Occupant behavioral modeling: An agent-based modeling approach to building performance analysis

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Lund University

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The degree project is the final part of the master programme leading to a Master of Science (120 credits) in Energy-efficient and Environmental Buildings.

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Abstract

Finite resources and increasing rate of consumption have made efficiency a key component in every energy-consuming sector. The building industry, as a major contributor, has been the target of various initiatives and regulations aiming to lower its impact with varying degrees of success. Measurement of this impact has not always been easy, especially for buildings not yet built. Therefore, simulation tools have been heavily utilized to provide predictions.

However, the results from simulations are not always in line with the measurements. The extent of this variation is often so remarkable that it calls into question the reliability of building simulation tools and methods. A major contributor to this discrepancy has been identified as the oversimplification of occupancy inside the buildings, which neglects their impact on energy usage.

This study investigated this performance gap by comparing a normal energy model of a case study with a more realistic energy model that considers occupants and their behavior through an agent-based modeling approach while relying on real loads and set points. The normal model relied on Swedish building code and was modeled using Honeybee in Grasshopper, while the agent-based model utilized the normal model as a base case while changing different loads and set points to match the measured data. Furthermore, to model occupants, Occupancy Simulator was used to create occupant profiles as an obXML file, while a survey with a complementary code defined behavioral models for each individual; this file was then used for co-simulation via obFMU and EnergyPlus to create the agent-based model. Additionally, a comparative analysis was performed to investigate the impact of adopting an occupant-centric metric compared to energy use intensity to measure the performance of the simulations. Lastly, the accuracy of the agent-based model was evaluated.

The results demonstrated a significant gap between the total energy use of the two models, with an even larger disparity observed when using the occupant-centric metric. Furthermore, it showed that stochastic modeling of occupant's presence, movement, and interaction in the building had a considerable effect on energy usage. However, relying on inaccurate set points and schedules for the highest energy-consuming system that offered no control to the occupants was the major contributor to the performance gap. The agent-based model was shown to perform correctly most of the time, although certain inaccuracies were identified.

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Abbreviations

A_{temp}	Heated floor area
BBR	Boverket's Building Regulations
BPS	Building performance simulation
DNAS	Drivers, Needs, Actions, Systems
EUI	Energy Use Intensity (kWh/m²)
FMI	Functional Mockup Interface
FMU	Functional Mockup Unit
GH	Grasshopper
HB	Honeybee
HVAC	Heating, Ventilation, and Air Conditioning
IEQ	Indoor Environmental Quality
obFMU	occupant behavior Functional Mockup Unit
obXML	occupant behavior Extensible Markup Language
OSim	Occupancy Simulator
U-value	Thermal transmittance (W/(m²·K))

Terminology

Accuracy

The variation between the measured and simulated value. The higher the variation, the less accurate the simulation results are

Building Performance

In the context of this study, building performance is used to indicate the level of energy consumption in simulations

Deterministic

Use of fixed schedules

Hawthorne effect

The behavioral changes in people due to the awareness that they are being observed

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1 Introduction

1.1 Problem motivation

Buildings form an integral part of our daily lives, providing essential spaces for dwelling, work, and leisure, directly affecting our well-being, it has been reported that people spend on average 87 % of their time indoors (Klepeis et al., 2001). The building sector also plays a substantial role in global energy consumption and emissions, accounting for over 30 % in 2022 (IEA, 2024), in the United States, residential and commercial sectors have been responsible for 36 % of the overall energy consumption (EIA, 2022) and they represented the largest energy-consuming sector in Europe at 40 % in 2023 (Energy Performance of Buildings Directive, 2024). Consequently, initiatives like Nearly zero-emission building (NZEB) have emerged to address this issue.

Therefore, accurate prediction of the energy consumption of the current and future building stock is essential. However, studies have pointed to inconsistencies between the measured and expected energy usage in buildings, often labeled the" performance gap". In one study, the result from monitored energy consumption compared to expected consumption varied up to 287 % in renovated German buildings built in the 1950s (Calì et al., 2016). De Wilde (2014) has defined three reasons for the performance gap: design stage issues like inaccurate assumptions on inputs used in simulation programs and errors in simulations, construction stage issues such as poor assembly and craftsmanship, operational stage issues which are mainly caused by occupant behavior and a lack of realistic presentation of their actions in the building; Yet, performance gap can also be related to characteristics unique to each building (Menezes et al., 2012).

The International Energy Agency (IEA), Energy in the Buildings and Communities Program (EBC), Annex 53: Total Energy Use in Buildings has identified six key elements influencing energy consumption in buildings: 1) climate, 2) building envelop, 3) building services and energy systems, 4) building operation and maintenance, 5) indoor environmental quality (IEQ), 6) occupant activities and behavior (Yoshino et al., 2017). While energy use in buildings is a function of human activity, not of the buildings themselves (Janda, 2011), the first five factors have always received more attention. Occupants are also neglected in the metrics that are used in evaluating building's performance like energy use intensity (EUI) (O'Brien et al., 2017), they are only viewed as a homogenous energy-consuming and producing unit described by a fixed set of schedules and thresholds (Yan et al., 2015).

This contradicts the complex nature of occupants' behavior and their interaction with the building, which impacts energy use and subsequently influences occupant behavior, leading to be one of the main reasons for inaccuracies in building performance simulations (BPS) (Yan et al., 2015). For instance, Hong & Lin (2013) have shown that different workstyles in a private office setting can significantly impact energy consumption, resulting in potential deviations of up to 90 % (increase) or 50 % (decrease) from baseline usage.

Occupants' needs and actions can also vary not only between individuals but also for a single person based on shifting conditions. For example, individual preferences for desk illuminance diverged significantly in office workers with dimmable lighting, ranging from 230 lux to 1000 lux, and in another setup 57 % of subjects sitting near windows used no electric lights, while others added 20 lux to 450 lux (Galasiu & Veitch, 2006).

1.2 Aim and objectives

This project aims to analyze the performance gap originating from the unrealistic representation of occupants in BPS. This is realized by developing an occupant behavior model that simulates occupants' presence and interaction with building systems more accurately, which is then compared with a base case model created using standards and the current Swedish building code.

To fulfill this aim, the objectives are to:

- Review the state of the art
- Identify the correct methods for collecting data that would then be used for simulation

- Investigate the applicability of an agent-based, discrete event and system dynamic modeling approach in occupant behavior model simulation and use the most suitable option
- Explore metrics that are more effective in performance analysis related to occupancy
- Validate the predictive performance of the occupant behavioral model
- Make recommendations

2 Background

2.1 Occupant behavior

An accurate prediction of the overall energy consumption in buildings relies upon a detailed understanding of how occupant behavior impacts this consumption. Occupants can influence energy use through occupancy and their behavior (Yoshino et al., 2017). Occupancy refers to the number of occupants and their presence or absence. Accurate prediction of occupancy is crucial as occupants contribute to latent and sensible heat gains, and occupancy is a prerequisite for any occupant behavior to occur.

Occupant behavior is categorized into adaptive and non-adaptive actions. Adaptive actions are those in which occupants try to either adapt their environment to match their own preferences, such as turning on/off the heating or cooling system, turning on/off the lights, opening or closing the windows, or try to adapt themselves to the environment for example by changing their clothes. Non-adaptive actions are not related to environmental adaptation but still impact energy consumption, like using electric equipment (Hong et al., 2017).

Furthermore, the behavior of occupants is stochastic, meaning it does not follow a predefined pattern and can be described as random. It can also evolve and depend on multiple variables (O'Brien & Tahmasebi, 2023). To be able to explain why humans behave the way they do multiple theories have been developed, three of which are discussed in this section.

The social cognitive theory

Social Cognitive Theory (SCT), developed by Bandura (1989) offers a framework for understanding human behavior as a product of personal, behavioral, and environmental influences, with each factor reciprocally influencing the others. This means that we learn by observing others and our environment, while our own actions also shape our beliefs and the world around us.

The theory of planned behavior

The theory of planned behavior (TPB) suggests that the behavior of individuals is largely determined by their intention to perform that behavior. Intentions are shaped by their attitude, subjective norms, and their belief in their ability to control their behavior. The likelihood of a behavior being performed has a direct correlation with the intensity of their intention. However, even with strong intentions, they may not be able to perform that behavior if they lack the necessary resources (Ajzen, 1991).

Drivers, Needs, Actions, Systems

The Drivers, Needs, Actions, Systems (DNAS) framework was developed to create a structured and standard approach for documenting the impact of occupant behavior on energy consumption in buildings and enhancing the comparability and reusability of data across different simulations. As a detailed ontology, it provides a technical vocabulary to address critical issues, such as the oversimplification of human interactions in building design and the misalignment between occupant behavior and building controls (Hong et al., 2015). This framework includes four components:

Drivers

Drivers are various factors that generate a desire for change to satisfy physical, psychological or physiological needs. This category includes five elements:

1) Building: Attributes such as orientation, building material, interior layout, etc. as driver

2) Occupant: Characteristics including age, gender, and physical mobility

3) Environment: Climate, weather, air temperature and humidity levels and solar radiation.

4) Systems: The current state of a building's systems can determine whether an occupant would interact with a system

5) Time: The location of the occupants and some of their habits are time-driven, for example, day of the week would determine where an occupant would be and the time of the day could be a factor for opening and closing windows or blinds

Needs

Needs are the physical and non-physical conditions that, when realized, result in the occupant feeling comfortable with their environment. If these conditions are not met, discomfort arises, and if it extends beyond the occupant's tolerance level, they may react by adjusting their environment through different actions. The threshold for this tolerance varies from individual to individual.

Physical needs include:

1) Thermal comfort

2) Visual comfort

3) Acoustic comfort

4) Indoor environmental health including IAQ and humidity

Non-physical needs consist of elements such as privacy or view to the outside.

Actions

Actions involve interacting with a system in order to fulfill a need. Additionally, inaction is possible, where the occupant chooses to endure the discomfort without taking any measures.

Systems

Systems are the devices that occupants interact with to enhance their environmental comfort, which in turn affects the building's energy use. Examples of such systems include windows, blinds, lights, thermostats, and electrical equipment.

2.2 Model development

2.2.1 Model selection

An effective model must balance accuracy with useability. Absolute precision is not the goal, models are generally expected to generate sufficiently accurate predictions of occupant behavior (Yan et al., 2015). The accuracy of prediction is not solely determined by using a fixed or a probabilistic schedule, the quality of the inputs or assumptions that were used to create the model have been shown to have a major impact (Tahmasebi & Mahdavi, 2017). As George Box noted, 'All models are wrong, but some are useful.' (Box, 1976) thus the goal should be to create a useful model. There have been many attempts at devising a framework for proper model selection, such as:

Occupancy resolution model

Melfi et al. (2011) proposed a model in which the information regarding the occupancy would be divided into three categories:

Table 2.1. Occupancy resolution model

Spatial resolution	Occupant resolution	Temporal resolution
Room	Activity of each individual	Seconds

Floor	Identifying each person	Minutes
Building	Occupancy count	Hours
Building block	State of present or absence	Days

Spatial resolution refers to the granularity in the representation of spatial data within a model. Occupant resolution refers to the level of detail in recording and reporting information about the occupants. Temporal resolution refers to the shortest time interval in which a sensor can detect and report changes in spatial and occupant resolution.

Increasing the resolution by choosing a smaller unit would result in higher accuracy but at the cost of more computing power to perform the simulation. Ultimately, the model's objective would define the right resolution.

Fit-for-purpose

Simulations don't always benefit from the highest possible resolution, as shown by Mahdavi & Tahmasebi (2016) where the non-probabilistic model outperformed the probabilistic one for short-term prediction of occupant behavior. This suggests that higher accuracy requires the right resolution that would fit the purpose of the simulation (O'Brien & Tahmasebi, 2023). As Heppenstall et al. (2012) states "At the extreme, if a model becomes as complicated as the real world, it will be just as difficult to interpret and offer no explanatory power". In order to find a suitable model Gaetani et al. (2016) proposed a method that relies on consideration of elements that could influence the choice of modeling approach, they are classified into four categories:

1) Object-related factors such as the building's function, specification, and level of control over systems inside the building

2) Aim of simulation such as policy making, design or renovation

3) Performance indicators such as energy consumption or peak loads

4) Phases of building life cycle such as design, construction or operation

Identifying the relevant factors provides a suitable range of modeling options, and subsequently, the simplest approach that aligns with the specific need should be chosen.

2.2.2 Data collection

2.2.2.1 Methods

In-situ

In-situ studies monitor occupants in their natural settings, primarily using sensors integrated into building automation systems or installed for research. These studies are advantageous for realistically replicating occupant behavior but face challenges including privacy concerns, the invasive nature of research visits, and potential interference with daily activities. Although they minimize the Hawthorne effect, these studies often lack detailed contextual insights. Setup and data collection require substantial time and resources, and maintaining sensor integrity without disturbing occupants can reduce data accuracy. Ethical issues, participant recruitment, and informed consent are also significant considerations in conducting in-situ research (Yan & Hong, 2018).

Laboratory

Laboratory studies involve participants interacting within constructed environments designed to closely mimic real indoor settings, enabling detailed control over variables like layout and environmental conditions. These settings are beneficial for studying occupant behavior and environmental impact efficiently, offering flexibility in participant recruitment without the constraints of actual building occupancy. However, the artificial nature and high visibility of monitoring equipment can influence participant behavior, potentially leading to skewed results. Additionally, the cost of setting up and running these facilities is significantly higher than in-situ studies, and the presence of unknown persons may further affect participants' behavior due to the Hawthorne effect (Yan & Hong, 2018).

Survey

Surveys provide a unique approach to data collection by collecting self-reported data through methods like questionnaires and focus groups, which differ fundamentally from sensor-based in-situ and laboratory studies. They are particularly useful for delving into the reasons behind occupant behaviors. Despite their cost-effectiveness and ability to reach large numbers of participants, surveys can be susceptible to biases such as the Hawthorne effect and social desirability bias. Additionally, the need for active participant engagement limits the frequency of data collection, posing challenges for longitudinal studies.(Yan & Hong, 2018)

2.2.2.2 Technologies

Motion detectors

Motion sensors identify whether an occupant is present by detecting their movements. Key types of these sensors include passive infrared (PIR) sensors, ultrasonic Doppler, microwave Doppler, and ultrasonic ranging sensors (Wagner et al., 2018)

Human in the loop

The human-in-the-loop methodology involves human participation in collecting data related to occupancy and behaviors within a space, there are several methods within this category: manual observation, internet-based and device interactions (Wagner et al., 2018).

Manual observation entails individuals recording data directly, such as counting people in a specific area. This technique is particularly valuable for gathering specific data that automated systems might miss, like clothing level or contextual elements related to the physical and psychological environment.

Internet-based methods use data from social media, calendars, or surveys provided by occupants. This approach raises privacy issues but is cost-effective because many organizations already collect this type of data.

Device interactions involve analyzing how occupants interact with devices like thermostats or light switches. The data from these interactions can be used to create models that predict occupant behavior and presence.

2.2.3 Modeling approaches

Markov chain

A Markov chain is a stochastic process in which the probability of the transition to the next state is only dependent on the current state and not the chain of events before it. Markov chains are used to predict the state of occupancy, window opening, turning on/off the lights, equipment usage, and blind and thermostat adjustment (Yan & Hong, 2018).

Discrete event

Currently, BPS programs simulate event occurrences based on discrete time changes, meaning that an event can only happen in the predefined time-step; this approach prevents normal or emergency events from happening if they are between these time-steps. Discrete event formalism, in this regard, equates to alternating time-steps that correspond to the occurrence of an event. Therefore, the gaps between time advancements rely on the moment an event occurs in the future. This approach is currently not applied in building energy simulation, but similar results can be achieved by using very small time-steps (one minute or less) that would simulate a continuous flow of time and thus eliminate the time-step barrier (Gunay et al., 2014).

System dynamics

System dynamics refers to the dynamic relationship of major components of a system and the patterns with which they influence one another over time. This is an abstract method that does not consider the details of each individual element (Andrew Ford, 1999).

Agent-based modeling

No definitive definition has been established for an agent-based model. An agent can be an individual or a group of occupants with a set of rules and attributes assigned to them; they are able to interact with the environment and each other, and the location of each agent can be defined separately. The key aspect defining an agent-based model is the autonomy of each agent in their behavior within the constraints of that system. These features enable agent-based modeling to represent the random nature of occupants realistically (Malik et al., 2022).

Level of detail (LoD) is an approach that optimizes the simulation in order to reduce unnecessary complexities and the required computational power while reaching a level of accuracy that meets the goal of the simulation. Malik et al. (2022) have proposed a framework for level-of-details in agent-based models which, upon reflecting on the objective of the simulation, the desired performance metric, building classification, and special resolution, enables the appropriate agent-based model to be identified based on ten occupant-centric features that are divided into complicatedness and complexity categories as shown in Table 2.2.Table 2.2

Table 2.2. Level of details in agent-based models

	Complicatedness (model structure)					Complexity (model behavior)				
Level of detail	Representation	Heterogeneity	Zoning	Occupancy	Modeling formalism	Interaction	Sensing	Prediction	Learning	Collectives
LoD O-0	Average occupant	None	Building level	Static-deterministic	Static-deterministic	No	No	No	No	No
LoD O-1	Average occupant	None	Floor level	Dynamic-deterministic	Dynamic-deterministic	No	Yes	Yes	No	No
LoD O-2	Group of occupants	Yes	Detailed space type	Static-probabilistic	Static-probabilistic	Yes	Yes	Yes	Yes	No
LoD O-3	Individual occupant	Yes	Individual space	Dynamic-probabilistic	Dynamic-probabilistic	Yes	Yes	Yes	Yes	Yes

2.2.4 Modeling tools and implementation

2.2.4.1 Energy modeling tools

Energyplus

EnergyPlus is a building energy simulation software capable of simulating HVAC, lighting and equipment energy usage for different building geometries created through user input (EnergyPlus, 2022).

Rhinoceros

Rhinoceros (Rhino) is a 3D modeling tool frequently used by architects and other professions (Rhino, 2024).

Grasshopper

Grasshopper (GH) is a visual programming language as a component of Rhino that enables parametric modeling in the Rhino environment (Rhino, 2024).

Honeybee

Honeybee (HB) is a software component for GH that can create and simulate energy models through EnergyPlus (Ladybug Tools | Honeybee, 2024).

2.2.4.2 Occupancy and occupant behavioral modeling tools

Extensible Markup Language (XML)

XML is a text and file format designed to organize, maintain, and share data, ensuring a standardized encoding system that is understandable by both humans and machines (*XML*, 2024).

occupant behavior Extensible Markup Language (obXML)

obXML is an XML schema describing the content and format of the data and structure of the XML file based on the DNAS ontology. It is designed to support the development of new methods that standardize and solidify descriptions of occupant behavior, capturing the inherent complexity and unpredictability of real-world scenarios in simulations. Its structure is intended to be flexible, facilitating the widespread standardization of occupant behavior modeling (Hong et al., 2015).

The DNAS framework topology is structured in the obXML schema, centering around the OccupantBehavior main root element, which diverges into six sub-elements: Buildings, Occupants, Behavior, Seasons, TimeofDay and Holidays. This root element is uniquely identified by an ID and version attribute. The framework allows for specific inputs pertaining to buildings, occupants, behaviors, seasons, times of day and holidays (Hong et al., 2015). Detailed visualizations of each of these elements are available in Appendix F.

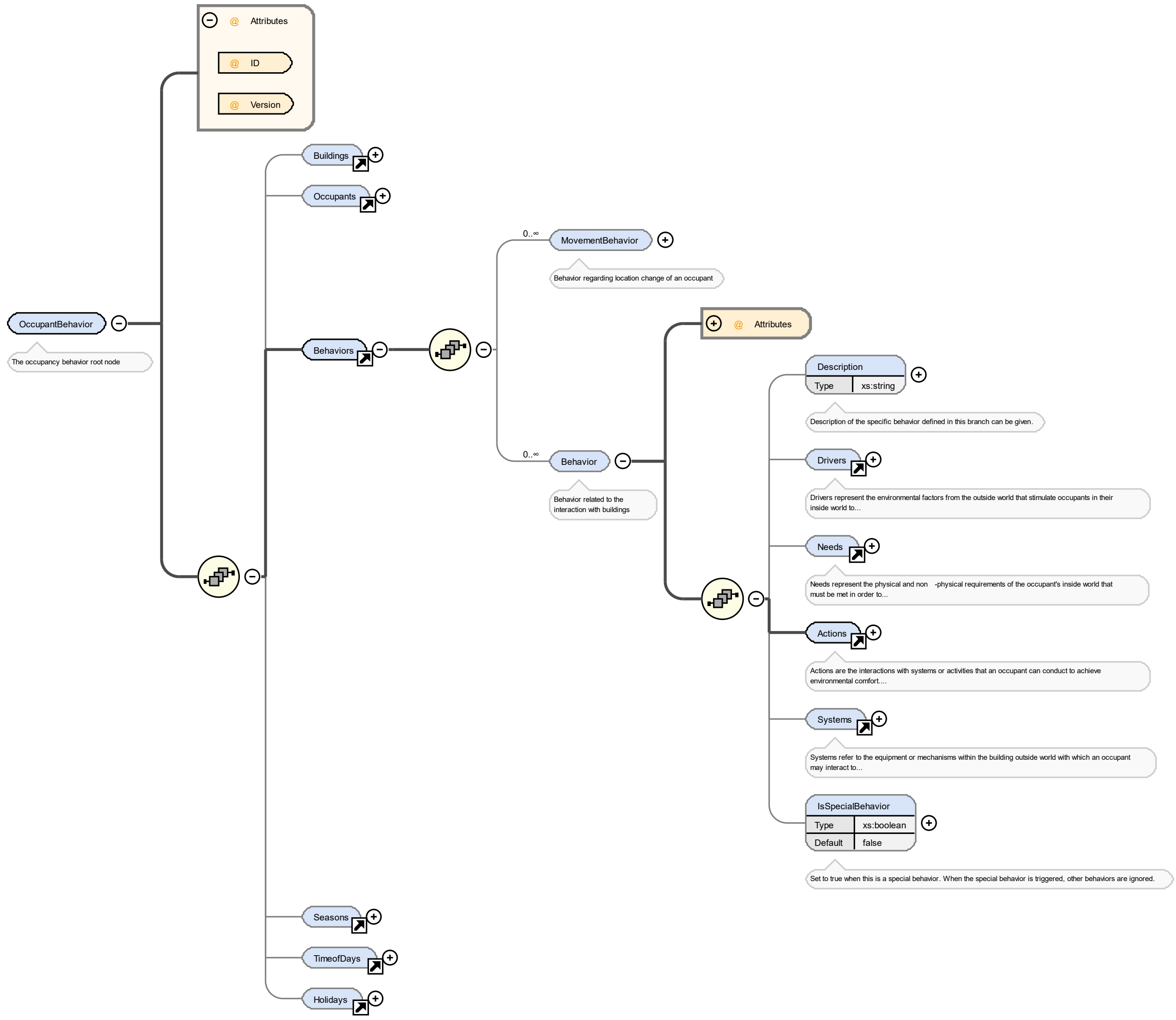

Figure 2.1. Structure of the obXML schema

Furthermore, 127 occupant behavior models from the past four decades were reviewed, and 52 models were selected and represented as a library of occupant behavior models using the obXML schema (Deme et al., 2019).

V1.3.3 of the library contains 45 models. Both obXML and the library of occupant behavior models are publicly available (ObXML, 2024).

Occupancy Simulator (OSim)

The Occupancy Simulator (OSim) is a freely accessible agent-based web application available at (Occupancy Simulator, 2024) developed by the Lawrence Berkeley National Laboratory for simulating the movement and presence of occupants in the building, where each occupant and each space are modeled as separate agents. In order to streamline data entry, it allows for grouping similar occupants and spaces into categories known as OccupantType and SpaceType. These profiles allow the simulation of occupancy at three distinct levels: the entire building, individual spaces, and individual occupants' locations. The simulator uses occupant profiles formatted in obXML schema to produce downloadable schedules in CSV and EnergyPlus input data file (IDF) format, along with obXML and obCoSim XML files used for co-simulation via obFMU (Luo et al., 2017).

OSim incorporates three models. The first model, Reinhart (2004) LIGHTSWITCH-2002 is used to manage status transitions such as arrivals and departures. The second model, based on Wang et al. (2011) homogeneous Markov chain, addresses random movements within the building, facilitating simulations of activities like restroom visits or movement to other offices. The third model orchestrates meetings, simulating the interactions of multiple occupants within a designated space, typically controlled by room agents (Chen et al., 2018).

However, the simulator does not account for personal absences like sick days or the influence of environmental conditions within spaces on occupant presence. Additionally, it does not consider the time it takes occupants to move between spaces and is currently only capable of simulating small to large office buildings. Despite these limitations, Osim has been demonstrated to accurately replicate the real-world occupancy patterns within office buildings (Chen et al., 2018; Luo et al., 2017).

Anylogic

Anylogic is a Java-based proprietary modeling software that supports various simulation methods such as agent-based, discrete event, system dynamics and a combination of all three with the possibility of visualizing the results. It offers a free personal learning edition with limited features (AnyLogic, 2024).

NetLogo

NetLogo is a Java-based open-source multi-agent programmable modeling environment used for simulating complex systems (NetLogo, 2024).

Matlab

MATLAB is a numerical computing environment that can be used for discrete event and agent-based modeling using Simulink (MATLAB & Simulink, 2024).

2.2.4.3 Implementation in BPS

Direct input

This method involves fixed or dynamic schedules for various elements including occupancy and different building systems. It lacks real-time communication between the scheduling module and BPS, preventing the formation of a feedback loop that uses the model’s output to adjust its input. This means that the environmental conditions created through the simulation cannot be used as input for creating new schedules that would affect the simulation, which in turn would affect the environmental conditions, creating a cycle while the simulation is running. Furthermore, it does not support the generation of stochastic models capable of predicting the probability of an action being performed based on different input parameters. This approach however is compatible with nearly all BPS programs, is the simplest to implement, and is used most often (Hong et al., 2018).

User function or custom code

The user function or custom code method enables users to override the schedules and controls by inserting custom scripts or functions into a building energy model's input file, facilitating real-time communication, energy management system in EnergyPlus and IDA Script in IDA ICE are examples of this approach. Moreover, it supports both deterministic and stochastic OB models (Hong et al., 2018).

Co-simulation

Co-simulation is a method where two or more programs exchange outputs and inputs, forming a feedback loop allowing for real-time communication and exchange of various types of information during simulation.

occupant behavior Functional Mockup Unit (obFMU)

The Functional Mockup Interface (FMI) is a tool-independent standardized framework designed to facilitate the seamless integration, exchange, and co-simulation of dynamic models across different software environments. A Functional Mock-up Unit (FMU) serves as a container that complies with the FMI specifications, stored as a zip file with a ".fmu" extension (Blockwitz et al., 2012).

obFMU is an FMU designed for co-simulation of occupant behavior via FMI. Figure 2.2 illustrates a co-simulation scenario between obFMU and Energyplys through ExternalInterface:FunctionalMockupUnitImport object in Energyplus. First, three categories of input data are sent to obFMU. Occupant behavior data, which is stored in the obXML file structured according to the obXML schema adhering to the DNAS ontology, is processed by obFMU using its obXML Parser. Information about the environment provided by Energyplus, and lastly, co-simulation information, which is contained in a separate XML file (obCoSim.xml) detailing space mapping between the obXML file and the building energy model. Afterward, each simulation zone is managed by a separate instance of obFMU. Finally, obFMU generates and exports schedules to Energyplus replacing the previous ones in order to represent the occupant action towards different building systems for that time-step. This process is repeated for each timestep till the end of the simulation and results from EnergyPlus and each zone in obFMU are stored separately as EnergyPlus output file formats and CSV respectively (Luo, 2016).

