environment Agency. Accessed: Feb. 12, 2025.

[2] Z. Ma, Z. Yan, M. He, H. Zhao, and J. Song, "A review of the influencing factors of building energy consumption and the prediction and optimization of energy consumption," *AIMS Energy*, vol. 13, no. 1, pp. 35–85, 2025.

[3] Shuo Chen, Guomin Zhang, Xiaobo Xia, Yixing Chen, Sujeeva Setunge, and Long Shi, "The impacts of occupant behavior on building energy consumption: A review," *Sustainable Energy Technologies and Assessments*, vol. 45, p. 101212, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2213138821002228

[4] K. P. Amber, M. W. Aslam, A. Mahmood, A. Kousar, M. Y. Younis, B. Akbar, G. Q. Chaudhary, and S. K. Hussain, "Energy consumption forecasting for university sector buildings," *Energies*, vol. 10, no. 10, p. 1579, 2017.

[5] Z. Wang, C. C. Federspiel, and F. Rubinstein, "Modeling occupancy in buildings through a stochastic process," *Energy and Buildings*, vol. 37, no. 2, pp. 121–126, 2005.

[6] Francesco Lombardi, Sergio Balderrama, Sylvain Quoilin, and Emanuela Colombo, "Generating high-resolution multi-energy load profiles for remote areas with an open-source stochastic model," *Energy*, vol. 177, pp. 433–444, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544219307303

[7] F. Lombardi, P.-F. Duc, M. A. Tahavori, C. Sanchez-Solis, S. Eckhoff, M. C. G. Hart, F. Sanvito, G. Ireland, S. Balderrama, J. Kraft, G. Dhungel, and S. Quoilin, "Ramp: stochastic simulation of user-driven energy demand time series," *Journal of Open Source Software*, vol. 9, no. 98, p. 6418, 2024.

[8] S. Hilpert, C. Kaldemeyer, U. Krien, S. Günther, C. Wingenbach, and G. Plessmann, "The open energy modelling framework (oemof) - a new approach to facilitate open science in energy system modelling," *Energy Strategy Reviews*, vol. 22, pp. 16–25, 2018.

[9] A. Parker, S. Moayedi, K. James, D. Peng, and M. A. Alahmad, "A case study to quantify variability in building load profiles," *IEEE Access*, vol. 9, pp. 127 799–127 813, 2021.

[10] A. Sandhaas, H. Kim, and N. Hartmann, “Methodology for generating synthetic load profiles for different industry types,” *Energies*, vol. 15, no. 10, 2022. [Online]. Available: https://www.mdpi.com/1996-1073/15/10/3683

[11] M. Schlemminger, R. Niepelt, and R. Brendel, “A cross-country model for end-use specific aggregated household load profiles,” *Energies*, vol. 14, no. 8, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/8/2167

[12] A. Parker, K. James, D. Peng, and M. A. Alahmad, “Framework for extracting and characterizing load profile variability based on a comparative study of different wavelet functions,” *IEEE Access*, vol. 8, pp. 217 483–217 498, 2020.

[13] J. B. Magdaong, A. B. Culaba, A. T. Ubando, and N. S. Lopez, “Generating synthetic building electrical load profiles using machine learning based on the crisp-ml(q) framework,” *IOP Conference Series: Earth and Environmental Science*, vol. 1372, no. 1, p. 012082, 2024.

[14] J. Torres-Navarro, P. Bastida-Molina, A. Honrubia-Escribano, and E. G. Lázaro, “Analysis of electricity consumption in university buildings and possible improvements due to spanish financial helps announcement. study of the state of the art,” *RE&PQJ*, vol. 20, no. 1, 2022.

[15] D. W. Kim, J. W. Jung, H. T. Seok, and J. H. Yang, “Survey and analysis of energy consumption in university campuses,” in *Proc. Int. Conf. Sustainable Building Asia (SB10)*, Seoul, Korea, 2010, pp. 595–600.

[16] B. Akbar, K. Pervez Amber, A. Kousar, M. Waqar Aslam, M. Anser Bashir, and M. Sajid Khan, “Data-driven predictive models for daily electricity consumption of academic buildings,” *AIMS Energy*, vol. 8, no. 5, pp. 783–801, 2020.

[17] D. Lee, J. Kim, S. Kim, and K. Kim, “Comparison analysis for electricity consumption prediction of multiple campus buildings using deep recurrent neural networks,” *Energies*, vol. 16, no. 24, p. 8038, 2023.

