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Exploring the Influence of Occupancy Modeling Assumptions Regarding Thermal Performance Simulations

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ZUSAMMENFASSUNG

Im Rahmen des Trends zur Verbessrung der Gebäudeleistung ist Versorgung der realistischen Belegungsprofile ein entscheidender Faktor um die Diskrepanzen zwischen dem tatsächlichen und simulierten Energieverbrauch zu reduzieren. Es scheint aber als die meisten Bemühungen zur Modellierung der Belegung für die Simulation der Gebäudeleistung würden die Implikation der Auswahl der verschiedenen Ansätze der Präsenzmodellierung auf die Ergebnisse der Simulation der Gebäudeleistung ignorieren. Genauer gesagt, die Simulation der thermischen Gebäudeleistung würde wohl von dem Stand der Arbeitsbereiche auf Bauschicht und von einer stündlichen Spitzenbelastung auf eine jährliche Bedarfsberechnung von den Belegungsmodellen beeinflusst. In diesem Fall, die Auswahl der verschiedenen Belegungsmodelle (wie die sogenannten deterministischen und stochastischen Modelle) könnte auf den Aspekten der Gebäudeleistung basieren. Dementsprechend wird in dieser These die thermische Leistung von zwei Bürogebäuden (einem virtuellen Prototyp des Bürogebäudes und einem tatsächlichen Bürogebäude) erforscht, wo unterschiedliche Ansätze bei der Modellierung der Belegung berücksichtigt werden. Die Simulationen werden in Bezug auf das Wiener Klima durchgeführt und die Simulationssoftware „EnergyPlus" ermöglicht die Einfügung der mehreren fix und zufällig generierten Belegungsprofile in den Gebäudemodellen. Um den Einfluss der Annahme der Belegungsmodelle auf die thermische Leistung zu erforschen, wurden unterschiedliche Gebäudeleistungsindikatoren für die Heiz- und Kühlsaisons mit den unterschiedlichen Berichtsfrequenzen (z.B. stündlichen, monatlichen und jährlichen) beobachtet. Aus den Ergebnissen ist zu folgern, dass zwar die stochastische Präsenzmodelle realistischere Verteilung der Belegung ergeben aber kein merklicher Unterschied zwischen konventionellen und stochastischen Belegungsprofile besteht; weder im Hinblick auf den berechneten Werten der jährlichen und Spitzenbelastung des Heiz- und Kühlbedarfs, noch durch die Anwendung der unterschiedlichen Stufen des Bewohners Interaktionen.

ABSTRACT

With the trend towards improving the building performance, providing realistic occupancy profiles is a key factor in reducing the discrepancies between the actual and simulated energy consumption. Yet, it seems that most of the efforts in modeling occupancy for building performance simulation, disregard the implication of selecting different presence modeling approaches on building performance simulation results. More precisely, the building thermal performance simulation, from the level of workspaces to the building level, and from an hourly peak load to an annual demand calculation may be influenced differently from the occupancy models. If so, selecting among different types of occupancy models (such as the so-called deterministic and stochastic models) can be based on the building performance aspects, which are to be studied. Given this background, this thesis studies the thermal performance of two office buildings (one virtual prototype office building & one real office building), adopting different approaches in modeling occupancy. The simulations are performed regarding Vienna's climate and by using EnergyPlus as the simulation software, which enables the incorporations of multiple fixed and randomly generated occupancy profiles into the building models. In order to explore the influence of occupancy modeling assumption on building thermal performance, different building performance indicators for heating and cooling seasons with different reporting frequencies (such as hourly, monthly and annual) were studied. From the results, it is concluded that even though the stochastic presence models offer more realistic distribution of occupancy, there is not a noticeable difference between conventional and stochastic occupants' presence models in view of the computed values of annual and peak heating and cooling demands, even by applying different levels of occupant's interactions.

Keywords

Building performance simulation, occupancy models, stochastic occupancy models, fixed presence profiles, annual heating and cooling demand, peak heating and cooling loads

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"Life is full of surprises; you don't know what will hit you."

… to my second chance of living

CONTENTS

1 INTRODUCTION

1.1 Overview

Energy use measured in buildings demonstrates large discrepancies even between buildings with similar functions and climatic conditions. Among various factors contributing to the discrepancies, occupant behavior is a driving factor which is also one of the most significant sources that limit the ability of energy models to accurate the prediction of building performance. The significance of occupant presence and his energy-related behavior in buildings can be defined in two aspects:

A) The building performance and B) The building performance simulations;

Building performance is affected a) by occupant presence; due to releasing sensible and latent heat gains through their clothing, behavior and activity ranges. And b) by occupant actions; due to the interacting with building systems such as: opening/closing windows, operating shading devices, tuning light intensity or turning them on/off, regulating thermostat and HVAC systems and finally using all the electronic appliances which consume energy and produce heat.

Building performance simulations are affected a) by different approaches in modeling occupancy; such as applying “Fixed typical schedules” or “Random non-repeating schedules”. And also b) by the implications of the occupancy modeling approaches in common simulation results; which interprets the way that the results are derived, analyzed and presented.

Concerning this context, the current thesis is intended to investigate the influence of the occupancy modeling assumptions on thermal performance simulation results. In order to explore this effect more precisely, it was necessary to access to a complete and accurate source of monitored data for the real building prototype. Since this possibility was provided by one of the office building of the Vienna University of Technology, for which high-resolution monitored occupancy data was available, correspondingly as the virtual prototype was also an office building selected. In each simulation scene, different scenarios according to the presence and interaction of occupant were applied.

1.2 Motivation

Referring to the IEA EBC[1] Annex 53[2] ; six affective factors define the energy performance of buildings: climate, building envelope, building system, operation and maintenance, occupant behavior, and indoor environmental conditions. In this concept and due to the functionality of the office buildings, occupant behavior plays a significant role in the building's final energy demand. Furthermore with the trend towards improving the building performance, providing realistic occupancy profiles is a key factor in reducing the discrepancies between the actual and simulated energy consumption.

Yet, it seems that most of the efforts in modeling the occupancy, disregard the implications of modeling assumptions on different aspects of building thermal performance. More precisely, the building thermal performance simulation, from the level of workspaces to the building level, and from an hourly peak demand to an annual load calculation may be influenced differently from the occupancy models. If so, selecting among different types of occupancy models (such as the so-called deterministic and stochastic models) can be based on the building performance aspects, which are to be studied. As a result, the aim of this thesis is to investigate more distinctly and deeply the effect of different modeling assumptions in building energy performance.

1.3 Background

Occupancy models are intended to provide a representation of building users in building performance simulation models in the absence of high-resolution data in the design phase. Frequently, occupancy patterns are represented in the building models by average profiles of presence probability. In this context, a widely used set of occupancy schedules for different types of buildings has been provided in ANSI/ASHRAE/IES Standard 90.1-2013 (ASHRAE 2013a). In addition, multiple efforts are being undertaken to derive more reliable building occupancy profiles. See (Davis and Nutter 2010) and (Daurte et al. 2013).

While simulation tools mostly reproduce the deterministic physical behavior of buildings in more detail, the behavior of their inhabitants has so far been represented by repeating standard patterns of occupant presence and the consumption of elements such as light and other appliances. Some studies show that these assumptions lead to considerable errors in the prediction of the peak demand in resources of a building. Which in turn will strongly influence the choice and sizing of the means (HVAC systems, supplies for power and water - hot and cold) to cover that demand. As Jessen Page has claimed this in his thesis

[1] IEA EBC: International Energy Agency- Energy in Buildings and Communities Program
[2] Annex 53: Total energy use in buildings – assessment and analysis methods

(2007) : "*[…] the randomness linked to occupants, i.e. the differences in behavior between occupants and the variation in time of each behavior, plays an ever more important role in the discrepancy between the simulated and real performances of buildings. This is most relevant in estimating the peak demand of energy (for heating, cooling, electrical appliances, etc.) which in turn influences the choice of technology and the size of the equipment installed to service the building*."

As one of the first attempts, Newsham (Newsham et al. 1995) considered the probabilistic nature of occupancy while developing a stochastic model to predict lighting profiles for a typical office. Their model deployed the probability of first arrival and last departure as well as the probability of intermediate departures from and returning back to the workstations. Reinhart (2001) further developed this model by using the inverse transform sampling method to generate samples of arrival and departure times, and by deploying distributions of break lengths. Subsequently Page (2007) has developed a stochastic model by using an algorithm for the simulation of occupant presence, considering occupant presence as an inhomogeneous Markov chain interrupted by occasional periods of long absence. The model is able to simulate the presence of occupants and their interactions with the building and the equipment present and it generates a time series of the state of presence (absent or present) of each occupant of a zone, for each zone of any number of buildings.

Furthermore some other studies (Aerts and Minnen 2013; Yan et al. 2015; Yu 2010) have suggested that by implementing the variety of ways that people occupy a building and interact with it, in building simulation tools can conceive and assess new ways to save energy and enhance occupants' comfort in the buildings. As a result stochastic occupancy modeling was proposed to provide a more realistic picture of the period which the occupants spend in the zone and how often they might interact with the indoor environment. It is claimed that these models will help to provide information on the distribution of the demand in energy and therefore demonstrating how the production plans should be sized.

In this context, it is necessary to demonstrate the influences of applying different occupancy modeling assumptions on the building energy demand. As an example of such an evaluation of occupancy models, Mahdavi and Tahmasebi (2015) studied a number of probabilistic and non-probabilistic occupancy models considering short-term occupancy predictions for simulation-powered predictive building systems control. Yet, studying the conventional use of simulation models for calculation of buildings' heating and cooling demand has not been done.

2 METHOD

2.1 Overview

In order to investigate the influences of implementing different occupancy models on the energy performance of a building, in current study two types of office buildings regarding their thermal performance (heating and cooling demands) were explored and simulated; A Virtual and a Real office building.

EnergyPlus was chosen as the simulation software based on its possibilities to simulate the building models through multiple fixed and randomly generated occupancy profiles. Also the building thermal performance could be simulated in the level of workspaces as well as the building levels. The result was produced with different reporting frequencies, namely annual, monthly, hourly and 15-min time-steps, which provided the evaluation with a precise peak demand.

