DIPLOMARBEIT

APPLICATION OF AGENT-BASED MODELING TO ASSESS THE IMPACT OF OCCUPANT BEHAVIOR ON BUILDINGS' ENERGY USE

unter der Leitung von

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Abstract
In the building simulation, there are often serious differences between the calculated and the actual energy demand. The reasons for this can be many, but one of the biggest factors is the behaviour of users in the building which is difficult to predict, but has a significant influence on the actual energy demand. Conventional software mainly replicates presence and interactions with time-step based tables. In recent years, agent-based modeling has been increasingly used as a new approach. This involves creating individual units that perform various actions based on a set of rules. These building users, called agents, can differ according to need. Depending on the current input, their actions change accordingly. The present work aims to combine a dynamic energy simulation of an office building with an Agent-based model. The model will investigate how different types of users affect the final energy demand. For this purpose, a behavioural model for building users was created in the software Netlogo. This comprises four different types of users, each of which have a high or low energy load and are additionally divided in their tolerance with regard to the indoor climate conditions. The model is then connected to the energy simulation programme EnergyPlus using a co-simulation. The co-simulation is carried out by combining the software Building Control Virtual Test Bed and the Python programming language. In a fictitious office building, the energy demand is investigated for one representative week per season with several user compositions. For each time step, the actions of the building users are simulated based on the current climatic conditions and fed back to EnergyPlus as input. The work describes both the underlying behavioural model and the connection between the tools. Subsequently, the results of the simulations are compared and analysed. It becomes clear that the energy awareness of the building users has a significant influence on the energy consumption. In addition, it is shown that in some cases a greater tolerance - in the simulation model associated with reduced influence on the building - can lead to an increased energy consumption. It is also apparent that the commercial use of more precise energy simulation models with co-simulations is still in its infancy due to the exceptional effort required to create them.

Keywords: Agent-Based-Modelling, Building-Energy-Modelling, Occupancy, Energy Consumption, Behaviour Modelling

Kurzfassung
In der Gebäudesimulation gibt es oft gravierende Unterschiede zwischen dem berechneten und dem tatsächlichen Energiebedarf. Die Gründe dafür können vielfältig sein, jedoch wird als einer der größten Faktoren das Verhalten von Nutzern im Gebäude benannt. Dieses ist schwer vorauszusagen, hat jedoch einen signifikanten Einfluss auf den tatsächlichen Energiebedarf. Herkömmliche Software bildet vor allem mit zeitschrittbasierten Tabellen die Anwesenheit und Interaktionen von Gebäudenutzern nach. Als alternativer Ansatz wird in den letzten Jahren immer öfter die sogenannte Agentenbasierte Modellierung verwendet. Dabei werden individuelle Einheiten erstellt, die basierend auf einem Regelset verschiedene Aktionen ausführen. Diese als Agents bezeichneten Gebäudenutzer können sich je nach Modell unterscheiden. Abhängig von dem aktuellen Input ändern sich dementsprechend ihre Aktionen. Die vorliegende Arbeit zielt darauf ab, eine Energiesimulation eines Bürogebäudes mit einem Agenten basierten Modell zu verbinden. Das Modell soll untersuchen, wie sich verschiedene Nutzertypen auf den Endenergiebedarf auswirken. Dazu wurde in dem Programm Netlogo ein Verhaltensmodell für Gebäudenutzer erstellt. Dieses umfasst vier verschiedene Typen, die jeweils einen hohen oder niedrigen Energieverbrauch aufweisen und sich zusätzlich in ihrer Toleranz bezüglich des Raumklimas aufteilen. Dieses Modell wird anschließend mit dem Energiesimulationsprogramm EnergyPlus mithilfe einer Co-Simulation verbunden. In einem fiktiven Bürogebäude wird für jeweils eine repräsentative Woche pro Jahreszeit mit Hilfe mehrerer Nutzerzusammensetzungen der Energiebedarf untersucht. Die Co-Simulation erfolgt dabei über eine Verbindung aus dem Programm Building Control Virtual Test Bed und der Programmiersprache Python. Für jeden Zeitschritt werden die Handlungen der Gebäudenutzer basierend auf den aktuellen klimatischen Bedingungen simuliert und als Input zurück an EnergyPlus gegeben. Die Arbeit beschreibt dabei sowohl das zugrundeliegende Verhaltensmodell, als auch die Verbindung der Programme miteinander. Im Anschluss werden die Ergebnisse der Simulationen verglichen und untersucht. Dabei wird deutlich, dass das Energiebewusstsein der Gebäudenutzer einen großen Einfluss auf den Verbrauch hat. Zusätzlich zeigt sich, dass in einigen Fällen eine größere Toleranz - und im Simulationsmodell damit verbunden ein Unterlassen der Einflussnahme auf das Gebäude - zu einem erhöhten Energieverbrauch führen kann. Zudem zeigt sich, dass die kommerzielle Nutzung von präziseren Energiesimulationsmodellen mit Co-Simulationen, bedingt durch den großen Aufwand zur Erstellung, noch an ihrem Anfang steht.

Stichwörter:
Agentenbasierte Modellierung, Gebäudesimulation, Nutzerverhalten, Co-Simulation, Energieverbrauch

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List of abbreviations

ABM	Agent Based Model
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning
BCVTB	Building Controls Virtual Test Bed
BEM	Building Energy Modelling
DNAS	Drivers-Needs-Action-Systems
EP	EnergyPlus
HVAC	Heating Ventilation and Cooling
PPD	Predicted Percentage of Dissatisfied
PMV	Predicted Mean Vote
SP	Setpoint

Contents

1 Introduction **7**
1.1 Motivation . . . 7
1.2 Background . . . 8

2 Method **12**
2.1 Overview . . . 12
2.2 Model description . . . 12
2.2.1 Environment and Building Energy Model . . . 12
2.2.2 Occupants and Agent-Based-Model . . . 14
2.2.3 Simulation Period and Time Steps . . . 17
2.2.4 Agents Environmental Perception and Decision Making . . . 19
2.2.5 Limitations . . . 22
2.3 Hypothesis . . . 22
2.4 Statistical Analysis . . . 22

3 Results **24**
3.1 Overview . . . 24
3.2 General results . . . 24
3.3 Comparison of Scenarios . . . 25
3.4 Comparison of Occupant Types . . . 28
3.5 Concluding reflections . . . 32

4 Discussion **33**
4.1 Overview . . . 33
4.2 Occupant types . . . 33
4.3 Scenarios . . . 36
4.4 Limitations and Considerations . . . 37

5 Conclusion **40**

6 Literature **41**

7 Appendix **45**

1 Introduction

1.1 Motivation

The building sector, including occupants, is responsible for approximately one-third of the global energy demand (Ürge-Vorsatz et al. 2012). Using building simulation to improve design, operation and retrofit offers a promising opportunity to reduce buildings energy demand and improve the CO_2-output. But despite being used more often in recent years, building simulation still struggles with some major problems (Hong et al. 2018). Stated by Hong et al. (2018) one of the main things to overcome is the difference in energy use between the simulated model and the actual energy use of the building. This performance gap reduces the credibility of building performance simulation which is mainly due to the insufficient representation of building occupants (Yan et al. 2015). This includes their movement in the building as well as their actions, influencing the envelope and the energy consumption. Examples are opening windows or changing the Heating Ventilation and Cooling (HVAC) thermostat which will change the energy load significantly. Modelling human interaction with the building has the potential to improve the comfort for the users (Hong et al. 2018). While most occupant models are only stochastic, recent trends show a huge potential for Agent Based Models (ABM) (Langevin et al. 2015). Here, individual units called agents, with each one using an individual set of rules can interact with their environment. This allows to capture complex system dynamics (Wilensky and Rand 2015). In the field of building science using ABM could help to address some lacking options in pure stochastic models such as the missing possibility for a dynamic occupant response on changing environmental factors. Using ABM is a complex task. This thesis aims to develop a behavioural model by using a Co-Simulation between a Building Energy Simulation software and an Agent Based Model. Different occupant types for the same building allow predictions on how the human interactions with the building change the energy consumption. To say it in the words of Albert Einstein (1933): „The supreme goal of all theory is to make the irreducible basic elements as simple and as few as possible without having to surrender the adequate representation of a single datum of experience.“

1.2 Background

On the next pages a general overview is given on how occupants are currently represented in building simulation. Also, it is described what agent-based modeling is, how it works and how it has been used in past research.

Building Energy Modelling

Building energy modeling is a physics-based modeling technique to digitally represent the energy-flows of a building. It takes the building itself, such as the geometry and materials, the energy systems, for example HVAC and the according control strategies, as well as descriptions on the buildings usage with for example schedules for occupancy and thermal loads as input. Based on this information the software can calculate, depending on the location of the building the estimated energy consumption, thermal comfort, energy costs etc. Building Energy Modelling (BEM) is used in a wide arrange of fields, for example in building design strategies, retrofit, certifications or real-time energy monitoring (Office of Energy Efficiency and renewable Energy 2021). For this thesis especially the schedules for the input and several environmental states for the output are important. Schedules are input values for the simulation software for each time step. They can be individually designed, having for example different ones for an office room and a conference room (Wulfinghoff et al. 2010). The outputs of a building simulation process are normally several different files. The most important ones for this thesis are the error- and the time step dependent results files. The error files give insight to possible problems which might have occurred during the simulation process while the result files hand out the values for specified parameters at each time step. Examples are the hourly heating energy usage for each zone, window openings or inside surface temperatures (Wulfinghoff et al. 2010). Especially for occupant related research the output of the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD) are relevant. The most used PMV model is developed by Ole Fanger. The PMV-value offers insight on how the mean perception of the environment is. The scale ranges from -3 (cold) to +3 (hot) with an optimum value of 0.0 (neutral). Dependent on the PMV-value the PPD-value gives a curve for the percentage of dissatisfied people. The curve with the corresponding PPD-values is displayed in figure 1. Having more extreme conditions in a room leads to more dissatisfied occupants, always having a minimum of at least 5% at a PMV of 0.0 (Langevin et al. 2013).

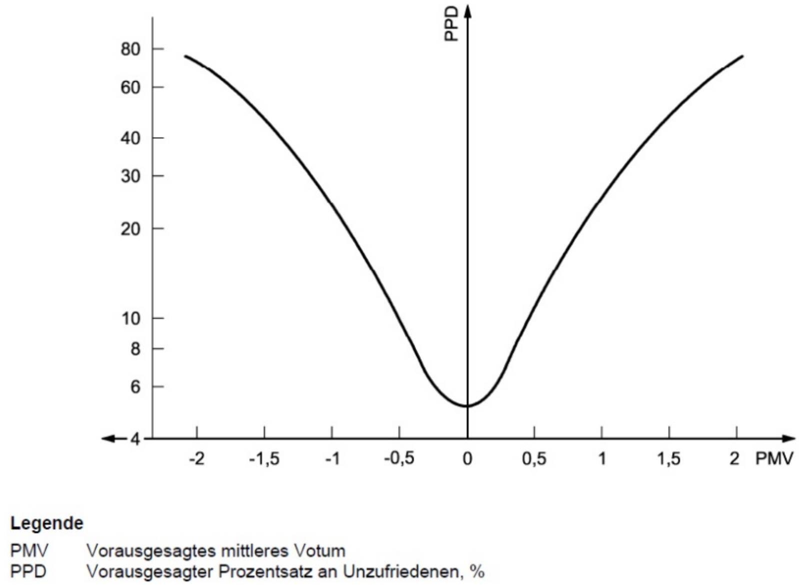

Figure 1: PPD as function of PMV (DIN Deutsches Institut für Normung e. V. 2005)

Current description of occupancy in BEM

Currently occupancy modeling for most of the practical building simulations is done with static schedules based on previous research (Dong et al. 2018). These schedules take a ratio of the maximum given occupants in the room at a specific time (Dong et al. 2018). For example, often used energy simulation software such as EnergyPlus (EP) or IDA ICE are working with this technique. Having more accurate data about future building usage can lead therefore to a more accurate simulation. However, often this data is not given and standard-schedules are used for example as provided by the American Society of Heating, Refrigerating and Air-Conditioning (ASHRAE). For the office case these occupancy schedules are displayed in figure 2. Even if precise schedules are available, they are still static. This can lead to a possible difference between simulated energy loads and actual energy consumption (Dong et al. 2018). More recent approaches are using probabilistic and non-probabilistic models. While each of these modeling techniques offers individual advantages and disadvantages and is useful for specific use-cases none of them can simulate occupant behaviour in a flexible way. As a relatively new approach, Agent-Based Modelling offers a chance to capture building usage in a more realistic way (Berger 2020). This is also recognized by the Annex 66, a scientific collaboration research for occupant behaviour in buildings. Findings of Annex 66 include progress in the Co-Simulation domain with Drivers-Needs-Actions-Systems (DNAS). Still there is remaining work to do (Yan et al. 2017). Stated by Yan et al. 2017: „Human behaviour is a critical dimension that is as important as technological factors in ensuring the energy-efficient design, construction and operation in buildings.“ In recent years the number of studies, conducted for the use of agent-based modeling in building context has risen significantly (Berger 2020). There are multiple reasons for this. Significant influence has the improved computational power in computers which allows faster and more accurate models. Another reason for the increased interest in the use of agent-based modeling is the desire to use the full potential of building simulation. Stated by Hong et al. 2018 one of the main differences between a building simulation and actual energy usage are the occupants' actions. Current simulation software is not able to take complex behaviour into account.

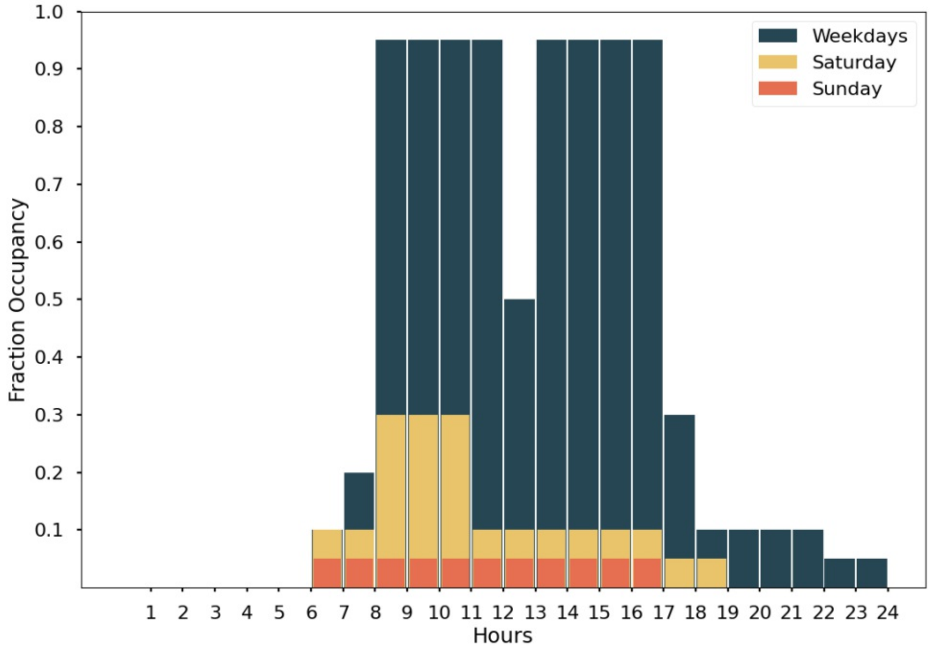

Figure 2: Office occupancy schedules from ASHRAE 90.1

Agent-based modeling in Building Energy Modelling

According to Wilensky and Rand 2015 an Agent-based-model (ABM) is „a form of computational modeling whereby a phenomenon is modeled in terms of agents and their interactions.“ Agents are individual acting instances with specific properties and actions (Wilensky and Rand 2015). In BEM, these agents can represent either individual building occupants, groups of people or even specific systems. Depending on a set of rules the agents interact with each other and defined building components. In recent years a variety of studies concerned with ABM has been conducted (Berger and Mahdavi 2020). Depending on the research goal they differ in the use of agents, environment, behavioural theory and task. While most of the studies are aiming to investigate the influence of occupants on energy consumption, there are also studies regarding visual comfort or even water usage (Berger and Mahdavi 2020). Most models have in common that they show a strong correlation between occupants' behaviour and building energy use. For example, Deuk-Woo et al. 2013 shows that with their adopting ABM the simulation tools can provide realistic results when compared with actual data. Putra et al. 2017 developed a model for exploring different factors on their influence on load-shedding activities in office buildings. The analysis of adaptive thermal comfort behaviour with PMV was done by Thomas et al. 2016. Likewise, Lee and Malkawi 2014 investigated in the decision-making process based on comfort-parameters. By Kashif et al. 2013 a slightly different approach with a believe system for the agents regarding their power management in residential buildings was developed. Validated with real-world data, Jia et al. 2018 tested and improved the accuracy of their ABM to 83% for their target objects. In general, validation of the ABM is often complicated since an extensive amount of data is needed as well as surveys have to be conducted to investigate in the reasons behind certain behaviour. Therefore, the models are often based on behaviour theory instead of real-world data. Yet, validating the models is an important task (Yan et al. 2017).

In general, most of the models try to simulate the behaviour of occupants in buildings in a more realistic way compared to static schedules. They approach this with either a more general way, like for example Langevin et al. 2015 who developed a model responding to different seasons etc., or by answering a very specific question such as Deuk-Woo et al. 2013, where a four-person household for one day was extensively analysed.

Each developed model not only differs in its behavioural approach but also in the number of agents and their interaction with each other. While single occupants in zones or rooms tend to perform more actions to influence their environmental perception, with multiple people this number decreases (Heydarian et al. 2020). Having more than one person in the room therefore leads to the necessity of an additional behaviour theory layer (Yan et al. 2015).

Berger provides a comprehensive summary of current studies regarding Agent-based Modelling in building simulation in her diploma thesis (Berger 2020) and in the paper „Review of current trends in agent-based modeling of building occupants for energy and indoor-environmental performance analysis“ (Berger and Mahdavi 2020).

2 Method

2.1 Overview

This thesis aims to investigate the use of ABM in combination with BEM to simulate the impact of thermal tolerance of individuals in combination with their energy consciousness. For this a Co-Simulation of the BEM-software EP and the ABM-tool Netlogo is used. The connection was done via the Co-Simulation software environment Building Control Virtual Test Bed (BCVTB) in combination with the programming language Python. In an office building with six single-offices EP is used to simulate the thermal and visual performance of each room at each time step. This environmental information is handed to Netlogo where for each agent the likeliness for an action is calculated based on his tolerance and on his energy consciousness. The agents can change their environment to adapt it more to their preference. For the thermal preference, the PMV value and for visual performance the illuminance in the middle of each room is used. The changes in the schedules are given back to EP, where for the next time step the building performance indicators calculated based on the new input. The following chapters describe the setup of the BEM-model, the ABM with the associated routines and the connection between them.

Table 1: Programs and software used

Software	Usage	Version
EnergyPlus (EP) [NREL, various DOE National Laboratories, academic institutions, and private firms 2021]	Energy Simulation	8.9.0
SketchUp Make [(Trimble 2017)]	Building Geometry	2.6.0
OpenStudio SketchUp Plug-in [NREL, ANL, LBNL, ORNL, and PNNL 2021]	Building Geometry	17.2.2555 64-bit
Netlogo [Center for Connected Learning and Computer-Based-Modeling 2016]	Occupant representation	6.1.1
Building Control Virtual Test Bed (BCVTB) [Michael Wetter, Thierry S. Nouidui and Philip Haves 2016]	Connection EP and Python	1.6.0 April 20 2016
Python [Python Software Foundation 2021]	Connection BCVTB and Netlogo	3.7

2.2 Model description

2.2.1 Environment and Building Energy Model

The environmental state is calculated in EP which is a widely used, free software funded by the U.S. Department of Energy´s (DOE). The main use for engineers, architects and researchers is the simulation of building energy usage (U.S. Department of Energy's 2021). Relevant features include the simulation of individual zones, calculation of the PMV-value for each zone, calculation of light conditions and energy usage. EP also offers the possibility for Co-Simulation.