[18] S. Ferrari, M. Beccali, P. Caputo, and G. Zizzo, “Electricity consumption analysis of tertiary buildings: An empirical approach for two university campuses,” *Journal of Architectural Engineering*, vol. 26, no. 2, 2020.

[19] N. Pflugradt, P. Stenzel, L. Kotzur, and D. Stolten, “Loadprofilegenerator: An agent-based behavior simulation for generating residential load profiles,” *Journal of Open Source Software*, vol. 7, no. 71, p. 3574, 2022.

[20] N. Pflugradt, “Load profile generator manual and application examples,” https://www.loadprofilegenerator.de, 2016, accessed: Mar. 14, 2025.

[21] M. Wirtz, "npro: A web-based planning tool for designing district energy systems and thermal networks," *Energy*, vol. 268, p. 126575, 2023.

[22] H. E. LLC, "Homer pro software," https://www.homerenergy.com/products/pro/index.html, 2023, accessed: Mar. 14, 2025.

[23] U.S. Department of Energy, "Energyplus building energy simulation software," https://energyplus.net, 2023, accessed: Mar. 14, 2025.

[24] D. A. Broden, K. Paridari, and L. Nordstrom, "Matlab applications to generate synthetic electricity load profiles of office buildings and detached houses," in *2017 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*. IEEE, 2017, pp. 1–6.

[25] Norce Research, "Energy management for a novel hybrid energy storage system for the integration of renewable energy sources into the power grid," https://www.norceresearch.no/prosjekter/energy-management-hybrid-energy-storage, 2025, accessed: Mar. 14, 2025.

[26] Fraunhofer Institute for Solar Energy Systems ISE, "synghd: Synthetic high-resolution load profiles for building energy systems," https://www.ise.fraunhofer.de/en/research-projects/synghd.html, 2024, accessed: Feb. 27, 2025.

[27] T. A. Papadopoulos, G. T. Giannakopoulos, V. C. Nikolaidis, A. S. Safigianni, and I. P. Panapakidis, "Study of electricity load profiles in university campuses: the case study of democritus university of thrace," in *Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MedPower 2016)*. Institution of Engineering and Technology, 2016, pp. 15 (8 .)–15 (8 .).

[28] G. G. Pillai, G. A. Putrus, and N. M. Pearsall, "Generation of synthetic benchmark electrical load profiles using publicly available load and weather data," *International Journal of Electrical Power & Energy Systems*, vol. 61, pp. 1–10, 2014.

[29] X. Liang, Z. Wang, and H. Wang, "Synthetic data generation for residential load patterns via recurrent gan and ensemble method," 2024.

[30] L. Moosbrugger, V. Seiler, G. Huber, and P. Kepplinger, "Improve load forecasting in energy communities through transfer learning using open-access synthetic profiles." [Online]. Available: http://arxiv.org/pdf/2407.08434v1

[31] Hochschule Nordhausen, "Location and campus plan," https://www.hs-nordhausen.de/en/our-hsn/location-and-campus-plan-2/, 2025, accessed: Mar. 14, 2025.

[32] I. Richardson, M. Thomson, D. Infield, and C. Clifford, "Domestic electricity use: A high-resolution energy demand model," *Energy and Buildings*, vol. 42, no. 10, pp. 1878–1887, 2010.

[33] J. Torriti, “A review of time use models of residential electricity demand,” *Renewable and Sustainable Energy Reviews*, vol. 37, pp. 265–272, 2014.

[34] R. Balasoltanov, T. Raddau, and S. Schubert, “Projektarbeitsmodul thermische energiesysteme: Energiecampus,” Hochschule Nordhausen, 2015, studiengang Systems Engineering, HS Nordhausen.

[35] R. K. B. Krishnan, A. Oberdorfer, and V. W. T. R. C. S., “Effects of decentralized energy supply on standard load profiles in the electricity sector,” in *REGWA Energie-Symposium 2022*, 2022, pp. 02–05.

[36] DIN Deutsches Institut für Normung e.V., “DIN EN 12464-1:2021-11 - Light and lighting - Lighting of work places - Part 1: Indoor work places; German version EN 12464-1:2021,” Berlin, Germany, 2021. [Online]. Available: https://www.beuth.de/en/standard/din-en-12464-1/341112720

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"‘I herewith declare that I have composed the present thesis myself and without use of any other than the cited sources and aids. Sentences or parts of sentences quoted literally are marked as such; other references with regard to the statement and scope are indicated by full details of the publications concerned.

In particular, I have not utilised commercial advice. Third parties have neither received direct nor indirect monetary benefits from me for actions which are related to the content of the submitted work.

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