In the simulation phase three main stages were required; A) Creation of building model (Input definition), B) Utilizing the simulation program, EnergyPlus, (Running/Debugging the inputs) and C) Analysis of the simulation results (Outputs).

The sequence of simulations was accomplished considering following points:

- To which extent do the results of simulations using stochastic occupancy models differ from using conventional diversity profiles?
- Does the level of difference depend on the temporal aggregation interval (e.g. annual, versus hourly)?
- What are the additional effects of user-based actions (i.e., operation of shades and mechanical ventilation)?

To accomplish the comparison, two approaches were planned. In first approach the building is once simulated with the fixed occupancy profiles through year with different reporting frequency and user-based actions. Afterward in second approach it is simulated by deploying the randomized occupancy profiles. The concept of two approaches was the same for both case studies, but in details they had some differences; since for the real office building besides the ASHRAE typical profiles, real-time data was also available. In the following sections further details on the modeling approaches, the assumptions and scenarios, and finally the results and discussion associated with each office building will be delineated.

2.2 Occupancy modeling approaches

In the following section a description of the considered approach is provided. Since the two buildings were different in the nature of their model, the assigned scenario to each of them could be formed and evaluated specifically and individually. Respectively all the discussed topics are divided into two sub-sections, where each of them describes the intended topic for the associated case study.

2.2.1 Virtual office building

As it mentioned in previous section, the model of virtual office building was simulated based on two approaches. In first set of simulations the conventional fixed profiles were deployed and in second set of simulations the random non-repeating schedules were applied. The approaches were characterized as following:

1) Fixed profiles for weekdays and weekends, using ASHRAE 90.1-2013 (ASHRAE 2013b) schedules for office occupancy, lighting, and plug loads;

2) Random daily occupancy profiles, generated by a stochastic occupancy model (Page et al. 2008) using the same schedules from ASHRAE 90.1-2013 as input, together with associated lighting and plug loads.

Besides, in each approach different levels of occupants' interaction with building systems (Mechanical devices, Shading devices) were applied. Subsequently as it is shown in the Table 1, the virtual office building was simulated through six different scenarios.

Table 1: Virtual office - Key characteristics of developed simulation models

Model	Occupancy	Lighting & plug loads	Mechanical ventilation	Shading devices
1a	Fixed profiles	Fixed profiles	Constant air flow[1]	-
1b	Random profiles	Proportional to occupancy profiles	Constant air flow[1]	-
2a	Fixed profiles	Fixed profiles	Occupancy-dependent[2]	-
2b	Random profiles	Proportional to occupancy profiles	Occupancy-dependent[2]	-
3a	Fixed profiles	Fixed profiles	Occupancy-dependent	Operable exterior blinds[3]
3b	Random profiles	Proportional to occupancy profiles	Occupancy-dependent	Operable exterior blinds[3]

1. Constant airflow: 0.007 m3/s per person for maximal occupancy

2. Occupancy – dependent: Base fresh air flow rate of 0.001 m3/s per person for maximal occupancy
The presence of each occupant adds 0.006 m3/s to the fresh air flow rate

3. Operable Exterior blinds: If solar irradiance on the window exceeds 150 W/m2
In model 3b each blind is coupled with one occupant.
In model 3a, the number of operated blinds is based on the occ. fraction from the fixed schedule

2.2.2 Real office building

Since the real office model was provided with full-year real data, the simulation sets were formed through three approaches. The first two approaches were the same as the virtual office building; applying the fixed profiles in first one and the randomized profiles to the second one. Yet in this model each of the approaches included two sub-sets of simulations;

One was formed by the ASHRAE fixed schedules, and the other was derived by processing the monitored data for an average person and for individuals. And finally the third approach, where the whole data (time-steps) was used directly as input. The idea behind the third approach is to compare the outcome of all other scenarios with the result derived from the real monitored data, and to obtain the relative difference referring to the last model. The final procured scenarios are shown in the Table 2.

Table 2: Real office - Key characteristics of developed simulation models

Model	Occupancy, Light and Plug Loads
1a	ASHRAE schedules for office occupancy, light and plug loads Same schedule for all 8 Occupants
1b	Randomized ASHRAE schedule for office occupancy, light and plug loads Same schedule for all 8 Occupants
2a	One empirically-based aggregate schedule for occupancy, light and plug loads Same schedule for all 8 occupants
2b	Randomization of one empirically-based aggregate schedule for occupancy, light and plug Same schedule for all 8 occupants
3a	8 individual empirically-based schedules for occupancy, light and plug loads Light and Plug is coupled to Occupancy
3b	Randomization of 8 individual empirically-based schedules for occupancy, light and plug loads Light and Plug is coupled to Occupancy
4	Full year 15-min empirically based data for occupancy, light and plug

Following description provides an overview of the three approaches:

1) Fixed profiles for weekdays and weekends;

A. Using ASHRAE 90.1-2013 (ASHRAE 2013b) schedules for office occupancy, lighting, and plug loads;

B. Using Real time monitored data for occupancy, lighting, and plug loads; whereas the intended value was derived in two different ways and correspondingly it eventuated two sets of results.

a. Individual: Yearly averaged value for each time step

b. Aggregate: Mean of individual values

2) Random daily occupancy profiles, generated by a stochastic occupancy model (Page et al. 2008) for the whole year;

A. Using the same schedules from ASHRAE 90.1-2013 as input, together with associated lighting and plug loads.

B. Using the same schedules from monitored data for occupancy, lighting, and plug loads; while the fixed profiles values were derived with the same individual and aggregate method.

3) Full year monitored data

2.3 Case studies

2.3.1 Virtual office building

`The virtual office building is a “small office” reference building model developed by the U.S. Department of Energy (DOE, 2015). It was modeled in EnergyPlus v8.1, building simulation tool [further information is available in (Crawley, 2001)]. As it is shown in the figure 1, the model was composed of five zones, where one core zone was surrounded with four zones. The zones’ area is not the same (Figure 3) and they were also simulated with different number of occupants. The total area of the building was 511.2 m^2, where the whole office area was simulated as conditioned area. The building was assumed multi-story (Figure 2), where the office area was located in a middle floor. Subsequently in the thermal model the surface of office floors and ceilings were set as adiabatic. Also it was assumed that the building is exposed to typical meteorological year weather data for Vienna, Austria.

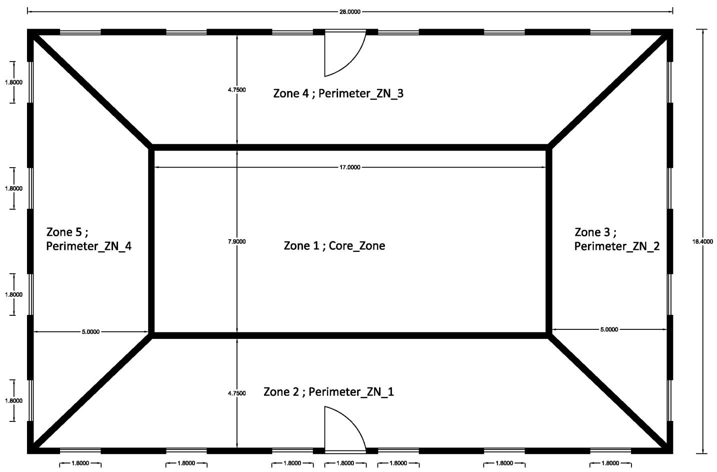

Figure 1: The Virtual office floor plan

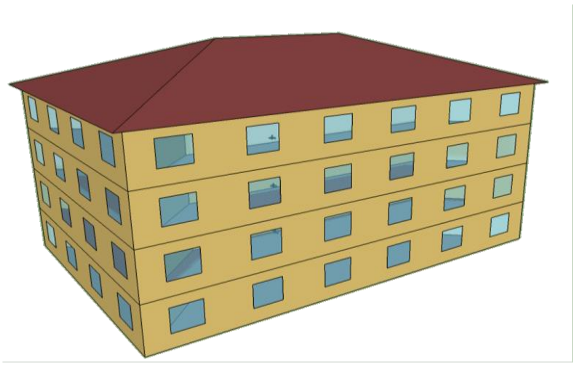

Figure 2:Multi-story Building – Virtual Office

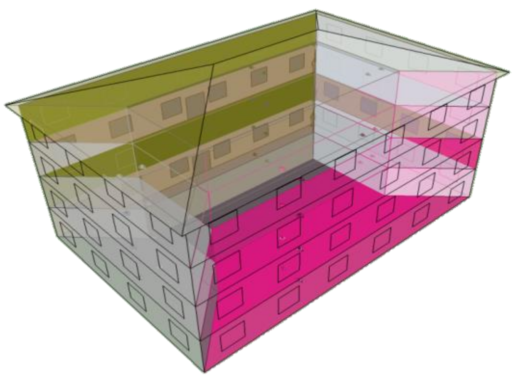

Figure 3: Schematic thermal zones – Virtual Office

Table 3 presents comprehensive information about the reference model of the virtual office building.

Table 3: Reference Virtual office building data and modeling assumptions

Building data / model input parameters		Value	Unit
Total building area		511.2	m^2
Net conditioned building area		511.2	m^2
Gross wall Area		281.5	m^2
Gross window-wall ratio (all façades)		19.8	%
Exterior walls U-value		0.36	$W.m^{-1}.K$
Exterior windows U-value		2.37	$W.m^{-1}.K$
Infiltration rate		0.20	h^{-1}
Mechanical ventilation		0.007	$m^3.s^{-1}.Person^{-1}$
Heating set-point		20	°C
Cooling set-point		26	°C
HVAC availability on Weekdays		6:00 – 22:00	-
HVAC availability on Weekends		6:00 – 18:00	-
Maximum number of people	Total	31	-
	North zone	7	-
	East zone	4	-
	South zone	7	-
	West zone	4	-
	Core zone	9	-
Occupants' activity level		120	$W.Person^{-1}$
Maximum lighting power density		8.8	$W.m^{-2}$
Maximum equipment power density		8.1	$W.m^{-2}$

2.3.2 Real office building

In the second building, as a real case study, it was necessary to have a full monitored data of the intended office building. Since one of the office buildings of the Vienna University of Technology was comprehensively under monitor, it was decided to choose it as the real prototype and the full monitored data of 2014 was picked out as the reference data.