The input file is text-based, which makes it easier to change individual parameters in the setup for each simulation case. For the building environment, a simple office building was chosen which is displayed in figure 3 . The geometry was modeled in Sketchup and exported to EP with the OpenStudio-Plugin.

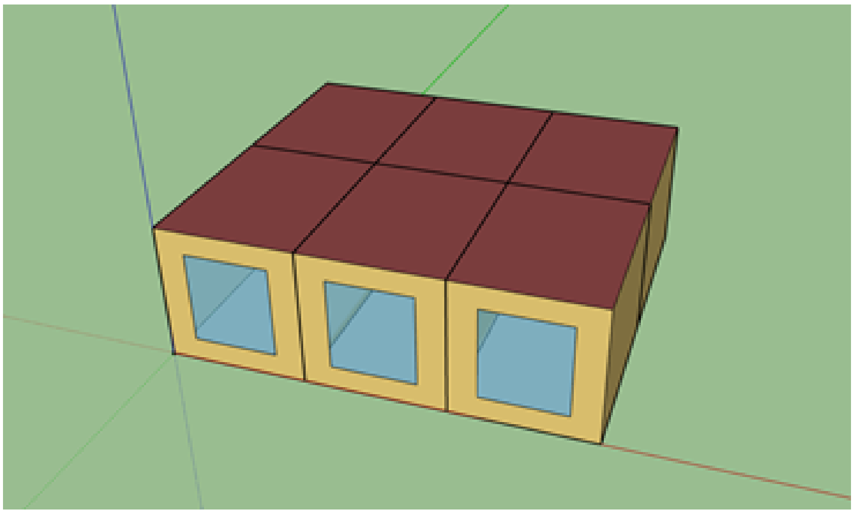

Figure 3: Representation of the building geometry in SketchUp

The office building consists of 6 single-office rooms. The facade with the windows of three of the rooms face south and the other three rooms face north. The building has only one storey and a flat roof. The building component properties are designed to meet the minimum requirements of the Austrian Guideline OiB 6 (Österreichisches Institut für Bautechnik 2019). Table 2 summarizes the assumptions for the building.

Table 2: Building assumptions

Input EnergyPlus	**Value**
Buildingtype	Office
Floors	1
Zones	6
Zone Size [m^2]	12
Zone Hight [m]	3
Window-to-Wall ratio [%]	40
U-Value Roof [$W\,m^{-2}\,K^{-1}$]	0.15
U-Value Floor [$W\,m^{-2}\,K^{-1}$]	0.11
U-Value Window [$W\,m^{-2}\,K^{-1}$]	1.11
U-Value Outside-Wall [$W\,m^{-2}\,K^{-1}$]	0.20
Shading Type	Interior Blinds

The building is assumed to be in Vienna, Austria and as a weather file „Vienna Schwechat 110360 (IWEC)“ is used (U.S. Department of Energy's (DOE) Building Technologies Office n.d.). All schedules for the basic simulation without Co-Simulation are using the predefined ASHRAE 90.1 office schedules (U.S. Department of Energy's 2021). The buildings geometry, the different building parts and the standard schedules are equal throughout all cases. Therefore, the only difference in the total energy loads can be found and compared in the building occupants' behaviour. Occupants have several options to influence the buildings energy loads and their thermal environment. For this thesis each agent has its own zone. The zones are thermally connected with each other. Each zone has its own window. In the basic model, the windows are opened twice a day for the duration of one time step. In contrast, the agents in the co-simulation can open the window whenever their routine allows it. „HVAC Ideal Loads Air System“ was used as the heating and cooling system. This system, predefined in EP, has no energy limitation and can reach the specified numbers even with high loads. It was chosen for better comparability and because the focus is not on the energy systems but on the occupants. For shading, an internal shading system was chosen. For all cases the metabolic equivalent (met) is set to an equivalent of a seated office job. This is also the case for the Co-Simulations. The ASHRAE 90.1 schedule is used for the electrical equipment.

2.2.2 Occupants and Agent-Based-Model

For the ABM, the free of charge software Netlogo was used. In Netlogo it is possible to programme multi-agent environments (Wilensky 1999). It can help to understand natural and social world phenomenons and problems using individual entities called agents in a defined environment (Wilensky and Rand 2015). An agent is defined as „autonomous computational individual or object with particular properties and actions“ (Wilensky and Rand 2015). In Agent-based Modelling a real-world situation is modeled using agents and their connections with each other and the environment (Wilensky and Rand 2015).
As previously suggested ABM offers a promising tool to investigate in human behaviour in buildings. The focus of this thesis is in the influence of energy consciousness and thermal preference range on the building's energy demand. Different occupant types in the offices allow a comparison of usages and an estimation of the influence on the energy consumption. In total four different types of occupants are defined as shown in figure 4. They differ in their thermal acceptability range and their energy consciousness.

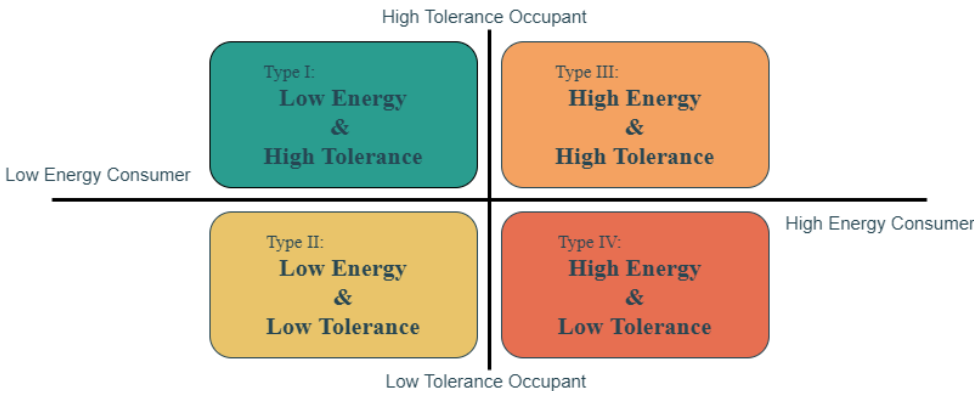

Figure 4: Occupant types in the model

The thermal acceptability range describes the possibility of someone to change his environment. High-Tolerance-Occupants are better adapting to their room while Low-Tolerance-Occupants are more likely to change something to optimise their perception. In the model the tolerance is represented by a function based on the Predicted-Mean-Vote (PMV) of Fanger (Langevin et al. 2013). The formula to calculate the Percentage-of-Dissatisfied (PPD) is slightly modified for Low- and High-Tolerance-Occupants and the resulting percentage number is used as probability for the agent to trigger a change. In general, the agents try to optimise their PMV-value to be near 0.0 which is also suggested to be the case by Langevin et al. 2015. More extreme climate conditions result in faster changes. Like in the PMV-curve from Fanger an optimum is never reached, even at PMV-value of 0.0 the chance for the occupants to perform an action is still 5%. The formula for high tolerance occupants is shown in Eq. 1 while the formula for low tolerance occupants is shown in Eq. 2. The 5% ensure on one hand a certain degree of chance and takes on the other hand non-calculable actions like for example hygiene-based ventilating into account. Occupants always belong to one of these two groups.

$$\text{High Tolerance Occupant } [\%] = 100 - 95 * exp^{(-0.03353*PMV^4 - 0.2179*PMV^2)*0.5} \quad (1)$$

$$\text{Low Tolerance Occupant } [\%] = 100 - 95 * exp^{(-0.03353*PMV^4 - 0.2179*PMV^2)*2} \quad (2)$$

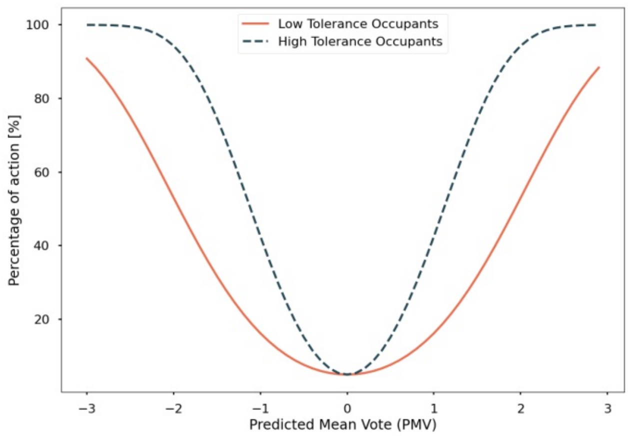

Figure 5: Curves for low- and high-tolerance-occupants

The distinction for the energy consciousness is between low- and high-energy-consumer. An occupant who is conscious about the energy usage performs a different set of action compared to someone who only wants to improve his thermal well-being. Building users in the first group are more likely to adopt their cloth to improve the PMV-Value. Non-conscious occupants on the other side have a higher percentage to change the thermostat stepoint (SP).
Since there are four different occupant types and six offices, simulating every possible scenario would exceed the scope of this thesis. Building simulation – especially Co-Simulation – can be time-consuming. Therefore, four scenarios where chosen to cover all occupant types. As shown in figure 6 Scenario I and IV completely consist of agents of the same type. Presumably these scenarios are the ones with the lowest and highest energy loads and mark the extreme conditions. Scenarios II and III are occupied by a variety of agent types. This mix ensures that all agent types are covered. The energy load is presumed to be in between Scenario I and the Scenario IV. In Scenario II, the low-energy consumers are more represented, while in Scenario III the high-energy consumers predominate. Having all occupants present in the scenarios allows later to extract the individual occupant types and analyse the different types in combination with each other. The Base Case with Type 0 occupants denotes the simple BEM-simulation in EP

without coupled ABM agents but with fixed schedules according to ASHRAE. Since the offices are only occupied by one person this can be used as comparison type.

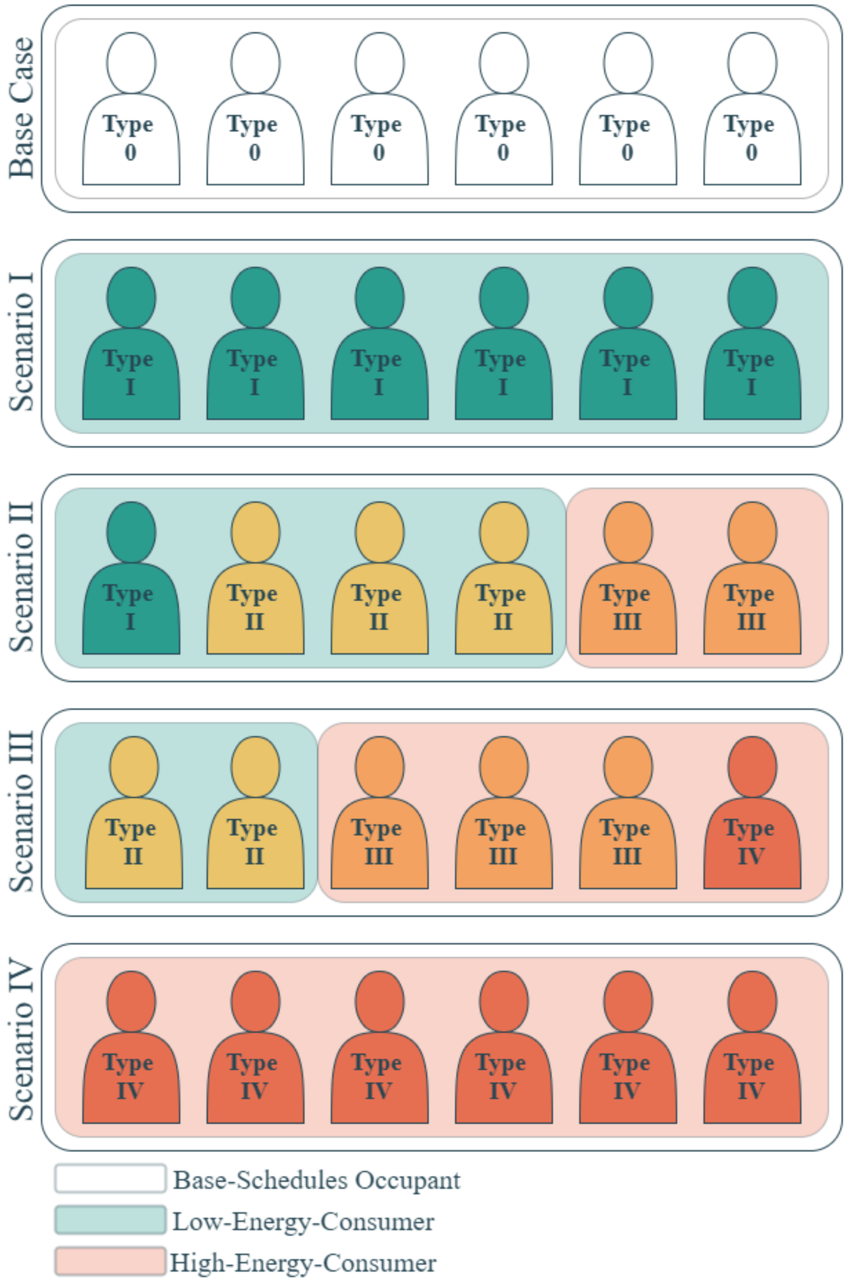

Figure 6: Occupancy scenarios

While for the thermal perception of the environment the described ABM was used, for the light a different approach was chosen. For the evaluation of lighting perception, a non-probabilistic model is used. This means, the agents decide based on rules what they are doing. The decisions are based on threshold values depending on the energy-consciousness of the agent. Table 3 shows the sP for both energy-consumer types. Depending on the energy-use type the agents have a wider or narrower light threshold range. This means a low-energy-user will tolerate less daylight before he will turn on the artificial light in his office and has also a higher upper threshold-value before he will operate the shades compared to a high-energy-user.

In figure 7 an overview of the previously described model is shown. In the centre is the agent in

Table 3: Shading threshold values

Consumer Type	Lower End [lux]	Upper End [lux]
Low-Energy-Consumer	700	3000
High-Energy-Consumer	300	2000

his zone. The red circle above the zone contains all parameters that are calculated by EP. The corresponding values are passed on via BCVTB and Python. The Occupant Type, shown here in the blue circle to the right of the zone, is specified in Netlogo. The yellow circle on the left side contains the values that can be changed by the agents. All sub-points in the yellow and red circles are recalculated at each time step. The points in the blue circle are set at the beginning of each simulation and remain unchanged over the entire period.

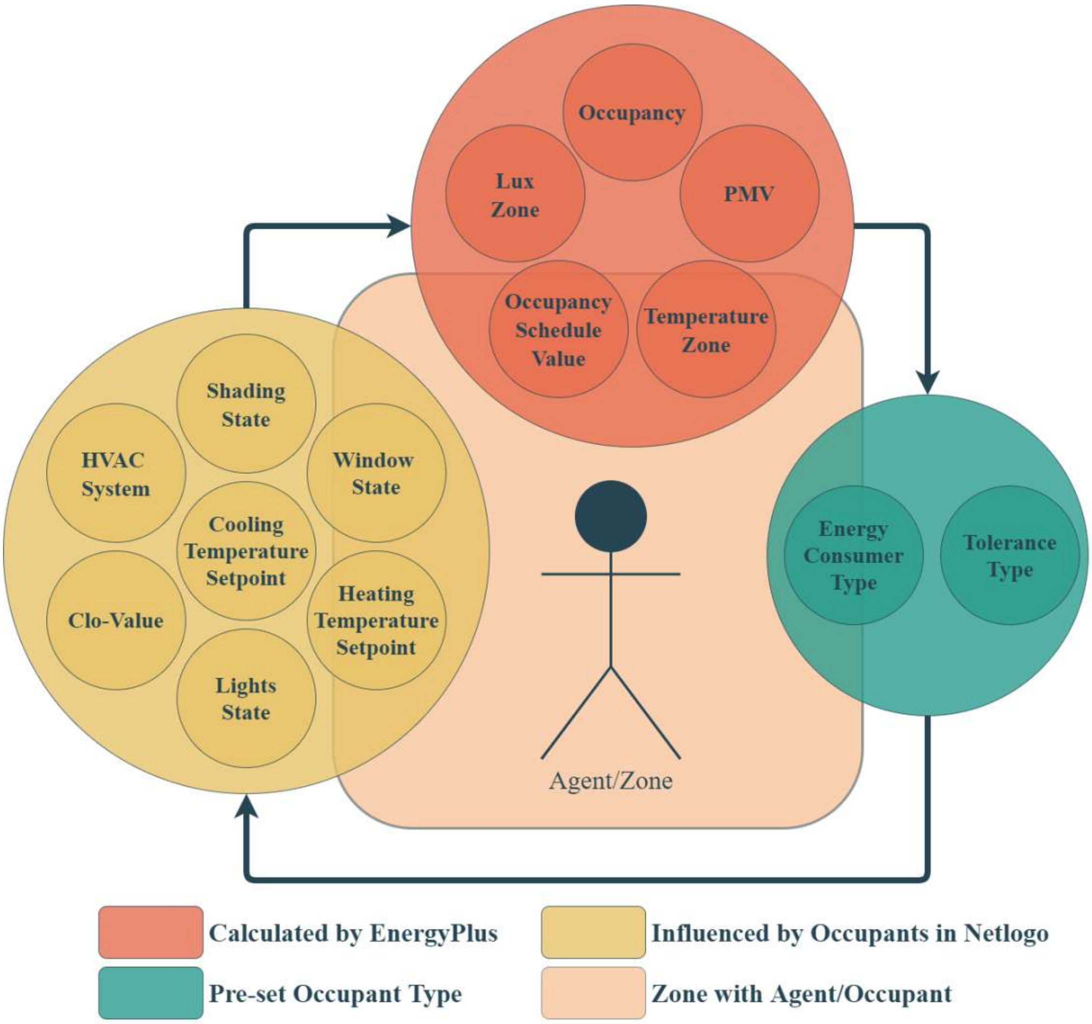

Figure 7: Occupants influence on parameters

2.2.3 Simulation Period and Time Steps

Time steps are the intervals in which the computer calculates the state of the building (Wulfinghoff et al. 2010). Stated in Yan et al. 2015 time steps in building occupant simulation should be in range of 15 minutes to 1 hour for an annual simulation. Due to the complexity of Co-Simulation models an annual simulation in the scope of this thesis is not possible. The simulation time would exceed a reasonable limit. One-day simulations on the other hand often do not provide sufficient insight on the influence of occupants. To balance the time needed for one scenario-run and getting suitable data the simulations were performed for one-week periods. The time steps are fixed to 30-minute intervals because previous test-runs with longer time steps resulted in unrealistic behaviour of the agents. Occupants' actions are depending on the outside temperature and season (Langevin et al. 2013). To take this into account one representative week for each season was simulated.

Table 4: Simulation periods

Time	**Period**
Timesteps	30 minutes
Winter	14.01 – 21.01
Spring	14.04 – 21.04
Summer	14.07 – 21.07
Autumn	14.10 – 21.10

Each time step starts with EP to calculate the current state of the building. This includes among other things energy usage, temperature, light, and the PMV-value. The process is shown in figure 8. After the calculation EP is paused and PMV-value, outdoor and indoor temperature and the illuminance for each room are read out by BCVTB which hands them to Python [1]. In Python the data format is adopted to be suitable as input for Netlogo. Via Python Netlogo is launched and the environmental conditions are assigned to each zone and agent as setup procedure [2]. Netlogo then calculates for each occupant the action he performs and hands the updated schedules back to Python [3]. In Python the data is converted such that it is accepted by BCVTB and EP [4]. With the updated schedules EP now calculates the new environmental state of the building and the process repeats for the next time step. The script for Netlogo and Python can be found in the appendix.