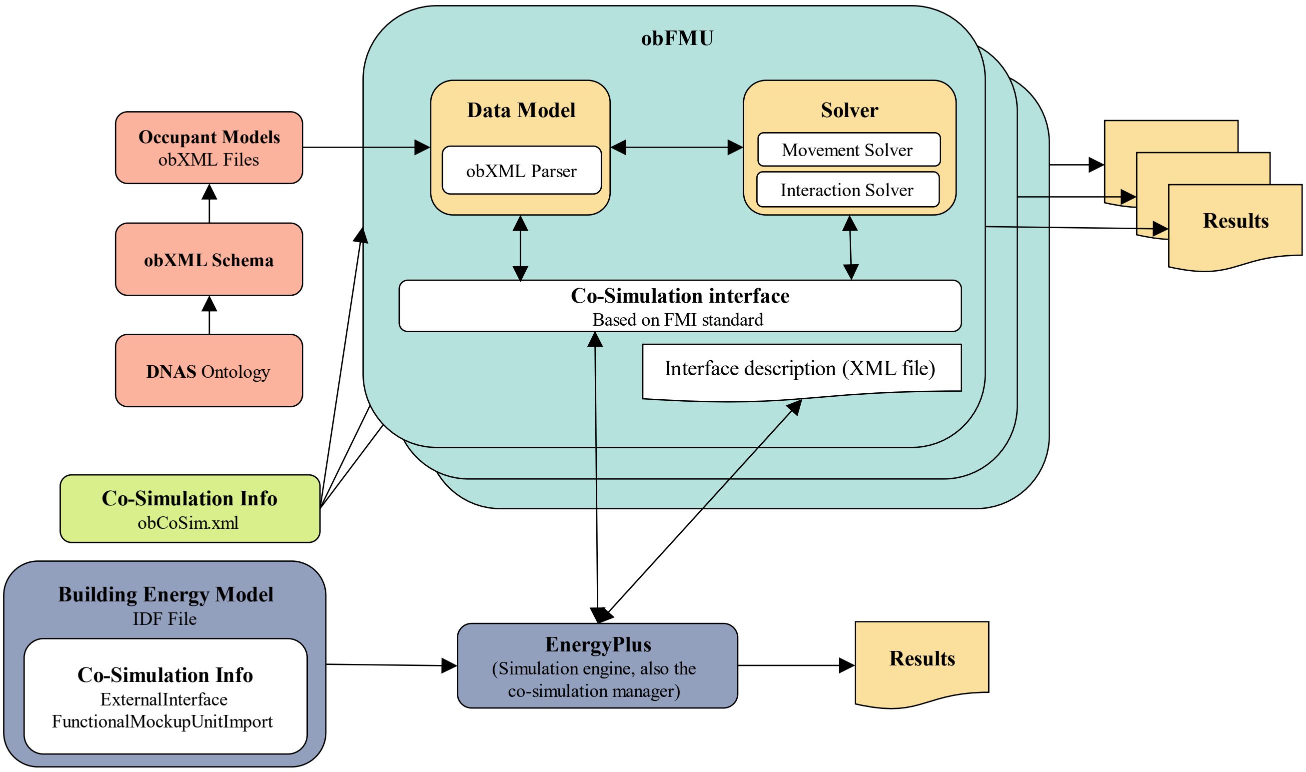

Figure 2.2. Overview of the co-simulation process between obFMU and EnergyPlus adopted from (Hong et al., 2016)

obFMU is comprised of two solvers: the movement solver and the interaction solver. The movement solver utilizes the same movement solver engine that was developed for OSim and is used once for each co-simulation to determine the location of each occupant at each time-step. Interaction solver on the other hand operates continuously, executing at every time-step for each obFMU instance to simulate how a user might interact with a system in the specified zone. Six input variables (Zone air temperature, Zone illumination level, Zone CO_2 concentration, Zone lights electric power, Outdoor air temperature, Outdoor rain indicator) are imported from the BPS programs and seven schedules (Occupancy schedule, Lighting schedule, Plug load schedule, Window schedule, Shade/Blind schedule, Thermostat setpoint, HVAC schedule) are exported from obFMU to the BPS program replacing the schedules that were previously in use. This replacement allows the BPS program to operate different systems according to the calculated behavior of the occupants at each time-step. Figure 2.3 illustrates the information exchange when co-simulation is performed using Energyplus as the co-simulation master and the obFMU as the slave (Luo, 2016).

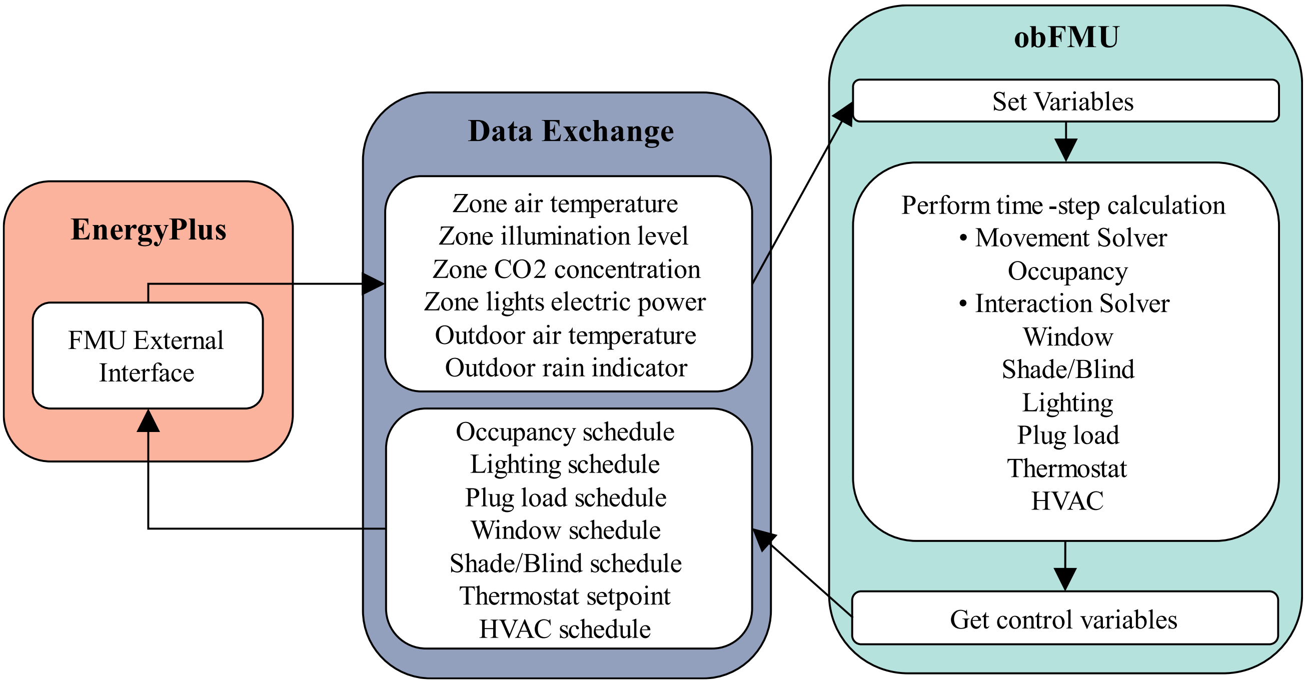

Figure 2.3. Information exchange between EnergyPlus and obFMU during a co-simulation adopted from (Luo, 2016)

There are several limitations within the current integration of EnergyPlus and obFMU. Notably, updates in EnergyPlus are delayed by one time-step in relation to obFMU iterations. In practice, this means that pre-existing schedules are consistently overwritten during each iteration. Additionally, the system faces challenges with managing multiple actions that occur simultaneously and sequencing occupant actions (Hong et al., 2016).

Python

By utilizing PyNetLogo, an interface that connects NetLogo to the Python environment, and PyFMI, which links the FMI to Python, Python can serve as the simulation master in co-simulations. This setup for example enables the integration of EnergyPlus through the FMI interface and NetLogo as the occupant modeling software, thus facilitating co-simulation (Fathollahzadeh & Tabares-Velasco, 2020; Jaxa-Rozen & Kwakkel, 2018).

Building Control Virtual Testbed (BCVTB)

The Building Controls Virtual Test Bed (BCVTB) is a Java-based open-source software based on the Ptolemy II software environment which serves as middleware enabling co-simulation by linking various programs such as EnergyPlus, Modelica, Radiance, MATLAB/Simulink, Netlogo and FMU (BCVTB, 2024; Fathollahzadeh & Tabares-Velasco, 2020).

2.3 Outcomes of occupant behavioral modeling

Occupant behavioral models can provide a clearer understanding of how buildings and occupants interact, leading to more accurate performance analyses and informed design decisions. This, in turn, helps reduce the performance gap creating a more comfortable living environment for occupants (Yan & Hong, 2018). They can also be designed for specific purposes such as evaluating the robustness of a building towards different levels of occupancy (Hoes et al., 2009). Also, they can be utilized for testing the energy saving potential of a technology by analyzing how occupants would interact with them (Yan et al., 2017).

2.4 Limitations and challenges

While an occupant behavioral model can provide a better understanding of the human-building relationship, relying on common metrics that normalize the energy use by floor area, such as EUI and (W/m^2) for peak demand intensity, excludes the impact of occupancy on the building performance. Therefore, using performance metrics that are suitable for the goal of the simulation and more occupant oriented could be beneficial. (O'Brien & Tahmasebi, 2023) provide several categories for occupant-centric metrics such as:

1) Resource and environmental impacts such as energy use via (kWh/ Occupant) or water use via (kg water/person)

2) Building services such as Underlit Occupancy Hours

3) Human-Building Interaction such as Controllability of HVAC

Additionally, as physical, psychological, physiological, cultural and financial factors can influence the way an occupant behaves, creation of an occupant model that is close to reality requires collaboration between experts from different disciplines (Mahdavi & Tahmasebi, 2017).

Furthermore, comparison between the outcomes of different research projects is not always possible as they rely on different sets and granularity of data with models that are specific to one type of building or a location, a model that takes the diversity of occupants into consideration can enable this comparison however collecting data on a large scale involving different attributes of an occupant raises privacy concerns and is not a trivial task (Hong et al., 2017).

During the literature review, it was noted that despite major advancements in this field over the years, no set of defined approaches and standards for modeling occupant behavior exists.

3 Methodology

The workflow of this study is illustrated in Figure 3.1. This process involved using the output of each section as the input for the next one. A base case model (BC) was created as the standard model, then data regarding occupancy and occupant behavior was collected. Afterward, this data was used to create the occupant profiles, and then these profiles, in combination with BC, were used to create the agent-based model (ABM). Finally, the results were analyzed and reported in the next chapter.

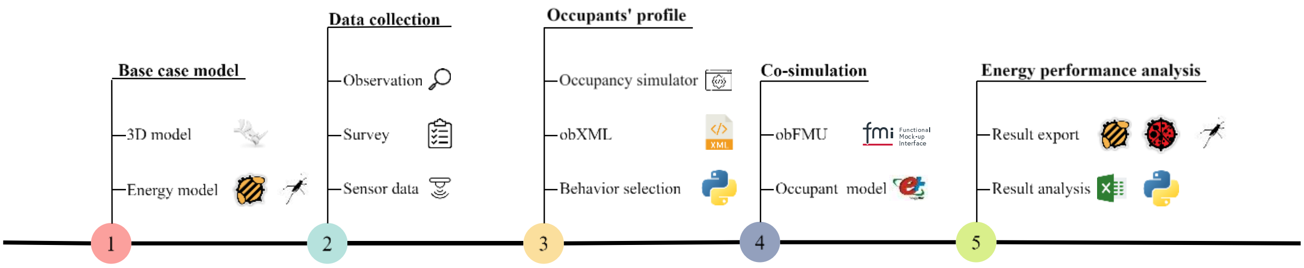

Figure 3.1. Workflow of the methods used in this section.

3.1 Case study

To conduct this case study, the north-east section of the second floor of the V-huset building, which is part of Lund University in Lund, was chosen as each room was equipped with occupancy sensors, and the number of rooms was suitable for the scope of this investigation.

Figure 3.2 . Corridor of the case study building

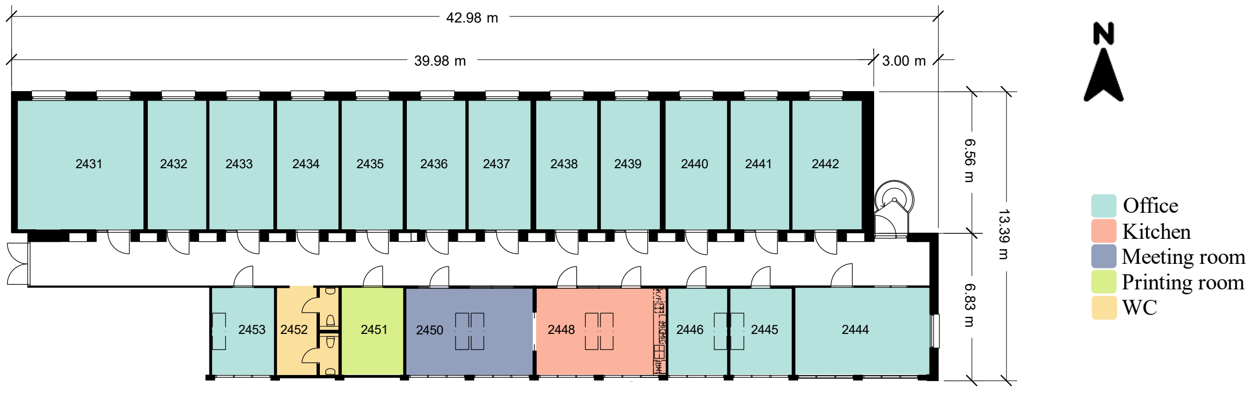

Figure 3.3. Plan of the selected section of V-huset

3.2 Base case energy model

To simulate the energy demand of this section of the building, an energy model (BC) was created using HB in GH. Wall construction properties were obtained from available drawings of similar buildings built for Lund University in 1960s by Klas Anshelm (*Academic House*, 2024). Although the building was renovated in 2016, only the exterior windows were replaced, and the walls and the roof remain untouched. Ventilation rate was set according to the Swedish building code (Boverket, 2018). People, lighting and equipment load, schedules and operative cooling and heating set points were set according to the Swedish building regulations for office spaces in universities (Boverket, 2017). Additionally, a second scenario (BC+) was considered in which the occupant density would match the real number of occupants, as described in section 3.7.

Table 3.1. Simulation inputs for BC

Energy simulation inputs		**Values**
Envelope *U*-value / (W/(m²K))	Exterior walls Roof	1.20 0.32
Windows *U*-value / (W/(m²K))	North and east South	0.59 1.85
Internal mass		columns
Shading		surrounding buildings
Ventilation	Always on	0.35 (l/s/m²) + 7 (l/s/p)
Infiltration (ACH at 50 Pa)		3.24
HVAC type		Ideal loads air system
Weather file (.epw)		Lund
Heated floor area (m²)		506
Natural ventilation	Always on	Within the limitations of set points during on hours with 1 °C difference
People load (W/person)		108
Lighting load (W/m² A_{temp})		11.4
Equipment load (W/m² A_{temp})		10
Occupancy and system schedules	Availability	8:00 – 17:00 working days
Occupant density (m² A_{temp}/person)	Base case Base case +	20 31
Heating set points (°C)	On hours Off hours	21 18
Cooling set points (°C)	On hours Off hours	24 28

3.3 Agent-based model

Agent-based modeling approach was chosen as it allowed for a stochastic representation of the occupants within the limitations of this case study originating from data availability, time constraints and availability of occupant modeling programs capable of co-simulation with EnergyPlus.

Occupants were represented as single individuals with each room representing one zone. Each zone had occupants and systems assigned to it, and each occupant had the ability to sense environmental variables and make limited predictions, avoiding certain actions as a result of predefined set points. The behavior of each occupant was defined based on DNAS ontology using obXML while their presence and absence and movement through the building were simulated using the movement simulator of OSim in obFMU.

3.4 Occupancy: movement and location

Each occupant was provided with a unique profile containing the arrival, departure and movement of that individual using OSim. This information was obtained through observational studies, conducting a survey and using data from presence sensors. The survey consisted of two parts: part one focused on occupancy, and part two on occupant behavior.

Information gathered through the first part of the survey and observations detailed the number of individuals in each office, whether the space was shared or private, and the daily number of visitors. It also included data on the occupants' break schedules, the frequency of meetings they attended, the average number of meeting participants, and the distribution of time spent in their own office, other offices, meeting rooms, utility rooms or outdoors.

Furthermore, data on occupancy, recorded at 10-minute intervals by the PD2400 infrared presence sensor integrated into Lindinvent TTC's supply air system in each room, was obtained from Akademiskahus for the year 2023. This system monitored and recorded states of presence and absence. To identify the most frequent arrival and departure hours, using Python, the data for each room was sorted to only show the first and last presence state for each day of the year; then, the first and last states were sorted separately to list all the filtered hours based on time of the day. These filtered lists were then analyzed using kernel density estimation (KDE) as the recorded data did not follow a pattern. Finally, the peak of the curve was chosen as the most frequent occurrence, which served as the mod for this data set, as shown in Figure 3.4Figure 3.4. The most frequent first and last recorded states were chosen as the typical arrival and departure hours for the whole year, respectively and standard deviation from this point was calculated to reveal their variation. The complete list of calculated hours can be found in Appendix A.

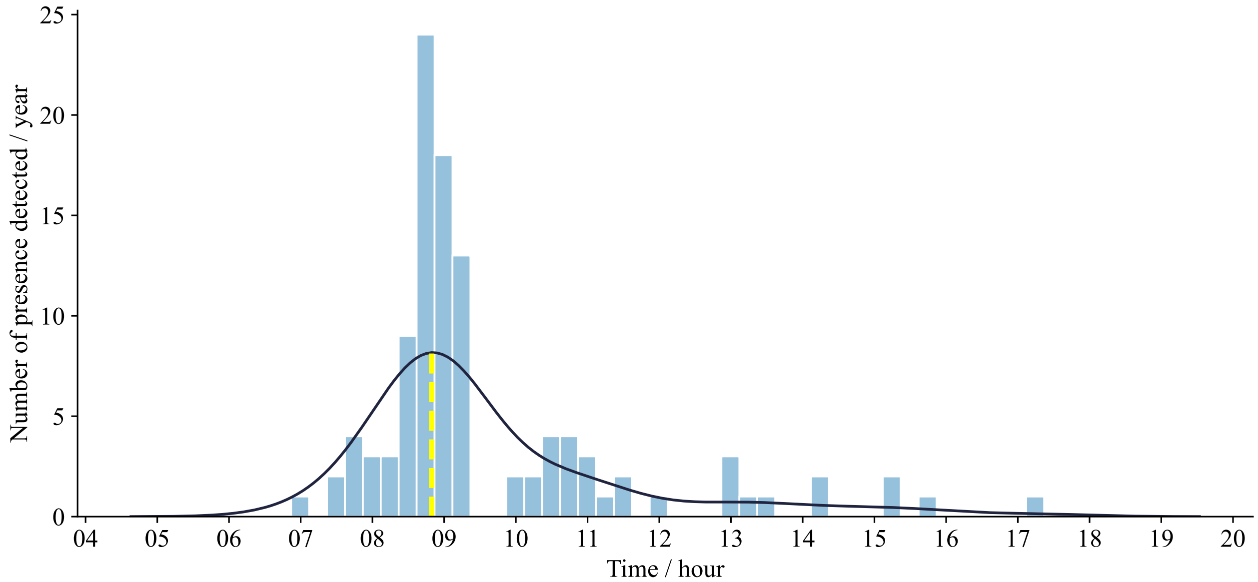

Figure 3.4. Example of a KDE for the first presence state detected at each hour throughout the year for room 34

Using this information, each occupant was modeled as a separate occupant type with its own set of movement and occupancy information, each room was also modeled separately and the corresponding occupants were assigned to them. Simulation period was set for one year, with 2023 Swedish holiday dates manually added. The simulation was performed at a 5-minute time-step. The obXML and obCoSim files generated by this simulation were then used for the next stages.

3.5 Behavior

The second part of the survey was used to find the right behavior model for the occupants, it was created based on a framework developed by D'Oca et al. (2017) uniting concepts from SCT, the DNAS ontology, and TBP to address the dynamics of energy-related behaviors within office settings affecting energy consumption and indoor comfort. It concentrates on how environmental and personal factors, along with societal norms, influence occupants' decisions to engage with building controls (D'oca et al., 2016).

This part of the survey was comprised of 5 main sections; the first section identified what the thermal, visual and IAQ needs of the occupants are and if these needs are satisfied. The second section assessed if occupants were allowed to interact with different systems in the building. The third section examined the occupants' knowledge of how to operate these systems. The fourth section analyzed occupants' intentions regarding the use of these systems. Finally, the fifth section collected data on the frequency of interaction with various systems inside the building. The list of survey questions can be found in Appendix B.

Answers from the survey were collected in an Excel sheet. A translation layer was developed according to the DNAS framework; the answers for each question were broken down and numbers, DNAS tags and weights were assigned to them. As demonstrated in the following examples from the survey where the participants were first questioned about how satisfied they were with their visual comfort. Only the state of dissatisfaction was considered s valid answer as a satisfied individual was unlikely to alter their condition. Afterward, the next question assigned the appropriate Drivers, Needs and Systems for each answer based on the conditions of this case study.

Question 1: On average, how would you rate the visual comfort (natural and/or artificial light levels and distribution that would let you see easily and clearly), in your usual workspace?

1. Very dissatisfied
2. Dissatisfied
3. Somewhat dissatisfied
4. Neither satisfied nor dissatisfied
5. Somewhat satisfied
6. Satisfied
7. Very satisfied

Translation:

```
Q1 =  {
   "1": {"Intensity" : "Very High" },
   "2": {"Intensity" : "High" },
   "3": {"Intensity" : "Medium" },
   "4": {"Intensity" : "Low" }
}
```

Question 2: If you are not satisfied with the visual comfort in your workspace, what is the main cause for visual discomfort? (You may choose more than one answer)

1. Too much artificial lighting
2. Too much natural lighting

Translation:

```
Q2 = {
        "1" :{
    "Drivers": "RoomWorkPlaneDaylightIlluminance",
    "Needs": "Visual",
    "Systems": "Lights"},
        "2" :{
    "Drivers": "RoomWorkPlaneDaylightIlluminance",
    "Needs": "Visual",
    "Systems": "ShadesAndBlinds"}}
```

Next, a complementary code written in Python was developed to find the right behavioral model from the library of behaviors included in obXML for each occupant, the process is demonstrated in Figure 3.5. First, the translation layer and library of behaviors defined using DNAS were added as dictionaries and the survey answers were loaded from the Excel file. Then, participant's thermal, visual and IEQ needs were analyzed, and if a need was present, the associated drivers and systems were identified and a dictionary containing the relevant drivers, needs and systems was assigned to that participant. In the next step, the level of access to different systems, level of knowledge about different systems and participant's intention level towards using different systems were assessed. Average and higher than average levels were assumed as a positive answer. Next, the usage frequency of different systems was examined; if the usage was frequent enough (more than never, once a year or six months) it was considered as a positive answer. Afterward, if the systems in the participant's dictionary had a positive access, knowledge and intent, the dictionary moved to the next stage, where it was checked against the frequency of actions with the same systems as the one in the participant's dictionary. The action was added to the dictionary if the outcome was positive. At this stage, the dictionary contained the participant's behavior defined through the DNAS framework and it was then compared with the behaviors from the library. Lastly, behaviors with identical identifiers were selected for the participant. This process was repeated for all the other participants, resulting in a final Excel file that contained the ID of occupants and their assigned behavior from the library. The behavior assignment code can be further explored in Appendix C.

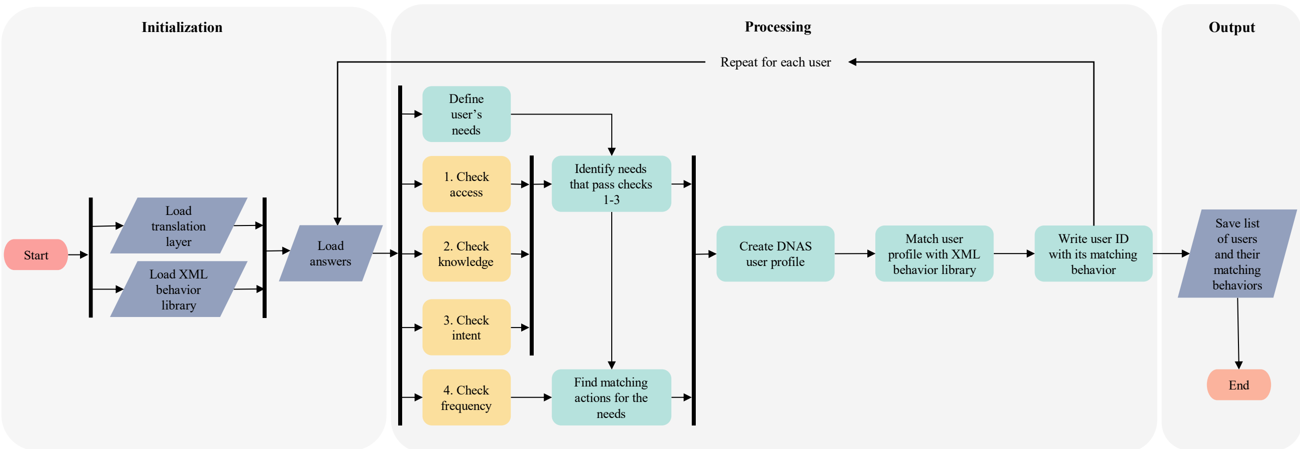

Figure 3.5. Workflow of the behavior assignment code

The list created using this code was used to complete the obXML file. Behaviors were added to `/OccupantBehavior/Behaviors` element, the IDs from these behaviors were added for each corresponding occupant in `/OccupantBehavior/Occupants/Occupant` element and the system involved in that behavior was also added to the corresponding room in `/OccupantBehavior/Buildings/Building/Spaces/Space` element

Furthermore, obXML file was further refined using knowledge and observations about the type of systems in use in this section of the building. For example, as each room was equipped with an automatic light-off switch connected to the occupancy sensor, this system was modeled in obXML. Lastly, the XML file was verified using the obXML schema to ensure it followed the correct structure.