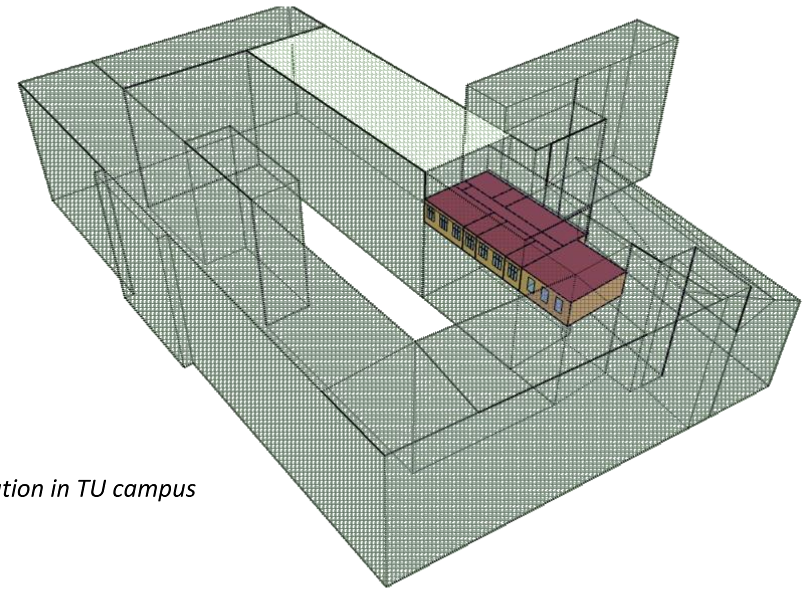

Figure 4: Real office location in TU campus

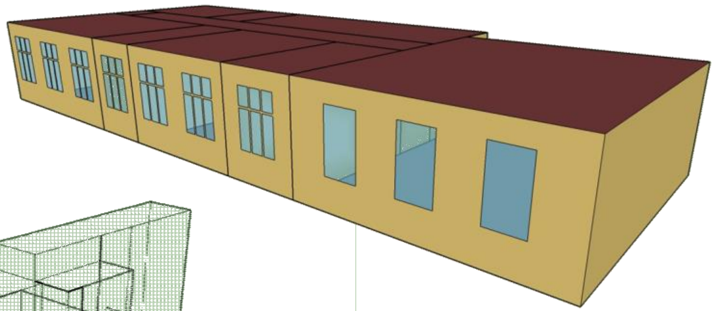

Figure 5: Real office building detached from campus

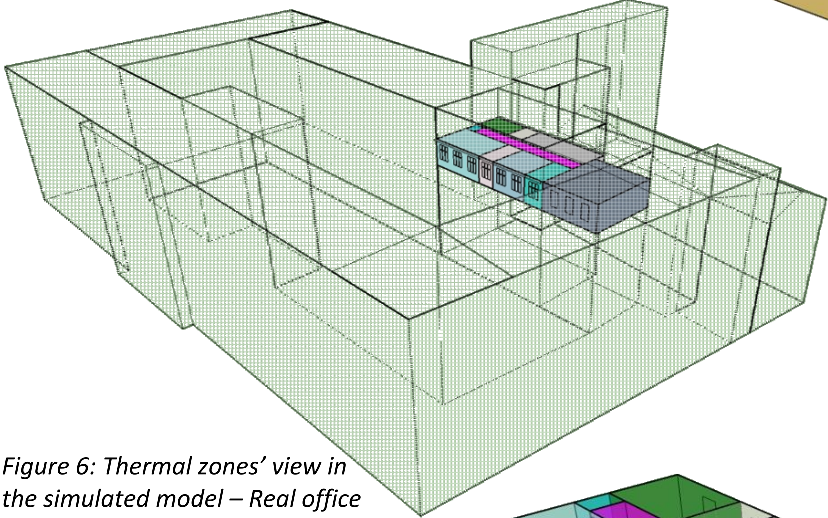

Figure 6: Thermal zones' view in the simulated model – Real office

Figure 7: Schematic thermal zones – Real Office

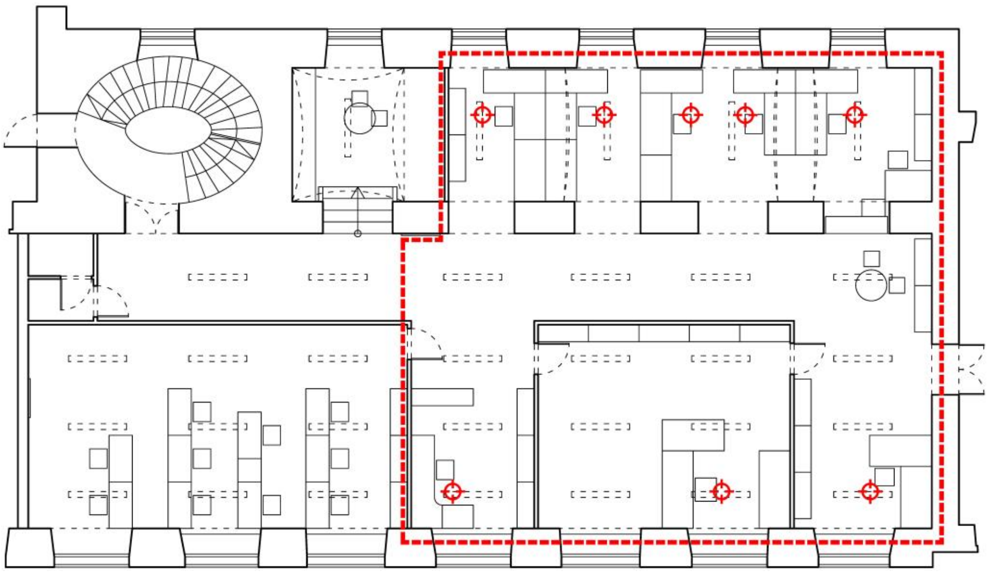

Figure 8: The Real office floor plan

The building was modeled in EnergyPlus v8.1 as well. The total office area was 407.3 m^2, including 10 zones; from which 187.57 m^2, five zones, is the conditioned area. As it is shown in the figure 8 (the modeled area and the position of motion detectors are drawn in red color), the size of the zones is different. Since the office area is located in the third floor of a four-story building, the thermal surface of the floors and ceilings was set as adiabatic. Figure 4 to 7 shows a view of building model and thermal zones. Obviously the building was exposed to the typical metrological year weather data for Vienna, Austria. A more detailed description of the reference real office building is presented in the Table 4.

Table 4: Reference Real office building data and modeling assumptions

Building data / model input parameters	Value	Unit
Total building area	407.3	m^2
Net conditioned building area	187.6	m^2
Gross wall Area	288.0	m^2
Conditioned Gross wall Area	120.1	m^2
Gross window-wall ratio (all façades)	25.1	%
Conditioned Gross window-wall ratio	26.7	%
Exterior walls U-value	0.65	$W.m^{-1}.K$
Exterior windows U-value	2.79	$W.m^{-1}.K$
Infiltration rate	0.20	h^{-1}
Mechanical ventilation	0.007	$m^3.s^{-1}.Person^{-1}$
Heating set-point	20	°C
Cooling set-point	25	°C
HVAC availability on Weekdays	6:00 – 22:00	-
HVAC availability on Weekends	6:00 – 18:00	-
Maximum number of people	8	-
Occupants' activity level	120	$W.Person^{-1}$
Maximum lighting power density	4.1	$W.m^{-2}$
Maximum equipment power density	9.9	$W.m^{-2}$

2.4 Typical profiles of occupancy and internal gains

2.4.1 Virtual office building

In the so called "Fixed" scenarios which are models 1a, 2a and 3a; the provided schedules for office buildings by ASHRAE 90.1 (ASHRAE 2013b) were used; The schedules (Figure 9-11) were applied into the occupancy, light and plug loads categories, whereby each of them was formed in three different day-types; weekdays, Saturdays and Sundays.

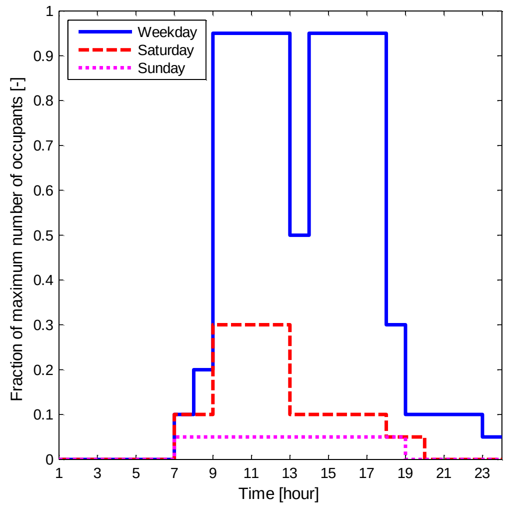

Figure 9: Fixed ASHRAE schedules for occupancy used for models 1a, 2a, and 3a - Virtual & Real Building

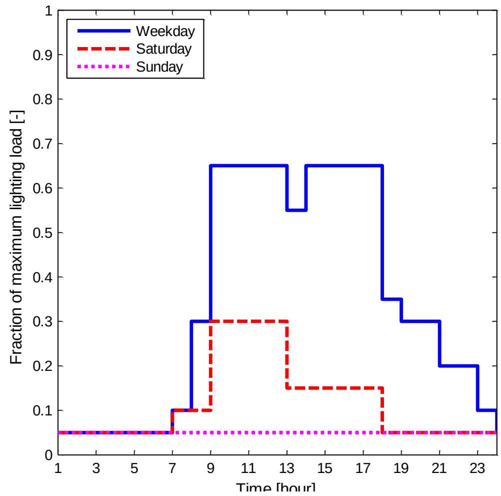

Figure 10: Fixed ASHRAE schedules for lights used for models 1a, 2a, and 3a - Virtual & Real Building

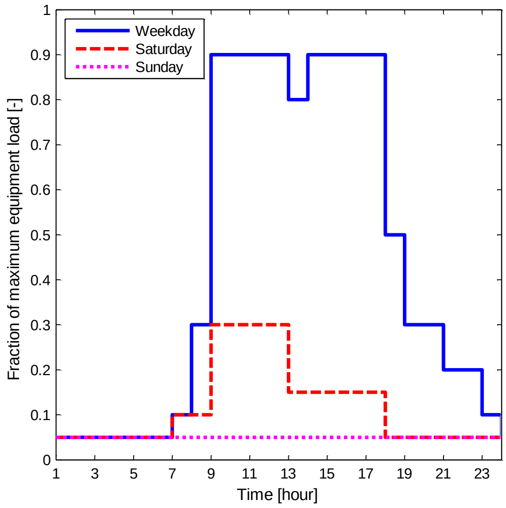

Figure 11: Fixed ASHRAE schedules for plug loads (right) used for models 1a, 2a, and 3a - Virtual & Real Building

2.4.2 Real office building

In the Real building, as it is mentioned in the approach section (2.2.2), there are three types of fixed schedules. The first type is the ASHRAE 90.1 (ASHRAE 2013b) fixed schedules, which is the same as the virtual building (Figure 9-11) and was applied to model 1a. The three shown profiles were assigned to the occupancy, light and plug loads schedules, and then were associated to each occupant, light and plug objects.