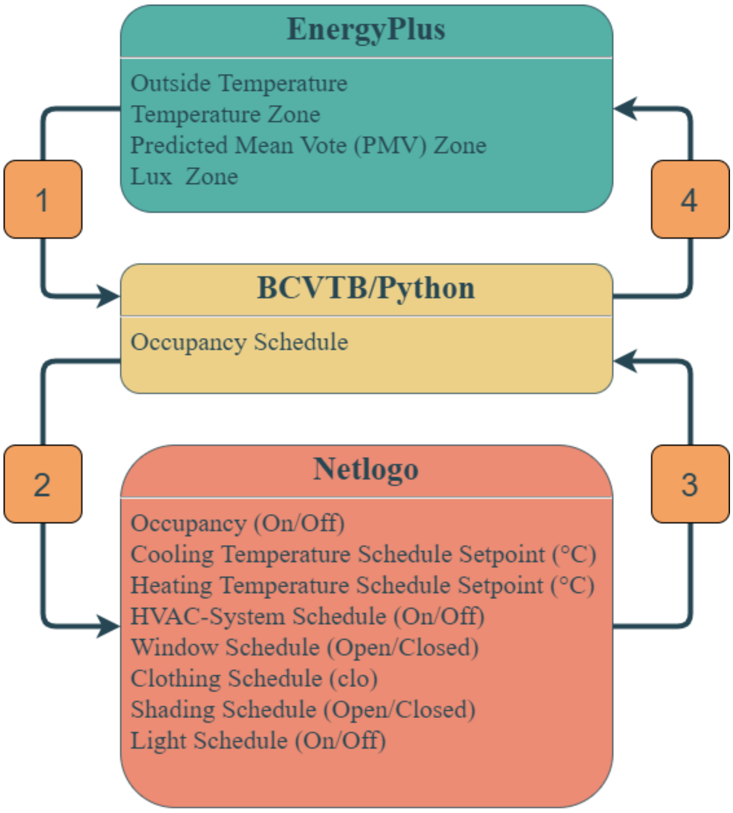

Figure 8: Data Exchange between used software

2.2.4 Agents Environmental Perception and Decision Making

For the agents' environmental perception and the resulting actions, a decision-making routine is defined for each time step. This process is an ordered sequence in which the agents decide what they are doing (Wilensky and Rand 2015).

As general input at first the schedule-number for this time step is needed. The agents then decides if he is in the room or not depending on this number. If he is not in the room all current schedules will be exported. In case the agent is in the room it is checked whether the calculation for the likeliness for an action is done for high- or low-tolerance. Again, if no action is performed, all current schedules are exported. If an action is performed the agent checks if he is a high- or low-energy-user and if he feels warm or cold. The tolerance and the energy usage are predefined for each agent. Warm or cold are set by the PMV-value, obtained from EP. The routine for warm is set by a positive algebraic sign while cold is triggered by a negative one. Depending on the energy usage type and thermal perception one of four routines is executed afterwards. These routines normally result in a change in one of the schedules to improve the thermal comfort. After a decision is made, the schedules are exported. Figure 9 shows the general decision process each agent makes at each time step. The four routines for warm and cold perception can be found in the attachments. Generally, the agents first try to reverse behaviour that might have led to discomfort for example by closing an opened window again. If this is possible the schedules are exported and the process for this time step ends. If no behaviour is to be reversed, depending on the agent type one of three options is executed. While the likeliness for each option differs, each agent has the possibility to influence his environment

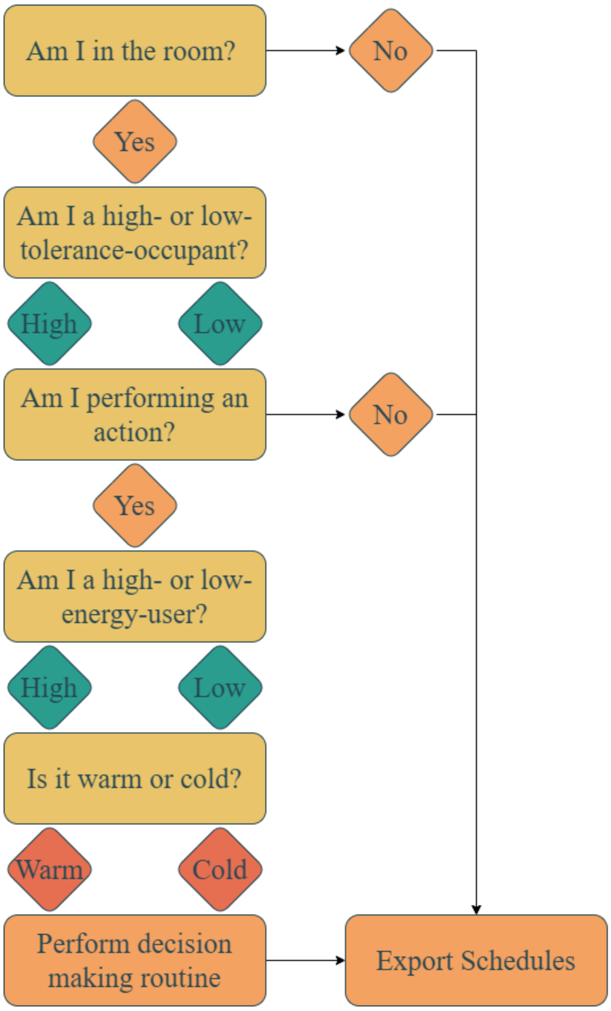

Figure 9: Decision making routine for the occupants

by opening or closing the window, changing his clothes and changing the HVAC-SP. The last one depends on the thermal perception, so either the heating SP is changed or the cooling SP. The cognition process for one of the agent types is shown in figure 10 while the other routines can be found in the appendix.

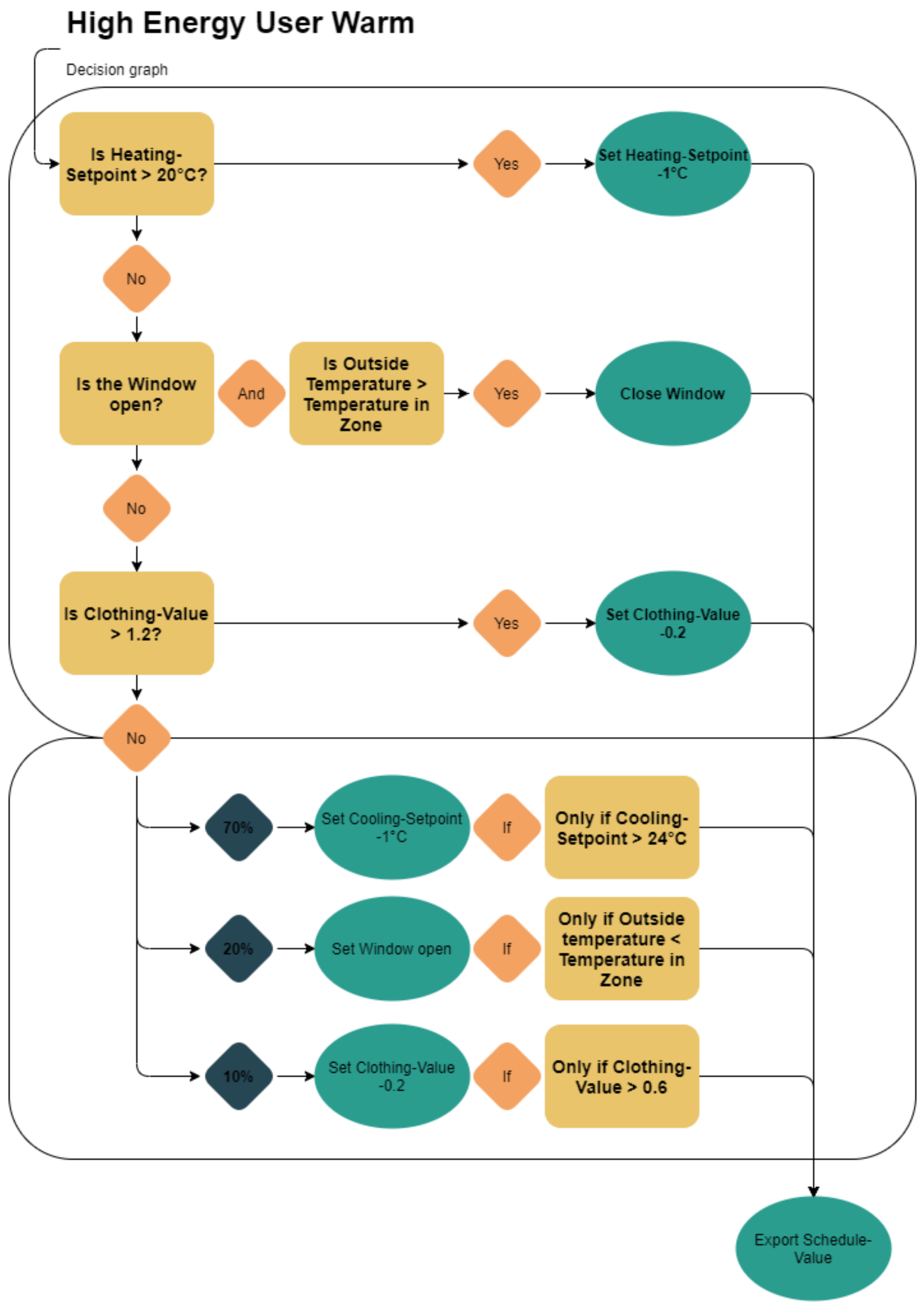

Figure 10: Cognition process for feeling warm for Type III and Type IV occupants (high-energy-user)

All options have certain limitations to prevent the agents from overcommitment to only one solution. For example, the maximum possible clothing number in the model is 1.4. If the action is not possible, the schedules are exported anyway. Depicted in figure 11 is an approximate illustration of the Clo numbers. These are calculated from the individual heat resistances of the clothes. 1 clo corresponds to $0.155\,\mathrm{K\,m^2\,W^{-1}}$ (Abdul Majid 2011). For the offices case 0.6 as lower and 1.4 as upper limit was chosen.

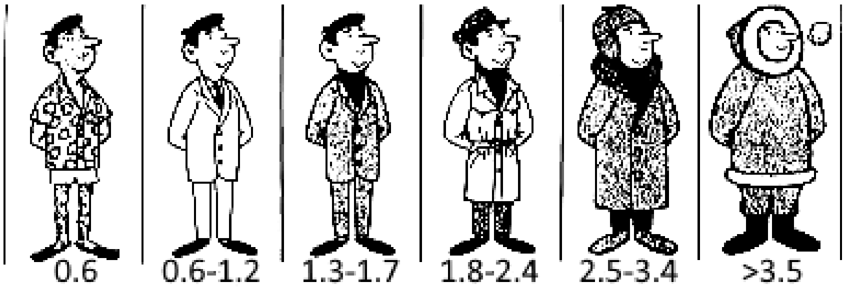

Figure 11: Illustration of clothing numbers (Abdul Majid 2011)

2.2.5 Limitations

Modelling occupant behaviour is a complex task. In order to reduce the complexity of the model, speed up the time needed for a simulation run and make the agents actions more comprehensible, certain limitations have to be made. While more agents and a higher number of offices would lead to more reliable data by providing less outliers, the effort to construct these models as well as the simulation time rises exponentially. Therefore, the model of the office building uses six single-offices. There are some studies (i.e. Barakat and Khoury 2016) investigating also in acoustical comfort, which is not considered in the scope of this thesis. Heydarian et al. 2020 states that window closing is connected to the outside noise level, however in this model the acoustical comfort is not considered. Having multiple occupants in one room adds an additional layer to the model (Yan et al. 2015). Building users that are not alone in a room tend to behave differently compared to group interactions (Yan et al. 2015). Modelling inter-occupant decision making has a strong connection to social sciences. The focus of this thesis is not on the occupant's interaction with each other but on how their individual preferences have influence on the buildings' energy demand. Therefore, only single offices with one occupant were chosen. The use of electricity contributes also to a building's energy demand. While lights and shades can be influenced by the occupants with the use of a non-probabilistic (rule-based) model (Berger 2020), the energy load for electric devices is schedule-based.

2.3 Hypothesis

The energy consciousness of occupants (low-energy-user and high-energy-user) has a strong effect on the overall energy load of a building. In addition, the occupant's energy usage is further influenced by their tolerance regarding the indoor climate.
The thesis aims to evaluate the influence of energy consciousness on the overall energy loads with the presented model on the example building. Parallelly, the tolerance to indoor climate is considered with two different functions for the agents to reduce or raise the possibility for changes to the buildings systems.

2.4 Statistical Analysis

EP allows a wide variety of output parameters. These can be defined in the input-file before a simulation starts. In combination with BCVTB it is also possible to hand out the input parameters for each time step. For answering the research question several different values need to be extracted at each time step of the simulation. Most important is the heating and cooling energy load since this will in the end show the influence of different occupant types. The schedule values at each time step are extracted as well to get a more in-depth analysis. These allow to investigate why agents perform certain actions as well as how these actions influence the environmental perception in return. Because the PMV-value is a major factor in this simulation model it is necessary to set this also as output. The PMV-value is strongly connected to the room/zone temperature which is also an output parameter together with the outside temperature. Shading, lighting, and the illuminance are included in the output file as well. It is important to remember that the mentioned variables are not only extracted for the building but for each zone which is results in six times the data for each simulation run compared to just an average annual building simulation.

While the Base-Case – the simulation without ABM – results are always the same, for the other scenarios this is not the case. Due to the randomness in how the agents take actions no simulation is exactly equal to the previous. Therefore, for each scenario several runs are performed to reduce the influence of outliers and make the model more reliable. A detailed overview is listed in table 5.

Table 5: Number of performed simulations

	Spring	**Summer**	**Autumn**	**Winter**
Scenario I	4	4	4	4
Scenario II	4	4	4	4
Scenario III	4	4	4	4
Scenario IV	4	4	4	4
Base Case	1	1	1	1
Sum	17	17	17	17

Having four different scenarios in combination with several runs for each scenario and in addition four seasonal weeks results in a huge amount of data. To avoid human-based errors and repetitive work in combining the data and analysing it, the programming language Python was used for semi-automatic data analysis. For Python several additional packages are available, including for example Pandas (*pandas* 2021) and Matplotlib (Hunter et al. 2012) which allow easy data import and data visualisation in the programming environment. Since the simulation period is only one week and for each case several runs where done, for most parts of the statistical analysis the average – or if more suitable the median – was taken. This way possible outliers which might have occurred are evened out or can be dismissed.

3 Results

3.1 Overview

The results of the scenarios are presented in three main categories. First, general findings are discussed. The second category is a comparison of the different previously described scenarios. It is important to note the necessity of comparing the scenarios in different seasons, since this influences the routines of the agents and therefore the overall results. In the last category, the different agent types are compared to each other, to be able to analyse the agent types and their behaviour in depth.

3.2 General results

Shown in figure 12 is a typical outcome of the occupancy function. The 1 denotes that the agent is in the room for this time step while a 0 indicates an empty space. The figure shows two days. In the example for the first day the occupant is in the room mostly in the morning and the afternoon, leaving just for short time periods during lunchtime and in the early afternoon. On the second day it is similar but in addition the agent was in the office also for some periods late at night.

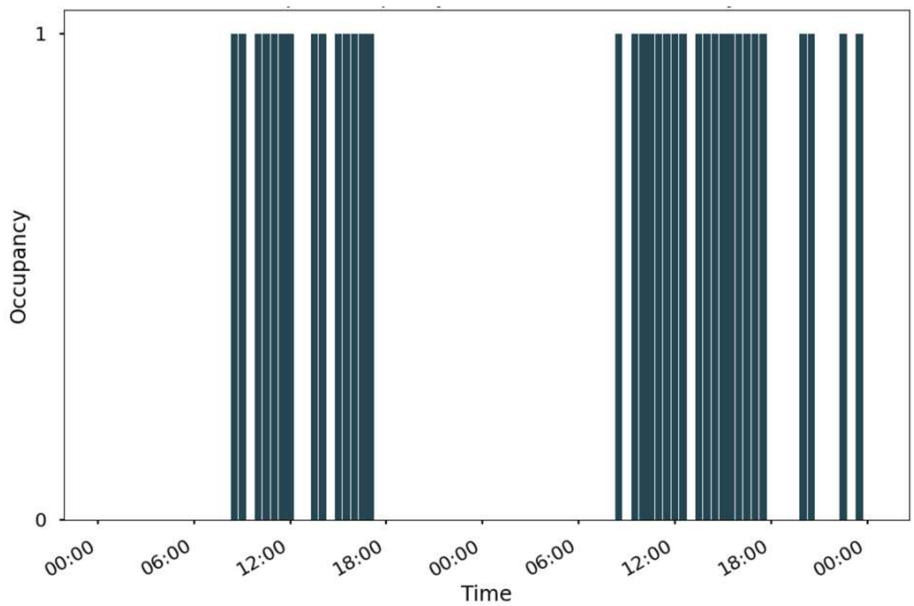

Figure 12: Example of occupancy for a room for two days

As described earlier, the occupants only perform actions while they are in the room. Therefore, this not only shows their occupancy but also denotes the possible time frame of action for each agent. Especially for analysing the different occupant types this is important.

3.3 Comparison of Scenarios

The results of the mean energy loads are shown in figure 13. The average is calculated over all simulations, meaning that there is not only one simulation per scenario and season but several as described earlier. Heating and cooling loads are combined in the plot. For the summer the energy loads are only for cooling. In autumn there are cooling and heating loads with the main emphasis on heating. The table displays especially in spring and autumn a rising trend in the energy loads for cases with more high-energy-consumer occupants. In both seasons the Base case energy load with the simple EP simulation is the lowest. Outstanding are summer and winter. For summer, in the first three scenarios the trend is like spring and autumn with a significant drop for the mean energy load for scenario IV. The average is even slightly below scenario I. In winter, the rising trend-line for scenarios I to IV of spring and autumn can basically be seen too. The differences are less pronounced.
Looking at the absolute numbers spring and autumn are similar while the energy load in summer is relatively low. For the winter season the energy load per zone is high.

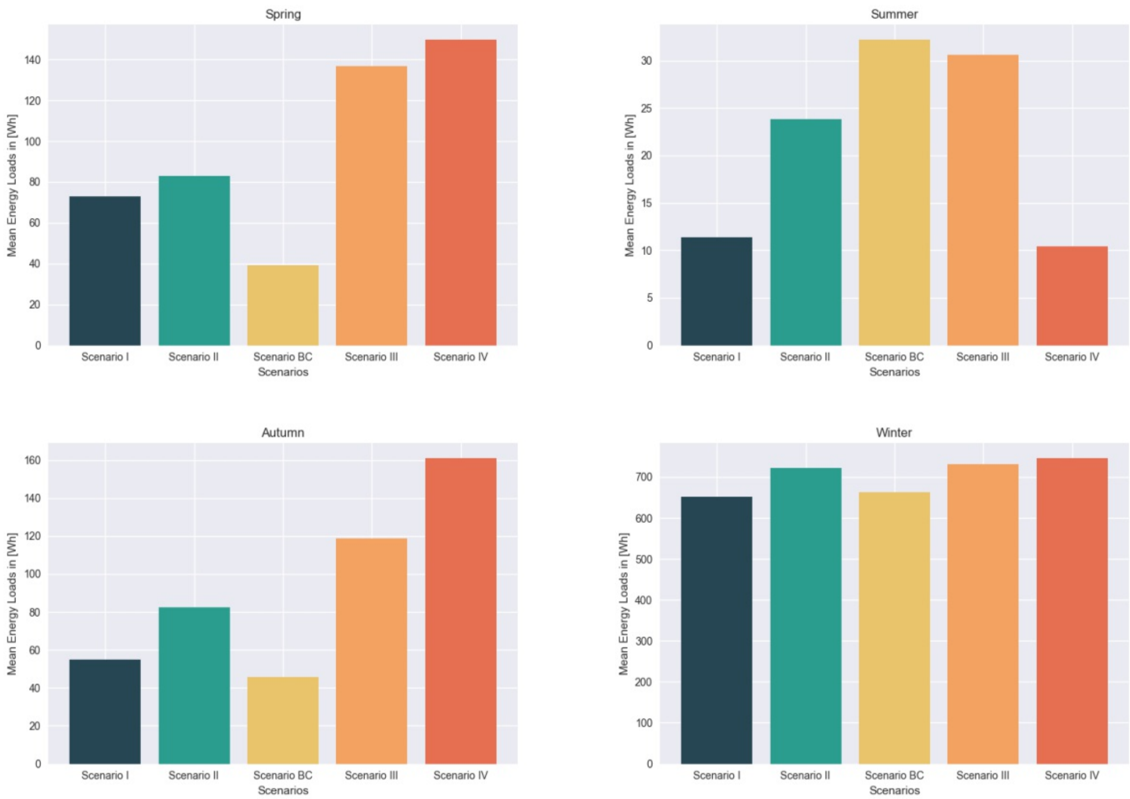

Figure 13: Mean energy loads in [Wh]

To validate the the data and give a better perspective on the energy loads a conversion to a common energy format for buildings was done. In most cases, the energy loads are given in $\mathrm{kW\,h\,m^{-2}\,a^{-1}}$. To obtain this number, the average hourly loads from each season were interpolated and added up. Displayed in figure 14 these numbers can be seen. The numbers are in line with findings from the city of Vienna for office buildings (Bayer et al. 2014).