3.6 Co-simulation

In order to use the occupant profiles in obXML with BC to run an energy simulation, a co-simulation was performed. To enable this co-simulation, the IDF file created from the simulation of BC was modified using EnergyPlus V 23.2 IDF Editor. obFMU as a Functional Mockup Unit (FMU) was imported to EnergyPlus as an external interface with EnergyPlus as the simulation manager.

Zone Mean Air Temperature, Daylighting Reference Point 1 Illuminance, Zone Air CO_2 Concentration, Zone Lights Electricity Rate, Site Outdoor Air Drybulb Temperature and Site Rain Status were defined as output variables and the following inputs were added in order to enable the export of these variables by EnergyPlus.

Table 3.2. Input for enabling co-simulation with obFMU in EnergyPlus

Output Variables	**IDF Object**	**Inputs and descriptions**
Daylighting Reference Point 1 Illuminance	Daylighting:Controls	Created for each zone and Daylighting reference points for each zone were assigned to them
Related Daylighting Reference Point 1 Illuminance schedule	Stepped Control	Availability Schedule Name: Off
Related Daylighting Reference Point 1 Illuminance schedule	Schedule:Compact	Name: Off Schedule Type Limits Name: Any Number Field 1: Through: 12/31 Field 2: For: AllDays Field 3: Until: 24:00 Field 4: 0
Daylighting Reference Point 1 Illuminance	Daylighting:ReferencePoint	One reference point was assigned to the center of each work desk in each zone at the height of 0.8 m from the floor
Zone Air CO_2 Concentration	ZoneAirContaminantBalance	Carbon Dioxide Concentration: Yes Outdoor Carbon Dioxide Schedule Name: Outdoor CO_2 Generic Contaminant Concentration: No
Related Zone Air CO_2 Concentration schedule	Schedule:Constant	Name: Outdoor CO_2 Schedule Type Limits Name: Any Number Hourly Value: 400
Zone Air CO_2 Concentration	People	Carbon Dioxide Generation Rate {m3/s-W}: 3.82×10^{-8} for each Occupant type (EN 16798-2, 2023)
Zone Lights Electricity Rate	Lights	Individual lights were assigned to each zone instead of how lights were previously assigned to space types that contained several zones
Site Rain Status	RunPeriod	Use Weather File Rain Indicators: Yes
Related schedule	ScheduleTypeLimits	Name: Fraction Lower Limit Value: 0.0 Upper Limit Value: 1.0 Numeric Type: CONTINUOUS
Related schedule	ScheduleTypeLimits	Name: Any Number

To read and send these variables from the external interface to obFMU, ExternalInterface:FunctionalMockupUnitImport:From:Variable was used, with the variables separately defined for each zone, as demonstrated in Table 3.3 for zone 2031.

Table 3.3. Input for enabling the export of output variable for zone 2031 as a sample

Output:Variable Name	**Variable inputs**
Zone Mean Air Temperature	Output:Variable Index Key Name: 2031 FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_Temperature
Zone Lights Electricity Rate	Output:Variable Index Key Name: 2031 FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031

	FMU Variable Name: OutdoorAir_Drybulb_Temperature
Site Outdoor Air Drybulb Temperature	Output:Variable Index Key Name: Environment FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_Temperature
Site Rain Status	Output:Variable Index Key Name: Environment FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Outdoor_Rain_Indicator
Daylighting Reference Point 1 Illuminance	Output:Variable Index Key Name: 2031 FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_illum
Zone Air CO_2 Concentration	Output:Variable Index Key Name: 2031 FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_CO_2

To import schedules from obFMU to the external interface, ExternalInterface:FunctionalMockupUnitImport:To:Schedule was used. Schedules for HVAC, light, infiltration, occupancy, plug load, thermostat, shade and blind were individually defined for each zone. An example of Zone 2031 is given in Table 3.4.

Table 3.4. Input for enabling the import of schedules for zone 2031 as a sample

Name	**Schedule inputs**
Zone_HVAC_SCH_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_HVAC_SCH Initial Value : 0
Zone_light_SCH_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_light_SCH Initial Value : 0
Zone_infil_SCH_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_infil_SCH Initial Value : 0
Zone_occ_SCH_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_occ_SCH Initial Value : 1
Zone_PlugLoad_SCH_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_PlugLoad_SCH Initial Value : 0
Zone_Thermostat_SCH_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_Thermostat_SCH Initial Value : 21

Zone_ShadeAndBlind_Room_2031	Schedule Type Limits Names: Fraction FMU File Name: obFMU.fmu FMU Instance Name: obm_Room_2031 FMU Variable Name: Zone_ShadeAndBlind_SCH Initial Value : 0

Afterward, the schedules for the number of occupants, lights, equipment, window opening, thermostat and blinds were replaced accordingly. The assignment of values for people, lighting and equipment were changed to separate zones from space types. Lighting load for each zone was set according to the type and number of lights installed in each room and their illuminance was measured using a Hagner E4-X lux meter and used accordingly in the 'Illuminance Setpoint at Reference Point {lux}' section of DAYLIGHTING:CONTROLS object in Energyplus. While the lights supported dimmable control, they were assumed only to turn on or off based on observations and interviews with the occupants and their usage patterns.

Equipment load for each zone was set to 120 W/m² based on observations of the number of electrical equipment and their usage, which fell below the average of the measured appliance use in offices (Gunay et al., 2016). The full list of lighting and equipment load for each room is accessible in Appendix D. Thermostat schedule and values were changed based on temperature recordings data obtained from Akademiskahus, a constant schedule was set for the cooling and heating set points and their values were changed to 21 °C and 24 °C respectively for the whole 24 hours of the day. HVAC inputs were not changed from the base-case model as a central control system operated the HVAC system in the building and occupants had no control over it. Corridor lights were set to 100 % luminance from 8:00 – 17:00 and to 20 % from 17:00 – 8:00 to accurately represent their real operation that was controlled automatically. The blinds were implemented by adding electrochromic glazing to the windows that required blind modeling as this option required the least amount of alternation to BC geometry and properties. Lastly Number of Timesteps per Hour in Timestep object was set to 12. An example of inputs for these changes for zone 2036 can be found in Table 3.5.

Table 3.5. Input for implementation of schedules for zone 2036 as a sample

Schedules	IDF object	Inputs
Occupants	People	Number of People Schedule: Zone_occ_SCH_Room_2036 Number of People Calculation Method: People Number of People: 1
Lighting	Lights	Schedule Name: Zone_light_SCH_Room_2036 Design Level Calculation Method: Watts/Area Watts per Zone Floor Area {W/m²}: 3.4
Equipment	ElectricEquipment	Schedule Name: Zone_PlugLoad_SCH_Room_2036 Design Level Calculation Method: Watts/Area Watts per Zone Floor Area {W/m²}: 6.2
Window opening	ZoneVentilation:WindandStackOpenArea	Opening Area Fraction Schedule Name: Zone_infil_SCH_Room_2036
Blinds	WindowShadingControl	Shading Type: SwitchableGlazing Shading Control Type: OnIfScheduleAllows Schedule Name: Zone_ShadeAndBlind_Room_2036

obCoSim.xml was updated to map the correct FMU instance name to the xml space ID, Movement calculation was set to Yes, start and end time and dates were set similarly as the inputs in RunPeriod object of IDF file for one year and timestep was set to 12. obXML.xml, obCoSim.xml, obFMU, BC IDF file and the weather file for

Lund were placed in the same folder. This folder was copied 10 times and the simulation for each one was performed separately to ensure no unintentional changes occurred to the input files by overwriting them. The average value from these 10 runs was used as the final result for ABM.

3.7 Analyses

As this study focused on how occupants impact the energy consumption in the building, (kWh/Occupant/year) was chosen as an occupant-centric metric to evaluate the total energy usage based on standard and measured occupancy levels throughout the year, which was then compared to the results that relied on EUI as the performance metric. Furthermore, to evaluate the significance of different parameters and lower the varying variables when using (kWh/Occupant/year), two new scenarios were introduced.

The first scenario looked at the significance of occupant count by simulating a base case model (BC+) with the same number of occupants as ABM as changing the number of occupants in ABM was not possible because it was representing the real number of people currently occupying this space and introducing more occupants would have resulted in creation of occupant profiles without any basis on reality unlike the ones created before.

The second scenario analyzed the parameters affecting lighting and equipment energy usage, by simulating the agent-based model (ABM+) using the same lighting and equipment loads as BC. This simulation was performed 10 times and the average was used to measure the significance of lighting and equipment loads in a probabilistic simulation.

Table 3.6. Specifications of different scenarios

Scenario	Number of occupants	Heating and cooling set points and schedule	lighting loads	Equipment load
BC	24	Standard	Standard lighting loads	Standard equipment loads
BC +	16	Standard	Standard lighting loads	Standard equipment loads
ABM	16	Real	Real lighting loads	Real equipment loads
ABM +	16	Real	Standard lighting loads	Standard equipment loads

While both models had the same number of occupants as input, the stochastic generation of occupancy in the ABM+ meant that the overall number of occupants present during a year would still not be the same in both models. Therefore, the total number of occupants present during the year was 32 853 and 37 441 for ABM+ and BC+ respectively.

Finally, regression analyses were performed to determine whether occupancy can explain the outcomes of lighting and equipment models.

4 Results

4.1 Occupant behavioral model

Using the output of the behavior assignment code, observations regarding the current state of systems installed in the offices and some general assumptions, light, window, blind and equipment behavioral models were selected for this simulation, detailed in Table 4.1. The full technical specifications of the behaviors are available in Appendix F.

Table 4.1. Selected behaviors.

Selected Behavior		
Model number	**System**	**Description**
1	Lights	Reinhart-Voss model for determining the probability of turning on the lights based on the current level of desk illuminance at arrival in the morning. This probability increases as the natural light level decreases below the comfort threshold (Reinhart & Voss, 2003)
2	Lights	Gunay model for determining the probability of switching on the lights with a focus on the immediate decision to turn on lights based on current desk illuminance levels when entering the room in the afternoon and evening based on Reinhart 2004 model without additional behavioral complexities (Gunay et al., 2016)
3	Lights	Model for turning off the lights when no occupancy is detected
4	Windows	Haldi-Robinson model for estimating the probability of opening the windows as a function of the indoor temperature (Haldi & Robinson, 2008)
5	Windows	Haldi-Robinson model for predicting window closing during the day based on indoor and outdoor temperature (Haldi & Robinson, 2009)
6	Windows	Model for opening the window if the CO_2 concentration is above the recommended threshold of (1100 ppm) for offices defined by (EN 16798-2, 2023)
7	Windows	Model for closing the window at the end of the workday
8	Blinds	Newsham model for opening the blinds in the morning upon arrival (Newsham, 1994)
9	Blinds	Model for closing the blinds at the end of the workday
10	Equipment	Model for turning on the equipment when entering the room
11	Equipment	Model for turning off the equipment when leaving the room
12	Equipment	Model for turning off the equipment when leaving the room for a short time (one hour)
13	Equipment	Model for turning off the equipment when leaving the room for a long time (six hours)

Table 4.2. Occupants and their assigned behavior.

Selected Behavior for each occupant	
Occupant ID	**Model number**
S1_31_Office_O1	1, 2, 3, 10, 11
S2_32_Office_O1	1, 2, 3, 10, 13
S3_33_Office_O1	1, 2, 3, 4, 5, 6, 7, 10, 11
S3_33_Office_O2	1, 2, 3, 10, 11
S4_34_Office_O1	1, 2, 3, 4, 5, 7, 10, 11
S5_35_Office_O1	1, 2, 3, 4, 5, 6, 7, 10, 12
S5_35_Office_O2	1, 2, 3, 6, 7, 10, 12
S6_36_Office_O1	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11
S7_37_Office_O1	1, 2, 3, 10, 11
S9_39_Office_O1	1, 2, 3, 10, 13
S10_40_Office_O1	1, 2, 3, 4, 6, 7, 10, 12

S11_41_Office_O1	1, 2, 3, 10, 12
S12_42_Office_O1	1, 2, 3, 8, 9, 10, 12
S13_44_Office_O1	1, 2, 3, 8, 9, 10, 12
S14_45_Office_O1	1, 2, 3, 10, 11
S16_53_Office_O1	1, 2, 3, 10, 12

4.2 Performance analyses

4.2.1 Total energy usage

The total annual energy use of BC simulation and the average of 10 separate runs of ABM are presented in Figure 4.1, as illustrated, ABM consumed 20 % more energy compared to BC.

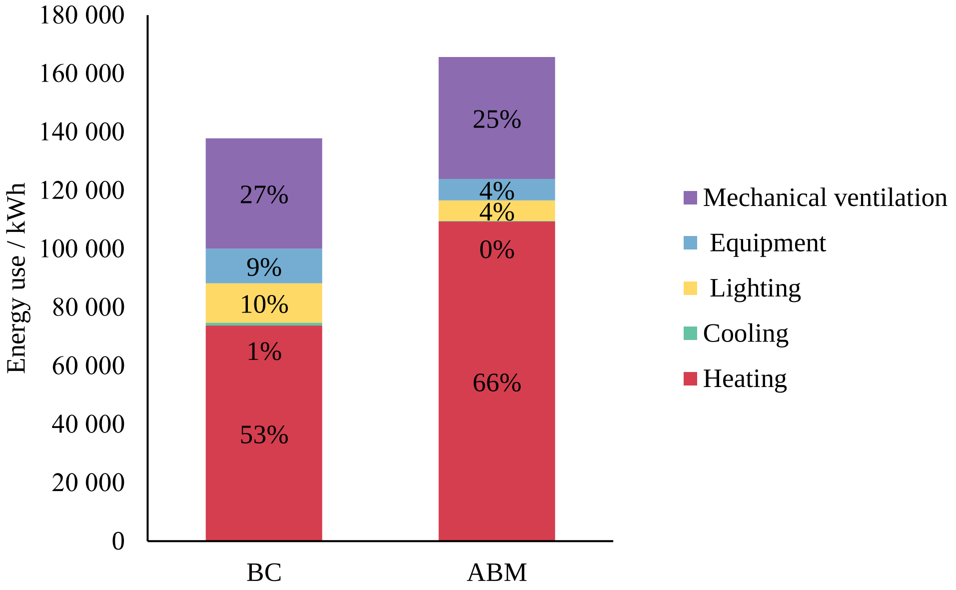

Figure 4.1. Annual energy use of BC and ABM

Figure 4.2 shows that heating increased by 48 %, followed by mechanical ventilation with 10 %. While cooling accounted for the lowest portion of the energy use, with only 1000 kWh rounding up to only 1 % of total energy use, a significant reduction of 74 % was observed, bringing the energy consumption down to 260 kWh in ABM. Lighting and Equipment also had a noticeable reduction, with 48 % and 38 %, respectively.

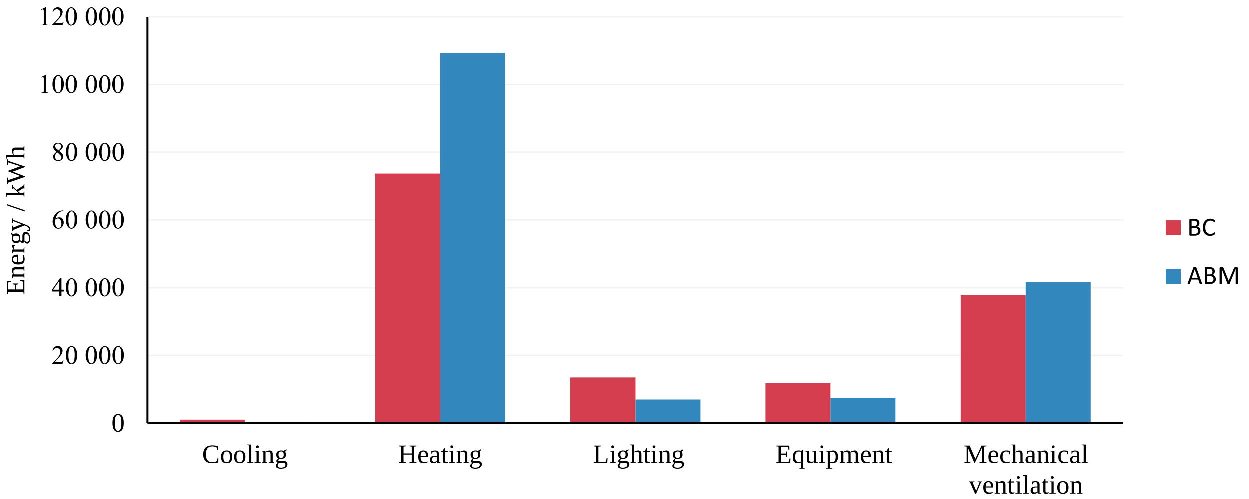

Figure 4.2. Annual energy use of different categories for BC and ABM

4.2.2 Energy balance

Figure 4.3 shows the Energy balance of the two models. Infiltration and transmission increased by 19 % and 47 %, respectively, whereas natural ventilation decreased by 58%. People load decreased by 44%, and solar gains remained unchanged.

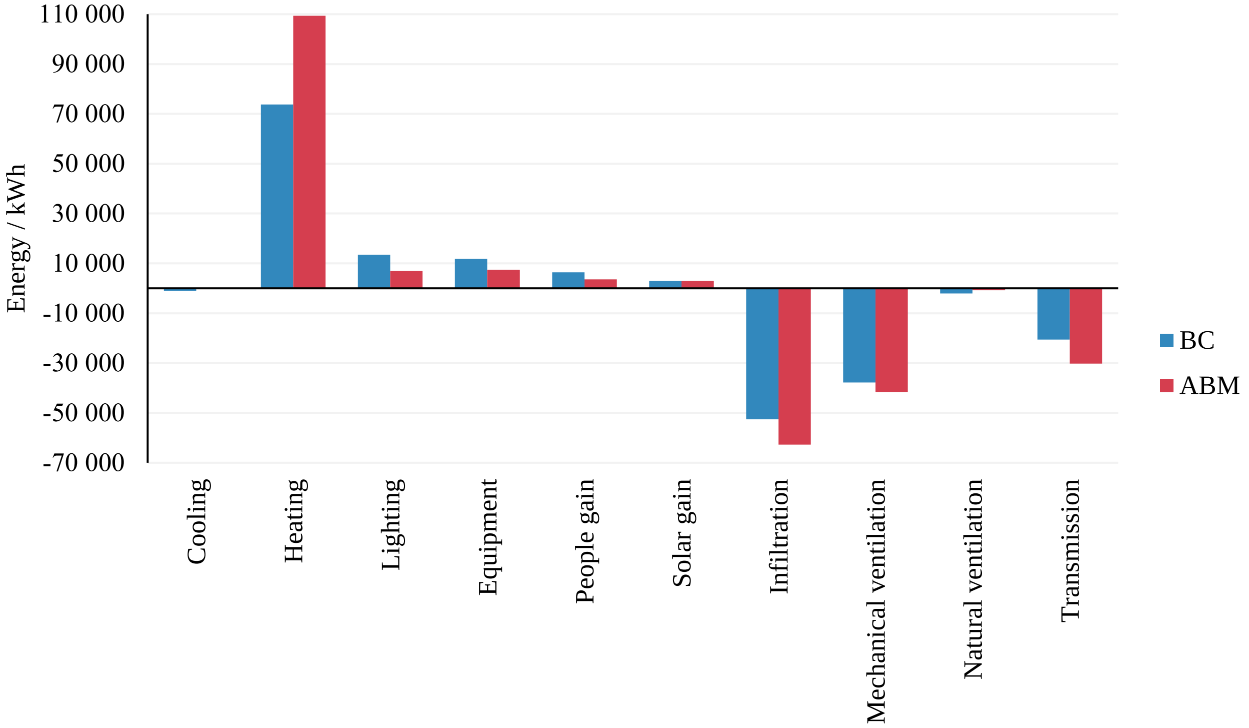

Figure 4.3. Energy balance of BC and ABM

4.2.3 Monthly breakdown

Figure 4.4 represents the monthly energy use for heating and cooling. It is noticeable that heating in the ABM had a steady trend of higher consumption with an average of 39 % increase in winter, spring and autumn and a 700 % increase compared to BC in summer. This overall increase can be attributed to the heating schedule, which was on for 24 hours every day. Cooling, on the other hand, decreased by 76 % on average over all the active months.

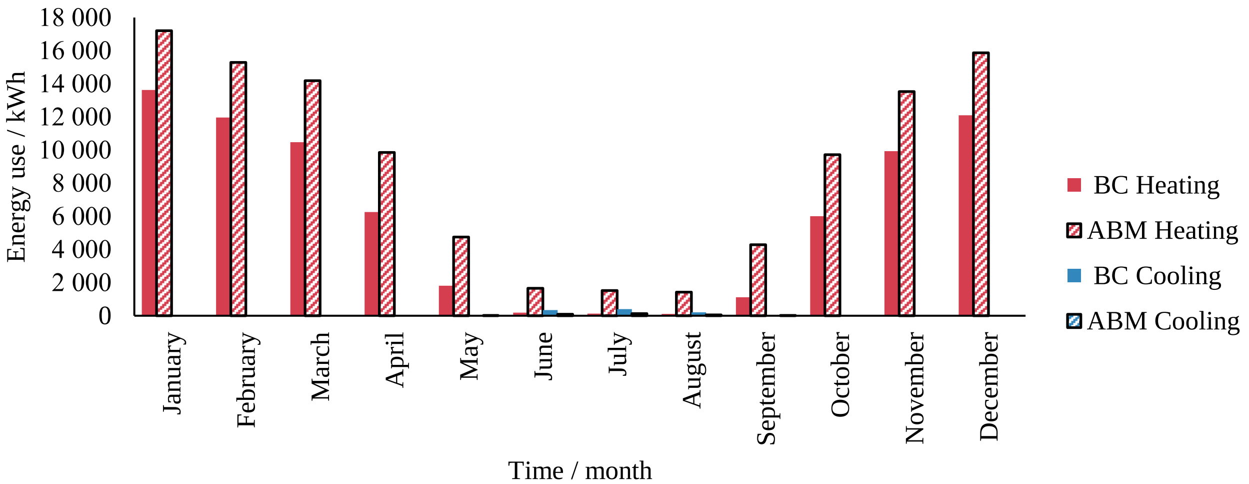

Figure 4.4. Monthly energy usage for heating and cooling in BC and ABM

Lighting and equipment energy use both had a noticeable decrease with an average of 48 % and 38 %, respectively, as shown in Figure 4.5. The highest reduction for lighting and equipment load was observed during May with 52 % and 42 %, respectively.

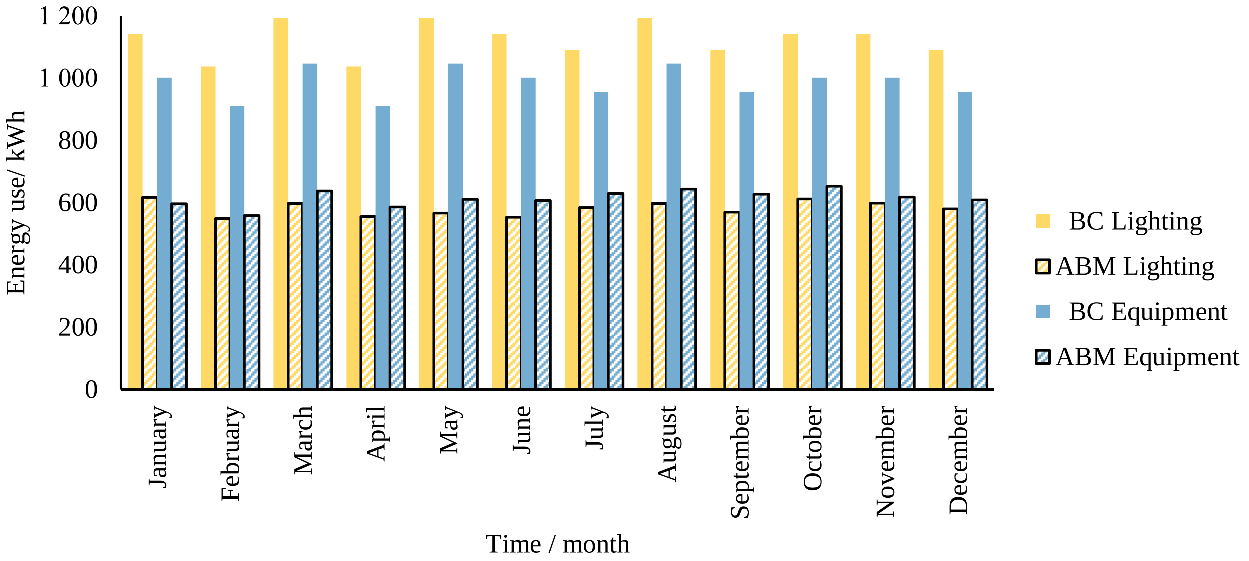

Figure 4.5. Monthly energy usage for lighting and equipment in BC and ABM

Mechanical ventilation increased by 11 % on average, with the highest surge in September at 25 %. Figure 4.6.

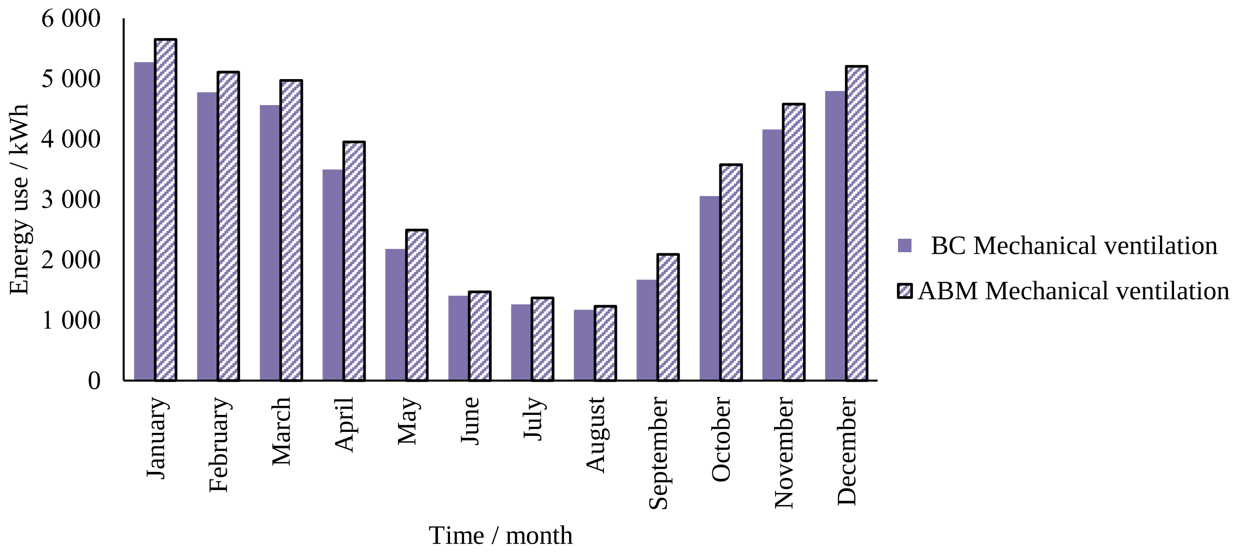

Figure 4.6. Monthly energy usage for mechanical ventilation in BC and ABM

4.2.4 Schedules

A comparison of the occupancy schedule for BC and ABM can be observed in Figure 4.7. Because of the stochastic nature of ABM, its schedule is different for each day; therefore, this graph is only a sample showing one day from the building to illustrate how the fixed office schedule of 8:00 to 17:00 differs from the stochastic occupancy simulated using OSim.