The two next types of schedules are observation-based diversity profiles, which mean the whole year 15-min interval data for occupancy, plug loads, and light state was obtained from the building monitoring infra-structure.

In the second type of fixed schedule (applied to model 2a), the observational data on occupants' presence, plug loads, and use of lights were averaged across all occupants. The resulting year-long data set for an average occupant was then processed to obtain a set of average profiles of presence probability, fraction of maximum lighting load, and fraction of maximum equipment load. This means the obtained profiles are now the average of each time step in whole year for weekdays, Saturday, as well as Sundays and public holidays. This process results one empirically aggregated schedule for each group for occupancy, light and plug loads. This means in each group one identical schedule was assigned to all occupants, light and plug loads and the diversity among occupants is neglected. As figure 12 presents, each graph belongs to one of the fixed profiles (occupancy, light and plug loads) and is formed by three line types which represent three day types; weekday, Saturdays and Sundays.

And the third type of fixed schedules (applied to model 3a), which is also observation-based were formed by averaging each 15-min time-step in whole year, whereby for each sensor of occupancy, light and plug load, an individual schedule was obtained. Correspondingly and as it is shown in figure 13, each group of occupancy, light and plug load, contains 8 types of lines, which indicates 8 occupants, light and plug loads.

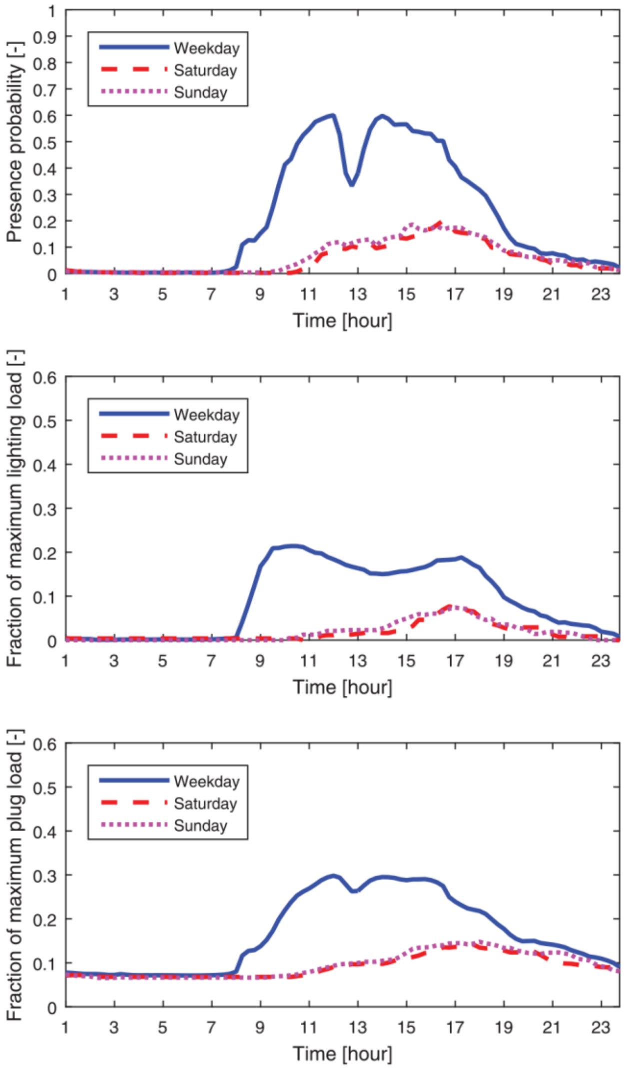

Figure 12: Observed average diversity profiles for occupancy (top), lights (middle), and plug loads (bottom) used in modeling scenario 2a

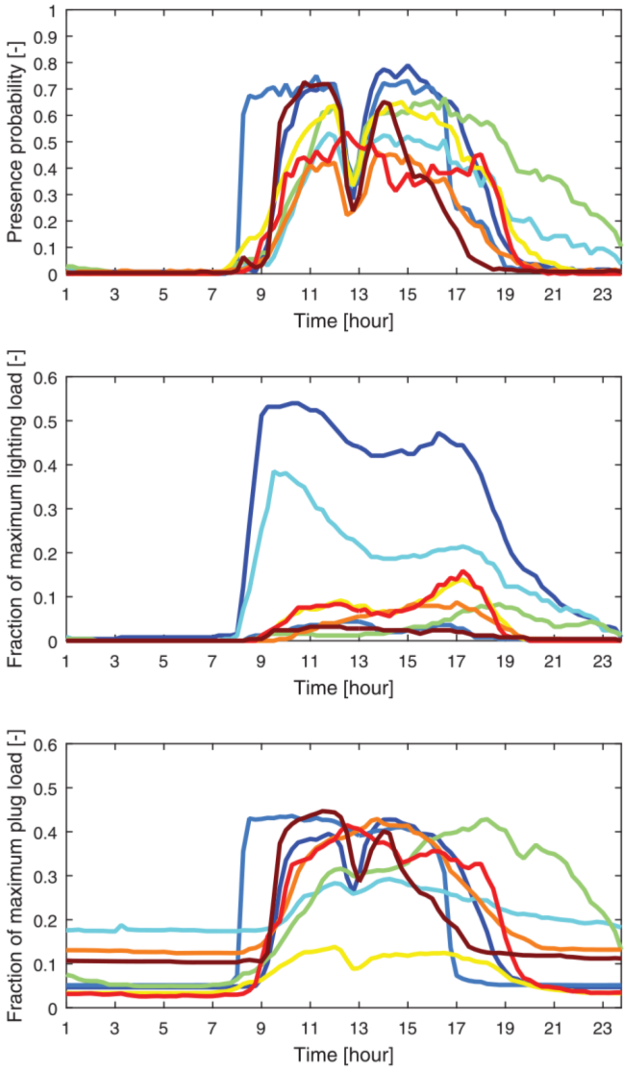

Figure 13: Observed individual diversity profiles for weekday occupancy (top), lights (middle), and plug loads (bottom) used in modeling scenario 3a

2.5 Random occupancy profiles and associated internal gains

In the randomized scenarios, the occupant presence profiles were derived by assigning the fixed schedules, which depends on their own scenario definition, in the stochastic model, developed by Page (Page et al. 2008). This model renders random non-repeating daily occupancy profiles by assigning two main inputs; a) profile of presence probability and b) parameter of mobility, which is defined by the ratio of state change probability to state persistence probability. The Page model is formed by the hypothesis that the value of occupancy at each time step depends on the previous occupancy state and the probability