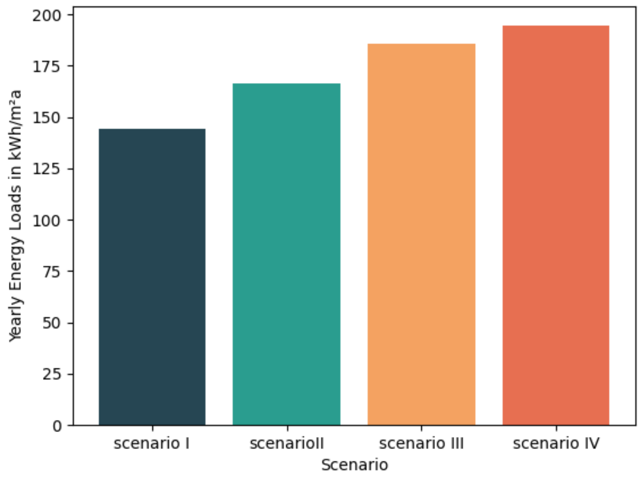

Figure 14: Yearly energy loads in $\mathrm{kW\,h\,m^{-2}\,a^{-1}}$

Figure 15 shows the deviation of the mean energy loads from the base case for each scenario and season in percent. The trendline described earlier can also be recognized for spring, autumn, and winter week. As seen in the bar figure 13 the summer week is an exception. While the trends are for the three colder seasons mainly the same, the deviation in the winter case is slightly less distinctive. Also shown in the graph are the deviations for the single simulation cases, so not only the average but each run. For the base case there are no further cases and therefore no deviation. For some parts of the other cases the spread is distinctively. For the winter season it is in a range of around 2.5%. For Spring and Autumn, it varies more. Again, the summer is an exception. Here, the spreading is significant.
Shown in figure 16 is the mean energy load for one week in spring. Graphs for the other seasons can be found in the appendix. Outstanding are especially the seasons summer and winter. For summer, the average energy load is mainly at the end of the week with some smaller spikes in the middle of the week. For the winter week the drops for the base case are outstanding. For spring and autumn, the course of the graphs is similar with spikes in the energy load for each night and drops on the days. For most of the time this is also the case in the winter week.

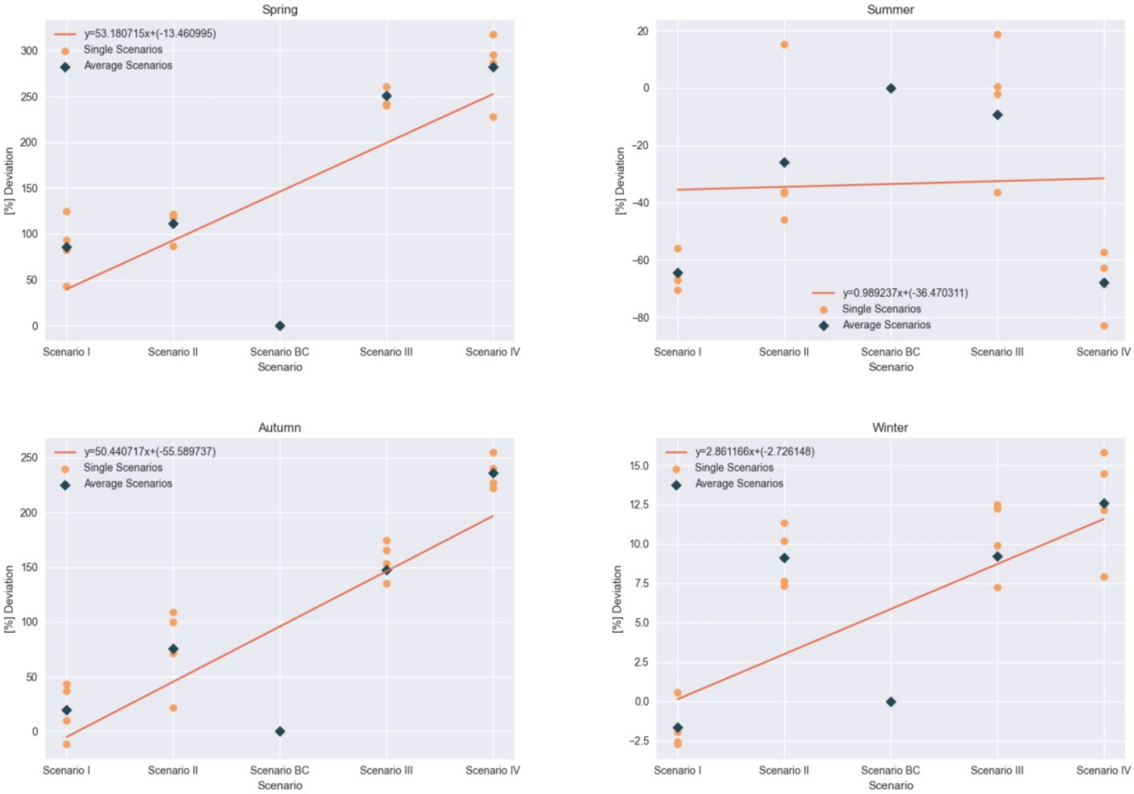

Figure 15: Mean energy load deviation from base case in percent for each season

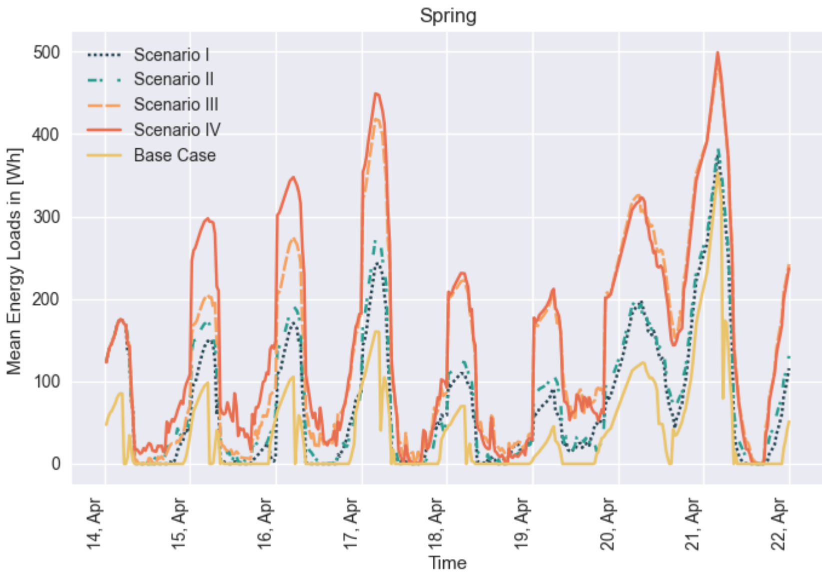

Figure 16: Mean energy loads over time for one week in Spring

Pictured in figure 17 are histogram plots for the PMV-values while the occupants are in the room. In the case of the present work, the statement of the graphs is more related to the probability of an action instead of the perception of the environment as originally intended by Fanger. For higher percentiles in the negative half of the x-axis the agents have felt colder and therefore performed more actions to counter this. For higher occurrence percentiles in the positive half more actions were performed to reduce the heat in the room. Two main points can be noticed.

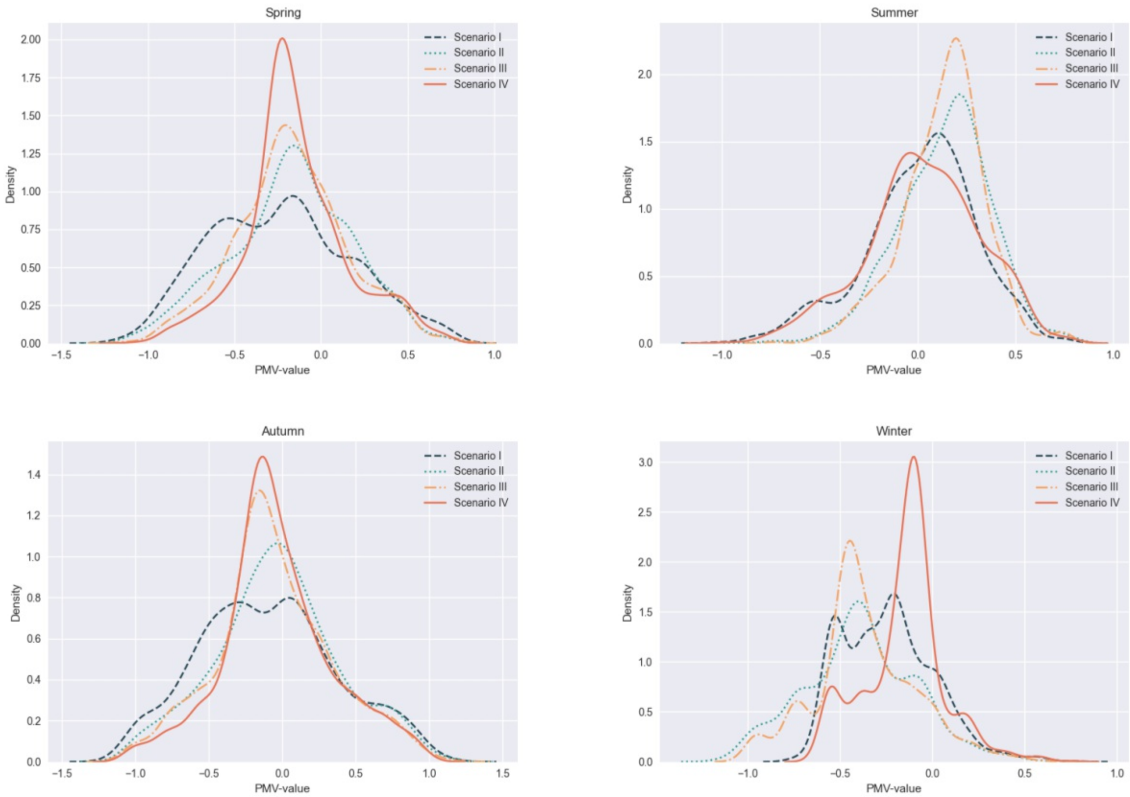

Figure 17: Cumulative distribution plot for PMV

In most seasons, scenario IV has the most occurrences between 0.0 and –0.25. To the outer edges the percentage drops fast. Contrary is scenario I with a much more even distribution from –0.75 to 0.25 for the three colder seasons. Scenario II and scenario III are distributed between these with II being more shifted to scenario I with an even distribution and III being more oriented to scenario IV. In winter the most occurrences for scenario III are on the –0.5 percentile while for scenario IV it is between –0.25 and 0.0. Scenarios I and II are again more evenly distributed with an emphasis on –0.5 to -0.25. For the summer season the percentiles are much more shifted in the positive half of the PMV-values. Specifically, the scenarios I – III are gathering around 0.25. Scenario IV has its most occurrences at 0.0. Contrary to spring and autumn –1.0 and 0.75 are never exceeded.

3.4 Comparison of Occupant Types

In general, there are four different occupant types and in addition the Type 0, which can be partly extracted from the Base-Case data since the offices are only occupied by one person. Type I and Type II are the Low-Energy-Consumer, while Type III and Type IV are the High-Energy-Consumer. Type I and Type III do have a wider tolerance range, while Type II and Type IV are using the narrow function. Looking at the energy load per occupant type in figure 18 for the transitional seasons the energy load of Type 0 occupants is the lowest. This was already indicated in figure 13. For all seasons energy loads of Type I and II are relatively low with I being slightly less than II. The main difference to the scenarios appears when looking at Type III and Type IV occupants. Type III occupants, despite having a wider tolerance range consume on average more energy compared to the Type IV occupants. In summer, Type I agents are using less energy than Type II agents. Similar to spring and autumn, the energy use for Type III is higher than for Type IV. Both high-energy-users consume in summer more energy than the low-energy consumers. The mean energy load for all occupant types is quite similar in winter.

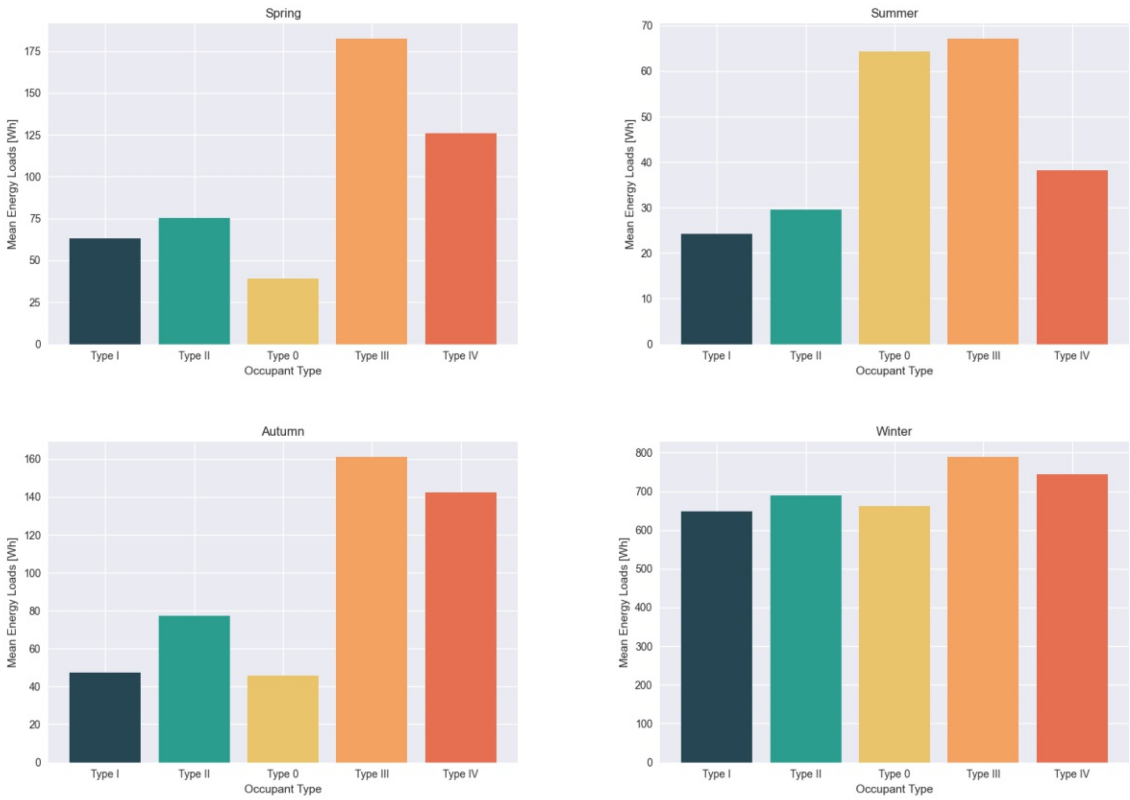

Figure 18: Mean energy loads for each occupant type

To further analyse the data and detect anomalies and outliers, the results are analysed with boxplots for the four occupant types as shown in figure 19. For spring and autumn, the plots indicate similar results. The medians for Type I and II are close to each other with II being slightly higher. The average energy load for Type III is for both cases the highest. The maximum for I and II and the maximum for III and IV is almost identical. For both I and II the boxes are relatively small compared to the other types. In summer the trend is different with Type II showing the lowest energy loads. Type II and IV show outliers. For the winter the median is rising from I to III and then dropping for occupant Type in the range between I and II. All boxes are relatively small, meaning that most of the data is in a narrow range. All four occupant types show outliers at the very low end.
Figure 20 shows the mean heating/cooling SP temperature for each occupant type. Type 0 can obviously not change the temperature, so all occupants use the same SP. This fixed number is also the starting SP for all other agent types. The graphs show for low-energy-consumers for the three cold seasons lower averages. High-energy-consumers have also higher SP numbers. For spring and autumn Type III has a slightly higher average SP compared to Type IV. In summer the SP for type III is the lowest. This is equal with the highest energy load, as cooling and

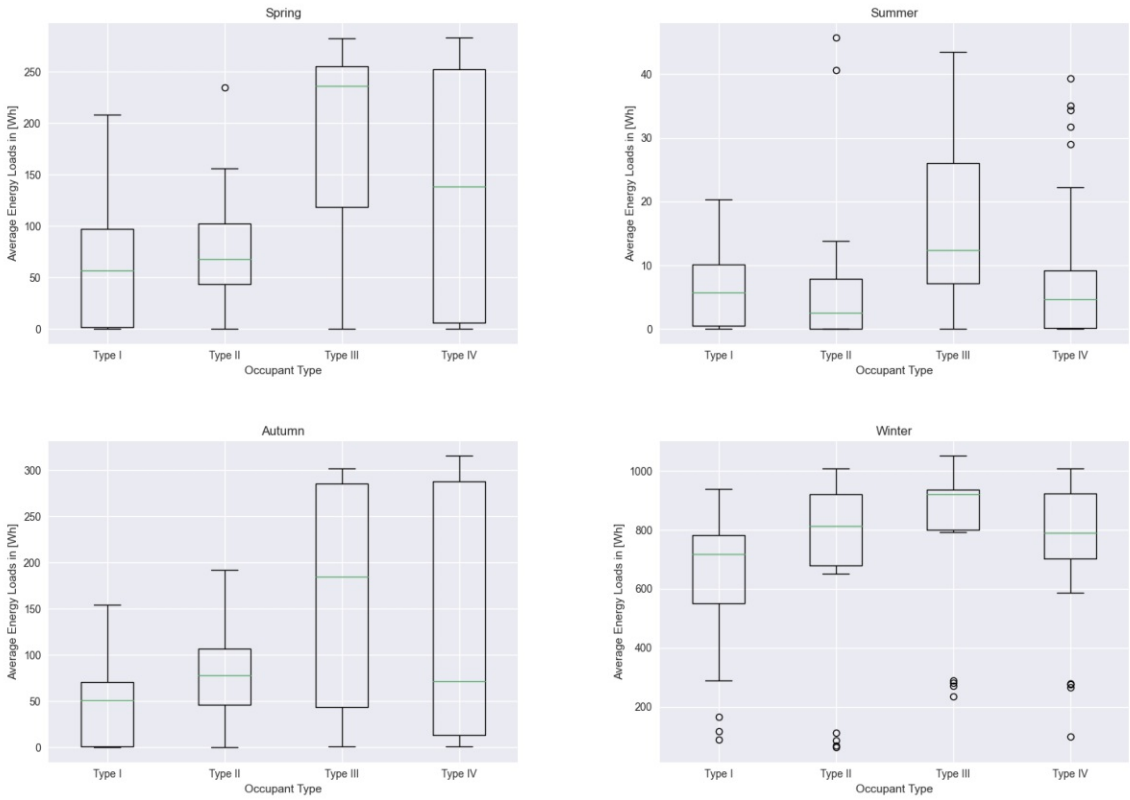

Figure 19: Boxplot for average energy loads per occupant type and season

not heating is required in summer. It is noticeable that Occupant Type IV does not have the highest SP in summer.

Comparing the average clothing number per hour in Figure 21, the contrary to the heating SP is noticeable. Colder seasons show higher averages for the low-energy-consuming occupants. Especially for Type II this is the case. This is reasonable since low-energy-consumers try to first alter their clothing. In contrast, the average numbers are lower for high-energy consumers. As before, the summer case is an exception. Here, the average clothing numbers are generally lower than for the other cases. It is noticeable that Type I and Type IV have the lowest numbers, while Type II and III form a line here.