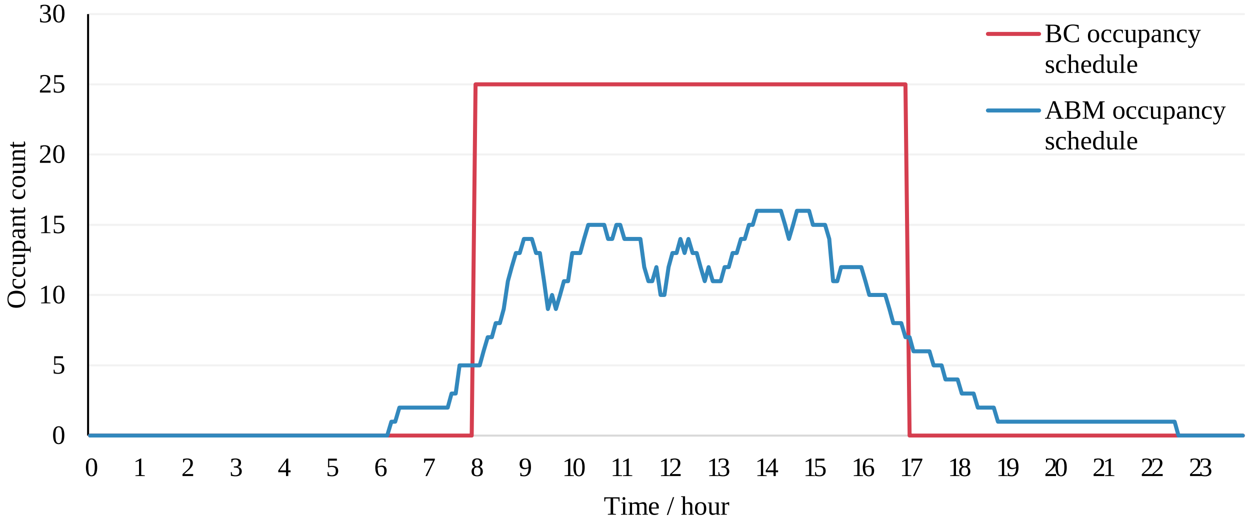

Figure 4.7. Sample of the occupancy schedule of one room for one week in BC and ABM

The cumulative distribution function of the number of occupants in the building throughout the year in Figure 4.8 shows the nature of the occupancy schedules in both models. It highlighted how the probability of the presence of different numbers of occupants differed in BC compared to ABM. BC had no occupants present for 75 % of the time (off hours) while all of the occupants were present at once for the rest of the time. The flat horizontal line showed the fixed occupant count throughout the working hours in the year. On the other hand, the line for ABM had a more gradual increase reflecting the stochastic nature of occupants and the more even distribution of their presence.

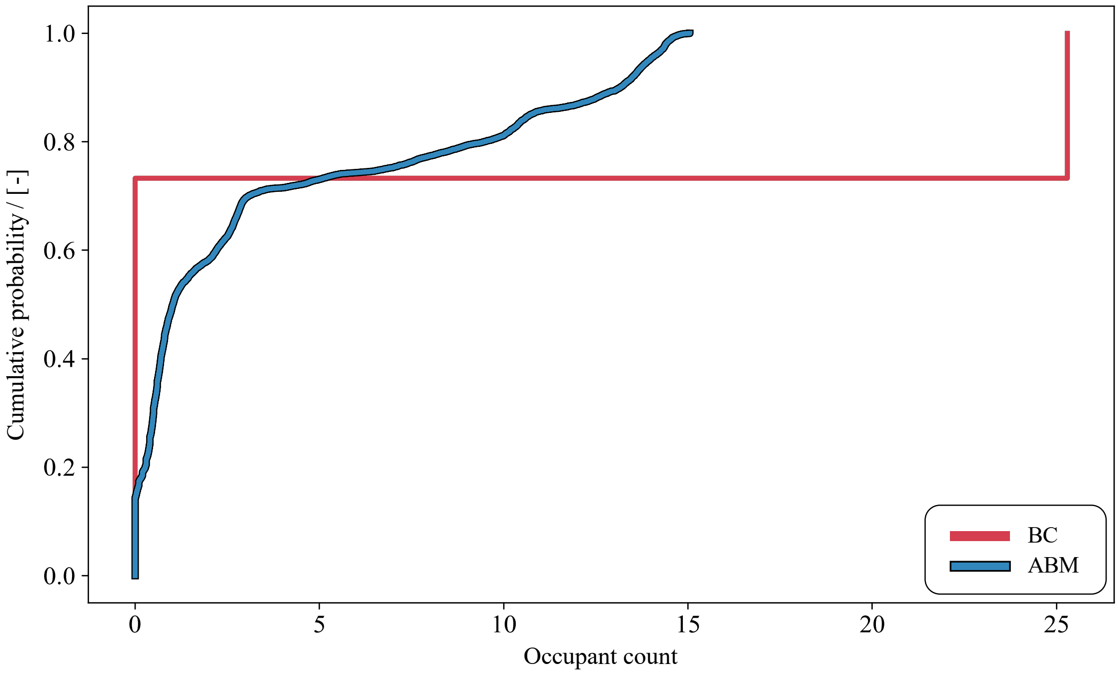

Figure 4.8. Cumulative distribution function of the total occupant count for BC and ABM

Figure 4.9 represents the schedule for equipment usage in one room for a week. Equipment usage was observed throughout the night in the ABM model, while in BC, it was tied to working hours.

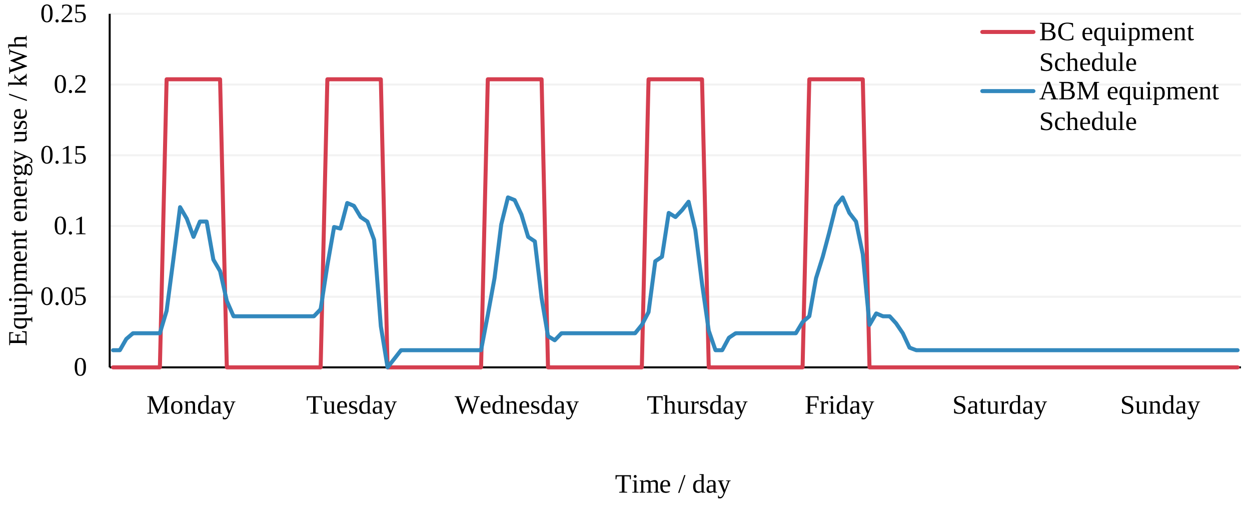

Figure 4.9. Sample of the equipment usage schedule shown through its energy consumption for one room during one week in BC and ABM

The same pattern can be observed for equipment usage in Figure 4.10, where all the equipment in the building in BC was used at the same time while ABM loads varied.

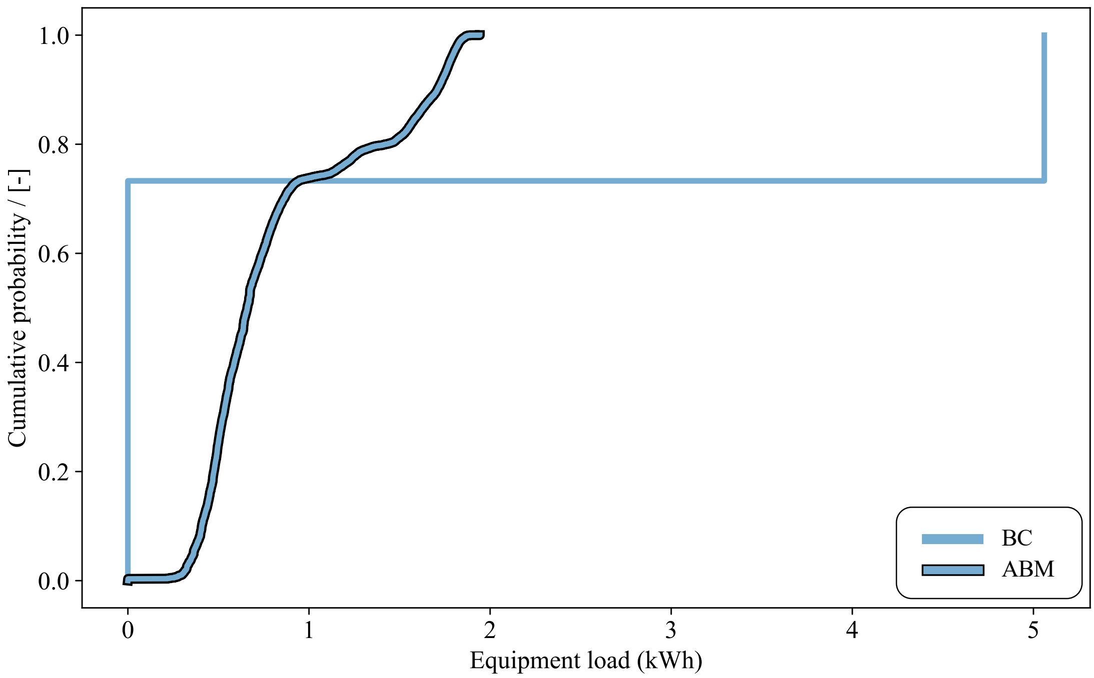

Figure 4.10. Cumulative distribution function of the total equipment load for BC and ABM

Figure 4.11 represents the lighting schedule for one week in one room in BC and ABM shown through its energy usage. As displayed, not only did lighting load vary throughout the day in ABM, but it was also less than one-fourth of the BC.

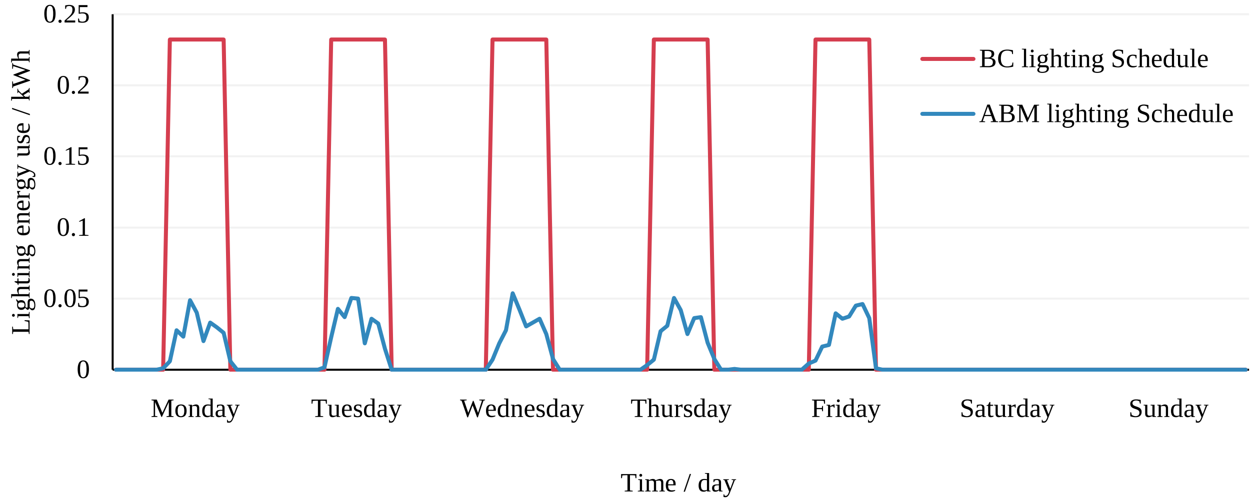

Figure 4.11. Sample of a lighting schedule shown through its energy consumption for one room during one week in BC and ABM

Figure 4.12 represents the cumulative distribution function of the lighting load for the whole building. The distribution of lighting load follows the same pattern as equipment load for the BC, while for the ABM, the majority of the load was concentrated near 0.3 kWh and peaking at 2 kWh.

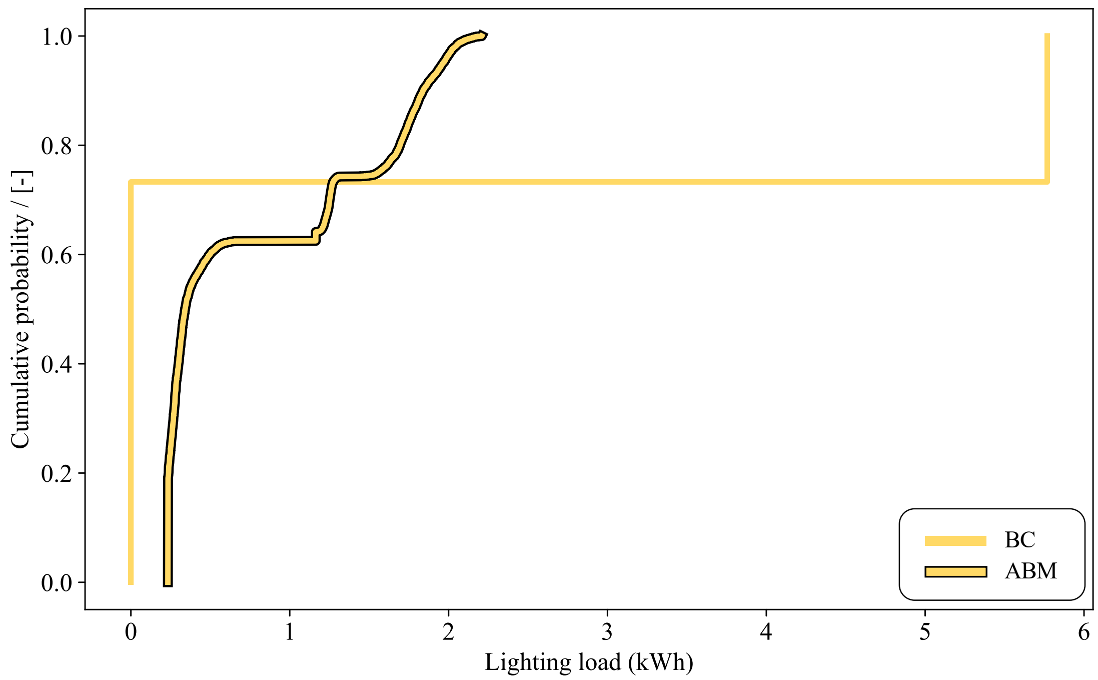

Figure 4.12. Cumulative distribution function of the total lighting load for BC and ABM

Figure 4.13 shows the schedule for window opening in BC and ABM for a week in the whole building. The dynamic schedule of the BC was seen to be close to the stochastic generation of window openings in ABM.

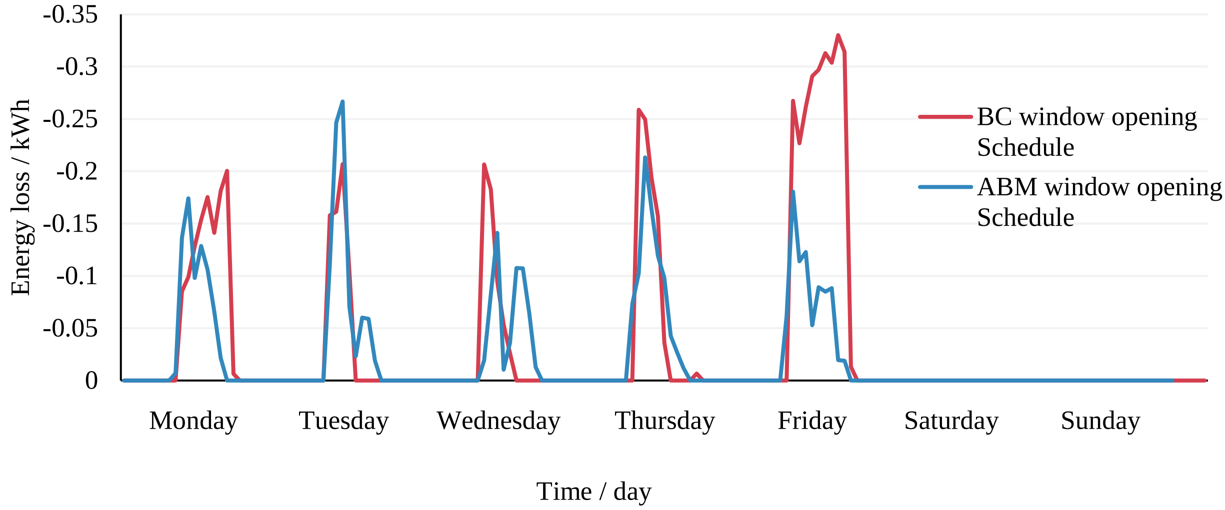

Figure 4.13. Sample of a window opening schedule shown through the annual energy loss via natural ventilation for the whole building during one week in BC and ABM

Figure 4.14 represents the cumulative distribution function of the annual energy loss through window opening in BC and ABM. Once again BC was showed to have a comparable performance in terms of variety of window opening occurances compared to ABM.

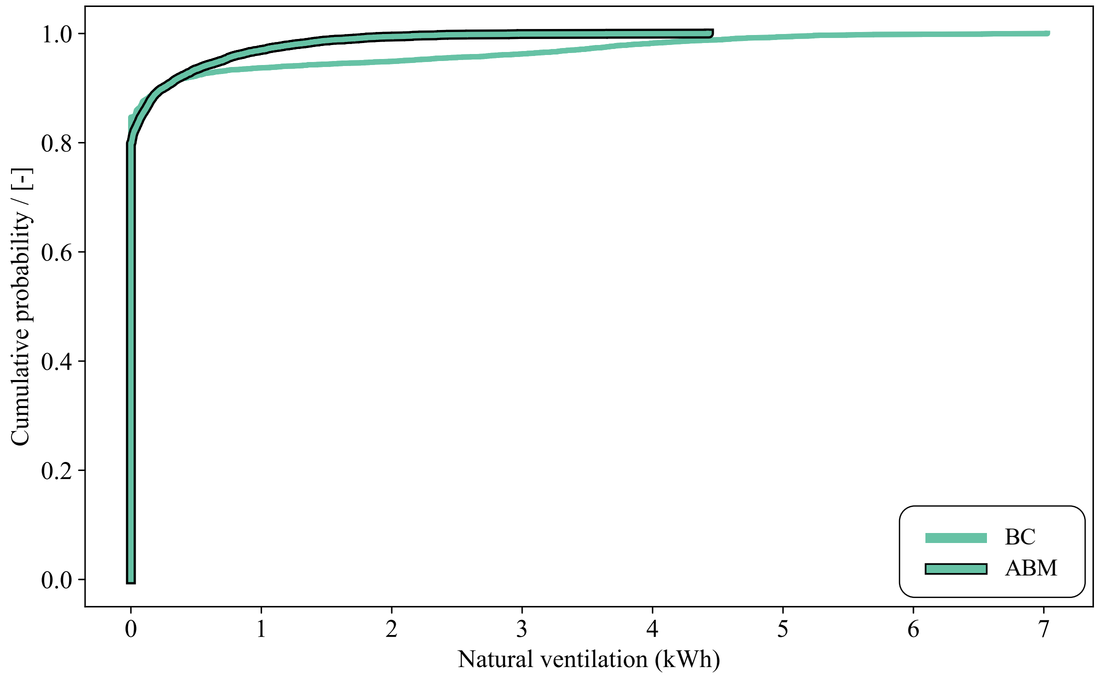

Figure 4.14. Cumulative distribution function of the total window opening for BC and ABM

4.2.5 Operative temperature

Figure 4.15 represents the operative temperature for each individual zone in both models with each column representing the minimum and maximum annual range for that zone.

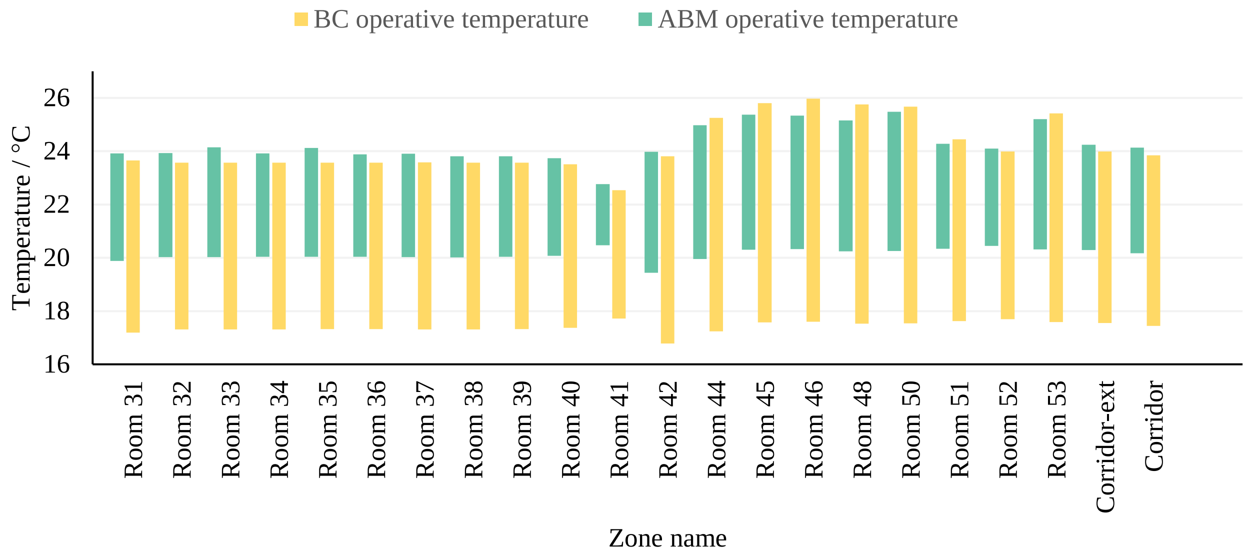

Figure 4.15. Annual operative temperature for each zone for BC and ABM

4.2.6 Peak loads

Figure 4.16 and Figure 4.17 represent the heating and cooling peak loads for ABM through November 27th and July 26th as the day with the highest heating and cooling load in the year, respectively.

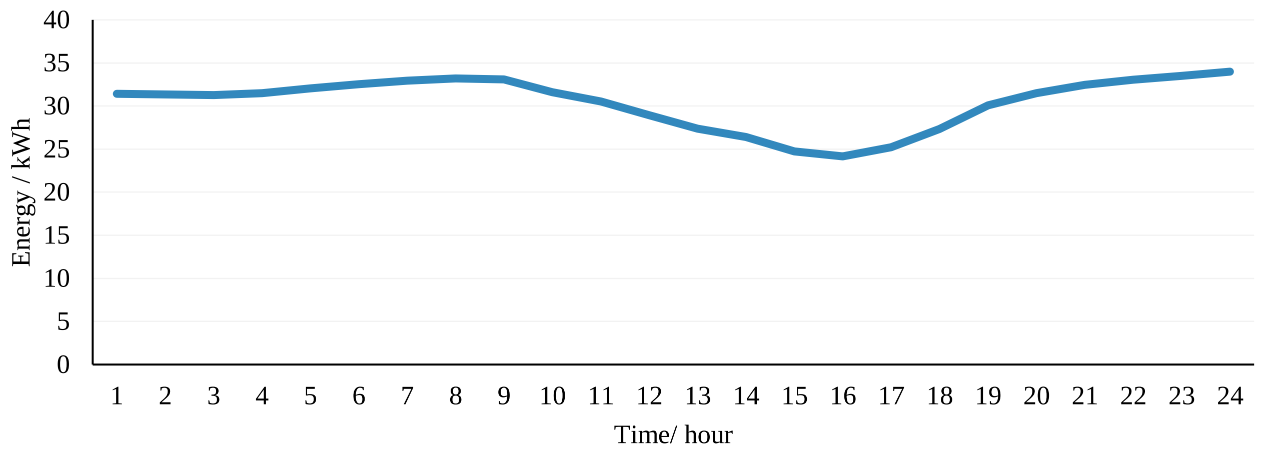

Figure 4.16. Heating peak load during November 27th for ABM

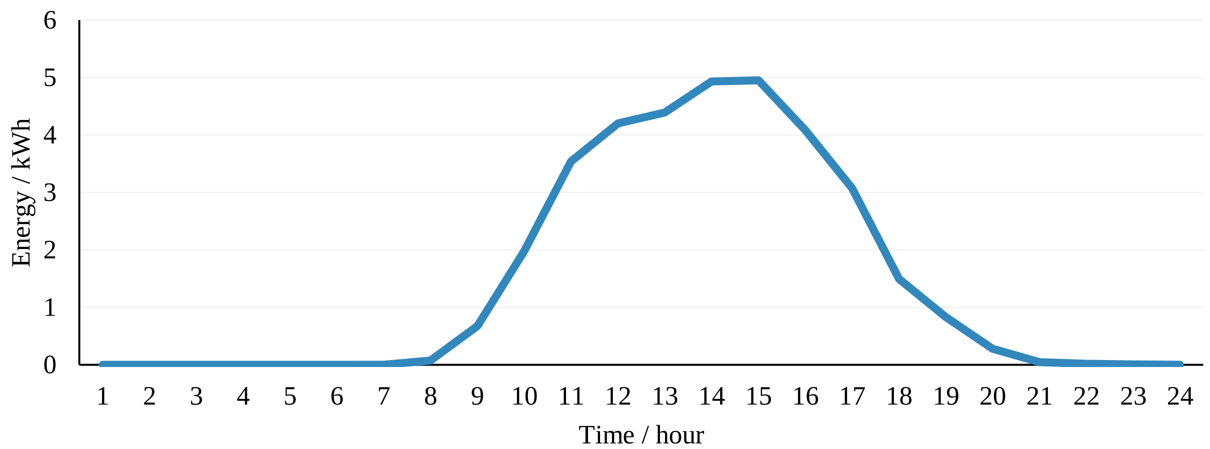

Figure 4.17. Cooling peak load during July 26th for ABM

Figure 4.18 and Figure 4.19 represent the heating and cooling peak loads for BC through November 27th and July 26th as the day with the highest heating and cooling load in the year, respectively.