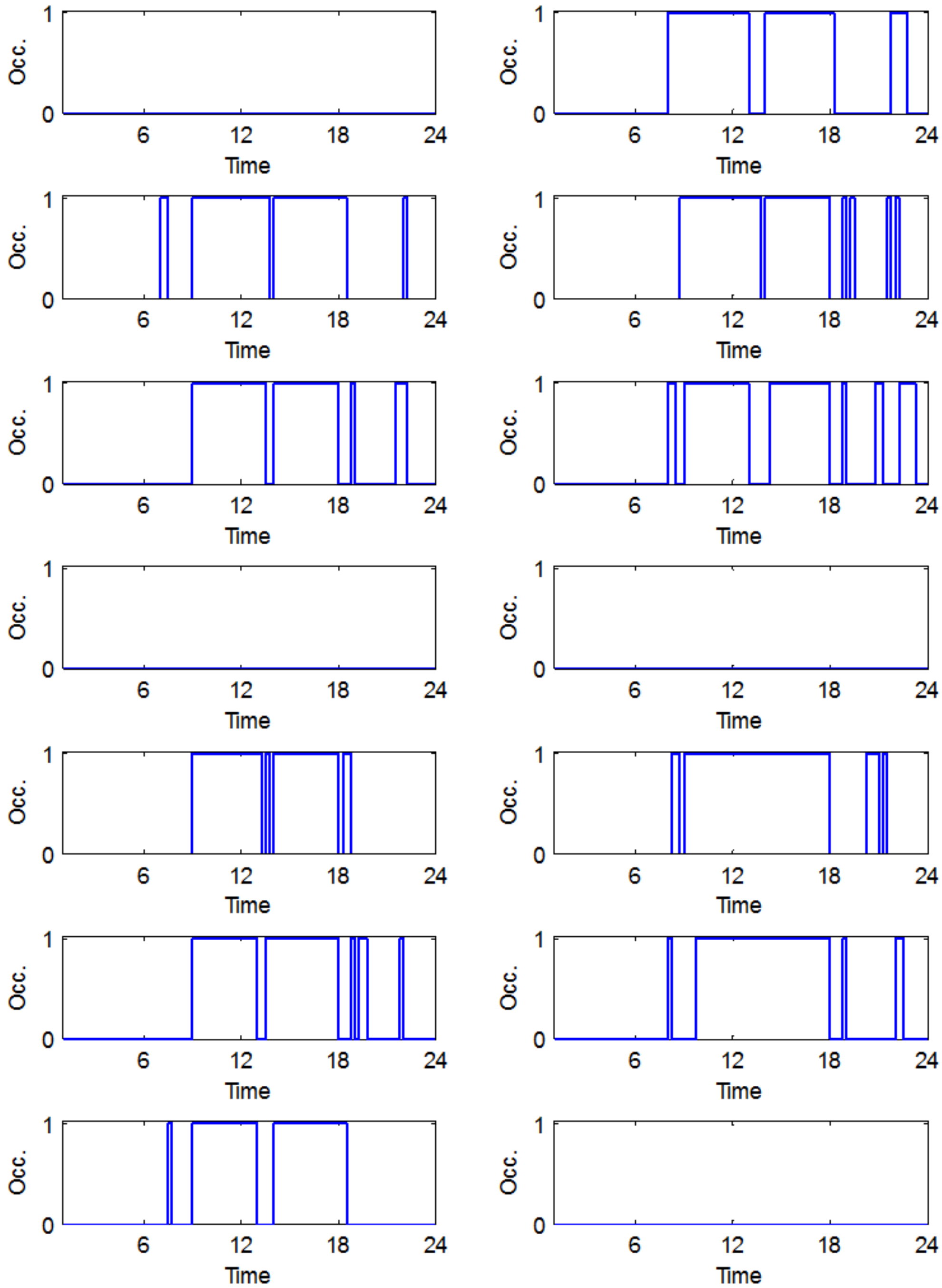

Figure 14: Sample of randomly generated daily occupancy profiles

of transition from this state to either the same state or its opposite state:

"[...] A central model of occupant presence, based on an inhomogeneous Markov chain, produces a time series of the number of occupants within a predefined zone of a building. Given a weekly profile of the probability of presence, simplified parameters relating to the periods of long absence and the mobility of the person to be simulated, it has proven itself capable of reproducing that person's patterns of occupancy (times of first arrival, of last departure and periods of intermediate absence and presence) to a good degree of accuracy. Its output is used as an input for models for the simulation of the behavior of occupants regarding the use of appliances in general, the use of lighting devices, the opening of windows and the production of waste. The appliance model adopts a detailed bottom-up approach, simulating each appliance with a black-box algorithm based on the probability of switching it on and the distribution of the duration and power of its use, whereas the interaction of the occupant with windows is determined by randomly changing environmental stimuli and the related thresholds of comfort randomly selected for each occupant. […]" (Page 2007).

In the other words, daily occupancy profiles are generated by the procedure, as it starts from the first time- step of the day with an unoccupied condition for commercial buildings. Afterwards for each time step, a random number between 0 and 1 will be generated. In the final step, in order to define if occupancy state is changed, the random generated number will be compared with the transition probabilities, which have already been calculated by using the input occupancy profile and parameter of mobility. Figure 14 presents a sample of randomly generated daily occupancy profiles.

Based on this process, in each building, different randomized profiles depending on the definition of the associated fixed models were derived. Following part provides a description on the generating of the randomized profiles in each building prototype.

2.5.1 Virtual office building

In the virtual office building, the same occupancy schedules; ASHRAE 90.1 (ASHRAE 2013b) with 15-min time-steps, were implemented into the Page stochastic model. Then the model was executed 365 times to obtain year-long random daily presence profiles for each occupant in the scenario 1b, 2b, and 3b. Since there were 31 people in the virtual building, the model produced 31 schedule files. Each file contained a column vector of 0 and 1 with length of 35040, the number of 15-min intervals in whole year. In the next step, these files were applied to the simulation models and were assigned to People objects in the each model.

As there were no holidays included in the fixed occupancy schedules, therefore in the stochastic occupancy models were also no “long absence” component implemented and the mobility parameter was set to 0.5 for all model executions. In order to have consistent days with the fixed profiles, the occupancy profiles for weekday, Saturday, and Sunday were applied to the model in the right order.

As it is shown in the figure 9-11, in the fixed schedules there is a base load for the light and plug schedules, which is applied separately to the models as base load for the randomized schedules and then by assigning occupancy dependent loads, the final light and plug loads are implemented. The base load was considered as 0.05 fraction of the lighting and plug loads and the loads associated with each occupant were derived from Equation 1 and based on ASHRAE 90.1 (ASHRAE 2013b) schedules for office occupancy, lighting, and plug loads.

$$L_{occupant}(t) = \frac{LF_{OD}(t)}{OF(t) \times O_{zone}} \times L_{zone}$$

Equation 1

Where, $\mathrm{L_{occupant}(t)}$ is the lighting or plug loads associated with each occupant at time step t, $\mathrm{LF_{OD}(t)}$ is the occupancy dependent fraction of lighting or plug loads at time step t, $\mathrm{OF(t)}$ is the fraction of occupancy at time step t, $\mathrm{O_{zone}}$ is the maximum number of occupants in the zone, and $\mathrm{L_{zone}}$ is the zone maximum lighting or plug loads.

2.5.2 Real office building

For the real building, just as its fixed scenarios, there are three types of randomized schedules, which are different in their inputs but not the method they were created with. In each randomized scenario, the associated fixed schedules were applied to the Page (Page et al. 2008) model as the input, and the output files were assigned to the occupancy, light and plug load objects in EnergyPlus. For the first and second randomized scenario, where in order the ASHRAE 90.1 (ASHRAE 2013b) and the yearly averaged value for each time-step were applied as the input, 24 schedule files were created as Page model output for each scenario. Whereby each schedule group, i.e. occupancy, light and plug loads was defined with 8 schedule files. In the third randomized scenario which was formed by on empirically aggregated value for each schedule group, three randomized file were created as output, which were assigned identically to the members of the associated group.

2.6 Mechanical Ventilation & Shading devices

2.6.1 Virtual office building

Since in the virtual office building, different levels of occupant interactions were also considered as separated scenarios, the definition of mechanical ventilation was different in one pair of scenarios.

As it is shown in Table 1, the first pair (model 1a and 1b) was designed during the working hours with constant mechanical ventilation rate, which was set 0.007 [$m^3.s^{-1}$] per person for maximal occupancy. In other models (2a, 2b, 3a and 3b) the mechanical ventilation was divided into two parts; a base part and an occupancy dependent part. The base part was regardless of occupants' presence, and each zone was provided with fresh air-flow rate of 0.001 [$m^3.s^{-1}$] per person for maximal occupancy. Moreover the second part was dependent to the presence of each occupant, whereby the presence of each occupant adds 0.006 [$m^3.s^{-1}$] to the fresh air flow rate. The infiltration rate was 0.2 [h^{-1}].

The HVAC system was designed to be available between 6:00 to 22:00 during weekdays and 6:00 to 18:00 for the weekends. The set-point was set on 20°c for the heating and 26°c for the cooling.

Presented in Table 1, the last pair of scenarios in the virtual office building (3a, 3b), was coupled with the shading device, as one of the occupant's interaction features. In act of shading device, exterior venetian blinds were added to all windows of building. The blind slats were assumed horizontally oriented, with beam solar reflectance of 0.5 and fixed angles of 30 degree.

Each window blind was deployed into simulation if the occupant associated with that window was present and if solar irradiance on the window exceeded 150 [$W.m^{-2}$]. In model 3b each blind was coupled with one occupant, whereas in model 3a, the number of blinds that may be operated are determined based on the occupancy fraction obtained from the fixed schedule.

2.6.2 Real office building

Opposed to the virtual building scenarios, in the real building all scenarios were defined with a same HVAC system and independent of occupant's interactions. Therefore the amount of outdoor air is assumed to be designed based on the maximum number of occupants and correspondingly as constant rate mechanical ventilation and not sensitive to the generated occupancy profiles in different modeling scenarios. This rate was set 0.007

[$m^3.s^{-1}$] per person for maximal occupancy. As it was also shown in the table 4, the HVAC set-point was set on 20°c for heating and 25°c for cooling, and the system was available 6:00 to 22:00 on weekdays and 6:00 to 18:00 for weekends. The infiltration rate was also set on 0.2 [h^{-1}].

As the occupants' interaction with operable shading devices were not monitored, the shading status was assumed constant and the same in all scenarios In the real office model. The blind slats were horizontally oriented with beam solar reflectance of 0.5 and fixed angles of 45 degree. As the occupants' interaction with operable shading devices were not monitored, the status was assumed constant in all scenarios

2.7 Simulation evaluation vantage point

As the simulated office buildings were different in nature and correspondingly the concept of their scenarios, each of them was evaluated regarding their own definitions, which is described in the following section.

2.7.1 Virtual office building

In the virtual office building the concept of different scenarios was implication of conventional and randomized presence profile coupled with different levels of user-based actions.

2.7.2 Real office building

For the real office building model in order to define the evaluation metrics, it was necessary to delineate the influence of different occupancy modeling assumption in two different perspectives; first in the view of predicting the occupant's presence and second in regarding to the building performance indicators. By means of these two perspectives, comparing the result of different occupancy modeling assumption would be not even more understandable but also much more accurate and systematic.

In this context, this section is divided in two sub-sections, to describe the intended subject in the two aforementioned points of view. Note that the both comparisons are done in reference to the model 4, since it has the highest resolution in terms of occupancy and it is entirely observation-based, which means it can act as so called "reality benchmark" as far as the actual occupancy circumstances are concerned.

2.7.2.1. Occupants' presence prediction

In this part, the predicted fraction of maximum occupancy by each model throughout the year was up to be inspected. And obviously this fraction is defined by the incorporated fixed or random occupancy profiles, so it can represent the ability and accuracy of each modeling assumption in regarding to the occupants' presence prediction.

In order to plan a quantitative evaluation and to examine the accuracy of the [forecast] occupants' presence prediction, three different metrics were looked at as following:

1. **Mean Error (ME)**; is the average of the error in the whole year time-steps (35040). The error itself refers to the difference of the predicted value and the reference value, and the value is the "Building Occupancy Fraction" (BOF). As already mentioned, hear reference value is the value obtained from the model 4 in each

time-step. Accordingly the Mean Error for each time-step would be defined as following (Equation 2):

$$Mean\ Error = \frac{\sum_{t=1}^{n}\left(BOF_p(t) - BOF_r(t)\right)}{n}$$

Equation 2: Mean Error

Where BOF $_p$ is the predicted value for building occupancy fraction at time step=t, BOF $_r$ is the reference value based on the model 4 for building occupancy fraction.