Figure 22 shows the averaged actions in relation to each other. The individual plots are divided into agent type and season. The top two circles always show the low-energy consumers. Based on the graphs the influence of changing the clothing number is clearly visible. For the cold seasons, the next largest part is the adjustment of the heating. For the high-energy users, the opposite is the case. Hardly any changes of clothing take place. Instead, it is mainly the HVAC system that is changed. This is also the case in summer. The autumn case is particularly striking. A large proportion of actions concerning cooling are carried out by the Type III and Type IV agents. However, the actual cooling energy consumed is comparatively low as already shown in figure 13. The graphs also show that the rate of window openings is relatively small. Only the summer case is an exception here, but even here the share is never greater than 25 percent. Due to the limitation in the routine, in winter the window on average is not opened at all. This is due to the limitation of the routine. Agents can only open the window under certain conditions that often cannot be fulfilled in winter. For the cold case, the outside temperature would have

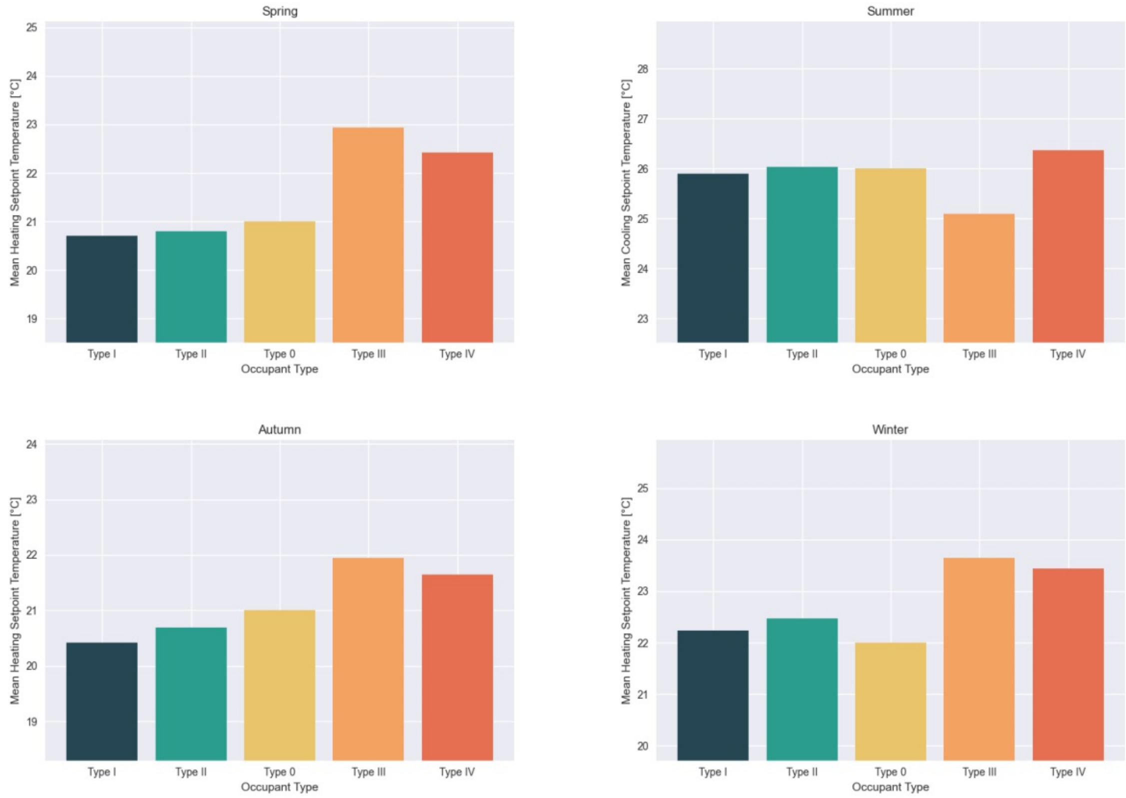

Figure 20: Average setpoint temperature for each occupant type in [°C] for each season

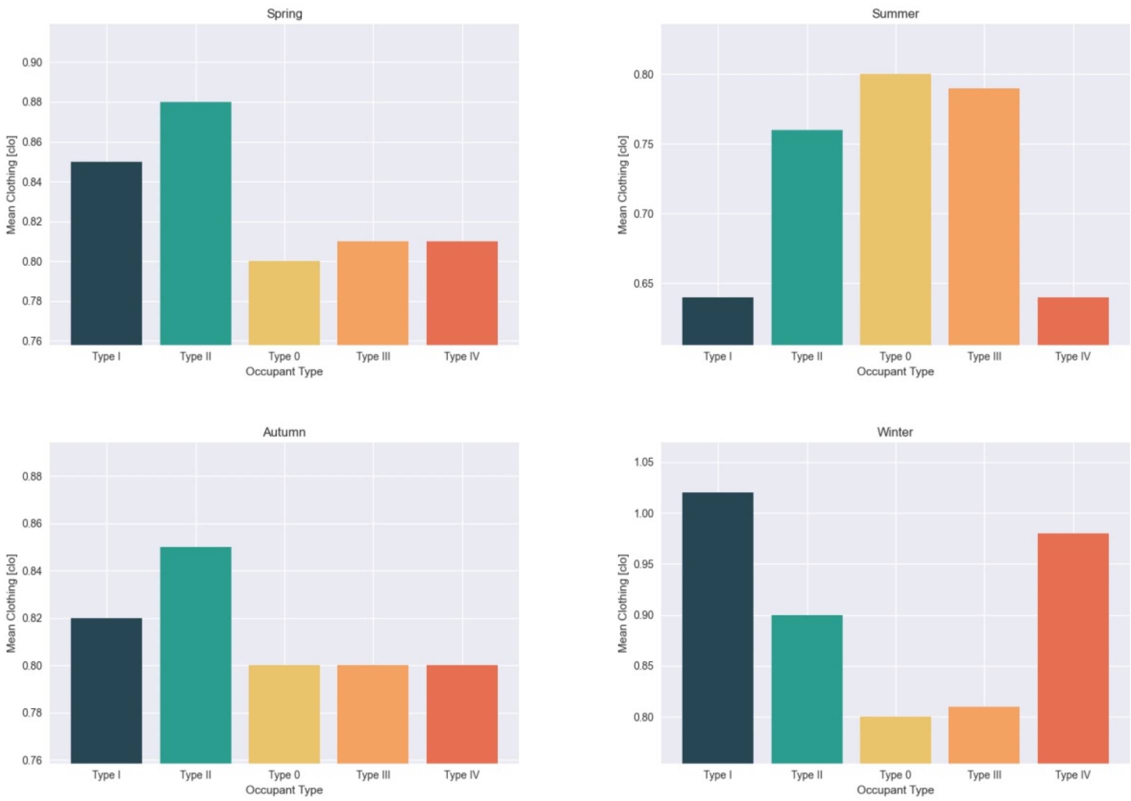

Figure 21: Average clothing number in [clo] for each occupant type for each season

to be higher than the inside temperature, which is for most of them not the case. As already shown in figure 17, for the winter case, during most of the occupancy-hours the PMV-value is below 0, which leads to the cold routines being executed most of the time.

Figure 22: Distribution of actions per occupant type and season

3.5 Concluding reflections

The energy load for the cold scenarios appears to be in line with the finding of Mahdavi et al. 2018. With more high-energy using occupants in the building the energy load rises. This can be observed not only in the graphs for average energy loads in figure 13 but also in the deviation in percent in figure 15. For the summer case not only the scenarios but also the occupant types differ strongly. Mainly it can be observed that with more high-energy-consumers the energy loads rise while in contrary with more low-energy consuming agents the energy loads fall. For the four observed scenarios in the colder months (spring, autumn, winter) this trend is obvious. Displayed in the boxplot in figure 19 the maximum mean energy load for Type I and II and the maximum mean energy loads for Type III and IV are almost equal. Surprisingly the Type III occupants have a higher median for the mean energy load compared to Type IV occupants. For all cases the summer scenario differs strongly. The reasons for this will be discussed in the next chapter.

4 Discussion

4.1 Overview

The behavioural model, oriented on Langevin et al. 2015 and Mahdavi et al. 2018, proves to be reasonable. High-energy-consumers and Low-energy-consumers differ and take reasonable actions according to their preference. The additional layer, introduced to reflect the tolerance towards the room climate, results in a variance in the energy-consumer groups and delivering additional results. An interpretation of the previously listed results is given in the following sections. The occupant types are described. From this evaluation it is possible to interpret the results for the energy simulations of the scenarios. Also, it is possible to give a more detailed insight how different combinations of occupants change the energy loads of the building. Finally, limitations to the model are discussed.

4.2 Occupant types

As shown in figure 19, in most scenarios occupant type number III is the highest energy consumer, which at a first glance is not reasonable. A typical assumption would be, that the occupants with a lower tolerance range and a high-energy consuming routine would also have the highest energy loads. Looking at the average SP temperatures for heating and cooling in figure 20 the same pattern can be observed. The reason behind this is in the routine in combination with the tolerance. Type III agents have a higher tolerance which results in less actions. Still, they belong to the group with high energy consumption. Therefore, their routine is to first change the SP and afterwards try to change their clothing. As observed in figure 17 the PMV-values are uniformly distributed compared to Type IV occupants. This means that they are less likely to take action which not only includes them feeling cold and turning the heating SP up but also turning it down in case they feel warm. SP temperatures set by Type III agents are therefore more likely to stay this way. Type IV occupants on the other hand are more likely to reduce the heating SP. This results in Type III using more energy because they are changing the SP temperatures to their favour and are less likely to set them back. In contrary, a Type II occupant is using more energy compared to Type I. The reason for this is defined in the tolerance curve. Type II occupants have a higher probability of performing an action. While they first adjust their clothing level, at some point the maximum clothing according to the predefined routine is reached, which is earlier for type II occupants than for type I occupants due to the lower tolerance. In order to further adjust the comfort level, the SP is now changed, which results in a higher energy demand.

While some occupants' actions have a very strong impact on energy demand, others show less correlation. Figure 23 shows the number of clothing changes per week and the corresponding average energy demand. No correlation can be found in the occupant groups themselves. The r-numbers are in large parts lower than 0.25. However, if one looks at the instances of clothing changes across all types, it becomes clear that for spring, summer and autumn there is a correlation between clothing changes and energy demand. In principle, it can be said that a higher clothing adaption rate leads to a lower average energy demand. A general statement on this should be made with caution. Figure 24 shows the connection between average SP and average energy consumption. A very pronounced correlation can be seen. Higher average SP also means higher energy loads. The summer case is reversed, but the statement is also confirmed here. The evaluation of the combination of all actions of the occupants in connection with the average energy demand, the situation is more difficult. In some cases, a clear correlation can be found, such as for Occupant Type III and IV for the transitional seasons. In the summer and winter cases, on the other hand, there are no clear manifestations as it can be seen in figure 25.

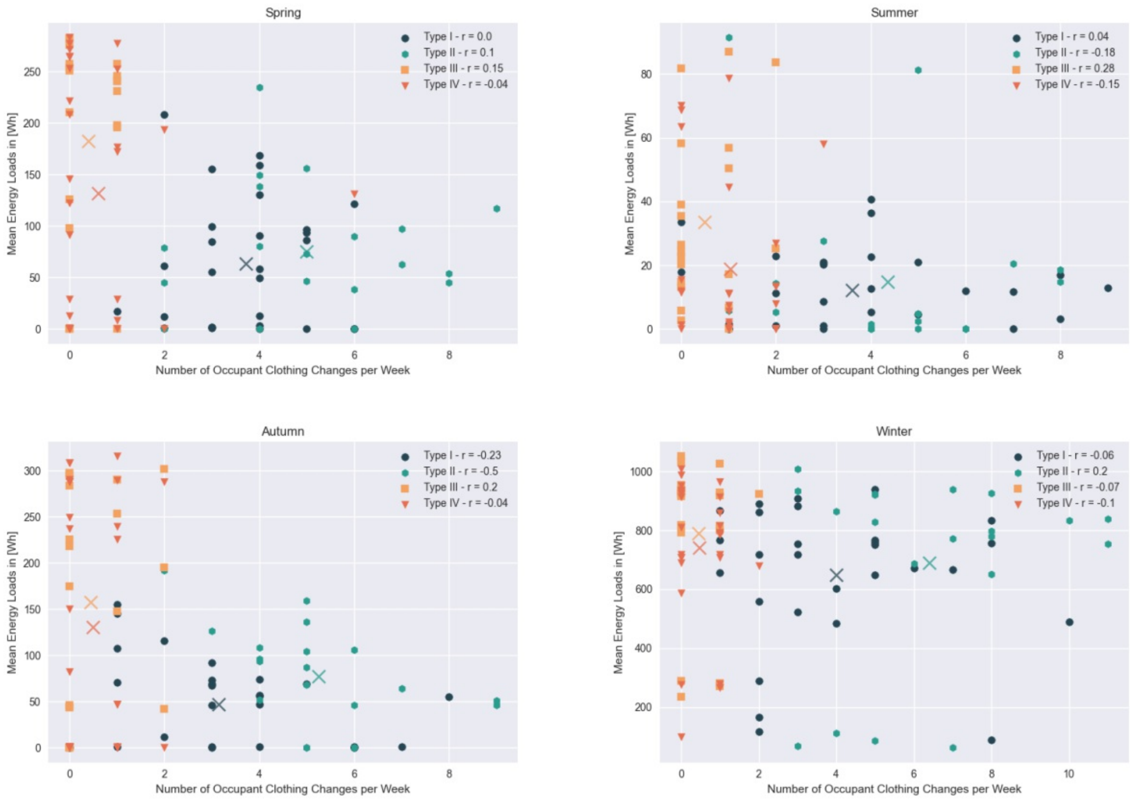

Figure 23: Correlation between change of clothing per week and mean energy loads in [Wh]

Figure 24 shows the average heating SP for the occupant types and the mean energy loads. For all cases a strong correlation can be observed. The regression lines not only show the slope and direction, but with their length also the range of numbers for the individual scenarios. This clearly shows that especially Type I occupants make small changes to the SP temperatures. For the winter case, Type III and Type IV show rather short regression lines. This is due to the fact that the maximum possible SP temperature in the model is 24 °C. This means the occupants cannot exceed 24°C in the cold seasons. While for the cool seasons the r-number is positive, for the summer case it is negative. Contrary to the other seasons the low-energy-consuming agents are on the right end of x-axis. The reason is due to the starting temperature for the simulation with 26°C. Since these occupants are more likely to change their clothing the range for SP changes is relatively low.

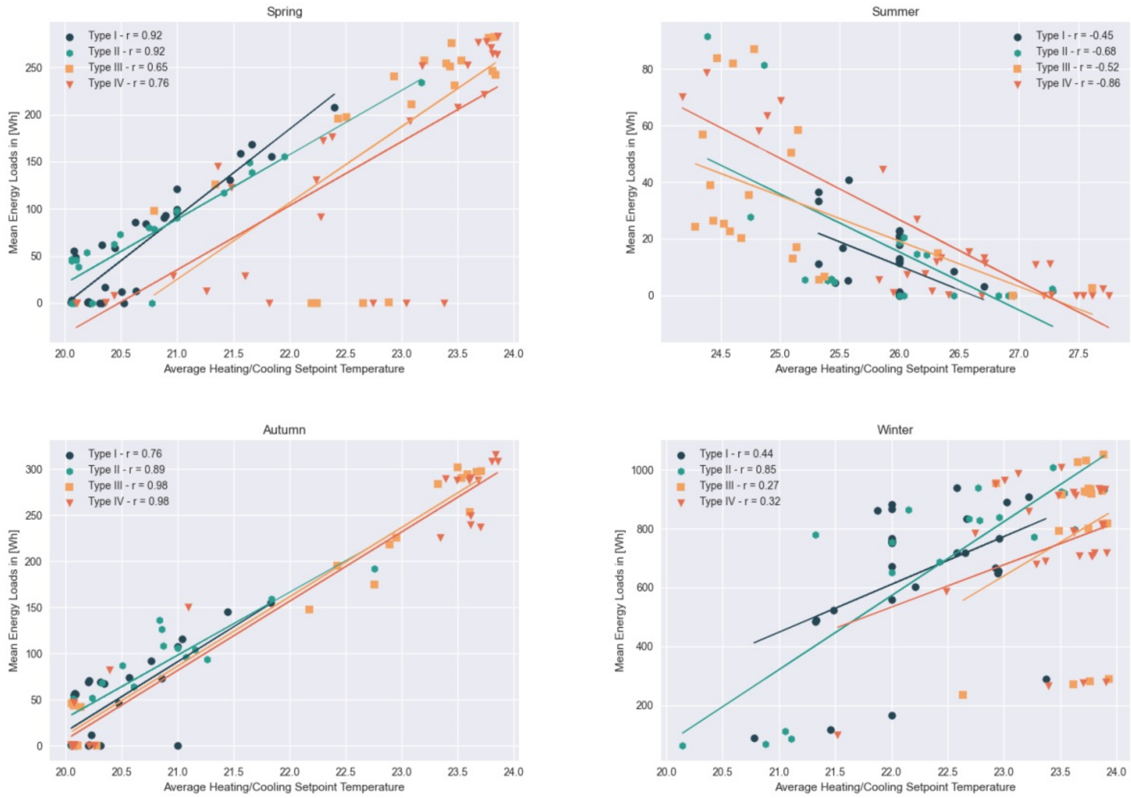

Figure 24: Correlation between average heating SP per week and mean energy loads in [Wh]

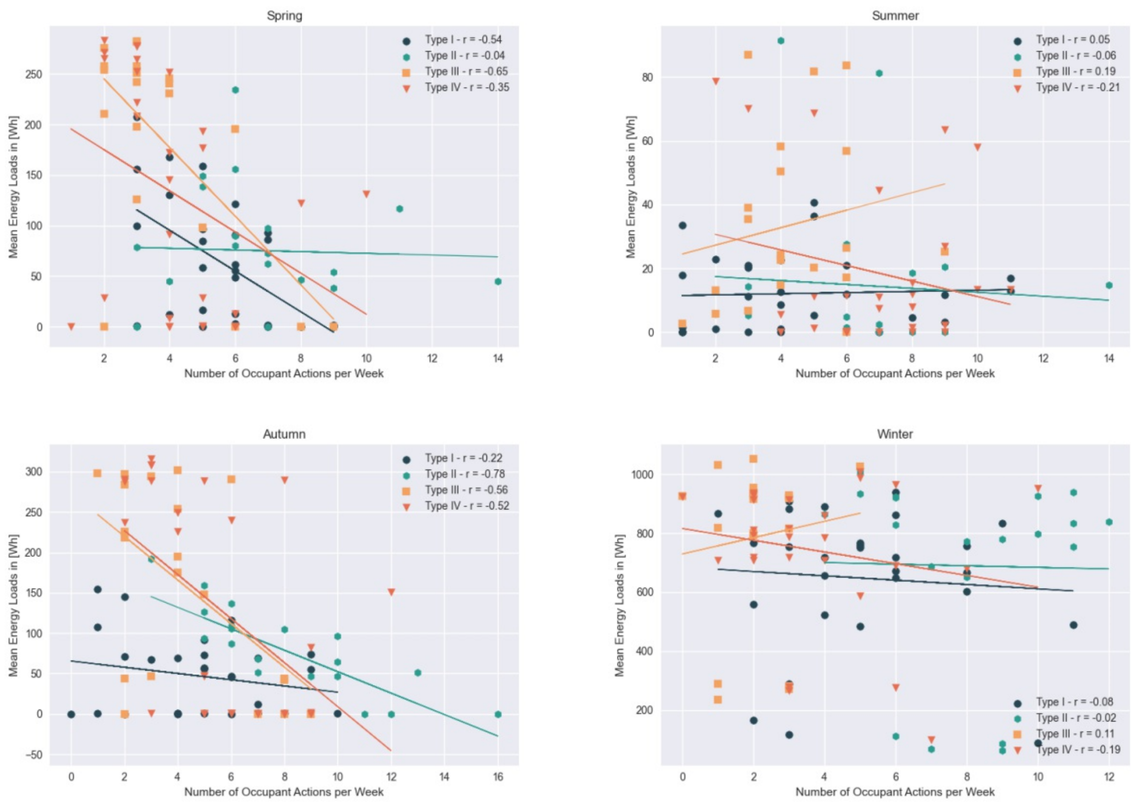

Figure 25: Correlation between average heating/cooling SP changes per week and mean energy loads in [Wh]

4.3 Scenarios

The results of the scenarios are as expected. While the Low-energy-consuming occupants need less energy, the High-energy-consuming occupants need more as described earlier. The combination with four occupant types and six offices however allows for more than the simulated results. To investigate further in how the different scenarios perform and what might be the best combination of occupants a heatmap was created. Depicted in figure 26 are all possible combinations of occupants in the six rooms. Both axis show possible combinations of three occupants which are depicted on the sides in Roman numbers. Looking for example at the first row and the first column, the average energy consumption for 6 type I occupants is shown. Another example would be the first row and the last column which shows the combination of occupant types I, I, I, III, IV and IV. The underlying results were calculated with the median of each occupant type. Important to remember is the uncertainty in these results. The rooms in the original simulations are influencing each other since they are in the same building. The location of the occupants is not taken into account. Also, the energy load is dependent on the room, the occupant is located in. Still, the heatmaps offer insight in where the arguably best and worst cases are to find. Indicated already in the earlier figures, occupant type III is using the highest amount of energy while – except for the summer case – Type I occupants need the least amount. Figure 26 indicates a higher number of energy load with darker colours.