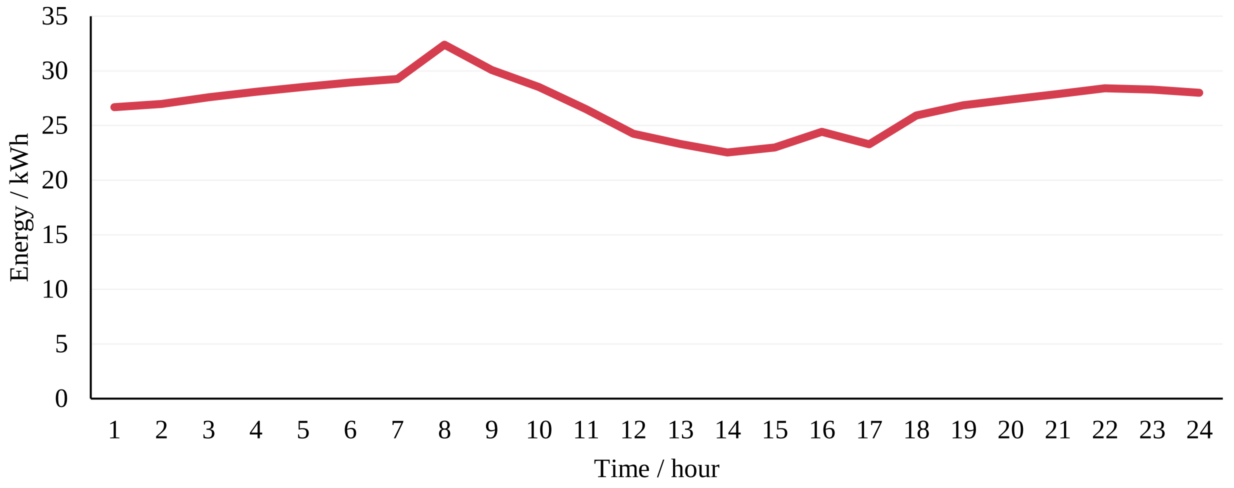

Figure 4.18. Heating peak load during November 27th for BC

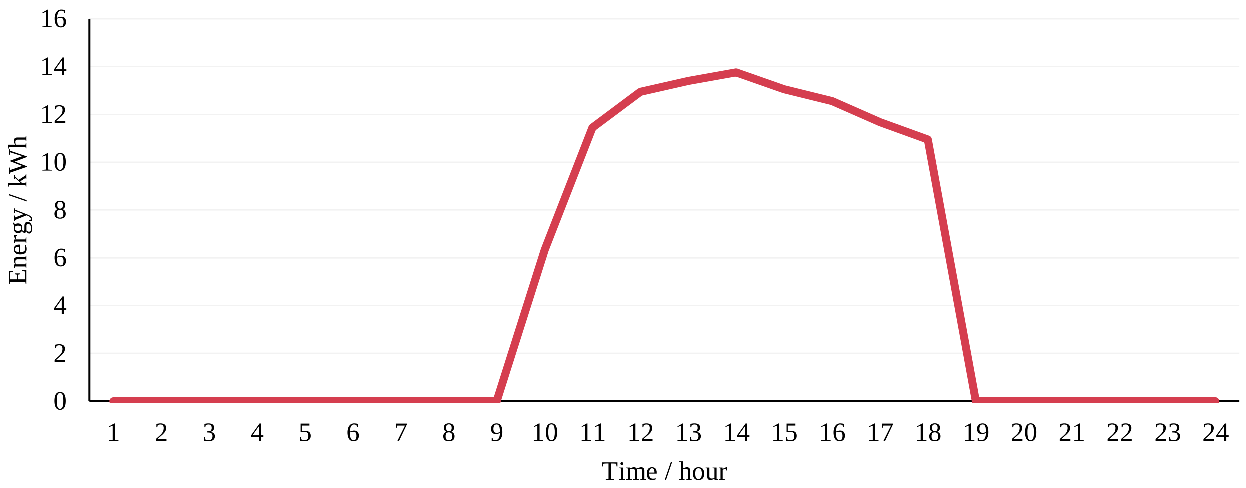

Figure 4.19. Cooling peak load during July 26th for BC

4.3 Performance analyses using an occupant-centric metric

In order to develop a better understanding of the performance of each model with respect to their occupancy levels, (kWh/Occupant/year) was used as the performance metric. Figure 4.20 represents the total energy use normalized by the total number of occupants present in a year for each model. ABM had an increase of 116 % compared to BC.

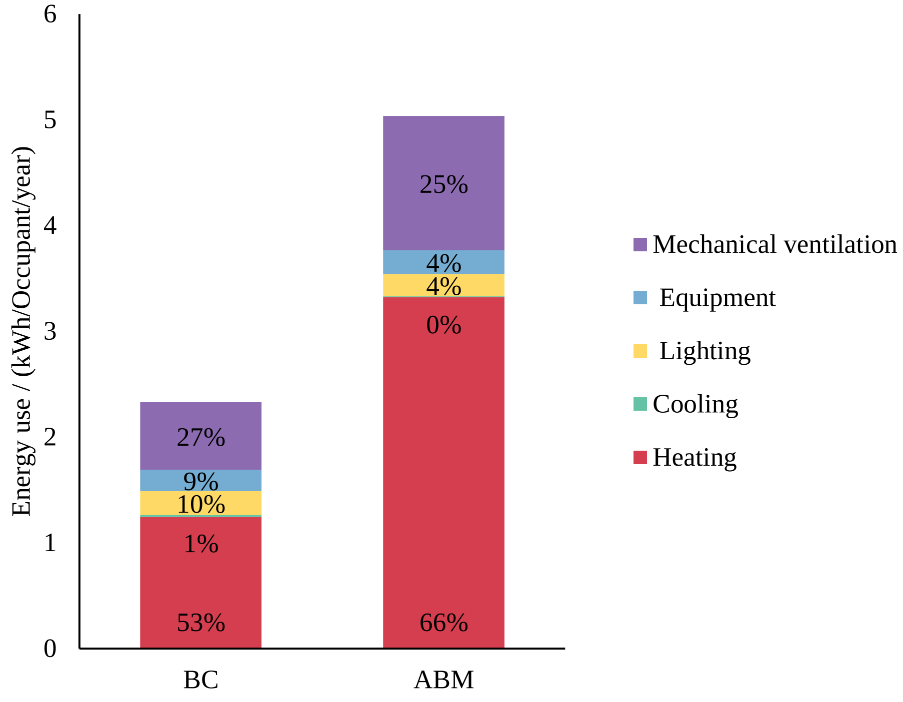

Figure 4.20. Total energy usage for the total number of occupants during the year for BC and ABM

Figure 4.21 and Figure 4.22 show a comparison between (kWh/Occupant/year) and EUI as performance metrics. Energy use for heating and mechanical ventilation was increased by 167 % and 98 %, respectively, while EUI only showed an increase of 48 % and 10 %, respectively. Lighting and cooling decreased by 7 % and 53 %, respectively, using the new metric, while they decreased by 48 % and 74 %, respectively, using EUI. However, equipment energy use displayed a reverse trend and increased by 12 % when normalized by the total number of occupants present in a year whereas EUI showed a 38 % decrease.

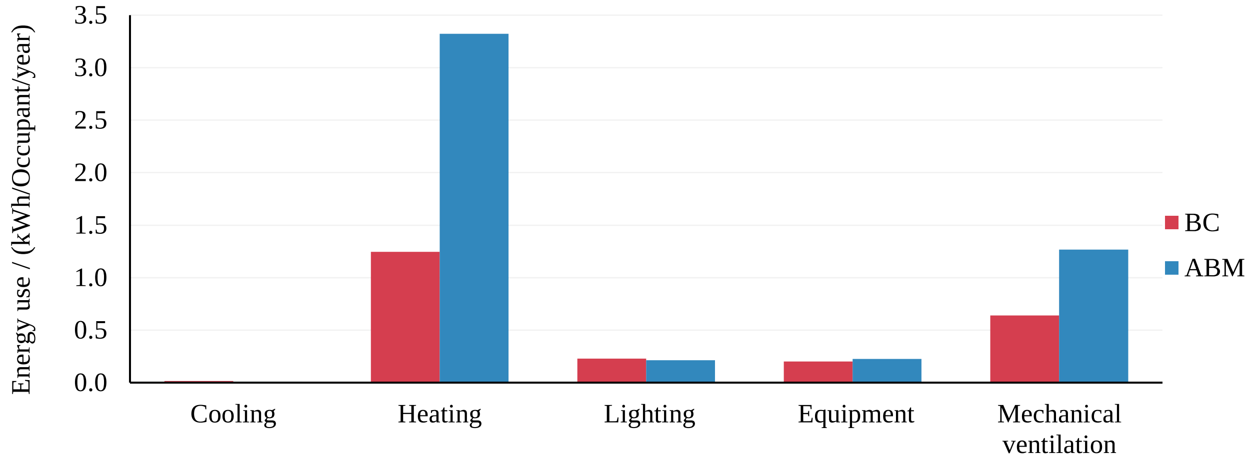

Figure 4.21. Total energy usage for different categories normalized by the total number of occupants present during the year for BC and ABM

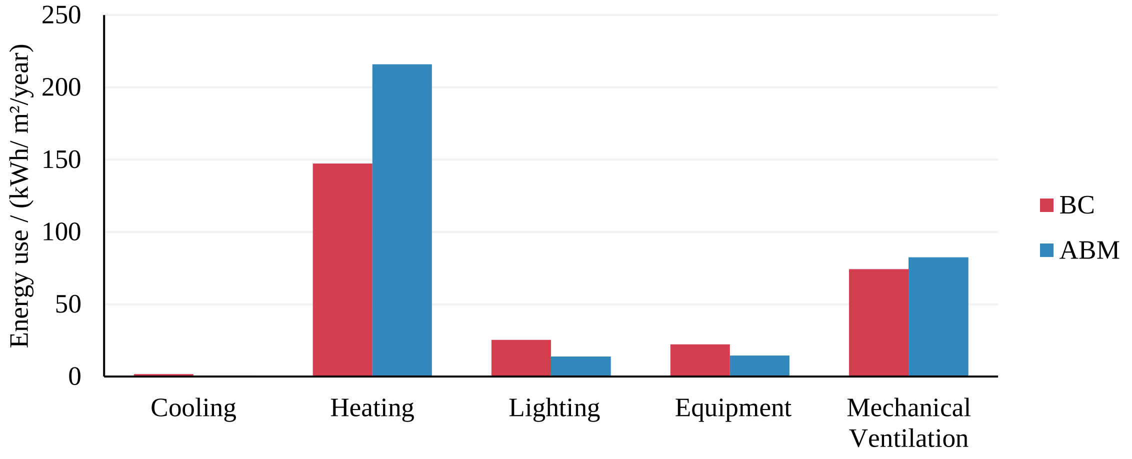

Figure 4.22. Energy use intensity for BC and ABM

4.3.1 Monthly breakdown

Figure 4.23 illustrates the monthly heating and cooling energy use in both models. Heating increased by 648 % on average and more than doubled in ABM during the cold months of the year and was up to twenty-two times higher in August. Cooling was reduced by 56 % on average in ABM with the highest reduction in May by 63 %.

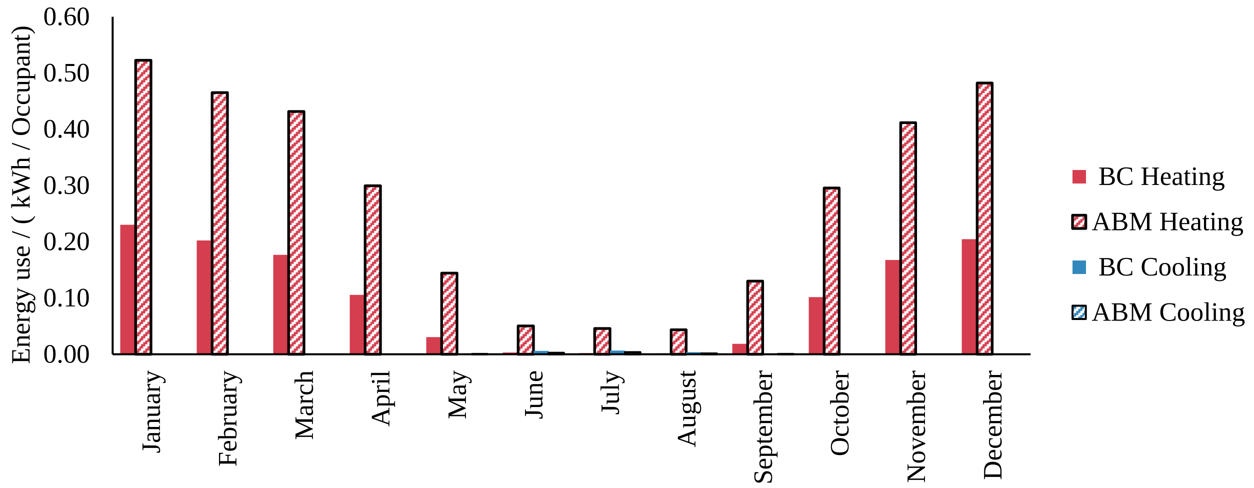

Figure 4.23. Monthly energy usage normalized by the total number of occupants present for heating and cooling in BC and ABM

Figure 4.24 represents the lighting and equipment energy usage per occupant hour in both models. Lighting energy use was reduced by 7 % on average, with the highest reduction in May at 14 %, while equipment energy use increased by 12 %, with the highest rise in July at 18 %.

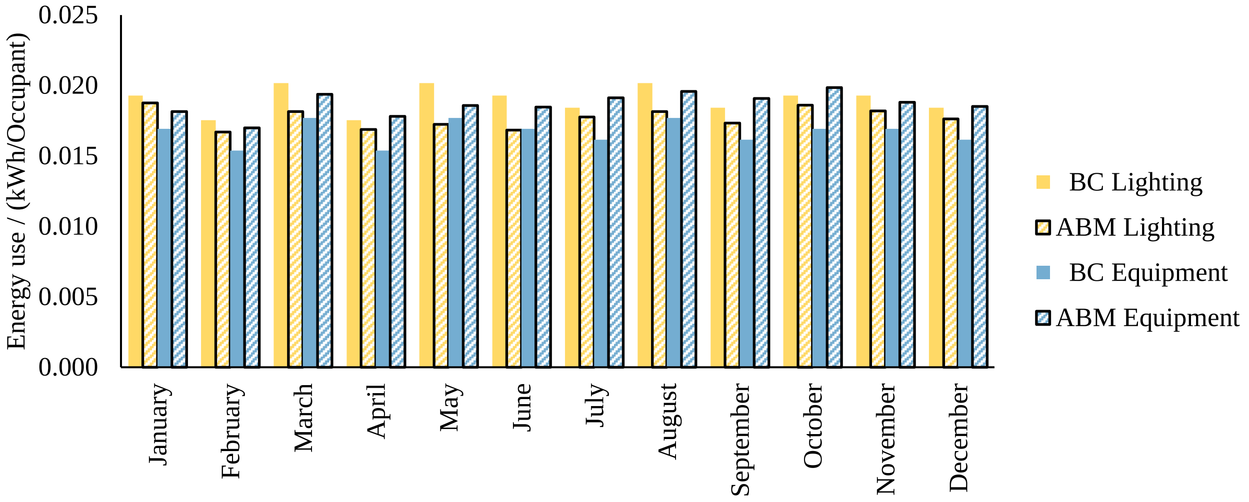

Figure 4.24. Monthly energy usage normalized by the total number of occupants present for lighting and equipment in BC and ABM

Figure 4.25 shows that mechanical ventilation energy usage for ABM increased by 99 % on average compared to BC, with the most significant increase in September, at 125 %.

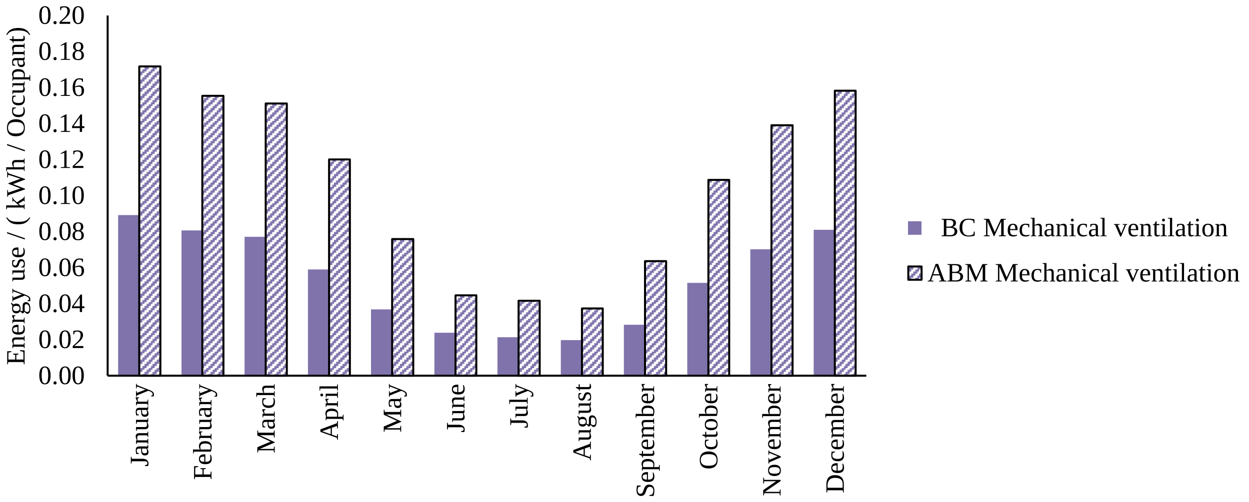

Figure 4.25. Monthly energy usage normalized by total number of occupants present for mechanical ventilation in BC and ABM

4.4 Comparative analyses

4.4.1 Performance analyses

Figure 4.26 compares the two main models (ABM and BC) and two additional scenarios (ABM+ and BC+) in terms of total energy use and the percentage of energy used by each category for the corresponding model. In total, ABM+ consumed 52 % more energy than BC+, and ABM consumed 116 % more energy than BC.

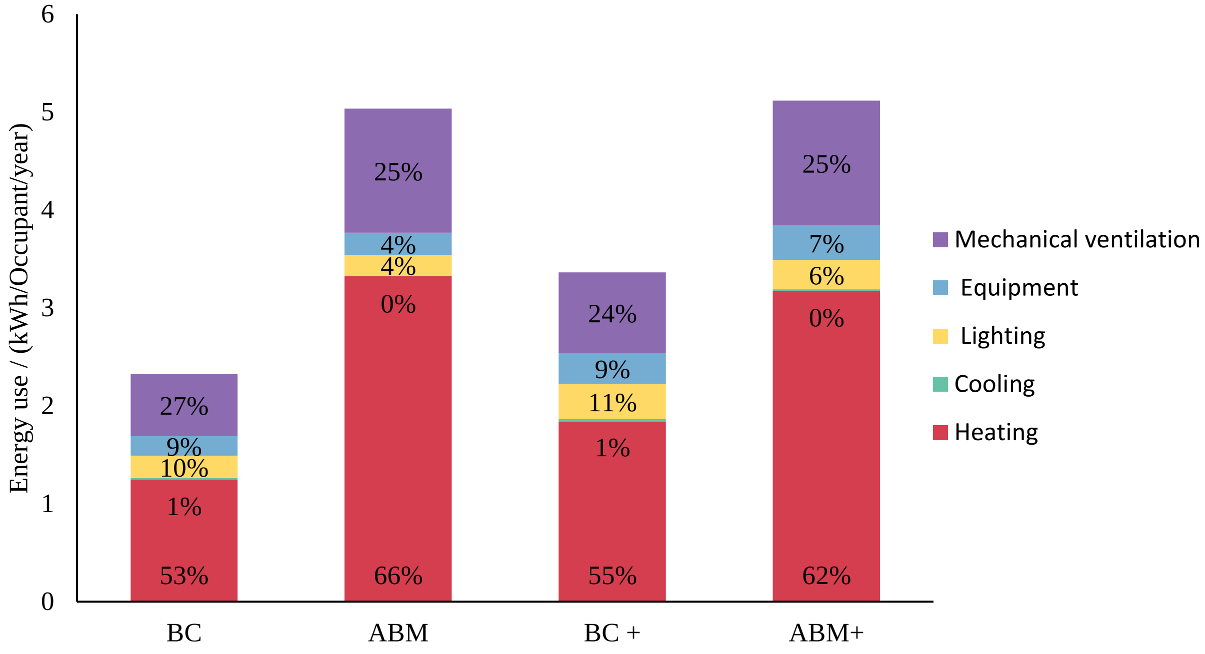

Figure 4.26. Energy usage normalized by the total number of occupants present in one year for four scenarios

Figure 4.27 shows that energy used for heating increased by 73 % for ABM+ compared to BC+; in comparison, there was a 167 % increase for ABM compared to BC. Cooling loads decreased by 40 % for ABM+ compared to BC+. This reduction was 53 % for ABM compared to BC. Energy used for lighting was reduced by 17 % in ABM+ compared to BC+. Previously this number was 7 % for ABM compared to BC. Equipment energy use increased by 12 % for ABM+ compared to BC+ resulting in the same amount of increase as ABM compared to BC. Mechanical ventilation energy use increased by 55 % for ABM+ compared to BC+ while there was a 98 % increase for ABM compared to BC.

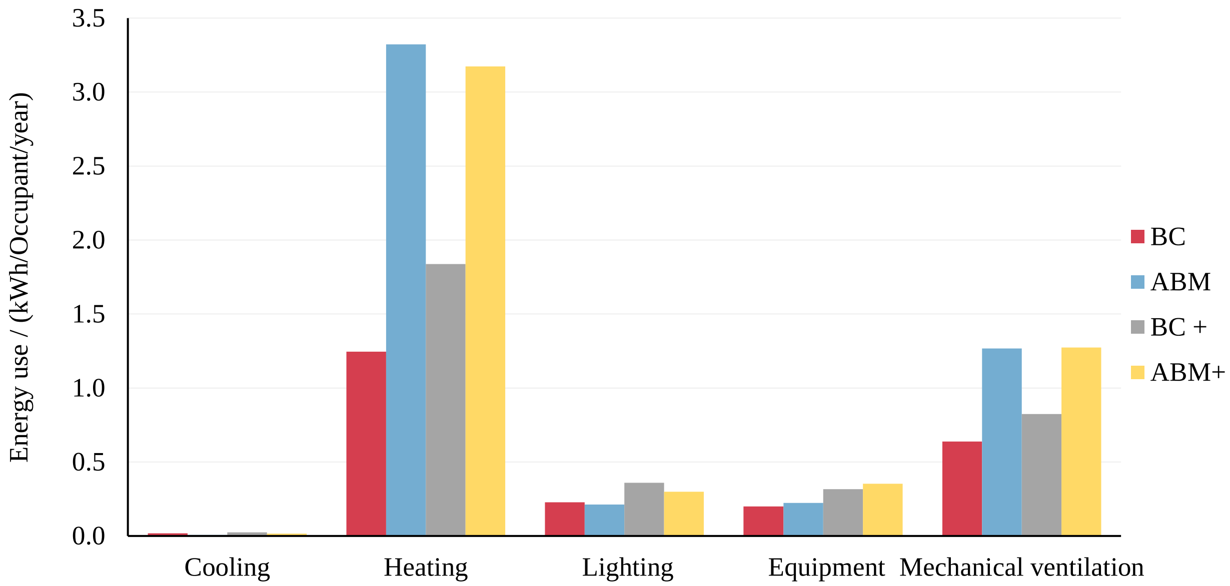

Figure 4.27. Comparison between energy used by the total number of occupants present in a year in different categories between four models

Figure 4.28 shows the energy use intensity in different categories for four models

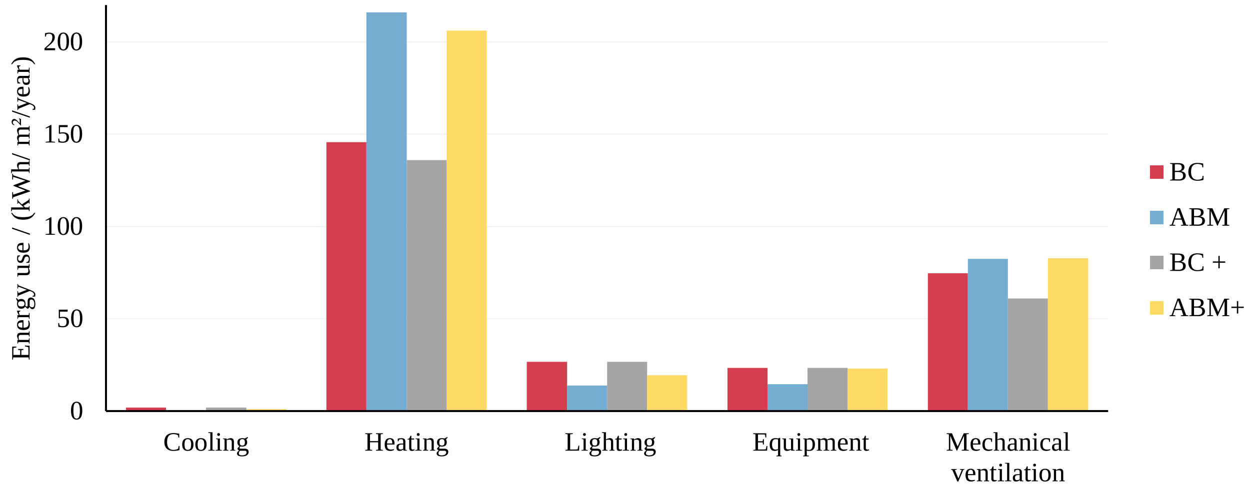

Figure 4.28. Energy use intensity in different categories for BC, BC+, ABM and ABM+

Figure 4.29 illustrates the difference in reported energy usage when using (kWh/Occupant/year) compared to EUI when comparing ABM to BC and ABM+ BC+. It can be observed that the comparison between ABM+ and BC+ showed a positive difference in different categories indicating that even with relatively similar models, energy usage reported by (kWh/Occupant/year) is higher compared to EUI.