2. **Root Mean Squared Error (RMSE)**; or the root-mean-square deviation (RMSD) is a frequently used measure of the differences between values [BOF] predicted by a model or an estimator and the values actually observed (Bulmer, 1979). Applied to the models, the equation would be as following (Equation 3):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(BOF_p(t) - BOF_r(t)\right)^2}{n}}$$

Equation 3: Root Mean Squared Error (RMSE)

Where same as the "Mean Error" equation, $BOF_p(t)$ is the predicted building-level occupancy fraction at time-step "t", $BOF_r(t)$ is the reference building-level occupancy fraction at time-step "t" (obtained fraction from model 4), and "n" is the number of simulation time-steps in a year, which equals to 35040.

3. **Jensen-Shannon Distance (JSD)**; is a metric referred to square root of the Jensen-Shannon divergence[3], which is a popular method of measuring the similarity between two probability distributions in probability theory and statistics (Bulmer, 1979). This divergence based on the "Kullback–Leibler" divergence, with some notable and useful differences, including that it is symmetric and it is always a finite value.

The Kullback–Leibler divergence measures use: $I(p_1, p_2) = \sum_{x \in X} p_1(x) log\ \frac{p_1(x)}{p_2(x)}$, where x is a discrete random variable and p_1 , p_2 are two probability distribution of X. The logarithmic base 2 ($\ln 2$) is used throughout this correspondence unless

[3] In statistics, probability theory, and information theory, divergence or a contrast function is a function which establishes the "distance" of one probability distribution to the other on a statistical manifold. The divergence is a weaker notion than that of the distance, in particular the divergence does not need to be symmetric (that is, in general the divergence from p to q is not equal to the divergence from q to p), and does not need to satisfy the triangle inequality (Bulmer, 1979). In other words being symmetric and obeying the triangle inequality makes distance preferable to divergence.

otherwise stated. It is well known that $I(p_1, p_2)$ is non-negative, additive but not symmetric.

To obtain a symmetric measure, one can define: $J(p_1, p_2) = I(p_1, p_2) + I(p_2, p_1)$, then: $J(p_1, p_2)$= $\sum_{x \in X}(p_1(x) - p_2(x))\ log\ \frac{p_1(x)}{p_2(x)}$, which is called the J divergence. Clearly I and J divergences share most of their properties. It should be noted that $I(p_1, p_2)$ is undefined if $p_2(x) = 0$ and $(p_1(x) \neq 0$ for any $x \in X$. This means that distribution p_1 has to be absolutely continuous with respect to distribution p_2 for $I(p_1, p_2)$ to be defined. Similarly, $J(p_1, p_2)$ requires that p_1 and p_2 be absolutely continuous with respect to each other. This is one of the problems with the Kullback–Leibler divergence measures (Lin, 1991) and where the "Jensen-Shannon" divergence is preferred to "Kullback-Leiber" divergence.

As it already mentioned the square root of Jensen-Shannon divergence $J(p_1, p_2)$ is Jensen-Shannon distance (JSD) $J(p_1, p_2)$; i.e. $S(p_1, p_2)$=$\sqrt{J(p_1, p_2)}$ which is equal to:

$S(p_1, p_2)$ = $\sqrt{(p_1(x) - p_2(x))log\ \frac{p_1(x)}{p_2(x)}}$ and if $M = \frac{1}{2}(p_1 + p_2)$ then :

$S(p_1, p_2)$=$\frac{1}{2}J(p_1, M) + \frac{1}{2}J(p_2, M)$

Equation 4: Jensen-Shannon distance

Jensen-Shannon distance equation (Equation 4) is used to measure the difference between two probability distributions p_1 and p_2. In applications, p_1 typically represents the "true" distribution of data, observations, or a precisely calculated theoretical distribution, while p_2 typically represents a theory, model, description, or approximation of p_1. Jensen-Shannon distance defines also the upper bound $\ln 2$ and the lower bound 0 (Bulmer, 1979). The equation was applied to measure the distance between probability distributions of occupancy levels resulted from the different modeling scenarios.

2.7.2.2. Building performance indicators

Alongside the inspection of occupants' presence prediction, evaluation of building performance is the aim of this study. In order to explore the influence of different occupants' presence models on the building performance simulation results, four basic building-level (i.e. entire modeled area) performance indicators are considered, which are commonly used by the simulation community especially when they intend to evaluate the thermal performance of a building without modeling a full HVAC system. These performance indicators are: Annual heating and cooling demands per floor area [$kWh.m^{-2}$], and peak heating and cooling loads per floor area [$W.m^{-2}$].

The amount of required energy to maintain the cooling and heating set-points was obtained each in 15 minutes interval, in view of the fact that simulations were conducted with 4 time-steps per hour. Accordingly, the four intended performance indicators were achieved simply by calculating the annual sum and maximum value of the reported time-step for heating and cooling demands and loads.

The heating and cooling demands are calculated by using an ideal unit that means it has an unlimited capacity. At the exhaust condition of the zone, air would be mixed with a specific amount of outdoor air and correspondingly depends on the temperature, heat would be added or removed at 100% efficiency [it meets all the load requirements and consumes no energy] in order to produce a supply air stream at the specified conditions (NREL, 2015).

As it is already mentioned, the simulation results for different modeling scenarios, could be compared in regarding to the model 4, which is quasi a “reality benchmark” and thus, the implication of various occupants’ presence models could be explored in view of the simulated values of building-level for the aforementioned performance indicators.

3 RESULTS

3.1 Overview

Since unlike to the real office building, for the virtual office there was no possibility to compare the models with a so called reality benchmark (model 4 in real office), this chapter is also divided to two sub-sections; one describes the result of virtual-office case study and the other presents the real-office's results. The results are presented as comprehensive tables for each case study, which makes it easier to compare between the results obtained by each model with each other. Besides it is tried to present the results as a descriptive charts as a quick glance for the analogy.

In the real-office case study, in addition to the result's table, there are also some other charts which specifically compare the results based on the aforementioned reality benchmark. There, in addition to the building performance indicators, the monitored occupants' presence patterns provide the opportunity to analyze the accuracy of occupancy prediction in each scenario.

3.2 Virtual office building

As mentioned in overview, the following tables (Table 5, 6, 7) present the result of each scenario in regarding to monthly and annual heating and cooling demands, as well as peak heating and cooling loads. It is necessary to mention that all the values are calculated per conditioned floor area of the virtual office building. The peak value is calculated hourly-based.

Table 5: Annual and peak heating and cooling demands per conditioned floor area-Virtual office

M	Occupancy modeling characteristics	Annual heating demand [$kWh.m^{-2}$]	Annual cooling demand [$kWh.m^{-2}$]	Peak heating demand [$W.m^{-2}$]	Peak cooling demand [$W.m^{-2}$]
1a	Fixed schedules for occupancy, lighting & plug loads	20.4	24.4	58.6	45.2
1b	Random schedules for occupancy, lighting & plug loads	20.5	24.4	58.8	45.3
2a	Fixed occupancy schedules, occupancy dependent ventilation	13.3	27.3	58.2	44.7
2b	Random occupancy schedules, occupancy dependent ventilation	13.3	27.4	58.3	45.0
3a	Fixed occupancy schedules, occupancy dependent ventilation, operable blinds	14.5	22.5	58.4	38.8
3b	Random occupancy schedules, occupancy dependent ventilation, operable blinds	14.5	22.7	58.8	39.5

Table 6: Monthly heating demands [kWh.m^{-2}] – Virtual Office

Model	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1a	5.9	4.3	1.4	0.3	0.0	0.0	0.0	0.0	0.0	0.4	2.7	5.4
1b	5.9	4.4	1.4	0.4	0.0	0.0	0.0	0.0	0.0	0.4	2.7	5.4
2a	4.3	2.9	0.6	0.1	0.0	0.0	0.0	0.0	0.0	0.1	1.5	3.8
2b	4.3	2.9	0.6	0.1	0.0	0.0	0.0	0.0	0.0	0.1	1.5	3.8
3a	4.5	3.3	0.8	0.1	0.0	0.0	0.0	0.0	0.0	0.1	1.7	4.0
3b	4.5	3.3	0.8	0.1	0.0	0.0	0.0	0.0	0.0	0.1	1.7	4.0

Table 7: Monthly cooling demands [kWh.m^{-2}] - Virtual office

Model	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1a	0.0	0.0	0.1	0.9	3.0	4.5	6.7	6.6	2.2	0.4	0.0	0.0
1b	0.0	0.0	0.1	0.9	3.0	4.5	6.6	6.6	2.3	0.4	0.0	0.0
2a	0.0	0.0	0.1	1.2	3.7	5.0	6.9	6.8	2.9	0.7	0.0	0.0
2b	0.0	0.0	0.1	1.2	3.7	5.1	6.8	6.8	2.9	0.7	0.0	0.0
3a	0.0	0.0	0.0	0.8	2.9	4.3	6.1	5.8	2.2	0.4	0.0	0.0
3b	0.0	0.0	0.0	0.9	3.0	4.3	6.1	5.8	2.2	0.4	0.0	0.0

Figures 15 to 16 are the graphical presentation of the building performance indicators, which are already mentioned in the tables. Each pair of bars indicates the value of fixed (left value) and randomized (right value) scenarios. Three pairs of values are representative for the three sets of scenario, each with a different level of occupant's interactions.