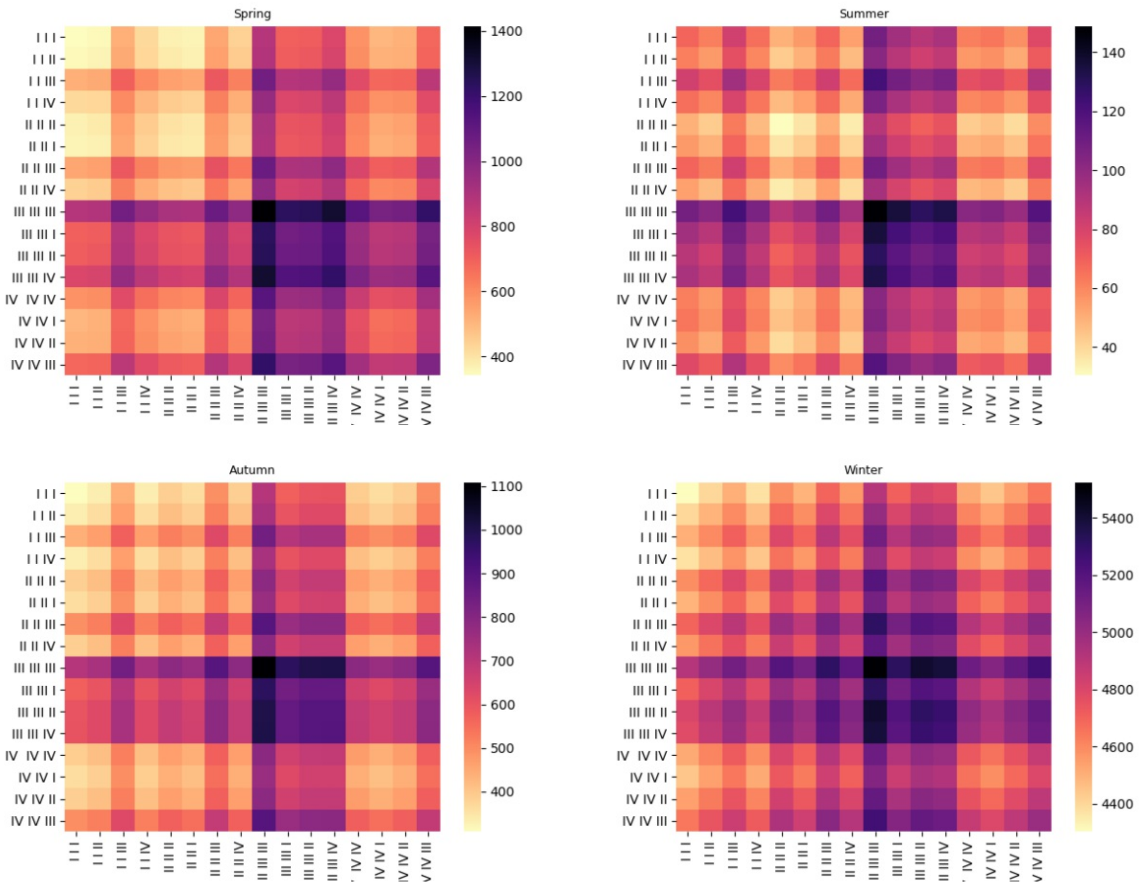

Figure 26: Heatmap for possible scenarios calculated with median for occupant types (Wh)

A similar visualisation offers figure 27. On the x-axis the number of a specific type of occupants

is displayed. On the y-axis the energy load in watt per hour is displayed. Since there are always six occupants in the building, for all numbers smaller than 6 the other occupants have to be filled with other types. The middle line of each colour shows the average of the possible cases while the upper and lower line show the maximum and minimum. Again, as load numbers for the occupant types the median was chosen. To give an example on how to read the graph: At first you chose the occupant you want to investigate. For example, Type IV. When you look at the graph, the x-axis starts with 0. Therefore, zero occupants of Type IV are in the building. The six other occupants can be Type I, II and III. The upper red dot at x = 0 denotes the maximum possible energy load. The middle point shows the average while the low point shows the lowest possible load. Moving on at the x-axis the range between upper and lower limit gets smaller since the number of possible scenarios and the uncertainty in the results also is reduced. At x equal to 6 all occupants are Type IV which is also why there is no longer a range in the points. The other occupant types can be read in a similar way.
Since the occupants of type III have the highest median for the energy load, for the right end of the x-axis they are always on top. For both the spring and winter cases, the peaks of the occupant types are very close to each other. The intersection of the middle lines at an x-number of 1.5 indicates where the average energy load would be with an even occupant type distribution. The field where all graphs overlap indicates the most probable energy load for the building. This area is marked in yellow in the graphs. To get the range of the most likely energy loads, the top and bottom points can be read. For example, the top point of the field in autumn would be about 750 Wh and the bottom point about 450 Wh. The range between the two now shows the most likely average energy load for the building for a hour in this autumn week. Compared with the maximum and minimum energy loads overall the range is for all seasons quite similar.

4.4 Limitations and Considerations

Depicting human behaviour is a very complex and comprehensive task. Even though the model developed in the thesis is limited to the aspect of user behaviour in buildings for the specific case of a single-room office, many parameters are still unclear. In addition, several other options need to be considered when developing such a model. For example, a highly complex and elaborate behavioural system for occupants cannot be reproduced in detail and thus complicates the analysis and reduces the significance. The following restrictions concerning the model were made and must be taken into account in the analysis:

- **Number of possible actions:** Occupants in buildings might have additional options to influence how they are perceiving the room. For example, making themselves a tea or turning on a ventilator. However, such options are not included in the model.
- **Trigger for occupants' actions:** In the model there are only two options that trigger the occupant to perform an action. The current PMV-value of the room and the illuminance. However, in reality there are several other possibilities because an occupant might want to influence his environment. For example, a window can be closed because of noise rather than the temperature.
- **MET:** The metabolic rate for the occupants is fixed. This might not be the case all the

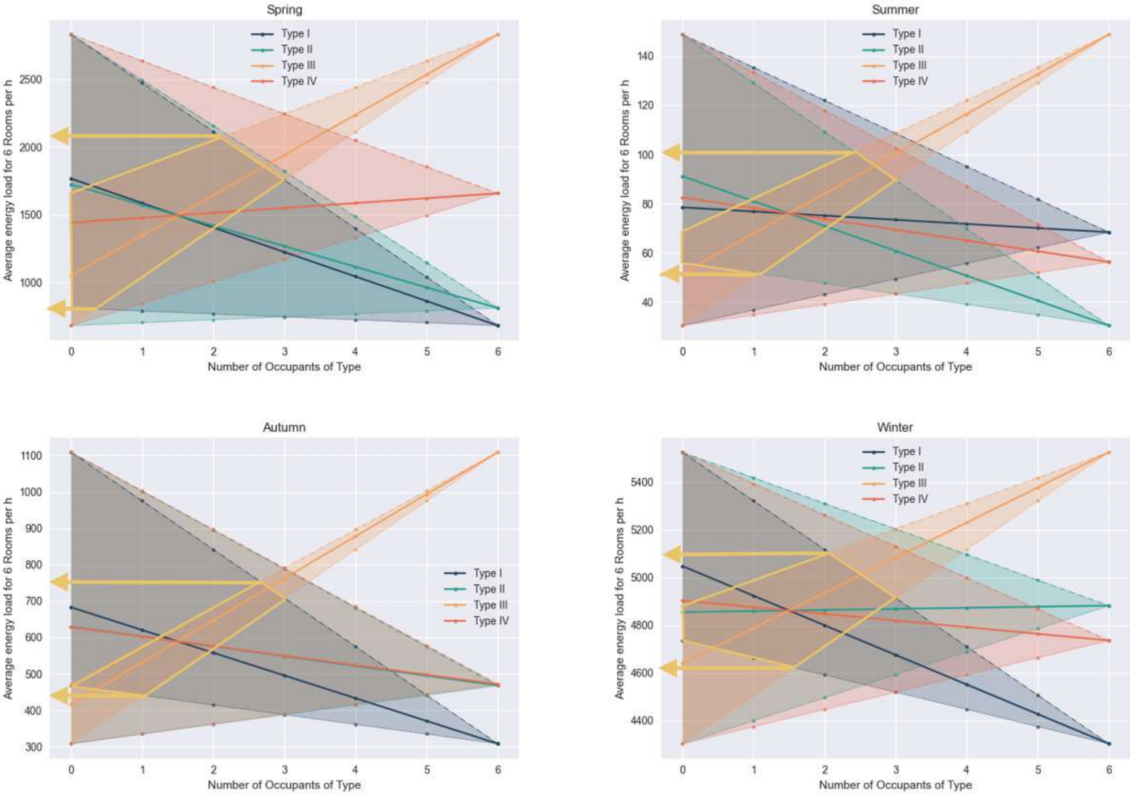

Figure 27: Average energy load range for different occupant combinations

time. For example, the model could be extended by giving occupants each time they come back to the room a higher metabolic rate for one time step.

- **Number of occupants in a room:** The discussed model uses six single offices. As described earlier having more than one occupant in the room introduces an additional layer of behaviour. This makes the decision making process much more complicated since not only the perception of one occupant but of several have to be taken into account. For example, a hierarchy needs to be considered to determine if something is done and what is done.

- **Tolerance curves:** The tolerance curves for the occupants were chosen to not force the agents at each time step to choose an action but to give them the opportunity to react so as to improve their environmental conditions. The percentages for low- and high-tolerance occupants are based on the PMV-value of Fanger. Since the PMV-value originally represents the perception of a group of people for a room it might not always be suitable for each situation. A different solution might be necessary to decouple it from the original Fanger model.

- **Number of offices/simulation runs:** As mentioned, the model currently works with six office rooms. To compensate this rather small number, several simulation runs with the same model where done. This ensured that the results have statistical relevance. However, more office rooms and additional simulation runs would strengthen the results. Additionally other agent combinations can be tested.

- **Simulation Period:** The simulation time period for one run was chosen to be one week. During the warm-up period of EP default numbers are used. This means, that at the start of the Co-Simulation and the actual use of the agents there might be unrealistic room conditions. For example, in summer the room might heat up to the temperature of the cooling SP because the shading is not operated. The starting PMV therefore could be very high which leads to an overcompensation reaction of the agent in this room. Longer simulation periods of a month or even a year would eliminate or at least reduce such problems.

- **Data validation:** The simulation results are missing a real-life case with measured and monitored data to validate the likeliness of such behaviour. Therefore, the model is a theoretical one.

5 Conclusion

This thesis shows the process of building a model to study the behaviour of different occupant types in an office building. For this purpose, different occupant types were defined and a behaviour model was created, depending on the PMV-value according to Fanger and various other parameters. EP was used as the BEM software and Netlogo as the software for the occupant definition routines. The two tools were connected via a co-simulation using BCVTB and Python. The creation of such a co-simulation is associated with an enormous effort, which by far precludes its use on a broad scale. Not only is it necessary to have at least a basic knowledge of various programming languages (Logo for Netlogo, e.g. Python as the connecting software), but knowledge of data processing and data conversion is also required. The use of a co-simulation is also made more difficult by the documentation, which is opaque for beginners, and the frequent lack of help in forums, as the user base is very limited. It might have been easier to use a paid programme to link the two simulation models, but this was not an option within the scope of the thesis. An additional obstacle for the further spread of co-simulations in Building Energy Modelling is the long simulation time. While a traditional dynamic energy simulation can be processed in a few seconds with sufficient computing power, the same simulation in combination with another tool takes significantly longer.

The model developed showed promising results. Depending on the energy consciousness of the occupants, the energy demand changed significantly. Similar results were already delivered in a study by Prof. Mahdavi et. al. 2018. In addition to the consumer types, a further dimension in behaviour was introduced with the implementation of a tolerance system. Occupants with higher tolerance performed fewer actions to influence the indoor climate. Due to different random parameters, each simulation yields different results, even in the case of exactly the same boundary conditions. To ensure statistical relevance, each case was therefore simulated four times. From the mean numbers, or alternative the median, various statements were made in the subsequent analysis. Surprisingly, a greater tolerance of the indoor climate did not automatically result in a lower energy demand. This is particularly clear in the case of Occupant Type III, which stood out as a high-energy consumer with a wide tolerance. However, the data showed that this tolerance can lead to an increased energy demand, because even at high temperatures during the heating period, for example, the reaction is not as fast and thus the ultimate energy demand increases. Basically, the data resulting from the simulations support the statement that user behaviour has a considerable influence on the energy demand. Depending on the energy consciousness of the occupants, this influence can be negative or positive.

The developed model tries to represent reality in a simplified way and tailored to a specific case. However, since human behaviour is complex and dependent on many different parameters, various limitations have to be accepted. Future research in the field of agent-based modeling should especially facilitate the modeling. The faster and easier creation of co-simulations would help to generate more models and thus a broader understanding of the influence of occupants. In addition, existing models can be extended to further define the performance gap problem addressed in the introduction and determine its impact. In conclusion, in the words of statistician George Box (1979), „All models are wrong, but some models are useful.“

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List of Figures

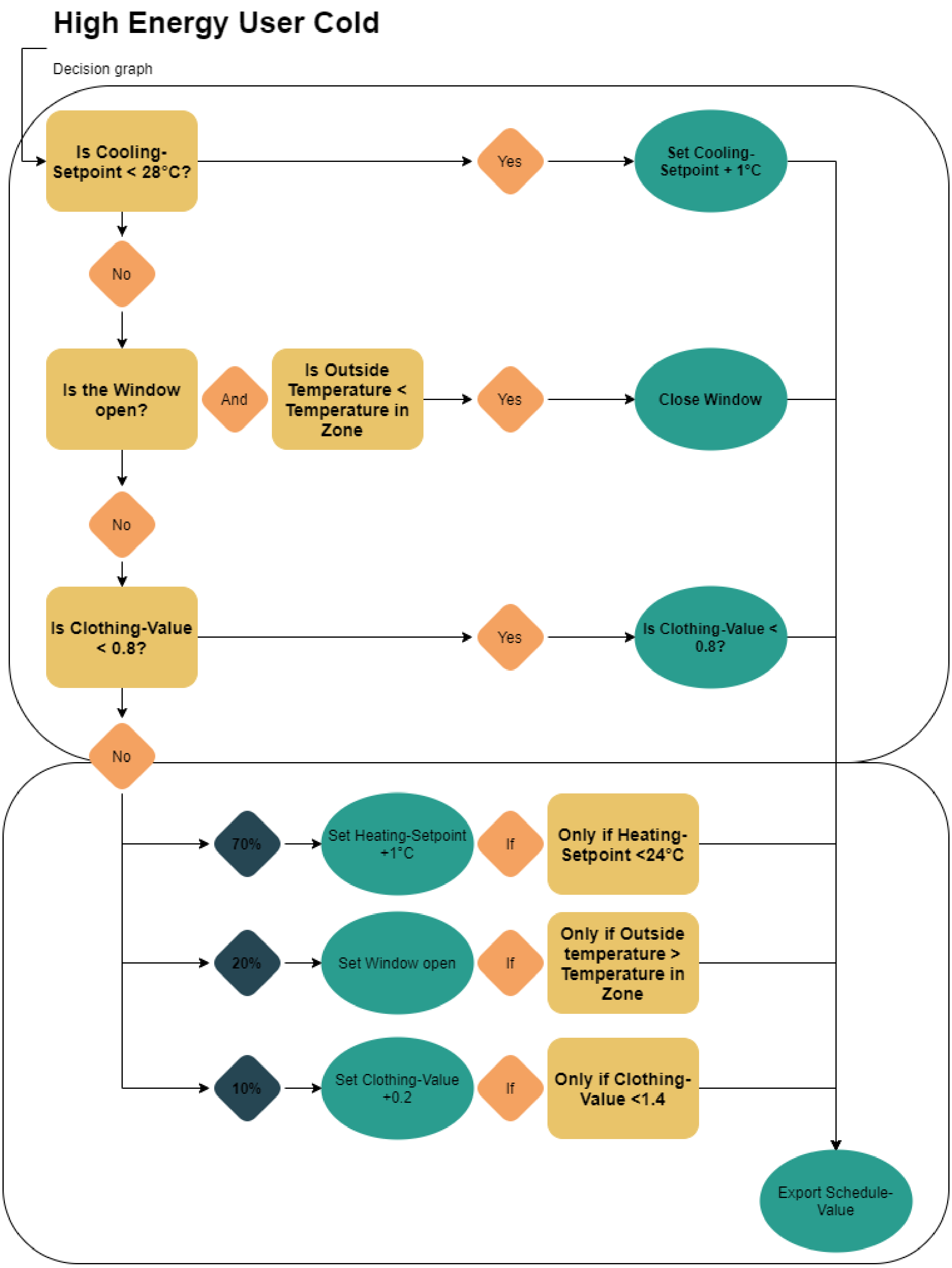
1 PPD as function of PMV (DIN Deutsches Institut für Normung e. V. 2005) . . . 9
2 Office occupancy schedules from ASHRAE 90.1 . . . 10
3 Representation of the building geometry in SketchUp . . . 13
4 Occupant types in the model . . . 14
5 Curves for low- and high-tolerance-occupants . . . 15
6 Occupancy scenarios . . . 16
7 Occupants influence on parameters . . . 17
8 Data Exchange between used software . . . 19
9 Decision making routine for the occupants . . . 20
10 Cognition process for feeling warm for Type III and Type IV occupants (high-energy-user) . . . 21
11 Illustration of clothing numbers (Abdul Majid 2011) . . . 22
12 Example of occupancy for a room for two days . . . 24
13 Mean energy loads in [Wh] . . . 25
14 Yearly energy loads in $\mathrm{kW\,h\,m^{-2}\,a^{-1}}$ . . . 26
15 Mean energy load deviation from base case in percent for each season . . . 27
16 Mean energy loads over time for one week in Spring . . . 27
17 Cumulative distribution plot for PMV . . . 28
18 Mean energy loads for each occupant type . . . 29
19 Boxplot for average energy loads per occupant type and season . . . 30
20 Average setpoint temperature for each occupant type in [°C] for each season . . . 31
21 Average clothing number in [clo] for each occupant type for each season . . . 31
22 Distribution of actions per occupant type and season . . . 32
23 Correlation between change of clothing per week and mean energy loads in [Wh] 34
24 Correlation between average heating SP per week and mean energy loads in [Wh] 35
25 Correlation between average heating/cooling SP changes per week and mean energy loads in [Wh] . . . 35
26 Heatmap for possible scenarios calculated with median for occupant types (Wh) 36
27 Average energy load range for different occupant combinations . . . 38