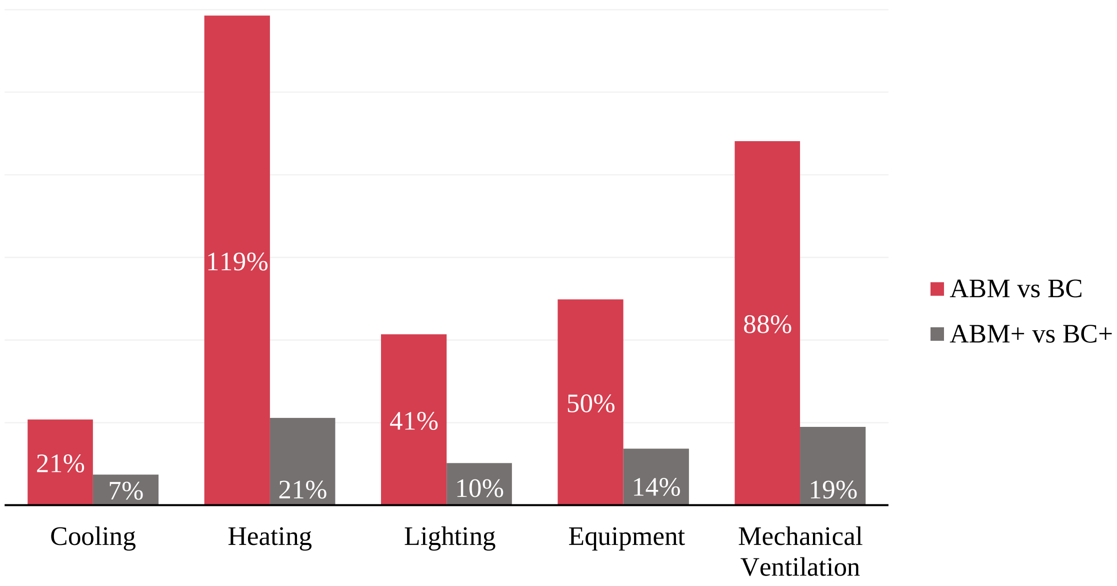

Figure 4.29. Comparison between the performance gap measured using (kWh/Occupant/year) vs EUI in different categories between the four models

Figure 4.30 indicates that, on average, the energy used by lighting decreased by 27 % for ABM+ compared to BC. The reduction in lighting energy use for ABM was 48 % in comparison.

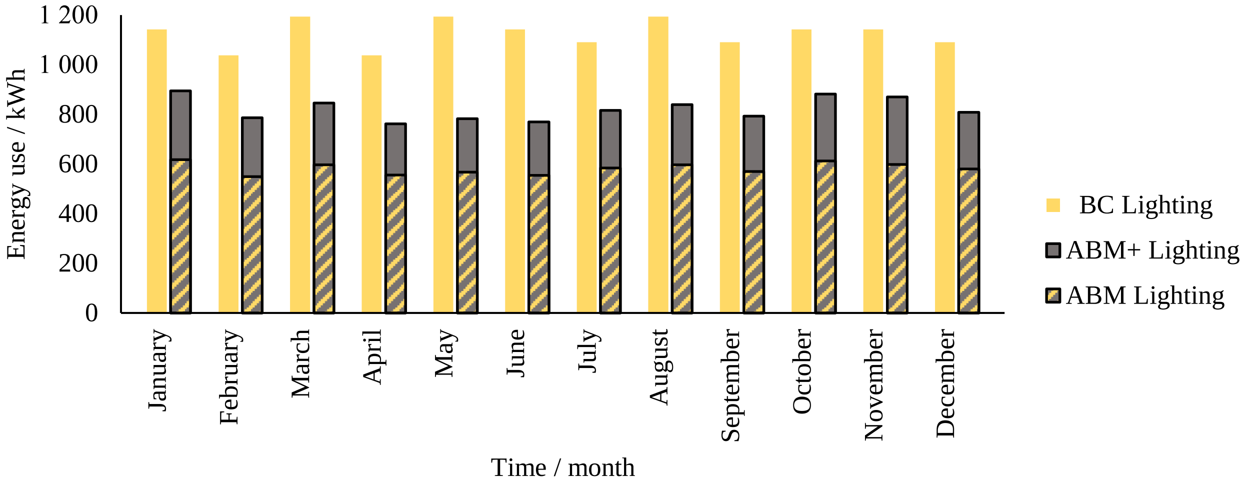

Figure 4.30. Comparison between the total energy used for lighting in 3 modeling scenarios (BC and BC+ had the same energy use for lighting; therefore, there was no difference between them for this comparison)

Figure 4.31 shows that energy from equipment use decreased by 2 % for the ABM+ compared to BC but increased by 2 % and 6 % in April and July, respectively, and remained the same in September and October. However, there was a uniform reduction pattern in equipment energy use for ABM, with 38 % compared to BC.

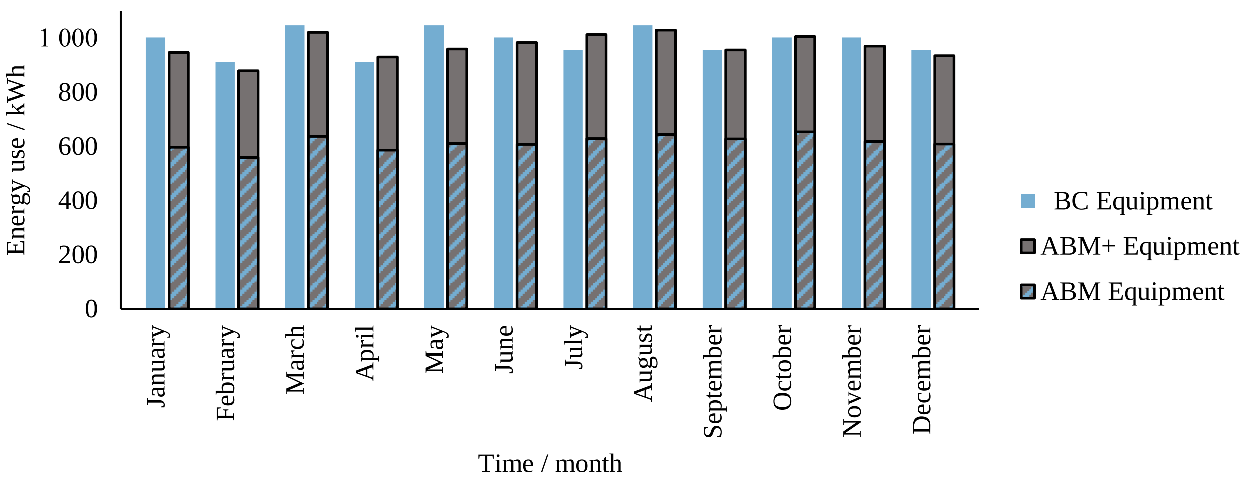

Figure 4.31. Comparison between the total energy used for equipment in 3 modeling scenarios (BC and BC+ had the same energy use for equipment; therefore, there was no difference between them for this comparison)

4.4.2 Regression analysis

In order to investigate the predictability of lighting and equipment usage based on occupancy, a linear regression analysis was performed. Figure 4.32 shows the linear regression of lighting and equipment use based on their total energy use relative to occupant count for the whole building. Occupancy is a better predictor of equipment use compared to lighting usage in this analysis.

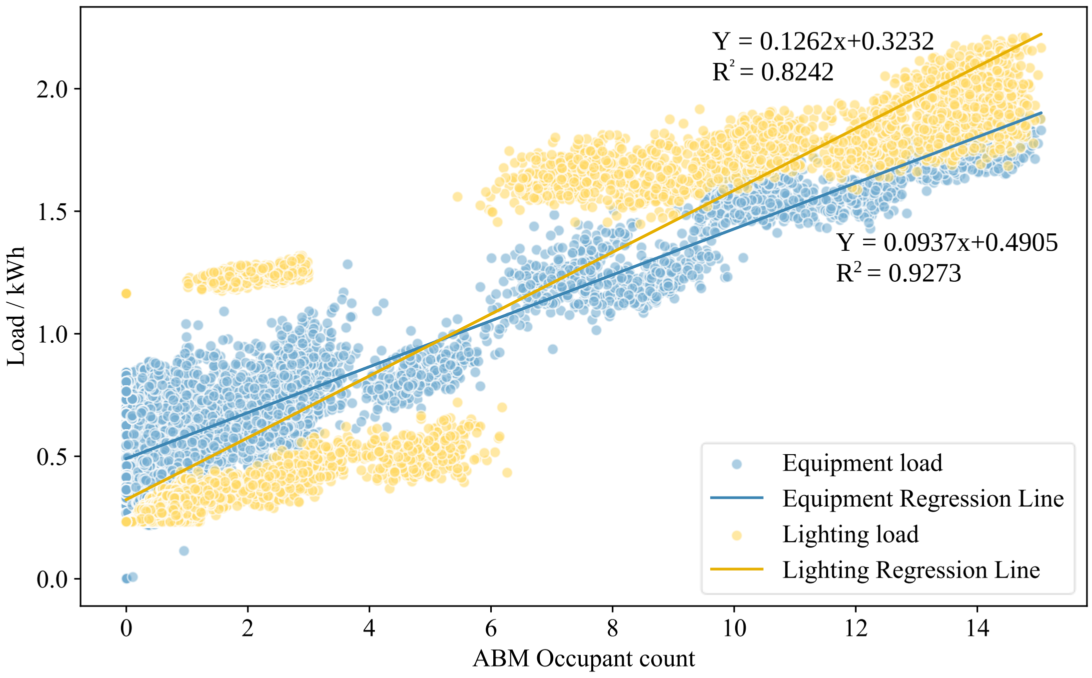

Figure 4.32. Regression analyses of equipment and lighting schedules in relation to ABM occupant count

4.4.3 Analysis of three office types

4.4.3.1 Room 31

Room 31, with a 41.53 m² area as the biggest room, only contained one occupant with an immediate equipment turn-off behavior. Figure 4.33 represents lighting and equipment use and their correlation with occupancy count. Occupancy was a better predictor for lighting use for this room. Occupancy in ABM was generated at a 5-minute interval. However, the output from Energyplus reported the results on an hourly basis; therefore, an occupant had to be present for every 12 time-steps of an hour for the occupancy to be registered for that hour, explaining the values for the x-axis.

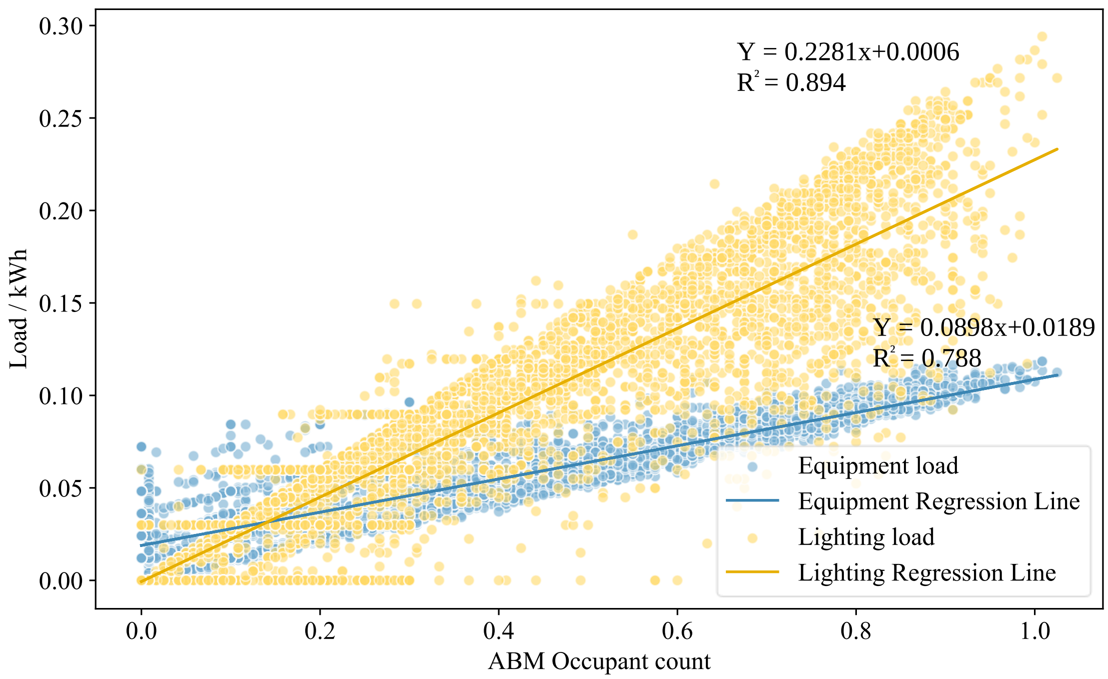

Figure 4.33. Regression analyses of equipment and lighting schedules in relation to ABM occupant count for room 31

Figure 4.34 shows the cumulative distribution function of annual equipment load for room 31 in BC and ABM.

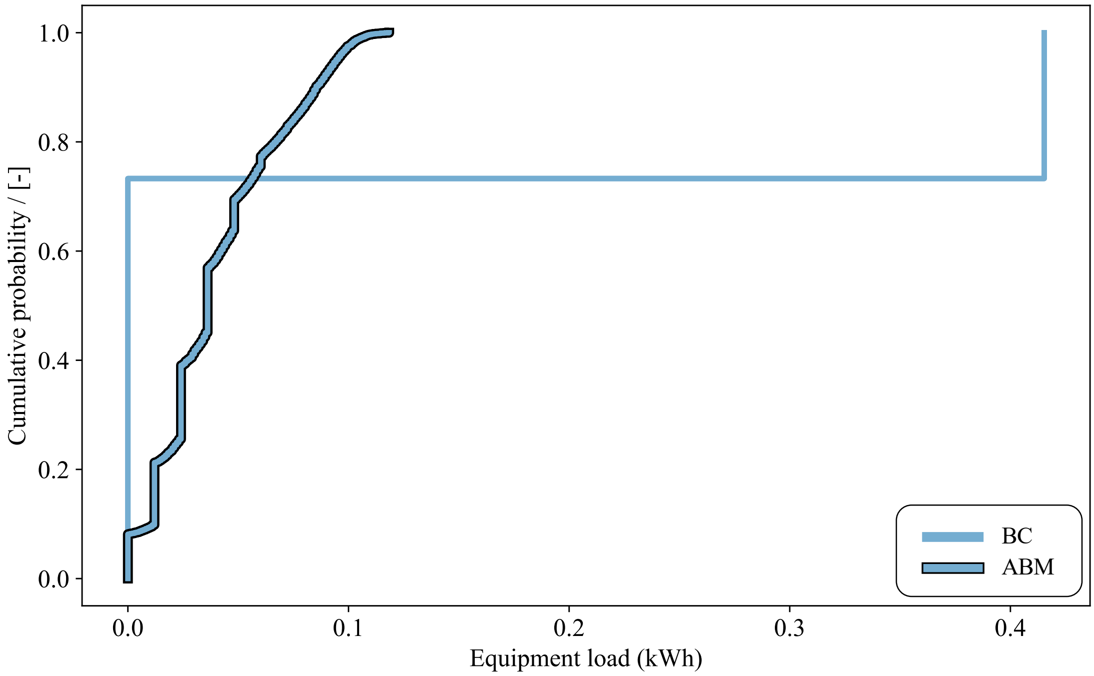

Figure 4.34. Cumulative distribution function of the total equipment load for BC and ABM

Figure 4.35 shows the cumulative distribution function of the annual lighting load for room 31 in BC and ABM.

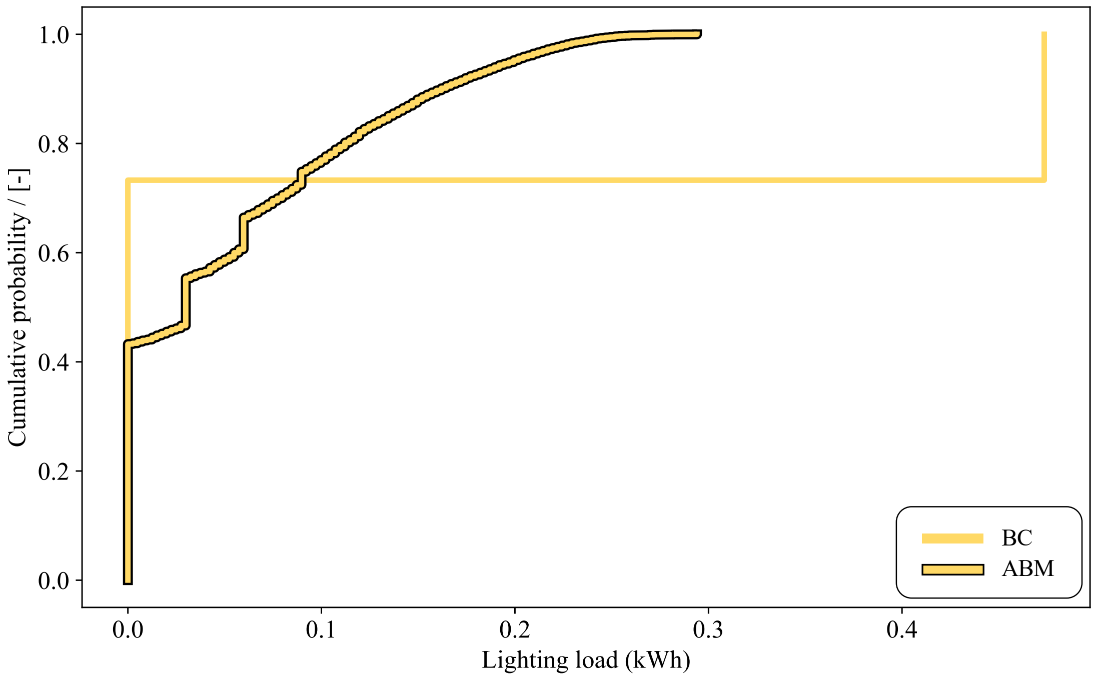

Figure 4.35. Cumulative distribution function of the total lighting load for room 31 in BC and ABM

4.4.3.2 Room 35

Room 35, while having the typical size of 20 m², was occupied by two people who had both chosen to turn off the equipment after one hour as their behavior. Figure 4.36 shows the equipment and lighting usage and their correlation with occupancy. Lighting energy usage had a stronger correlation with occupancy count.

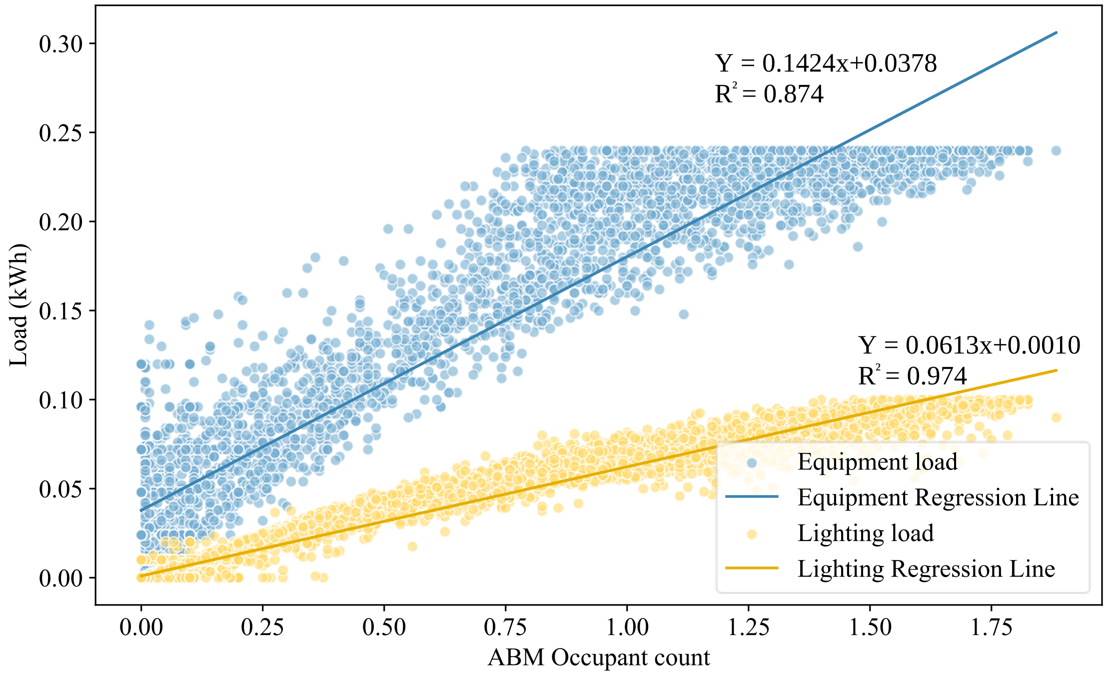

Figure 4.36. Regression analyses of equipment and lighting schedules in relation to ABM occupant count for room 35

Figure 4.37 displays the cumulative distribution function of annual equipment use in room 35 in BC and ABM. BC, with an occupant density of 20 m² /person, only contained one occupant. Equipment usage in ABM reached a higher peak load as a result of having two occupants and despite having a lower equipment load.

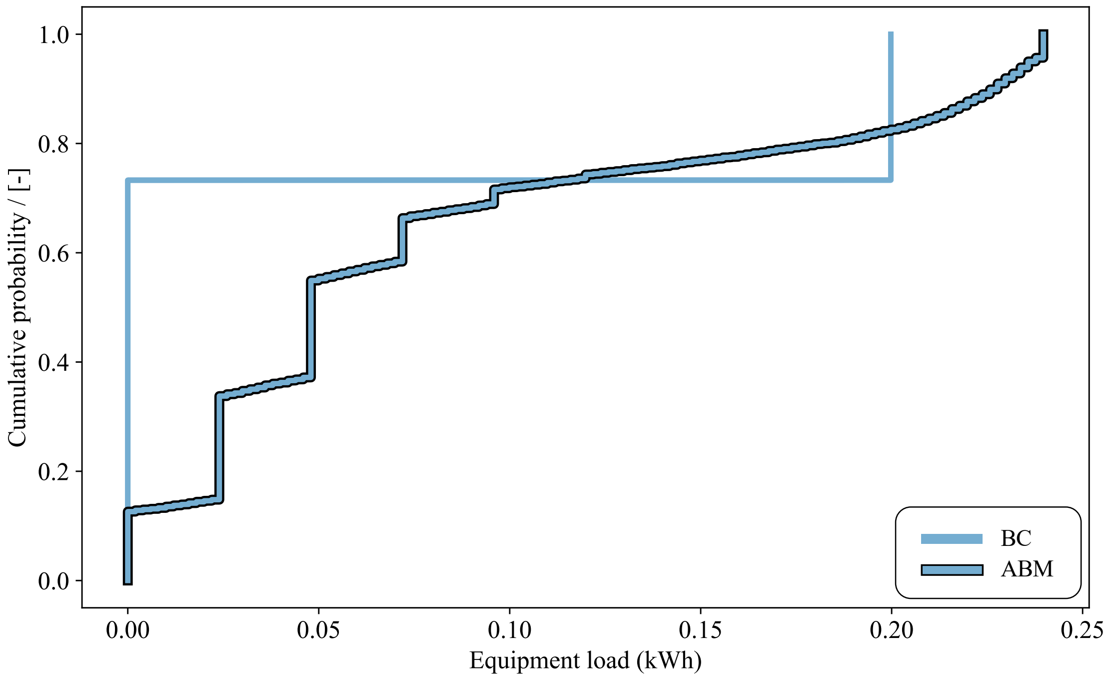

Figure 4.37 Cumulative distribution function of the total equipment load for room 35 in BC and ABM

Figure 4.38 represents the cumulative distribution function of annual lighting use in room 35 for BC and ABM. More efficient lighting loads and a more responsive turn-off behavior for lighting loads showed a lower peak load for the lighting while the occupancy count was higher.

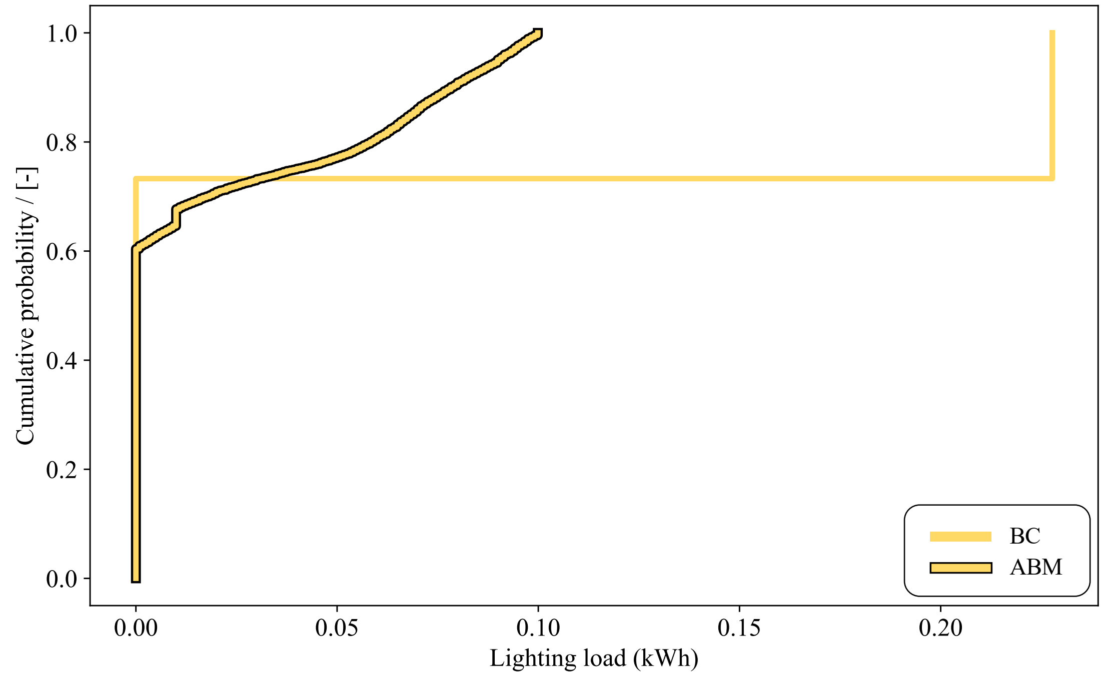

Figure 4.38. Cumulative distribution function of the total lighting load for room 35 in BC and ABM

4.4.3.3 Room 40

Only one occupant was occupying room 40 with an area of 20 m², equipment was selected to turn off after six hours for this room. Figure 4.39 demonstrates the equipment and lighting usage and their correlation with occupancy. Occupancy was a strong predictor of lighting usage.

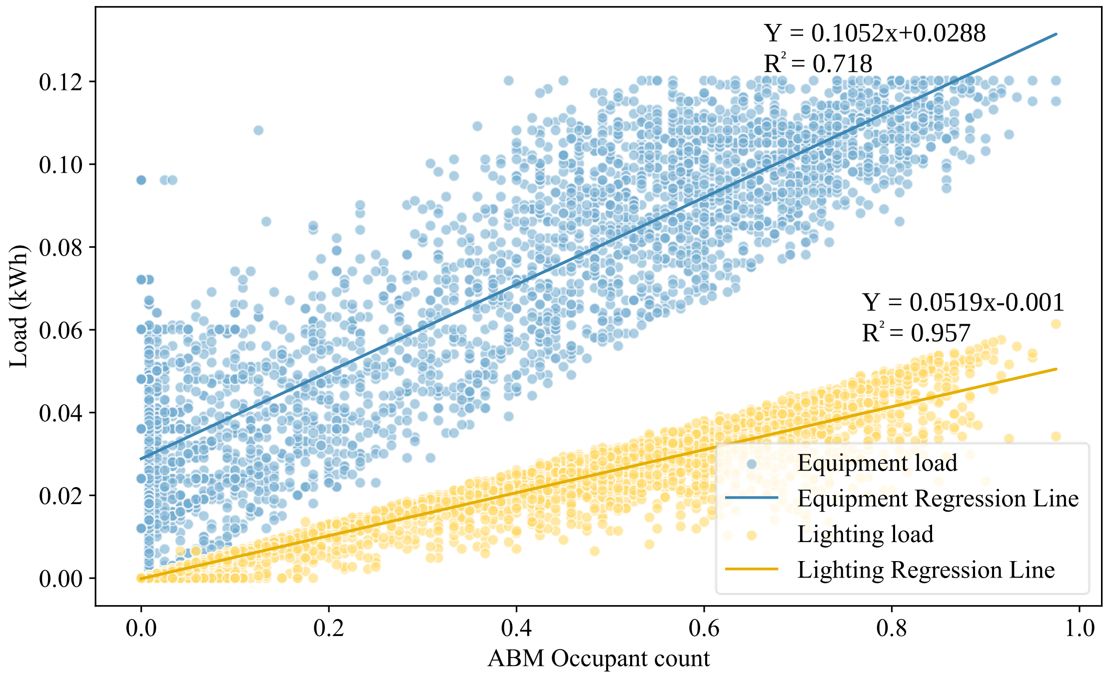

Figure 4.39. Regression analyses of equipment and lighting schedules in relation to ABM occupant count for room 40

Figure 4.40 shows the cumulative distribution function of the annual equipment load for room 40 in BC and ABM.