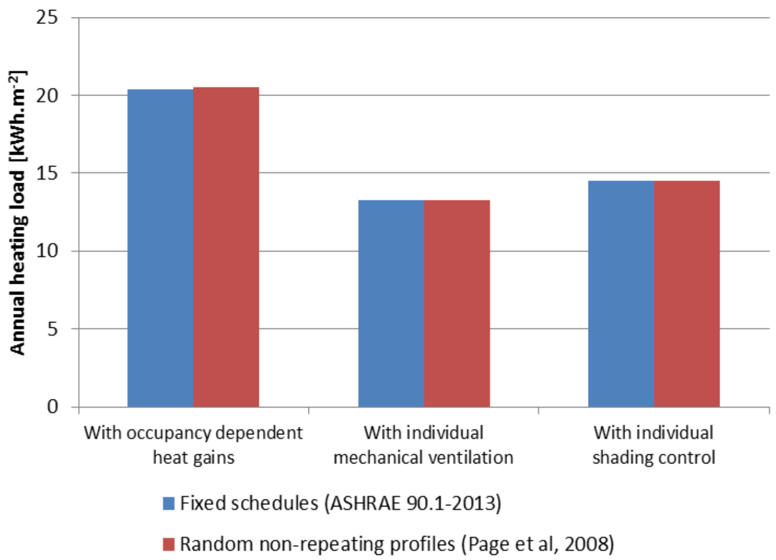

Figure 15: Annual Heating demand [kWh.m^{-2}]

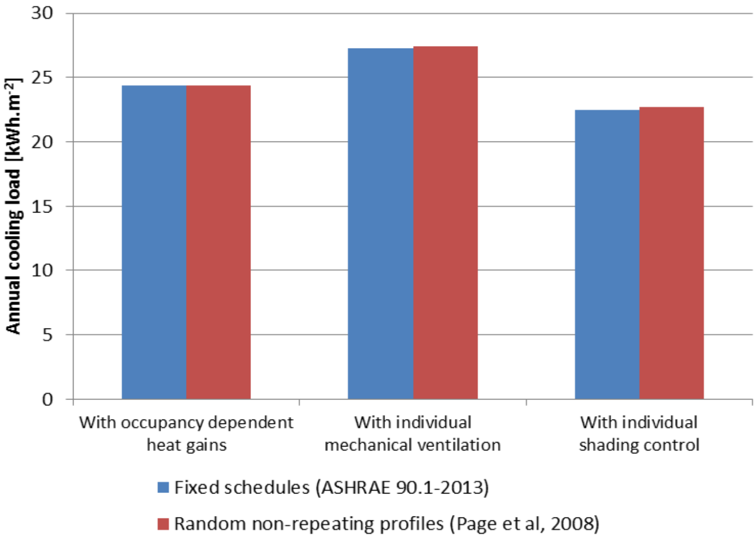

Figure 16: Annual Cooling demand [kWh.m^{-2}]

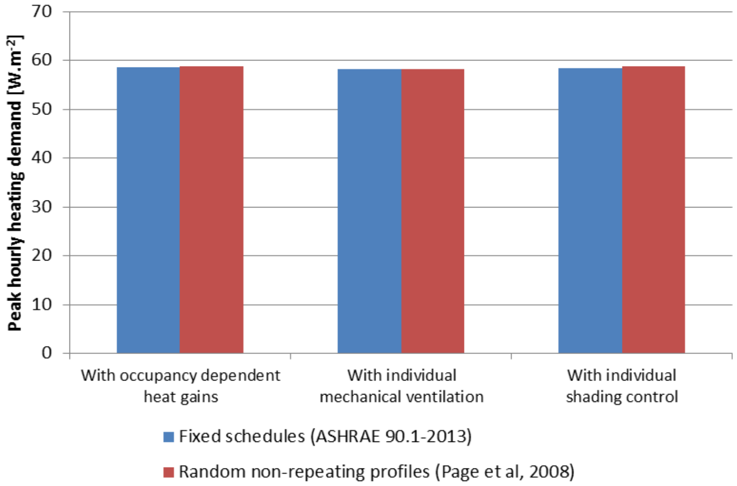

Figure 17: Peak Heating demand [W.m^{-2}]

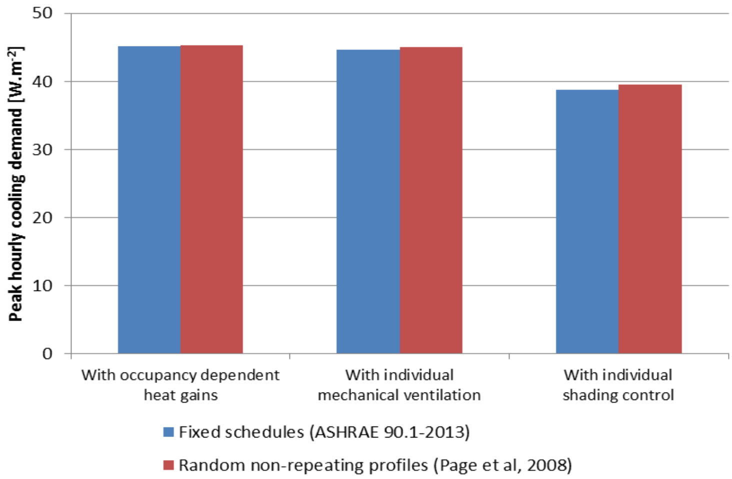

Figure 18: Peak Cooling demand [W.m^{-2}]

3.3 Real office building

Since the real office building was provided with full year monitored data, the result of different scenarios could be evaluated based on the last scenario as benchmark and according two points of views; First, accuracy of occupant presence prediction and second building performance indicators. In the Following the results of three pair of scenarios are presented in regarding to these two aspects.

3.3.1 Occupancy predictions

The first point of view represents the annual distribution of occupants' presence prediction; i.e. the result of each scenario is presented according to the predicted fraction of maximum occupancy throughout the year.

As it is shown in the figure 19, each line appointed the presence prediction for one of the scenarios and the discrepancy between the predicted fraction of each model is comparable regarding to the model 4 as well as other models. The horizontal axis indicates the percentage of maximum occupancy and the vertical one represents the occurrence frequency (happening rate) of each percentage per hour.

Table 8: ME, RMSE, and JSD values compared with model 4

Models	**ME [%]**	**RMSE [%]**	**JSD [-]**
1a	11.7%	27.9%	0.36
1b	11.9%	29.5%	0.26
2a	0.0%	15.6%	0.19
2b	0.0%	20.7%	0.04
3a	0.0%	15.6%	0.19
3b	0.0%	19.9%	0.05

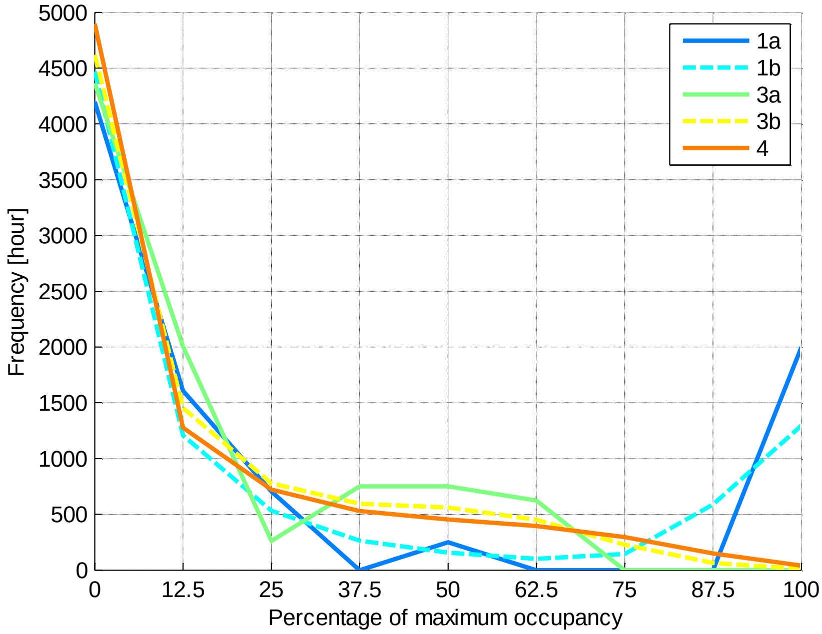

Figure 19: Distribution of occupancy levels in the real office building

Thereafter the difference between the predicted fraction by each model and the "reality benchmark", model 4, is calculated. The distance to the real occupancy pattern is evaluated through three metrics, which were described in the last chapter (2.7.); Mean Error (ME), Root Mean Squared Error (RMSE) and Jensen-Shannon distance (JSD) and the obtained distances are presented as time-step errors for each metric (Table 8).

3.3.2 Building performance indicators

The simulation results present the obtained values for the building performance indicators, which are the same as the virtual office building; Annual heating and cooling demand and peak heating and cooling loads. Table 9 shows these values for each scenario and thereupon figures 20-23 display the values of each indicator separately for seven scenarios; The first three pairs consist of two bars, which indicate their fixed and randomized scenarios. And the last column is the value of model 4, which is the full year monitored data and in fact the reality benchmark. All the values are per conditioned floor area of the real office building. Here, the same as virtual building, the peak value is calculated hourly-based.