List of Tables

1 Programs and software used . . . 12
2 Building assumptions . . . 13
3 Shading threshold values . . . 17
4 Simulation periods . . . 18
5 Number of performed simulations . . . 23

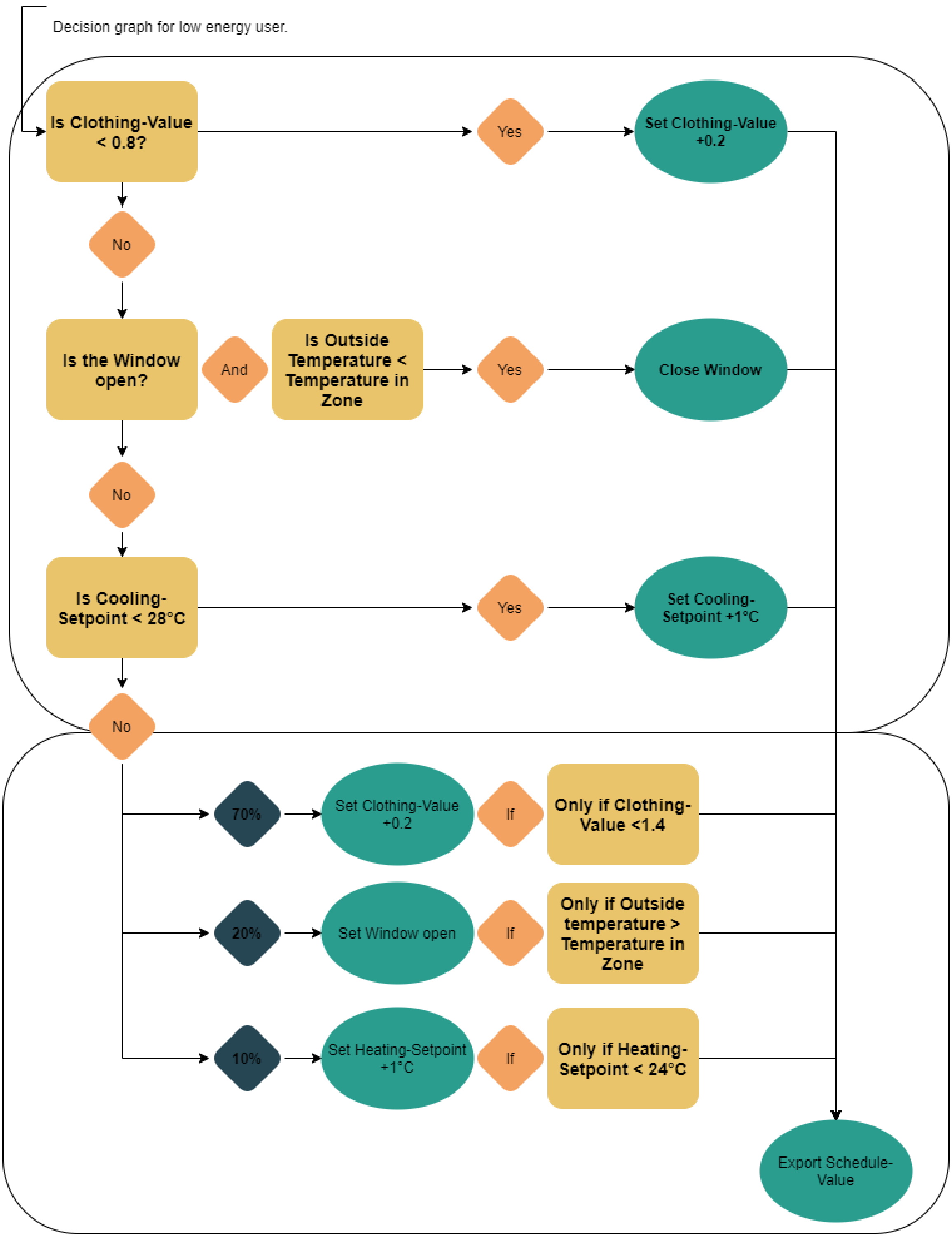
7 Appendix

Routine Flow Charts for Agent Types

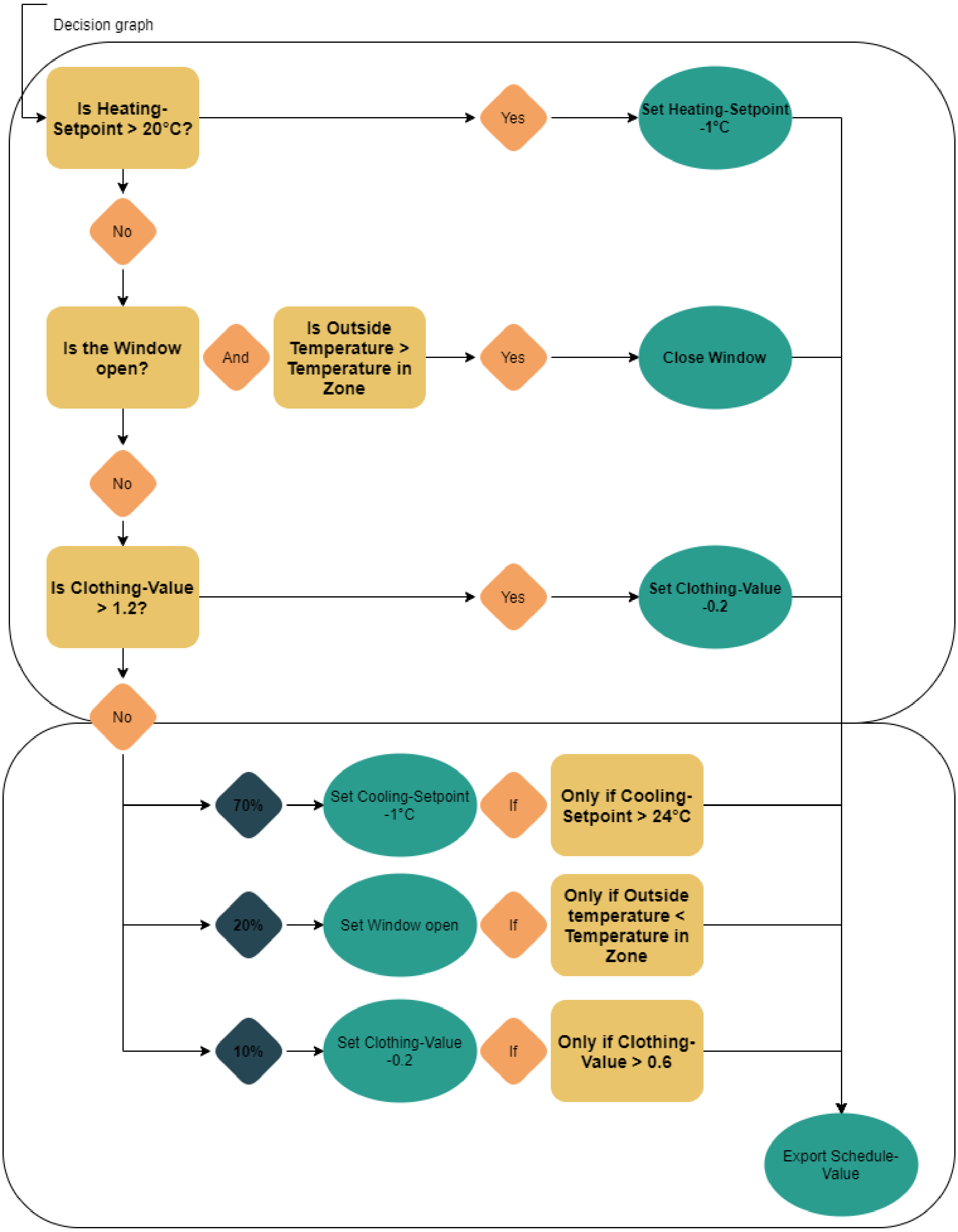


Low Energy User Cold

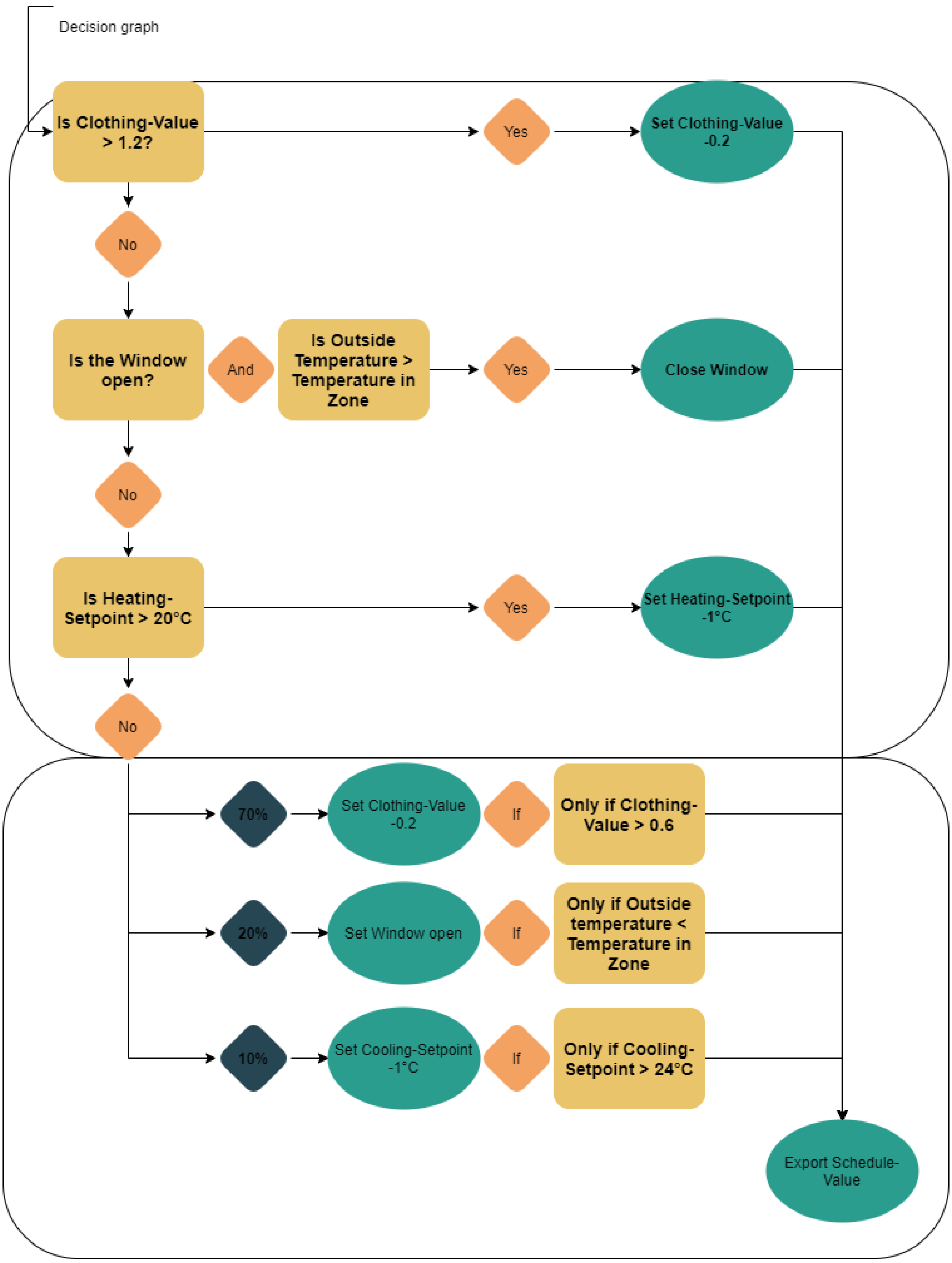
Decision graph for low energy user.



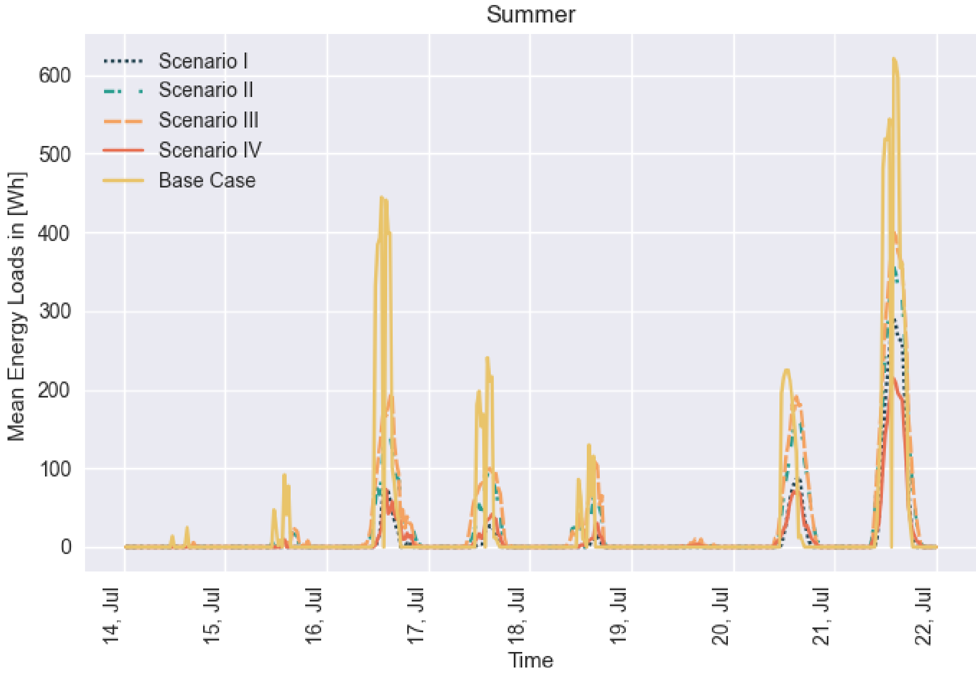
High Energy User Warm

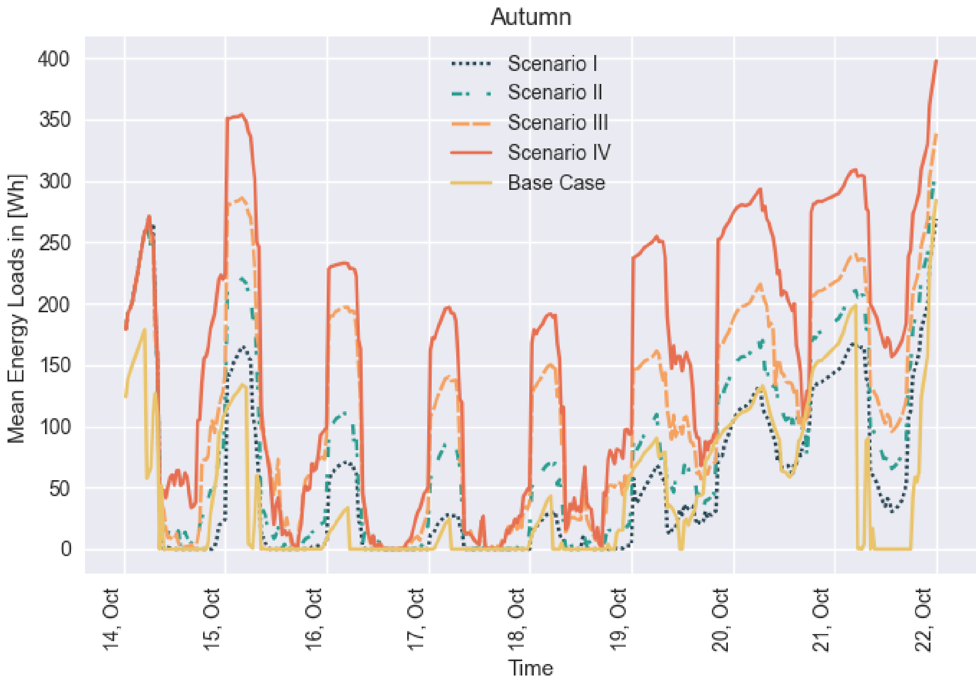


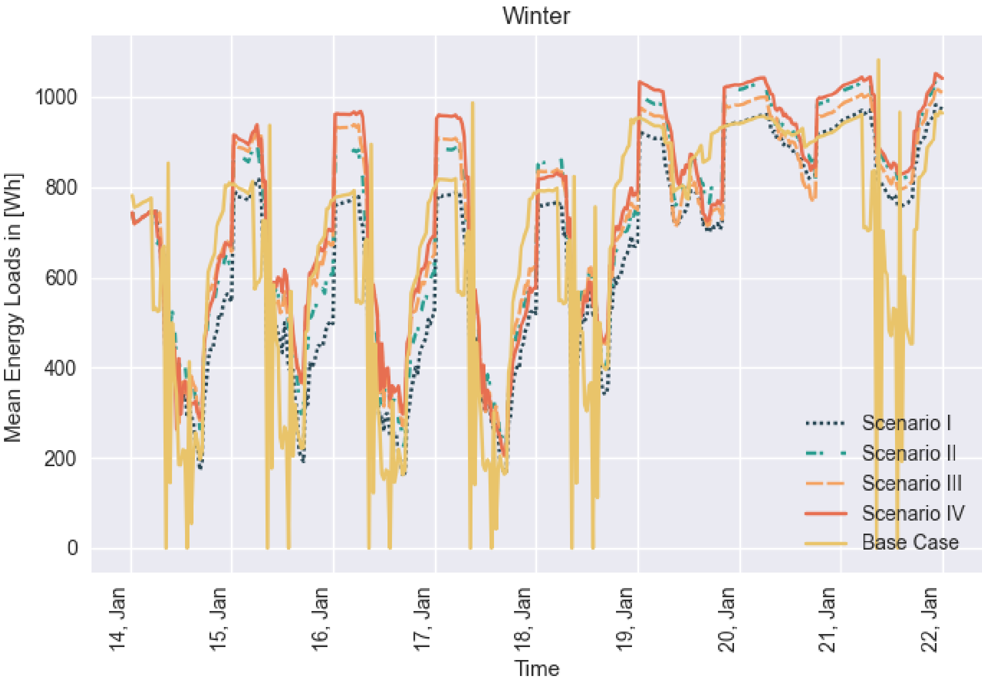
Low Energy User Warm



Mean Energy Consumption over time






Winter
Mean Energy Loads in [Wh]
1000
800
600
400
200
0
14, Jan
15, Jan
16, Jan
17, Jan
18, Jan
19, Jan
20, Jan
21, Jan
22, Jan
Time
Scenario I
Scenario II
Scenario III
Scenario IV
Base Case