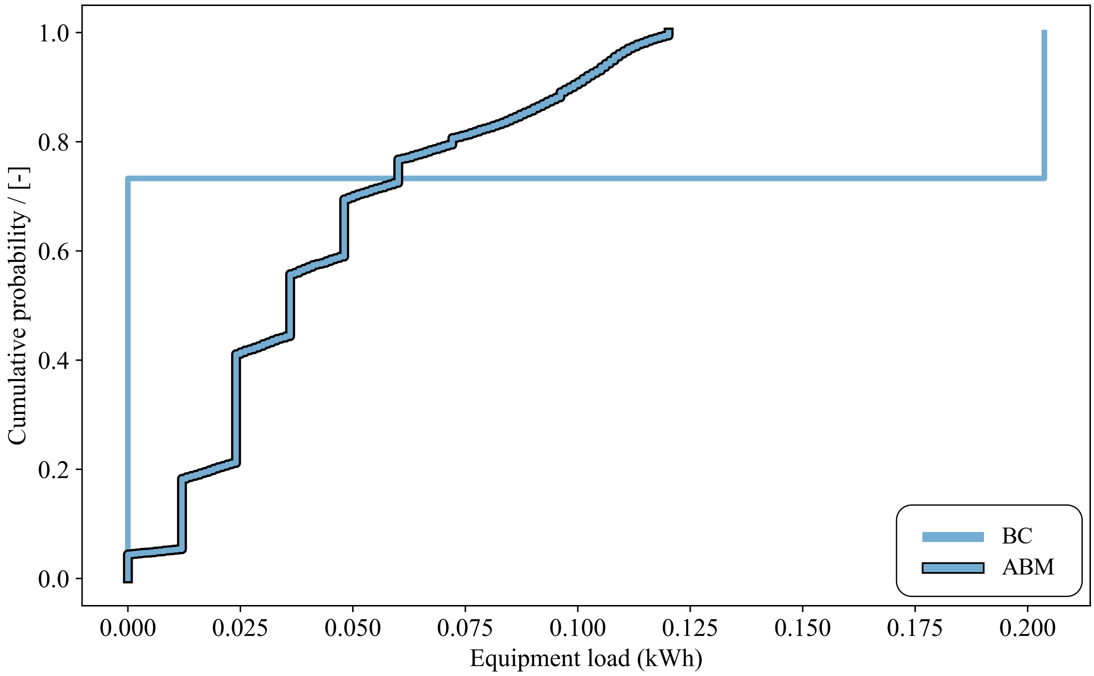

Figure 4.40. Cumulative distribution function of the total equipment load for room 40 in BC and ABM

Figure 4.41 shows the cumulative distribution function of annual lighting usage of room 40 in BC and ABM.

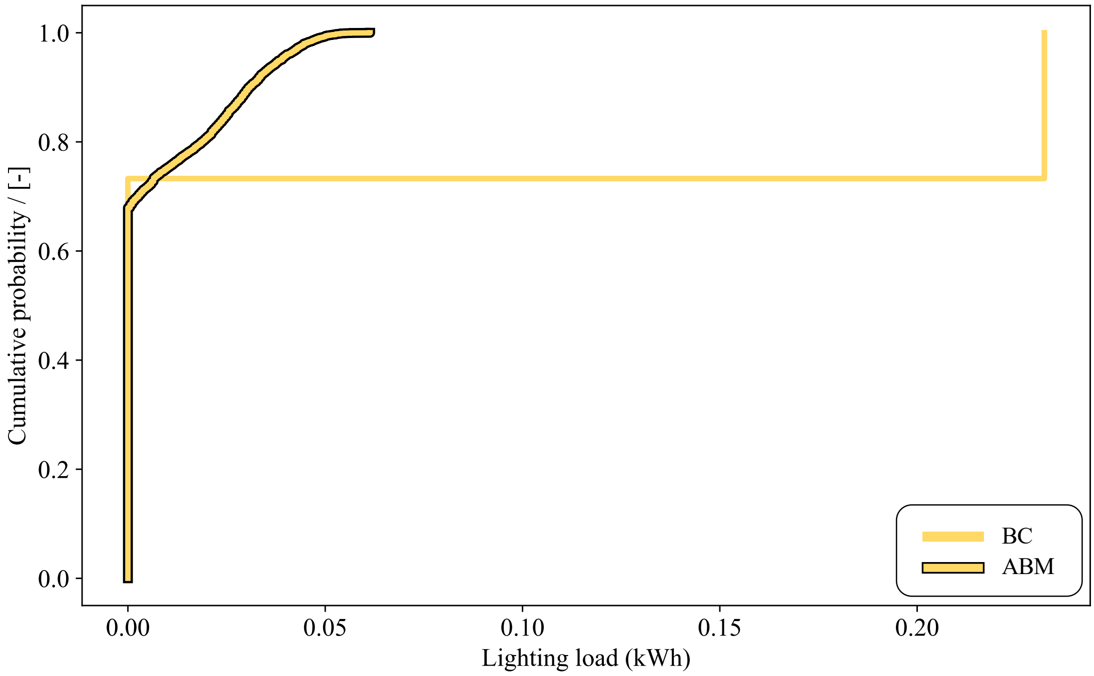

Figure 4.41. Cumulative distribution function of the total lighting load for room 40 in BC and ABM

5 Discussion

5.1 Modeling approach

The decision for the right modeling approach or a combination of different approaches was boiled down to the limitations posed by occupant modeling tools. While obFMU provided the opportunity to create an agent-based model, it relied heavily on a fixed time-step approach limiting holidays to the entire model instead of each occupant and, therefore, lacked the capability to model random absences such as sick leaves or personal absence periods like vacations. Therefore, a discrete event approach was not possible. Additionally, analyzing the energy usage feedback loops of different elements inside the building was limited to EnergyPlus's outputs; thus, a system dynamic approach was not realizable.

An agent-based model, on the other hand, allowed for more flexibility, with stochastic models chosen for the behaviors that required one and static schedules selected for systems that were not controllable by the occupants. Additionally, the desired resolution of each zone and person as an agent was applicable, adding to its benefits. However, the stochastic generation of occupancy and behaviors meant that the results from different runs were different; this difference was mostly caused by the probabilistic generation of the location for each occupant at each run resulting in different loads. The standard deviation from the 10 runs was low in all categories regardless. Furthermore, contrary to the popular belief that a simulation with similar outputs in each run is reliable, in reality, a building never performs the same, yet stochastic modeling is considered uncertain.

5.2 Occupant profiles

Data from the occupancy sensor was not able to differentiate between different individuals and measure the occupancy count in shared offices. Therefore, the same arrival and departure hours and their variation were assigned for occupants in shared spaces. Furthermore, no occupants were considered for rooms 38 and 46, and therefore, no occupant model was created for them due to inaccessibility to their occupants at the time of conducting the survey and lack of useable data.

The results from the survey revealed that only lights, windows, equipment and blinds were utilized by the occupants. The behavior for turning off the lights was modeled to replicate the real-life automatic light-off switch connected to the occupancy sensor that would turn off the lights when no occupancy was detected.

While some participants did not choose an answer for the question in the survey regarding equipment usage, the model for turning on the equipment was used for all the occupants as the lack of an equipment turn-on behavior resulted in zero equipment load for the whole simulation period creating an unrealistic behavior for an office space. Additionally, the model for immediately turning off the equipment when occupants leave the room was only applied to the occupants who did not answer the equipment turn-off behavior questions to prevent the equipment from being left on for the whole simulation period. Furthermore, standby or power-saving models were not considered for the equipment turn-off model.

A thin curtain was installed for each window that allowed light to enter the room and the orientation of the office windows towards the north meant that they were rarely used, as was observed in different visits and from the survey answers. Therefore, to simplify the model, blind usage behavior was only applied to the occupants who had selected the behavior and the rest of the windows had no blinds applied to them.

Window closing model at the end of the workday was implemented with the assumption that no occupant would leave their window open when leaving the office at the end of the day. Furthermore, limitations for window opening temperature range were set in EnergyPlus; this meant that windows could only be open according to the heating and cooling set points in order to prevent an overlap between the heating or cooling system being turned on when windows were open.

5.3 The performance gap

5.3.1 Total energy use

Results from the simulation showed that there is a discrepancy between the energy usage of BC and ABM. Energy used for heating had the most significant impact on this difference with the selection of a heating and cooling system that was active 24 hours every single day. Consequently, increased heating load resulted in increased infiltration and transmission due to higher temperature differences between inside and outside, leading to higher pressure differences. Furthermore, the increase in mechanical ventilation can be attributed to the choice of the HVAC system as it delivered heating through air. Additionally, as only a few occupants had chosen a window opening behavior, natural ventilation also had a noticeable decrease, while BC, with a higher number of occupants and a dynamic schedule, had more variety in the operation of windows.

The decrease in people load followed the decrease in occupancy count from 25 to 16 with a significantly less concentrated occupancy in ABM. Furthermore, as a result of the occupant behavioral models, lower loads, and fewer occupants, a noticeable reduction in lighting and equipment energy use was observed. As evident through the shape of the curve of their cumulative distribution function, the usage pattern varied more in ABM.

Operative temperature for both models stayed within the intended range; however, as BC had a lower set point for heating and a higher set point for cooling on off-hours, the range of the overall operative temperature was larger in general while it was similar to ABM in working hours. Heating and cooling peak loads showed similar patterns, happening during the same day and peaking at relatively similar hours; however, ABM had a smoother heating and cooling peak load as a result of an always-on HVAC system and fewer occupants and gains from lighting and equipment.

5.3.2 Occupant-centric metric

Relying on a performance metric tailored to the occupants' energy use revealed that a heating system not designed to consider occupancy results in an even greater performance gap when the occupancy count is lower in reality compared to the standards.

Stochastic generation of lighting and equipment usage was not as impactful when the new metric was used; however, the reversal trend of equipment usage initiated further investigations as ABM had a lower occupant count and lower equipment loads compared to BC. This was achieved by assigning the same loads for lighting and equipment in ABM as BC and performing a comparative analysis.

5.3.3 Comparative analyses and regression

The attempt to lower the differentiating variables in both models resulted in the total performance gap between ABM+ and BC+ being 52 % using (kWh/Occupant/year) while EUI reported 33 %. While the reduction from 116 % and 20 % in ABM and BC to 52 % and 33 % in ABM+ and BC+ was significant, the remaining gap between the reported results of the new metric and EUI for the new models revealed the insensitivity of EUI to the number of occupants.

The reduction in heating load for ABM+ compared to BC+ revealed that occupancy count was responsible for more than half of the increase in heating load for ABM compared to BC, and the rest were attributed to the operative schedule and set points of the HVAC system. This was in line with the findings of Mahdavi & Tahmasebi (2016) where a realistic assumption in regards to the number of occupants and not stochastic generation of occupancy was responsible for the accurate prediction of heating and cooling loads. Also, increased loads for lighting and equipment resulted in more cooling and less heating in ABM+ compared to ABM contributing to this reduction.

Equal lighting and equipment load as BC only accounted for half of the reduction previously observed in lighting energy use, showing that the generated probabilistic model was responsible for the other half. On the other hand, the reduction in equipment energy use in ABM proved to be highly reliant on the equipment load, indicating more frequent utilization of the equipment in ABM, contributing to the increased energy use.

The results from the regression analysis of the selected rooms also showed a strong correlation between the lighting and equipment schedule and occupancy, confirming the correct operation of these behaviors as their turn-on and turn-off actions were tied to occupancy, while the cumulative distribution function illustrated the variety in energy used for lighting and equipment throughout the year.

5.4 Accuracy of prediction

Using (kWh/Occupant/year) as the performance metric revealed that occupants in ABM were using the equipment more frequently; furthermore, the comparative analysis also revealed that the overall energy use reduction for equipment was connected to the defined loads instead of occupants' behavior. However, the results of the regression analyses for the equipment and lighting load for the whole building suggested a strong correlation between equipment load and occupancy and a lower correlation for lighting. Upon further investigation with the regression analyses of rooms, it was observed that lighting usage had a more significant correlation to the presence of occupants. This finding was in line with the broader picture of the inner workings of the building; as occupants had no control over the corridor lights, the dependency on occupants' presence for lighting usage would be less than equipment usage when investigating the whole building.

Regression analysis for room 40 showed a lower dependency of equipment usage on occupancy compared to lighting usage. This was mainly attributed to the behavior selected for the equipment in this room which was set to turn off the equipment after six hours of not detecting any occupants. This resulted in periods where no occupants were present in the room while the equipment was still on, as in the next six hours, an occupant would be detected in the time-step of the simulation. This was not far from reality as it was expected that occupants would leave their devices on when they took a short break and left the room or had to leave the office but were planning to return later during that day. However, regression results from room 31 with immediate equipment turn-off behavior showed a similar operation pattern while it was expected to perform as well as lighting.

Therefore, it was noticed that setting behavior event types as leaving room for the equipment turn-off behavior did not perform as expected. Figure 4.9 shows the schedule for equipment load in a sample week; as evident in this schedule, there were periods after working hours when no occupancy was detected for periods longer than six hours with the equipment left turned on. Finally, through debugging the output of obFMU, the turn-off behavior for equipment was observed to not initiate at some time-steps. The same problem was also observed in other behavioral models afterward. No specific pattern for this issue was found, as the same behavior worked correctly for the majority of the time, increasing the time-step of the model and obFMU was the only option that decreased these occurrences.

6 Conclusion

6.1 Aim and objectives

An occupant behavioral model was developed in order to investigate the significance of the stochastic nature of occupants in building performance. It was evident that in the case of an office space where occupants had zero control over the system with the highest energy consumption, using the correct loads and set points had a more meaningful impact on the overall energy use of the building than simulating the usage pattern of different systems probabilistically. However, employing a stochastic prediction for systems that occupants were able to interact with and had control over provided a more detailed usage pattern resulting in lower energy use. The key conclusions from this study are:

- A literature review was performed and main elements from the field of occupant behavioral modeling were described.

- Data collection was made possible by using data from occupancy sensors, conducting a survey and observations during site visits.

- Agent-based modeling was found to be the most suitable approach as it allowed for a combination of different levels of details and resolutions. Having the highest resolution reduced the errors caused by abstraction, while the increased parameters introduced new challenges in understanding the origin of the new results. Conversely, a major drawback of this approach was access to accurate and detailed information needed for high-resolution modeling.

- (kWh/Occupant/year) was utilized and showed a greater performance gap in comparison to EUI. Additionally, utilizing suitable performance metrics was able to speed up the analysis by providing new perspectives that were only noticeable through deeper inspections and better explaining the inner dependencies of the model.

- The accuracy of the prediction was investigated using a comparative and regression analysis and the issues were discovered through debugging the results.

- The lack of access to a system prevents an occupant behavior model from having any impact on it, but having the correct information about its schedule and loads would result in a more accurate model. However, occupants may not tolerate the lack of freedom they have in their environment and try to retain some level of control; this, in practice means that investigations about systems that they can’t control can reveal other methods in which they try to make themselves and the space they occupy more comfortable which creates new possibilities for occupant behavioral modeling.

- Whether an occupant behavioral model is the right approach depends on several factors, including the overall goal of the simulation, time constraints, and limitations regarding the occupant modeling tools. However, it is safe to assume that creating an occupant behavioral model for the system with the highest consumption can be beneficial if the occupants can control the system or if the system is sensitive to occupant count.

It is undeniable that using the correct inputs when creating the geometry and physical properties of an energy model is of the utmost importance and the accuracy and complexity of current programs used for simulation are at their highest, yet with respect to performance, the way a building is utilized is pivotal.

6.2 Future work

1) Creation of an agent-based model that is capable of modeling the interaction of occupants with each other, behaviors observed only when occupants are present in a group and occupants who are capable of learning from previous events and creating new decisions for similar events in the future

2) Analyzing the performance at a larger scale, for example the entirety of V-huset building, as it contains different sections with unique use cases

3) Streamlining the process of occupant profile creation and adjustments needed to allow co-simulation with obFMU and EnergyPlus through custom code

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Appendix A

Table A. 1. Arrival and departure times

Zone name	First or Last recorded state	Peak value/ (Time/h:m)	STD based on peak value/ (Time/m)
Room 31	First	08:57	122
Room 31	Last	16:46	173
Room 32	First	08:30	143
Room 32	Last	16:51	184
Room 33	First	08:28	89
Room 33	Last	15:45	138
Room 34	First	08:51	123
Room 34	Last	18:27	235
Room 35	First	08:37	116
Room 35	Last	16:12	139
Room 36	First	08:18	113
Room 36	Last	17:07	146
Room 37	First	08:13	139
Room 37	Last	16:25	176
Room 39	First	08:14	184
Room 39	Last	16:29	148
Room 40	First	08:20	172
Room 40	Last	15:38	143
Room 41	First	08:16	187
Room 41	Last	16:17	173
Room 42	First	08:25	91
Room 42	Last	15:31	110
Room 44	First	09:30	141
Room 44	Last	18:23	198
Room 45	First	08:40	144
Room 45	Last	17:13	154
Room 53	First	08:29	105
Room 53	Last	16:32	170

Appendix B

Table B. 1. Survey Questions

	Questions	Answers
	Occupancy	
2	On average, how many meetings do you attend per day?	0-6 and more
3	If the answer to the previous question is not zero, which days of the week do you typically have meetings?	Days of the week
4	If the answer to the first question is not zero, how many people are usually in your meetings?	Range of numbers up to 16
5	If the answer to the first question is not zero, on average, what percentage of your meetings typically last for each of the following durations? (The total percentage should equal 100 %). For example, 90 % of your meetings might last for 60 minutes and 10 % for 120 minutes.	Less than 30 minutes, 30, 60, 90, 120 minutes
6	Besides yourself, do others enter or occupy your office or workspace during the workday, even if they aren't directly using your equipment? This could include managers, administrators, colleagues, etc.	Yes/No
7	If the answer to the previous question is "Yes": Approximately what percentage of the workday do others spend in your office or workspace and what is their role? (You may choose more than one answer)	Blank field
8	When do you typically take your breaks (Lunch, coffee break, etc.) during the workday? Include both the time of day you usually take them and their duration in minutes. (You may choose more than one answer and please specify each one separately)	Blank field
9	Approximately what percentage of your workday do you spend in the following locations? (The total percentage should equal 100 %). For example, you might spend 90 % of the workday in your own office and 10 % in outdoors.)	Your own office, other offices, Meeting rooms, Auxiliary rooms (break rooms, storage, etc.), Outdoors
10	Approximately how long do you typically spend in each of these locations during a single visit?	Your own office, other offices, Meeting rooms, Auxiliary rooms (break rooms, storage, etc.), Outdoors
	Behavior and Interaction	
11	On average, how would you rate the temperature in your usual workspace?	7 scale from cold to hot
12	If the temperature in your workspace is causing you discomfort, what is the main cause of the discomfort? (You may choose more than one answer)	Conditional cold and hot temperature situations
13	On average, how would you rate the visual comfort (natural and/or artificial light levels and distribution that would let you see easily and clearly), in your usual workspace?	7 scale
14	If you are not satisfied with the visual comfort in your workspace, what is the main cause for visual discomfort? (You may choose more than one answer)	
15	On average, how would you rate the indoor air quality satisfaction in your usual workspace?	7 scale
16	If you are not satisfied with the indoor air quality in your workspace, what is the main cause for the discomfort? (You may choose more than one answer)	Stagnant air, Bad scents
17	What's your gender?	Male/Female/ No answer
18	What is your age?	Range from 18 to 65+
19	What is your current employment status?	Full time, Part time
20	What is your employment role? (Please specify if "other" is selected)	Employee, Manager, Student, Professor
21	What type of office do you work in?	Shared office (max 6 people), Shared office with another person, Single office

22	Are you able to adjust your clothing (removing/adding extra layers) based on temperature in your workplace?	Yes/ No
23	How would you rate the extent to which you are allowed to interact with control systems (windows, heating/cooling, blinds/curtains, lights) in your working space?	Windows, Cooling/heating, Blinds/Curtains, Lights 7 scale answer
24	How confident are you in your ability to use the control systems (windows, heating/cooling, blinds/curtains, lights) in your workspace?	Windows, Cooling/heating, Blinds/Curtains, Lights 7 scale answer
25	How inclined are you to use (windows, heating/cooling system, blinds/curtains, lights) and remove/add extra layers of clothing, to make yourself comfortable or save energy in your workspace?	Windows, Cooling/heating, Blinds/Curtains, Lights, Removing/adding extra layers of clothing 7 scale answer
26	How many times did you perform these actions to make yourself comfortable and/or save energy during last year? Opening window when feeling hot Closing window when feeling hot/cold Opening window for airing spaces Opening the blinds/curtains to provide natural lighting Closing the blinds/curtains to prevent glare Closing the blinds/curtains to prevent overheating Turning on the heater when feeling cold (winter) Turning off the heater when feeling too hot (winter) Turning on the cooling/fans when feeling hot (summer) Turning off the cooling/fans when feeling too cold (summer) Removing/adding extra layers of clothing Turning on the lights when it gets too dark Turning off the lights when leaving the room Turning on the lights when entering the room Turning on the equipment/computer when entering the room Turning off the equipment/computer when leaving the room for a short time (e.g., 1 hour) Turning off the equipment/computer when leaving the room for a long time (e.g., 6 hours)	Never, Once a month, Once a week, more than once a week, Once a day, more than once a day

Appendix C

Snippet from the Behavior assignment python code

```
q13 =  {
    "1": {"Intensity" : "Very High" },
    "2": {"Intensity" : "High" },
    "3": {"Intensity" : "Medium" },
    "4": {"Intensity" : "Low" }
}

q14 = {
    "1" :{
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Systems": "Lights"
    },
    "2" :{
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Systems": "Lights"
    },
    "3" :{
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Systems": "ShadesAndBlinds"
    },
    "4" :{
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Systems": "ShadesAndBlinds"
    },
    "5" :{
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Systems": "ShadesAndBlinds"
    },
    "6" :{
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Systems": "ShadesAndBlinds"

}
,
}
```

Fig C.1: translation layer for question 13 and 14 of the survey

```
XML_Library = {
    "1-Gunay_2015_light_on_arrival": {
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "EventType": "EnteringRoom",
        "Needs": "Visual",
        "Actions": "TurnOn",
        "Systems": "Lights",
        "Description": "Probability of switching on the lights based on desk illuminance at arrival based on Reinhart 2004 mod
    },
    "2-Gunay_2015_light_on_arrival_lunch": {
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "EventType": "EnteringRoom",
        "Needs": "Visual",
        "Actions": "TurnOn",
        "Systems": "Lights",
        "Description": "Probability of swithing on the lights based on desk illumminance at arrival and after lunch based on H
    },
    "3-Gunay_2015_light_on_intermediate": {
        "Drivers": "RoomWorkPlaneDaylightIlluminance",
        "Needs": "Visual",
        "Actions": "TurnOn",
        "Systems": "Lights",
        "Description": "Probability of swithing on the lights based on desk illumminance during the day (5 mins timestep) base
    },
    "4-Gunay_2015_window_close_arrival": {
        "Drivers": ["OutdoorDryBulbTemperature", "RoomAirTemperature"],
        "EventType": "EnteringRoom",
        "Needs": "Thermal",
        "Actions": "TurnOff",
        "Systems": "Windows",
        "Description": "Predicting window closing at arrival based on Haldi Robinson
2009 model",     },
    "5-Gunay_2015_window_close_cooling_room": {
        "Drivers": "RoomAirTemperature",
        "Needs": "Thermal",
        "Actions": "TurnOff",
        "Systems": "Windows",
        "Description": "Predicting window closing when indoor temp is less than 30C based on Yun Steemers 2008 model",
    },
```

Fig C.2: Some of the models from the XML library imported as dictionaries.

```
df_q13 = df.loc[df["Questions"] == "13", answer_col]
df_q14 = df.loc[df["Questions"].isin(["14-1","14-2","14-3","14-4","14-5","14-6"]), answer_col]

need_change2 = (1.0,2.0,3.0,4.0)                #range of acceptable answer for question 13
visual_need =  (1.0,2.0,3.0,4.0,5.0,6.0)        #range of acceptable answer for question 14

#Visual
visual_discomfort_added = False
for answer in df_q13:
    if answer in need_change2 :
        answer_str = str(int(answer))
        intensity = q13[answer_str]["Intensity"]
        match_found_in_df_q14 = False

        for answer in df_q14:
            if answer in visual_need:
                match_found_in_df_q14 = True
                answer_str = str(int(answer))
                output2 = q14[answer_str]
                need_results.append({"Visual": output2, "Systems": output2["Systems"] ,"intensity2": intensity})
                visual_discomfort_added = True

        if not match_found_in_df_q14 :
            need_results.append({"Visual": "Vidual need not met, but no need specified", "intensity2": intensity})
        break
    else:
        need_results.append({"Visual": "Nothing", "intensity2": None})
```

Fig C.3: function for identifying if the participant has a visual need and if the answer is positive what the visual need is

```python
def intent (df, answer_col):

    '''
This function assesses user's intent to use Window, HVAC/Thermostat, Blinds, Lights

    '''

    df_q25_detailed = df[df["Questions"].isin(["25-1", "25-2", "25-3", "25-4"])]
    options = (3.0,4.0,5.0,6.0,7.0)              #range of acceptable answer for question 25
    intent_results = []

    for _, row in df_q25_detailed.iterrows():
        question_part = row["Questions"].split("-")[-1]
        answer = row[answer_col]
        if answer in options:
            answer_str = str(int(answer))
            final3 = q25[question_part]["Systems"]
            Intent = q25[question_part]["Intensity"][answer_str]
            intent_results.append({"Systems": final3, "Intent level": Intent})

    return intent_results
```

Fig C.4: function for identifying participant's intent

```python
def second_phase(need_results, access_results, knowledge_results, intent_results):

    '''
This function takes the needs of the user from the first function and checks if for a given need,
they have the access to, knowledge to work with and intent to use the system that corresponds to that need
and returns only those needs that pass all these three functions
    '''
    part2_results = []
    KAI = [access_results, knowledge_results, intent_results]
    simplified_kai = set()

    for kai_results in [access_results, knowledge_results, intent_results]:
        for entry in kai_results:
            systems = entry['Systems']
            if isinstance(systems, tuple):
                simplified_kai.update(systems)
            else:
                simplified_kai.add(systems)


    for need_dict in need_results:

        systems_in_need = need_dict.get('Systems')
        if systems_in_need:
            if isinstance(systems_in_need, tuple):
                systems_in_need_set = set(systems_in_need)
            else:
                systems_in_need_set = {systems_in_need}



            if systems_in_need_set & simplified_kai:
                part2_results.append(need_dict)
        else:

            for category, info in need_dict.items():
                if isinstance(info, dict) and 'Systems' in info:
                    systems_in_info = info['Systems']
                    if isinstance(systems_in_info, tuple):
                        systems_in_info_set = set(systems_in_info)
                    else:
                        systems_in_info_set = {systems_in_info}

                    if systems_in_info_set & simplified_kai:
                        part2_results.append({category: info})


    return part2_results
```

Fig C.5: function for identifying which needs of the participant passes the 3 checks

Appendix D

Table D. 1. Lighting and equipment load for each zone

Zone name	Lighting loads (W/m²)	Equipment load (W/m²)
2431	7.2	2.9
2432	5.2	6.3
2433	4.8	11.6
2434	5	6
2435	5	12
2436	3.4	6.2
2437	4.9	5.9
2438	3.2	5.9
2439	3.3	6.1
2440	3.2	5.9
2441	3.4	6.2
2442	2.5	4.7
2444	3	4.3
2445	5.2	9.6
2446	5.4	10.1
2448	3.8	5
2450	4	10
2451	3.1	2
2452	2.5	7.7
2453	4.2	10
Crorridor-ext	4.8	10
Corridor	11.4	10

Appendix E

Table E. 1. obCoSim properties

obXML_SpaceID	FMU_InstanceName
S1_31_Office	obm_Room_2031
S2_32_Office	obm_Room_2032
S3_33_Office	obm_Room_2033
S4_34_Office	obm_Room_2034
S5_35_Office	obm_Room_2035
S6_36_Office	obm_Room_2036
S7_37_Office	obm_Room_2037
S8_38_Office	obm_Room_2038
S9_39_Office	obm_Room_2039
S10_40_Office	obm_Room_2040
S11_41_Office	obm_Room_2041
S12_42_Office	obm_Room_2042
S13_44_Office	obm_Room_2044
S14_45_Office	obm_Room_2045
S15_46_Office	obm_Room_2046
S16_53_Office	obm_Room_2053
S17_48-Kitchen	obm_Room_2048
S18_50-Meeting_room	obm_Room_2050
S19_51-Printing_room	obm_Room_2051
S20_52-WC	obm_Room_2052
S21_Corridor-name	obm_Corridor
S22_Corridor-ext	obm_Corridor_ext

IsLeapYear	No
DayofWeekForStartDay	Monday
IsDebugMode	No
DoMovementCalculation	Yes
StartMonth	1
StartDay	1
EndMonth	12
EndDay	31
NumberofTimestepsPerHour	12

Table E.2. Full Specification of every occupant behavior based on obXML

Behavior	Drivers				Needs	Actions		Systems	
	Time	Environment	EventType	OtherConstraint		Interaction Type	Formula	Type	System Type
1) B_Light_Reinhart_Voss_2003_arrival	TimeofDay : Morning DayofWeek : All	RoomWorkPlaneDaylightIlluminance				TurnOn	$p = A + \frac{C}{(1 + exp(-B \times [Log_{10}(P1) - D])}$ CoefficientA: -0.00238 CoefficientB: -3.0965 CoefficientC: 1.0157 CoefficientD: 1.8536	Lights	OnOff
2) B_Light_Gunay_2015_Office	TimeofDay : Morning TimeofDay : Evening DayofWeek : All	RoomWorkPlaneDaylightIlluminance	EnteringRoom			TurnOn	$P = \frac{exp(A \times P1 + B)}{exp(A \times P1 + B) + 1}$ CoefficientA: -0.009 CoefficientB: 1.6	Lights	OnOff
3) Light_off_NoOcccupancy	TimeofDay : Morning TimeofDay : Evening TimeofDay : Afternoon DayofWeek : All		LeavingRoom	NoOccupantsInRoom		TurnOff	ConstantValue: 1	Lights	OnOff
4) B_Window_Haldi_Robinson_2008_Office_Tin	TimeofDay : Morning TimeofDay : Afternoon DayofWeek : All SeasonType: All	RoomAirTemperature	StayingInRoom			TurnOn	$P = \frac{exp(A \times P1 + B)}{exp(A \times P1 + B) + 1}$ CoefficientA: 0.220 CoefficientB: -5.64	Windows	Operable
5) B_Window_Haldi_Robinson_2009_Office_intermed		RoomAirTemperature OutdoorDryBulbTemperature				TurnOff	$p = \frac{exp(A \times P1 + B \times P2 + C)}{exp(A \times P1 + B \times P2 + C) + 1}$ CoefficientA: 0.026 CoefficientB: -0.0625 CoefficientC: -4.14	Windows	Operable
6) Window_opening_for_airing	TimeofDay: Morning TimeofDay: Afternoon DayofWeek: Weekdays SeasonType: All	RoomCO2Concentration			ParameterRangeMax: 600	TurnOn	$p = (1 - \exp(-dT \times ((P1 - A)/B)^{C})) \times [((P1 - A)/B > 0)]$ CoefficientA>500 CoefficientB>200 CoefficientC>3	Windows	Operable
7) Window_closing_leaving	TimeofDay: All DayofWeek: All SeasonType: All		LeavingRoomMoreThan6Hours	NoOccupantsInRoom		TurnOff	CoefficientA: 1	Windows	Operable
8) B_Newsham_1994_Blind_Office_open	TimeofDay: Morning DayofWeek: All SeasonType: All		EnteringRoom			TurnOn	CoefficientA: 1	ShadesAndBlinds	Operable
9) Blind_closing_leaving	TimeofDay: Evening DayofWeek: All		LeavingRoomMoreThan6Hours	NoOccupantsInRoom		TurnOff	CoefficientA: 1	ShadesAndBlinds	Operable
10) Equipment_on_entering			EnteringRoom			TurnOn	CoefficientA: 1	PlugLoad	OnOff
11) Equipment_default_leaving	TimeofDay: All DayofWeek: All		LeavingRoom	NoOccupantsInRoom		TurnOff	CoefficientA: 1	PlugLoad	OnOff
12) Equipment_off_leaving_1	TimeofDay: All DayofWeek: All		LeavingRoomMoreThan1Hour	NoOccupantsInRoom		TurnOff	CoefficientA: 1	PlugLoad	OnOff
13) Equipment_off_leaving_6	TimeofDay: All DayofWeek: All		LeavingRoomMoreThan6Hours	NoOccupantsInRoom		TurnOff	CoefficientA: 1	PlugLoad	OnOff

Table E.3. Properties of each space based on obXML

Space	Space Type	Systems	System type	Occupant
S0_Outdoor	Outdoor			
S1_31_Office	OfficeShared	Light	OnOff	S1_31_Office_O1
		PlugLoad	OnOff	
S2_32_Office	OfficePrivate	Light	OnOff	S2_32_Office_O1
		PlugLoad	OnOff	
S3_33_Office	OfficeShared	Light	OnOff	S3_33_Office_O1
		Window	Operable	S3_33_Office_O2
		PlugLoad	OnOff	
		ShadeAndBlind	Operable	
S4_34_Office	OfficePrivate	Light	OnOff	S4_34_Office_O1
		Window	Operable	
		PlugLoad	OnOff	
		ShadeAndBlind	Operable	
S5_35_Office	OfficeShared	Light	OnOff	S5_35_Office_O1
		Window	Operable	S5_35_Office_O2
		PlugLoad	OnOff	
		ShadeAndBlind	Operable	
S6_36_Office	OfficePrivate	Light	OnOff	S6_36_Office_O1
		Window	Operable	
		PlugLoad	OnOff	
		ShadeAndBlind	Operable	
S7_37_Office	OfficePrivate	Light	OnOff	S7_37_Office_O1
		PlugLoad	OnOff	
S8_38_Office	OfficePrivate	Light	OnOff	
		PlugLoad	OnOff	
S9_39_Office	OfficePrivate	Light	OnOff	S9_39_Office_O1
		PlugLoad	OnOff	
S10_40_Office	OfficePrivate	Light	OnOff	S10_40_Office_O1
		Window	Operable	
		PlugLoad	OnOff	
S11_41_Office	OfficePrivate	Light	OnOff	S11_41_Office_O1
		PlugLoad	OnOff	
S12_42_Office	OfficePrivate	Light	OnOff	S12_42_Office_O1
		Window	Operable	
		PlugLoad	OnOff	
		ShadeAndBlind	Operable	
S13_44_Office	OfficePrivate	Light	OnOff	S13_44_Office_O1
		Window	Operable	
		PlugLoad	OnOff	
		ShadeAndBlind	Operable	
S14_45_Office	OfficePrivate	Light	OnOff	S14_45_Office_O1
		PlugLoad	OnOff	
S15_46_Office	OfficePrivate	Light	OnOff	
		PlugLoad	OnOff	
S16_53_Office	OfficePrivate	Light	OnOff	S16_53_Office_O1
		PlugLoad	OnOff	
S17_48-Kitchen	MeetingRoom	Light	OnOff	

		PlugLoad	OnOff
S18_50-Meeting_room	MeetingRoom	Light	OnOff
		PlugLoad	OnOff
S19_51-Printing_room	Other	Light	OnOff
		PlugLoad	OnOff
S20_52-WC	Other	Light	OnOff
S21_Corridor-name	Corridor	Light	OnOff
S22_Corridor-ext	Corridor	Light	OnOff

```xml
<?xml version="1.0"?>
<OccupantBehavior xmlns:xsi ="http://www.w3.org/2001/XMLSchema-instance"
xsi:noNamespaceSchemaLocation ="../obXML%20V1.3.3%20Release/obXML_v1.3.3.xsd"
 ID ="OS001" Version ="1.3.2" >
	<Buildings >
		<Building ID ="Building_1" >
			<Description > An office building which contains 22 spaces and 16 occupants. </Description >
			<Type >Office</ Type >
			<Spaces ID ="All_Spaces" >
		</Building >
	</Buildings >
	<Occupants >
	<Behaviors >
	<Seasons>
	<TimeofDays >
	<Holidays >
</OccupantBehavior >
```

Figure E.1: Overview of the Occupant model file in obXML

```xml
<Buildings>
	<Building ID="Building_1">
		<Description> An office building which contains 22 spaces and 16 occupants. </Description>
		<Type>Office</Type>
		<Spaces ID="All_Spaces">
			<Space ID="S0_Outdoor">
			<Space ID="S1_31_Office">
			<Space ID="S2_32_Office">
			<Space ID="S3_33_Office">
			<Space ID="S4_34_Office">
			<Space ID="S5_35_Office">
			<Space ID="S6_36_Office">
			<Space ID="S7_37_Office">
			<Space ID="S8_38_Office">
			<Space ID="S9_39_Office">
			<Space ID="S10_40_Office">
			<Space ID="S11_41_Office">
			<Space ID="S12_42_Office">
			<Space ID="S13_44_Office">
			<Space ID="S14_45_Office">
			<Space ID="S15_46_Office">
			<Space ID="S16_53_Office">
			<Space ID="S17_48-Kitchen">
			<Space ID="S18_50-Meeting_room">
			<Space ID="S19_51-Printing_room">
			<Space ID="S20_52-WC">
			<Space ID="S21_Corridor-name">
			<Space ID="S22_Corridor-ext">
		</Spaces>
	</Building>
</Buildings>
```

Figure E.2: Space section of obXML

```xml
<Space ID="S5_35_Office">
        <Type>OfficeShared</Type>

        <Systems>
        <Light><Type>OnOff</Type></Light>
        <Window><Type>Operable</Type></Window>
        <PlugLoad><Type>OnOff</Type></PlugLoad>
        <ShadeAndBlind><Type>Operable</Type></ShadeAndBlind>
        </Systems>

        <OccupantID>S5_35_Office_O1</OccupantID>
        <OccupantID>S5_35_Office_O2</OccupantID>
</Space>
```

Figure E.3: An example of a Space in obXML

```xml
<Space ID="S18_50-Meeting_room">
        <Type>MeetingRoom</Type>

        <Systems>
                <Light>
                        <Type>OnOff</Type>
                </Light>
                <PlugLoad>
                        <Type>OnOff</Type>
                </PlugLoad>
        </Systems>

        <MeetingEvent>
                <SeasonType>All</SeasonType>
                <DayofWeek>Weekdays</DayofWeek>
                <MinNumOccupantsPerMeeting>2</MinNumOccupantsPerMeeting>
                <MaxNumOccupantsPerMeeting>4</MaxNumOccupantsPerMeeting>
                <MinNumberOfMeetingsPerDay>1</MinNumberOfMeetingsPerDay>
                <MaxNumberOfMeetingsPerDay>4</MaxNumberOfMeetingsPerDay>
                <MeetingDurationProbability>
                        <MeetingDuration>PT30M</MeetingDuration>
                        <Probability>0.35000000000000003</Probability>
                </MeetingDurationProbability>
                <MeetingDurationProbability>
                        <MeetingDuration>PT60M</MeetingDuration>
                        <Probability>0.45</Probability>
                </MeetingDurationProbability>
                <MeetingDurationProbability>
                        <MeetingDuration>PT90M</MeetingDuration>
                        <Probability>0.1</Probability>
                </MeetingDurationProbability>
                <MeetingDurationProbability>
                        <MeetingDuration>PT120M</MeetingDuration>
                        <Probability>0.1</Probability>
                </MeetingDurationProbability>
        </MeetingEvent>
</Space>
```

Figure E.4: An example of a meeting pace in obXML

```xml
<Occupants>
        <Occupant ID="S1_31_Office_O1">
        <Occupant ID="S2_32_Office_O1">
        <Occupant ID="S3_33_Office_O1">
        <Occupant ID="S3_33_Office_O2">
        <Occupant ID="S4_34_Office_O1">
        <Occupant ID="S5_35_Office_O1">
        <Occupant ID="S5_35_Office_O2">
        <Occupant ID="S6_36_Office_O1">
        <Occupant ID="S7_37_Office_O1">
        <Occupant ID="S8_39_Office_O1">
        <Occupant ID="S10_40_Office_O1">
        <Occupant ID="S11_41_Office_O1">
        <Occupant ID="S12_42_Office_O1">
        <Occupant ID="S13_44_Office_O1">
        <Occupant ID="S14_45_Office_O1">
        <Occupant ID="S16_53_Office_O1">
</Occupants>
```


Figure E.5: Occupant section of obXML


```xml
<Occupant ID="S5_35_Office_O2">

        <Age>35</Age>
        <Gender>Male</Gender> 402      <LifeStyle>Norm</LifeStyle>
        <JobType>Lecturer_35</JobType>
        <MovementBehaviorID>Lecturer_35_0</MovementBehaviorID>

        <BehaviorID>Window_opening_for_airing</BehaviorID>
        <BehaviorID>Window_closing_leaving</BehaviorID>

        <BehaviorID>B_Light_Reinhart_Voss_2003_arrival</BehaviorID>
        <BehaviorID>B_Light_Gunay_2015_Office</BehaviorID>
        <BehaviorID>Light_off_NoOcccupancy</BehaviorID>

        <BehaviorID>Equipment_on_entering</BehaviorID>
        <BehaviorID>Equipment_off_leaving_1</BehaviorID>


</Occupant>
```


Figure E.6: An example of an occupant in obXML

```xml
<Behaviors>
    <MovementBehavior ID="Student_31_0">
    <MovementBehavior ID="Professor_32_0">
    <MovementBehavior ID="Lecturer_33_0">
    <MovementBehavior ID="Professor_33_0">
    <MovementBehavior ID="Employee_34_0">
    <MovementBehavior ID="Manager_35_0">
    <MovementBehavior ID="Lecturer_35_0">
    <MovementBehavior ID="Lecturer_36_0">
    <MovementBehavior ID="Professor_37_0">
    <MovementBehavior ID="Employee_39_0">
    <MovementBehavior ID="Researcher_40_0">
    <MovementBehavior ID="Professor_41_0">
    <MovementBehavior ID="Lecturer_42_0">
    <MovementBehavior ID="Manager_44_0">
    <MovementBehavior ID="Researcher_45_0">
    <MovementBehavior ID="Student_53_0">
    <Behavior ID="B_Light_Reinhart_Voss_2003_arrival">
    <Behavior ID="B_Light_Gunay_2015_Office">
    <Behavior ID="Light_off_NoOcccupancy">
    <Behavior ID="B_Window_Haldi_Robinson_2008_Office_Tin">
    <Behavior ID="B_Window_Haldi_Robinson_2009_Office_intermed">
    <Behavior ID="Window_opening_for_airing">
    <Behavior ID="Window_closing_leaving">
    <Behavior ID="B_Newsham_1994_Blind_Office_open">
    <Behavior ID="Blind_closing_leaving">
    <Behavior ID="Equipment_on_entering">
    <Behavior ID="Equipment_default_leaving">
    <Behavior ID="Equipment_off_leaving_1">
    <Behavior ID="Equipment_off_leaving_6">
</Behaviors>
```

Figure E.7: Behavior section of obXML

```xml
<MovementBehavior ID="Lecturer_35_0">
    <SeasonType>All</SeasonType>
    <DayofWeek>Weekdays</DayofWeek>
    <RandomMovementEvent>
        <SpaceOccupancy>
            <SpaceCategory>OwnOffice</SpaceCategory>
            <PercentTimePresence>70.0</PercentTimePresence>
            <Duration>PT360M</Duration>
        </SpaceOccupancy>
        <SpaceOccupancy>
            <SpaceCategory>OtherOffice</SpaceCategory>
            <PercentTimePresence>10.0</PercentTimePresence>
            <Duration>PT20M</Duration>
        </SpaceOccupancy>
        <SpaceOccupancy>
            <SpaceCategory>MeetingRoom</SpaceCategory>
            <PercentTimePresence>10.0</PercentTimePresence>
            <Duration>PT60M</Duration>
        </SpaceOccupancy>
        <SpaceOccupancy>
            <SpaceCategory>AuxRoom</SpaceCategory>
            <PercentTimePresence>0.0</PercentTimePresence>
            <Duration>PT0M</Duration>
        </SpaceOccupancy>
        <SpaceOccupancy>
            <SpaceCategory>Outdoor</SpaceCategory>
            <PercentTimePresence>10.0</PercentTimePresence>
            <Duration>PT60M</Duration>
        </SpaceOccupancy>
    </RandomMovementEvent>
    <StatusTransitionEvent>
        <EventType>Arrival</EventType>
        <EventOccurModel>
            <NormalProbabilityModel>
                <EarlyOccurTime>06:41:00</EarlyOccurTime>
                <TypicalOccurTime>08:37:00</TypicalOccurTime>
            </NormalProbabilityModel>
        </EventOccurModel>
    </StatusTransitionEvent>
    <StatusTransitionEvent>
        <EventType>Departure</EventType>
        <EventOccurModel>
            <NormalProbabilityModel>
                <EarlyOccurTime>13:53:00</EarlyOccurTime>
                <TypicalOccurTime>16:12:00</TypicalOccurTime>
            </NormalProbabilityModel>
        </EventOccurModel>
    </StatusTransitionEvent>
    <StatusTransitionEvent>
        <EventType>ShortTermLeaving</EventType>
        <EventOccurModel>
            <NormalProbabilityModel>
                <EarlyOccurTime>09:25:00</EarlyOccurTime>
                <TypicalOccurTime>09:30:00</TypicalOccurTime>
            </NormalProbabilityModel>
        </EventOccurModel>
        <EventDuration>
            <NormalDurationModel>
                <TypicalDuration>PT30M</TypicalDuration>
                <MinimumDuration>PT25M</MinimumDuration>
            </NormalDurationModel>
        </EventDuration>
    </StatusTransitionEvent>
    <StatusTransitionEvent>
        <EventType>ShortTermLeaving</EventType>
        <EventOccurModel>
            <NormalProbabilityModel>
                <EarlyOccurTime>12:20:00</EarlyOccurTime>
                <TypicalOccurTime>12:30:00</TypicalOccurTime>
            </NormalProbabilityModel>
        </EventOccurModel>
        <EventDuration>
            <NormalDurationModel>
                <TypicalDuration>PT60M</TypicalDuration>
                <MinimumDuration>PT50M</MinimumDuration>
            </NormalDurationModel>
        </EventDuration>
    </StatusTransitionEvent>
</MovementBehavior>
```

Figure E.9: Example of a MovementBehavior

```xml
<Behavior ID="B_Light_Reinhart_Voss_2003_arrival">
	<Description>Probability of swithing on the lights based on desk illumminance.</Description>
	<Drivers>
		<Time>
			<TimeofDay>Morning</TimeofDay>
			<DayofWeek>All</DayofWeek>
		</Time>
		<Environment>
			<Parameter ID="ReinhartVoss_illuminance" Name="Workplane_illuminance">
				<Type>RoomWorkPlaneDaylightIlluminance</Type>
			</Parameter>
		</Environment>
	</Drivers>
	<Actions>
		<Interaction>
			<Type>TurnOn</Type>
			<Formula>
				<Logit1DQuadratic>
					<Description>p = A + C / {1 + exp(-B*[log10(P1)-D]}</Description>
					<CoefficientA>-0.00238</CoefficientA>
					<CoefficientB>-3.0965</CoefficientB>
					<CoefficientC>1.0157</CoefficientC>
					<CoefficientD>1.8536</CoefficientD>
					<Parameter1ID>ReinhartVoss_illuminance</Parameter1ID>
				</Logit1DQuadratic>
			</Formula>
		</Interaction>
	</Actions>
	<Systems>
		<Lights>
			<LightType>OnOff</LightType>
		</Lights>
	</Systems>
</Behavior>
```

Figure E.8: Example of a behavior

```xml
<Seasons>
    <Season Type="All">
        <StartMonth>1</StartMonth>
        <StartDay>1</StartDay>
        <EndMonth>12</EndMonth>
        <EndDay>31</EndDay>
    </Season>
    <Season Type="Spring">
        <StartMonth>2</StartMonth>
        <StartDay>1</StartDay>
        <EndMonth>4</EndMonth>
        <EndDay>30</EndDay>
    </Season>
    <Season Type="Summer">
        <StartMonth>5</StartMonth>
        <StartDay>1</StartDay>
        <EndMonth>7</EndMonth>
        <EndDay>31</EndDay>
    </Season>
    <Season Type="Fall">
        <StartMonth>8</StartMonth>
        2178
         <StartDay>1</StartDay>
        <EndMonth>10</EndMonth>
        <EndDay>31</EndDay>
    </Season>
    <Season Type="Winter">
        <StartMonth>11</StartMonth>
        <StartDay>1</StartDay>
        <EndMonth>1</EndMonth>
        <EndDay>31</EndDay>
    </Season>
</Seasons>
```


Figure E.9: Expanded section for Seasons

```xml
<TimeofDays>
    <TimeofDay Type="All">
        <StartHour>0</StartHour>
        <StartMinute>0</StartMinute>
        <EndHour>24</EndHour>
        <EndMinute>0</EndMinute>
    </TimeofDay>
    <TimeofDay Type="Morning">
        <StartHour>6</StartHour>
        <StartMinute>0</StartMinute>
        <EndHour>12</EndHour>
        <EndMinute>0</EndMinute>
    </TimeofDay>
    <TimeofDay Type="Afternoon">
        <StartHour>12</StartHour>
        <StartMinute>0</StartMinute>
        <EndHour>18</EndHour>
        <EndMinute>0</EndMinute>
    </TimeofDay>
    <TimeofDay Type="Evening">
        <StartHour>18</StartHour>
        <StartMinute>0</StartMinute>
        <EndHour>24</EndHour>
        <EndMinute>0</EndMinute>
    </TimeofDay>
    <TimeofDay Type="Day">
        <StartHour>6</StartHour>
        <StartMinute>0</StartMinute>
        <EndHour>24</EndHour>
        <EndMinute>0</EndMinute>
    </TimeofDay>
    <TimeofDay Type="Night">
        <StartHour>24</StartHour>
        <StartMinute>0</StartMinute>
        <EndHour>6</EndHour>
        <EndMinute>0</EndMinute>
    </TimeofDay>
</TimeofDays>
```

Figure E.10: Expanded section for Time Of The Day

```xml
<Holidays>
    <Holiday Name="New Year's Day">
        <Date>2023-01-01</Date>
    </Holiday>
    <Holiday Name="Epiphany">
        <Date>2023-01-06</Date>
    </Holiday>
    <Holiday Name="Good Friday">
        <Date>2023-04-07</Date>
    </Holiday>
    <Holiday Name="Easter Sunday">
        <Date>2023-04-09</Date>
    </Holiday>
    <Holiday Name="Easter Monday">
        <Date>2023-04-10</Date>
    </Holiday>
    <Holiday Name="May 1st">
        <Date>2023-05-01</Date>
    </Holiday>
    <Holiday Name="Ascension Day">
        <Date>2023-05-18</Date>
    </Holiday>
    <Holiday Name="Whit Saturday">
        <Date>2023-05-27</Date>
    </Holiday>
    <Holiday Name="Mother's Day">
        <Date>2023-05-28</Date>
    </Holiday>
    <Holiday Name="National day">
        <Date>2023-06-06</Date>
    </Holiday>
    <Holiday Name="Midsummer Day">
        <Date>2023-06-24</Date>
    </Holiday>
    <Holiday Name="All Saints' Day">
        <Date>2023-11-04</Date>
    </Holiday>
    <Holiday Name="Fourth Advent Sunday">
        <Date>2023-12-24</Date>
    </Holiday>
    <Holiday Name="Christmas Day">
        <Date>2023-12-25</Date>
    </Holiday>
    <Holiday Name="Boxing Day">
        <Date>2023-12-26</Date>
    </Holiday>
    <Holiday Name="New Year's Eve">
        <Date>2023-12-31</Date>
    </Holiday>
</Holidays>
```


Figure E.11: Expanded section for Holidays

Appendix F

Declaration regarding the use of generative AI tools:

	Statement	Answer
1)	I used a Generative AI tool (e.g. ChatGPT or similar) in my report	Yes, Google Gemini was used.
2)	I used a GAI tool as language editor (i.e. to correct grammar mistakes, etc.)	Yes, only for correcting grammar.
3)	I used GAI to retrieve information	Yes, it was only used similarly to a search engine for identifying the common root causes for some of the errors encountered while running the Python code in the behavior section of methodology and not for writing the code itself
4)	I used GAI to get help in writing code	No
5)	I used GAI for translations	No
6)	I used GAI to generate graphs/images	No
7)	I used GAI to help structuring my content	No

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