Netlogo Code for Agents

```
extensions [ rnd ]          ;; needed for setting probabilities to actions

turtles-own [
 ConsumerType               ;; defines if the user is a low-energy-consumer (0) or a high-energy-consumer (1)
 ToleranceType              ;; defines if the user is a high-tolerance-occupant (0) or a low-tolerance-consumer (1)
 predictedaction            ;; how likely is a agent to perform a action
 OccupancyScheduleValue     ;; Daily schedule, value how likely the agent is in the room
 Occupancy                  ;; is the agent in the room -> 1; otherwise 0
 HVACSystem                 ;; if the window is open the HVAC system is not running (0) otherwise always on (1)
 TempZone                   ;; imports the temperature of the zone from E+ to compare it to the outside temperature

 PMV                        ;; predicted mean vote, imported from Python/BCVTB/EnergyPlus
 CooTempSetpoint            ;; Setpoint for HVAC System for this room/turtle, imported from .txt file
 HeaTempSetpoint            ;; Setpoint for HVAC System for this room/turtle, imported from .txt file
 WindowState                ;; Window open -> 1, Window closed 0, for this room/turtle, imported from .txt file
 CloValue                   ;; Clothing Value for this room/turtle, imported from .txt file

 Lux                        ;; Value from Python/BCVTB/EnergyPlus
 ShadingState               ;; Status of Shades -> 0 shades are open, 1 shades are closed
 LightsState                ;; Status of Lights -> 0 lights in office are off, 1 lights are on
]

to setup
 clear-all                  ;; delete all turtles/clear all patches
 create-turtles 6           ;; create 6 turtles/agents

 ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
 ;; open file for each turtle, import values, close files again
 ;; values are assigned to variables
 ;; think later on: ask turtle 1 [ file-open let CooTempSetpoint file-read let HeaTempSetpoint file-read let....
 ask turtle 0 [ set ConsumerType 1 ]
 ask turtle 1 [ set ConsumerType 1 ]
 ask turtle 2 [ set ConsumerType 1 ]
 ask turtle 3 [ set ConsumerType 1 ]
 ask turtle 4 [ set ConsumerType 1 ]
 ask turtle 5 [ set ConsumerType 1 ]

 ask turtle 0 [ set ToleranceType 1 ]
 ask turtle 1 [ set ToleranceType 1 ]
 ask turtle 2 [ set ToleranceType 1 ]
 ask turtle 3 [ set ToleranceType 1 ]
 ask turtle 4 [ set ToleranceType 1 ]
 ask turtle 5 [ set ToleranceType 1 ]

 ask turtle 0 [
  file-open "Zone0.txt"
   set Occupancy file-read
   set CooTempSetpoint file-read
   set HeaTempSetpoint file-read
   set WindowState file-read
   set CloValue file-read

   set ShadingState file-read
   set LightsState file-read
   set HVACSystem file-read
  file-close
 ]

  ask turtle 1 [
  file-open "Zone1.txt"
   set Occupancy file-read
   set CooTempSetpoint file-read
   set HeaTempSetpoint file-read
   set WindowState file-read
   set CloValue file-read

   set ShadingState file-read
   set LightsState file-read
   set HVACSystem file-read
  file-close
 ]

  ask turtle 2 [
  file-open "Zone2.txt"
   set Occupancy file-read
   set CooTempSetpoint file-read
   set HeaTempSetpoint file-read
   set WindowState file-read
   set CloValue file-read

   set ShadingState file-read
   set LightsState file-read
   set HVACSystem file-read
  file-close
 ]

  ask turtle 3 [
```

```
  file-open "Zone3.txt"
    set Occupancy file-read
    set CooTempSetpoint file-read
    set HeaTempSetpoint file-read
    set WindowState file-read
    set CloValue file-read

    set ShadingState file-read
    set LightsState file-read
    set HVACSystem file-read
  file-close
 ]

  ask turtle 4 [
  file-open "Zone4.txt"
    set Occupancy file-read
    set CooTempSetpoint file-read
    set HeaTempSetpoint file-read
    set WindowState file-read
    set CloValue file-read

    set ShadingState file-read
    set LightsState file-read
    set HVACSystem file-read
  file-close
 ]

  ask turtle 5 [
  file-open "Zone5.txt"
    set Occupancy file-read
    set CooTempSetpoint file-read
    set HeaTempSetpoint file-read
    set WindowState file-read
    set CloValue file-read

    set ShadingState file-read
    set LightsState file-read
    set HVACSystem file-read
  file-close
 ]

end


to go
 ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
 ;; turtles calculate if they are in the room
 ask turtles [ CalcOccupancy ]
 ;; calculate the likelyness of an agent/turtle to perform an action
 ask turtles [ CalcTolerance ]

 ;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
 ;; ask turtles to first check if they are in the room and if they are, perform the action
 ;; environmentsensing, otherwise do nothing
 ask turtles [
 if Occupancy = 1 [ EnvironmentSensing ]
 ifelse WindowState = 1 [ set HVACSystem 0 ][ set HVACSystem 1 ]
 if Occupancy = 1 [ LightSensing ]
 ;; shut down the lights, close the windows and reset the clothing at each new day
 if OccupancyScheduleValue = 0 [ set LightsState 0 ]
 if OccupancyScheduleValue = 0 [ set WindowState 0 ]
 if OccupancyScheduleValue = 0 [ set CloValue 0.8 ]
 ;; Finish timestep with writing all relevant value to schedule
 filewrite
 ]
end


to CalcOccupancy
 ;; calculate for the turtle if its in the room
 ifelse random-float 1 < OccupancyScheduleValue [ set Occupancy 1 ]
   [ set Occupancy 0 ]
end

 ;; predict the likelyness of an agent to perform a action to improve his thermal situation
 ;; more likely to perform an action the higher the PMV. At 0 PMV still 5% possibility that an action is performed
to CalcTolerance
 if ToleranceType = 0 [
  set predictedaction precision (100 - 95 * e ^ (( - 0.03363 * ( PMV ) ^ (4) - 0.2179 * ( PMV ) ^ ( 2 )) * 0.5 )) 2
  if predictedaction > 100 [ set predictedaction 100 ]
 ]
 if ToleranceType = 1 [
  set predictedaction precision (100 - 95 * e ^ (( - 0.03363 * ( PMV ) ^ (4) - 0.2179 * ( PMV ) ^ ( 2 )) * 2 )) 2
  if predictedaction > 100 [ set predictedaction 100 ]
 ]
end
```

```
;; check if the PMV indicates warm or cold environment for the agent
to EnvironmentSensing
  if PMV >= 0 [ warm ]
  if PMV < 0 [ cold ]
end

;; depending on occupant type more or less energy for the light is used
to LightSensing
 ifelse ConsumerType = 0 [
  if lux <= 300 [ dark ]
  if lux > 300 and lux < 3000 [ acceptlight ]
  if lux >= 3000 [ bright ]
 ][
  if lux <= 700 [ dark ]
  if lux > 700 and lux < 2000 [ acceptlight ]
  if lux >= 2000 [ bright ]
 ]
end

;; if environment is warm perform one of several options depending on the environment and the energy-user-type
to warm
 ;; low-energy-consumer routine
 ifelse ConsumerType = 0 [

  if random 100 < predictedaction [
    ifelse CloValue > 1.2 [set CloValue CloValue - 0.2 ][
     ifelse ( WindowState = 1 ) and ( OutsideTemp > TempZone ) [set WindowState 0 ][
      ifelse HeaTempSetpoint > 20 [set HeaTempSetpoint HeaTempSetpoint - 1 ][

        let probabilities [ 0.7 0.2 0.1 ]
        let options [ 1 2 3 ]
        let x first rnd:weighted-one-of-list (map list options probabilities) last
        if ( x = 1 ) and ( CloValue > 0.6 )        [ set CloValue CloValue - 0.2 ]
        if ( x = 2 ) and ( OutSideTemp < TempZone ) [ set WindowState 1 ]
        if ( x = 3 ) and ( CooTempSetpoint > 24 )  [ set CooTempSetpoint CooTempSetpoint - 1 ]
      ]
     ]
    ]
  ]
 ]
 ;; high energy consumer routine
 [
  if random 100 < predictedaction [
    ifelse HeaTempSetpoint > 20 [set HeaTempSetpoint HeaTempSetpoint - 1 ][
     ifelse ( WindowState = 1 ) and ( OutsideTemp > TempZone ) [set WindowState 0 ][
      ifelse CloValue > 1.2 [set CloValue CloValue - 0.2 ][

        let probabilities [ 0.7 0.2 0.1 ]
        let options [ 1 2 3 ]
        let x first rnd:weighted-one-of-list (map list options probabilities) last
        if ( x = 1 ) and ( CooTempSetpoint > 24 )  [ set CooTempSetpoint CooTempSetpoint - 1 ]
        if ( x = 2 ) and ( OutSideTemp < TempZone ) [ set WindowState 1 ]
        if ( x = 3 ) and ( CloValue > 0.6 )        [ set CloValue CloValue - 0.2 ]
      ]
     ]
    ]
  ]
 ]
end

;; if environment is cold perform on of several options depending on the environment
to cold
 ;; low-energy consumer routine
 ifelse ConsumerType = 0 [

  if random 100 < predictedaction [
    ifelse CloValue < 0.8 [ set CloValue CloValue + 0.2 ][
     ifelse ( WindowState = 1 ) and ( OutsideTemp < TempZone ) [set WindowState 0 ][
      ifelse CooTempSetpoint < 28 [ set CooTempSetpoint CooTempSetpoint + 1 ][

        let probabilities [ 0.7 0.2 0.1 ]
        let options [ 1 2 3 ]
        let x first rnd:weighted-one-of-list (map list options probabilities) last
        if ( x = 1 ) and ( CloValue < 1.4 )        [ set CloValue CloValue + 0.2]
        if ( x = 2 ) and ( OutSideTemp > TempZone ) [ set WindowState 1 ]
        if ( x = 3 ) and ( HeaTempSetpoint < 24 )  [ set HeaTempSetpoint HeaTempSetpoint + 1 ]
      ]
     ]
    ]
  ]
 ]
 ;; high-energy consumer routine
 [
  if random 100 < predictedaction [
    ifelse CooTempSetpoint < 28 [ set CooTempSetpoint CooTempSetpoint + 1 ][
     ifelse ( WindowState = 1 ) and ( OutsideTemp < TempZone ) [set WindowState 0 ][
```

```
          ifelse CloValue < 0.8 [ set CloValue CloValue + 0.2 ][

            let probabilities [ 0.7 0.2 0.1 ]
            let options [ 1 2 3 ]
            let x first rnd:weighted-one-of-list (map list options probabilities) last
            if ( x = 1 ) and ( HeaTempSetpoint < 24 )   [ set HeaTempSetpoint HeaTempSetpoint + 1 ]
            if ( x = 2 ) and ( OutSideTemp > TempZone ) [ set WindowState 1 ]
            if ( x = 3 ) and ( CloValue < 1.4 )         [ set CloValue CloValue + 0.2]
          ]
        ]
      ]
    ]
  ]
end

;; routines for setting the shades and the light
to dark
  ifelse ShadingState = 1 [ set Shadingstate 0 ] [ set LightsState 1 ]
end

to acceptlight
  set LightsState 0
  set ShadingState 0
end

to bright
  ifelse LightsState = 1 [ set LightsState 0 ] [ set Shadingstate 1 ]
end

 ;; the turtle will open its specific file and insert the current settings for each option
to filewrite
  ask turtle who [
    file-delete (word "Zone" who ".txt")
    file-open (word "Zone" who ".txt")
    file-write Occupancy
    file-write CooTempSetpoint
    file-write HeaTempSetpoint
    file-write WindowState
    file-write CloValue

    file-write ShadingState
    file-write LightsState
    file-write HVACSystem
    file-close
  ]
end
```

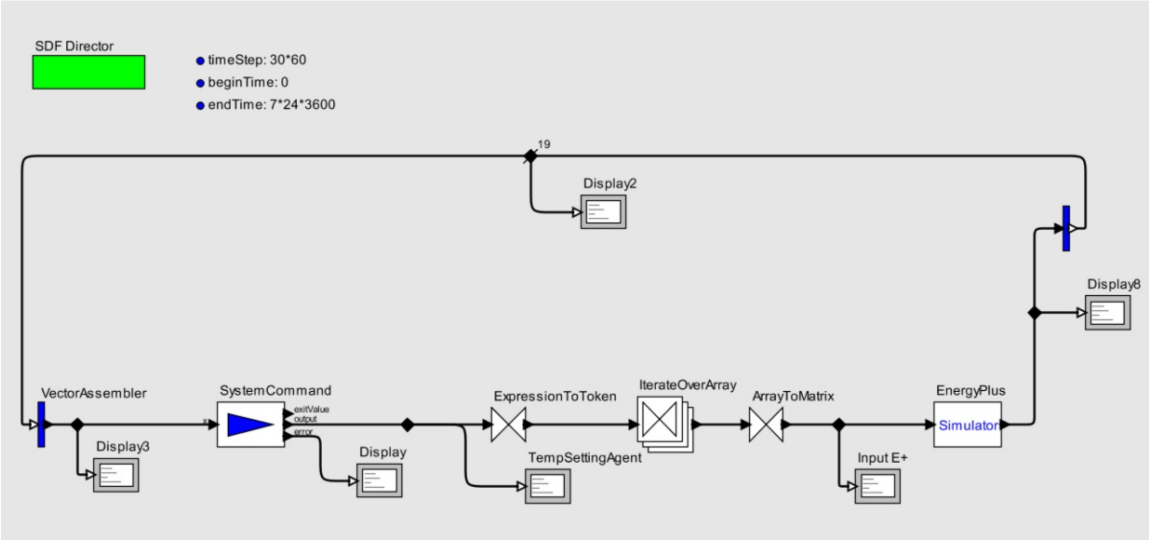
Python Code for Data Conversion to Netlogo

```
import sys                  # import sys to be able to adress get values from BCVTB
import pyNetLogo            # import pyNetLogo to be able to adress Netlogo from Python
import os                   # needed to automatically get the working direction and the files
import re                   # needed to automatically get the working direction and the files

# sys.argv is input vector from BCVTB; convert this to string
x = str(sys.argv[1])

# delete unnecessary characters in the string to prevent model from collapsing
x = x.replace(";","")
x = x.replace("[","")
x = x.replace("]","")

# split the string into a list
list = x.split()


# assign the different values to Zones
PMVvalueZone0 = list[0]
PMVvalueZone1 = list[1]
PMVvalueZone2 = list[2]
PMVvalueZone3 = list[3]
PMVvalueZone4 = list[4]
PMVvalueZone5 = list[5]
OutdoorTemp = list[6]

LuxZone0 = list[7]
LuxZone1 = list[8]
LuxZone2 = list[9]
LuxZone3 = list[10]
LuxZone4 = list[11]
LuxZone5 = list[12]

TempZone0 = list[13]
TempZone1 = list[14]
TempZone2 = list[15]
TempZone3 = list[16]
TempZone4 = list[17]
TempZone5 = list[18]
# OccupantType0 = 1
# OccupantType1 = 1
# OccupantType2 = 1
# OccupantType3 = 1
# OccupantType4 = 1
# OccupantType5 = 1

# get working directory:
WorkingDirectory = os.getcwd()

# Handle the Timesteps:
def timesetting():
    for file in os.listdir(WorkingDirectory):  # get working direction where file is located
        if re.search(".idf", file):                      # search for .idf file
            IDFfile = file                               # if idf file is found assign string to variable

    with open(IDFfile, "r") as eplusfile:                # open IDF file and search for the number of Timesteps
        for line in eplusfile:
            if "!- Number of Timesteps per Hour" in line:
                r = str(line)
                NumTimesteps = int(''.join(x for x in r if x.isdigit()))     # assign the number of timesteps to Variable


    with open("timesteps.txt", "r") as file:
        time = file.read()
        time = time.split()
```

```
        hours = int(time[0])

        days = int(time[1])


    with open("timesteps.txt", "w") as file:            # open the timestep handling file as writing file and overwrite old timestep
        if hours >= (24 * NumTimesteps):                 # if one day is over (multiply 24 hours with the number of timesteps) start from
            file.write(str(1)+" "+str(days+1))                              # beginning
        else:                                           # otherwise add +1 to timesteps
            file.write(str(hours + 1)+" "+str(days))

    if (days <= 5):
        x = hours / NumTimesteps                    # calculate the current time
        if x <= 6:                                 # begin of Occupancy Schedule
            occ = 0
        if x > 6 and x <= 7:
            occ = 0.1
        if x > 7 and x <= 8:
            occ = 0.2
        if x > 8 and x <= 12:
            occ = 0.95
        if x > 12 and x <= 13:
            occ = 0.5
        if x > 13 and x <= 17:
            occ = 0.95
        if x > 17 and x <= 18:
            occ = 0.3
        if x > 18 and x <= 22:
            occ = 0.1
        if x > 22 and x <= 24:
            occ = 0.05
    if (days == 6):
        x = hours / NumTimesteps                    # calculate the current time
        if x <= 6:                                 # begin of Occupancy Schedule
            occ = 0
        if x > 6 and x <= 8:
            occ = 0.1
        if x > 8 and x <= 11:
            occ = 0.3
        if x > 11 and x <= 18:
            occ = 0.1
        if x > 18 and x <= 20:
            occ = 0.05
        if x > 20 and x <= 24:
            occ = 0
    if (days >= 7):
        x = hours / NumTimesteps                    # calculate the current time
        if x <= 6:                                 # begin of Occupancy Schedule
            occ = 0
        if x > 6 and x <= 18:
            occ = 0.05
        if x > 18 and x <= 24:
            occ = 0
    timesetting.occ = occ                       # assign to variable which can be accessed from outside of the function
timesetting()

OccupancySchedule = str(timesetting.occ)         # reassign the Schedule value

# open Netlogo with pyNetLogo; set gui to be false so netlogo does not show up; speeds up the simulation
netlogo = pyNetLogo.NetLogoLink(gui=False)

# get Netlogo filepath:
NetlogoFile = WorkingDirectory+ '/3_NetlogoModel.nlogo'

# load the Netlogo Model
netlogo.load_model(NetlogoFile)
```

```
# set the calculated values from energyplus and the variables from last timestep to have the current
# state of the model, now done in Netlogo via Dataimport
# setup the model; this will set up turtles/agents, calculate if the agents are present, and
# calculate the predicted probability that a agent performs an action
netlogo.command('setup')

# netlogo.command('ask turtle 0 [ set OccupantType '+OccupantType0+']')
# netlogo.command('ask turtle 1 [ set OccupantType '+OccupantType1+']')
# netlogo.command('ask turtle 2 [ set OccupantType '+OccupantType2+']')
# netlogo.command('ask turtle 3 [ set OccupantType '+OccupantType3+']')
# netlogo.command('ask turtle 4 [ set OccupantType '+OccupantType4+']')
# netlogo.command('ask turtle 5 [ set OccupantType '+OccupantType5+']')

# set current pmv for each turtle from imported values
netlogo.command('set OutsideTemp '+OutdoorTemp)
netlogo.command('ask turtle 0 [set PMV '+PMVvalueZone0+']')
netlogo.command('ask turtle 1 [set PMV '+PMVvalueZone1+']')
netlogo.command('ask turtle 2 [set PMV '+PMVvalueZone2+']')
netlogo.command('ask turtle 3 [set PMV '+PMVvalueZone3+']')
netlogo.command('ask turtle 4 [set PMV '+PMVvalueZone4+']')
netlogo.command('ask turtle 5 [set PMV '+PMVvalueZone5+']')

netlogo.command('ask turtle 0 [set Lux '+LuxZone0+']')
netlogo.command('ask turtle 1 [set Lux '+LuxZone1+']')
netlogo.command('ask turtle 2 [set Lux '+LuxZone2+']')
netlogo.command('ask turtle 3 [set Lux '+LuxZone3+']')
netlogo.command('ask turtle 4 [set Lux '+LuxZone4+']')
netlogo.command('ask turtle 5 [set Lux '+LuxZone5+']')

netlogo.command('ask turtle 0 [set TempZone '+TempZone0+']')
netlogo.command('ask turtle 1 [set TempZone '+TempZone1+']')
netlogo.command('ask turtle 2 [set TempZone '+TempZone2+']')
netlogo.command('ask turtle 3 [set TempZone '+TempZone3+']')
netlogo.command('ask turtle 4 [set TempZone '+TempZone4+']')
netlogo.command('ask turtle 5 [set TempZone '+TempZone5+']')

netlogo.command('ask turtles [set OccupancyScheduleValue '+OccupancySchedule+']')

# if the turtles/agents are present it calculates if they are warm or cold and if the perform
# an action; after that a .txt file for data exchange is produced
netlogo.command('go')

# opens the .txt file (the one netlogo produced) and converts the data such that
# BCVTB can use it as input
Export = '{'
for x in range(0,6):
    y = 'Zone'+str(x)+'.txt'
    with open(y, 'r') as f:
        zone = str(f.read()).split()
        for i in zone:
            Export = Export + '"' + str(i) + '"' + ','
output = Export[:-1] + '}'

print(output)
# shuts down netlogo, otherwise the simulation will crash since serveral instances of the model would be open
netlogo.kill_workspace()

# outputs a 0 to the console/BCVTB if the simulation was successful (usefull if you depend your
# simulation on this parameter/perform a action depending on this)
sys.exit(0)
```

BCVTB Connection



BCVTB Folder Structure

1_PythonDataConversion.py
2_EnergyPlusModel.idf
3_NetlogoModel.nlogo
simulation.log
simulation2.log
system.xml
timesteps.txt
variables.cfg
Zone0.txt
Zone1.txt
Zone2.txt
Zone3.txt
Zone4.txt
Zone5.txt