Table 9: Annual and peak heating and cooling demands per conditioned floor area-Real building

Models	**Annual heating demand** [kWh/m^2]	**Annual cooling demand** [kWh/m^2]	**Peak heating demand** [W/m^2]	**Peak cooling demand** [W/m^2]
1a	65.9	18.5	49.4	39.4
1b	67.0	17.9	49.4	39.6
2a	79.9	9.7	58.5	30.0
2b	78.2	10.6	58.1	31.8
3a	79.5	9.9	58.6	30.2
3b	78.4	10.5	58.7	32.0
4	78.2	9.4	57.1	27.9

1a/1b	ASHRAE (Fix/Randomized) schedules for office occupancy, light and plug loads Same schedule for all 8 Occupants
2a/2b	One empirically-based aggregate (Fixed/Randomized) schedule for occupancy, light and plug loads Same schedule for all 8 occupants
3a/3b	8 individual empirically-based (Fixed/Randomized) schedules for occupancy, light and plug loads Light and Plug is coupled to Occupancy
4	Full year 15-min empirically based data for occupancy, light and plug

Table 10: Monthly heating demands [kWh.m^{-2}] – Real Office

Model	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1a	15.6	13.3	7.6	3.4	0.0	0.0	0.0	0.0	0.0	1.4	9.0	15.6
1b	15.9	13.5	7.8	3.5	0.0	0.0	0.0	0.0	0.0	1.5	9.3	15.6
2a	17.8	15.4	9.8	4.9	0.2	0.0	0.0	0.0	0.0	2.8	11.2	17.8
2b	17.6	15.2	9.5	4.6	0.1	0.0	0.0	0.0	0.0	2.6	11.0	17.5
3a	17.7	15.3	9.7	4.8	0.2	0.0	0.0	0.0	0.0	2.8	11.2	17.7
3b	17.7	15.3	9.6	4.6	0.1	0.0	0.0	0.0	0.0	2.6	11.0	17.5
4	17.2	14.9	9.4	5.0	0.2	0.0	0.0	0.0	0.0	2.6	10.8	18.1

Table 11: Monthly cooling demands [kWh.m^{-2}] – Real Office

Model	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
1a	0.0	0.0	0.0	0.1	0.8	2.0	7.4	6.5	1.6	0.1	0.0	0.0
1b	0.0	0.0	0.0	0.1	0.8	2.0	7.2	6.3	1.6	0.0	0.0	0.0
2a	0.0	0.0	0.0	0.0	0.0	0.6	4.6	4.2	0.3	0.0	0.0	0.0
2b	0.0	0.0	0.0	0.0	0.1	0.8	4.9	4.5	0.3	0.0	0.0	0.0
3a	0.0	0.0	0.0	0.0	0.0	0.7	4.6	4.3	0.3	0.0	0.0	0.0
3b	0.0	0.0	0.0	0.0	0.1	0.8	4.9	4.4	0.3	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.7	4.3	4.2	0.3	0.0	0.0	0.0

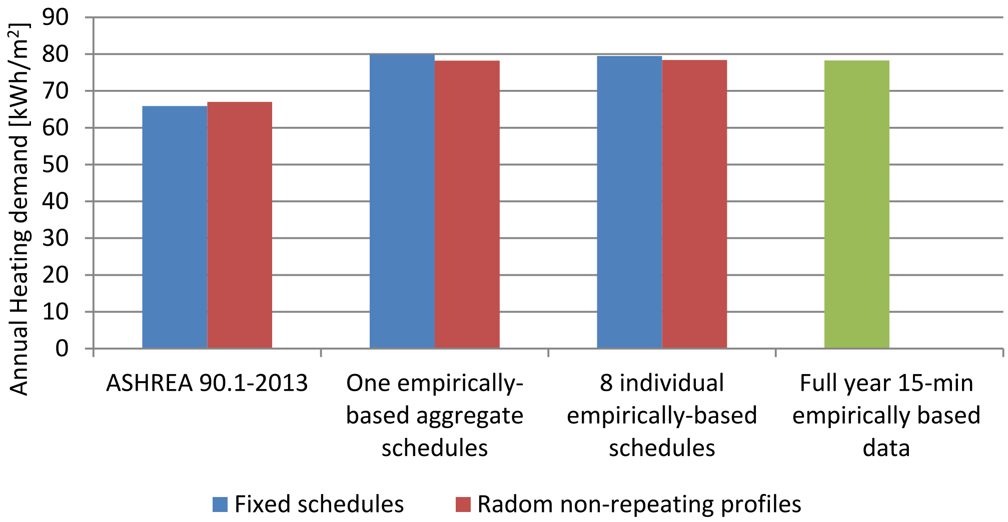

Figure 21: Annual heating demand [kWh.m^{-2}] obtained from seven scenarios

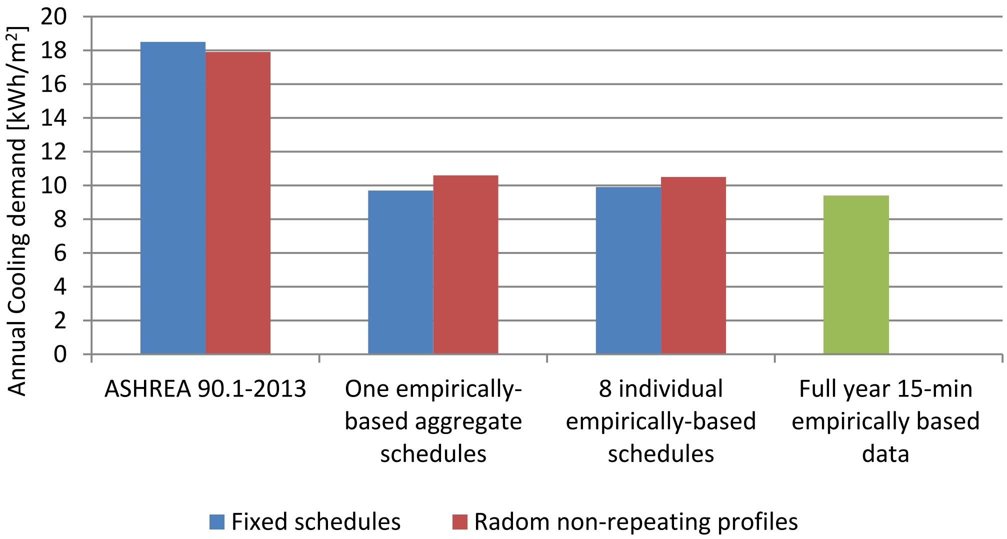

Figure 20: Annual cooling demand [kWh.m^{-2}] obtained from seven scenarios

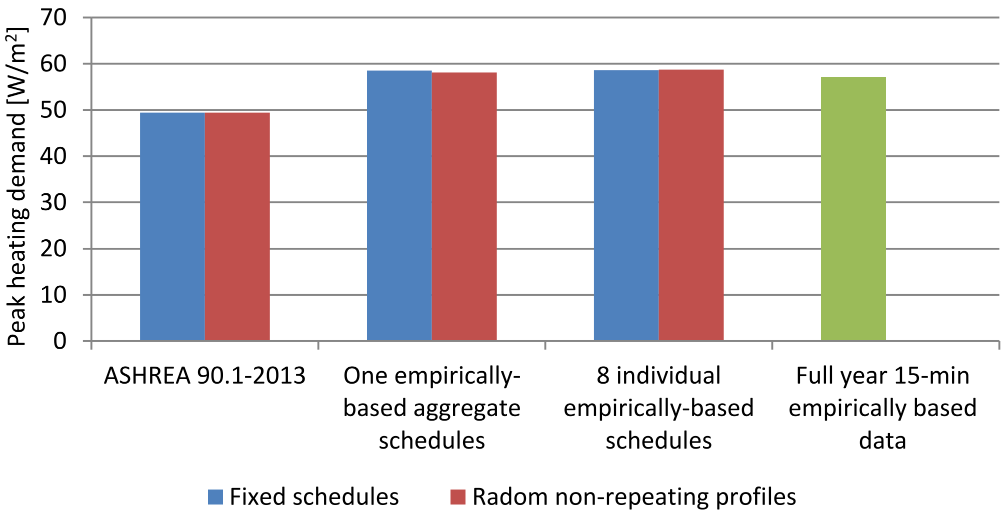

Figure 22: Hourly peak heating [W.m^{-2}] obtained from seven scenarios

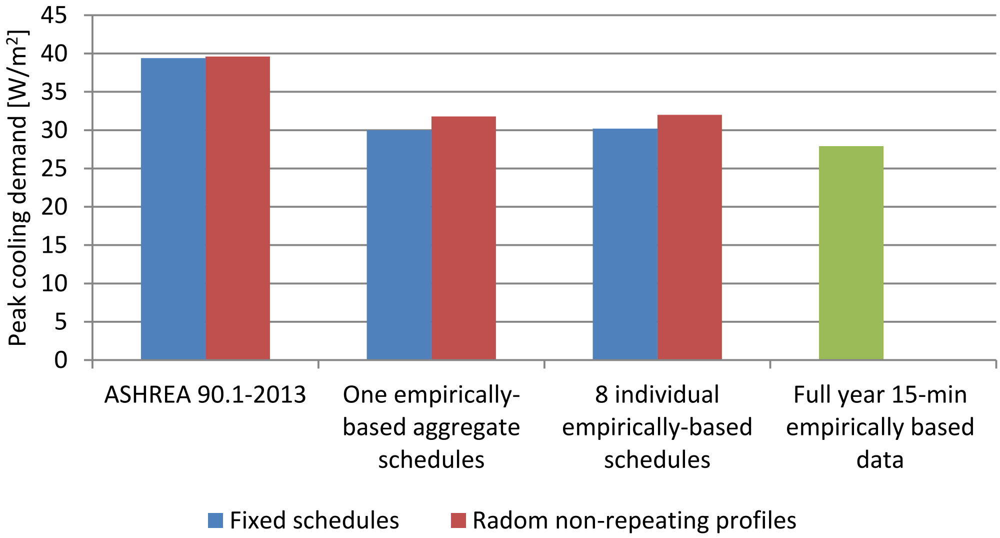

Figure 23: Hourly peak cooling [W.m^{-2}] obtained from seven scenarios

Besides the presented charts (Figure 20-23), in order to describe the distribution of values obtained by each model and to show the distance between the models, the cumulative distribution function (CDF) was applied for the heating and cooling load [W.m^{-2}] values. The result obtained by this function is presented in the figures 24 and 25, which illustrate the cumulative distribution of heating and cooling load values for models 1a, 1b, 3a, 3b and 4. It is necessary to mention that, since the results obtained from models 2a and 2b were very close to models 3a and 3b, they have not been plotted in the aforementioned figures. Subsequently, to demonstrate all data series, and to present the difference between the obtained results from all scenarios regarding the benchmark (model 4), the difference of each performance indicator in reference to model 4 is also calculated as relative error per percentage, which is displayed in table 12.

Table 12: Relative Error of simulated annual & peak heating and cooling demands regarding model 4

Model	Annual Heating Demand	Annual Cooling Demand	Peak Heating Demand	Peak Cooling Demand
1a	-15.7%	96.8%	-13.5%	41.2%
1b	-14.3%	90.4%	-13.5%	41.9%
2a	2.2%	3.2%	2.5%	7.5%
2b	0.0%	12.8%	1.8%	14.0%
3a	1.7%	5.3%	2.6%	8.2%
3b	0.3%	11.7%	2.8%	14.7%

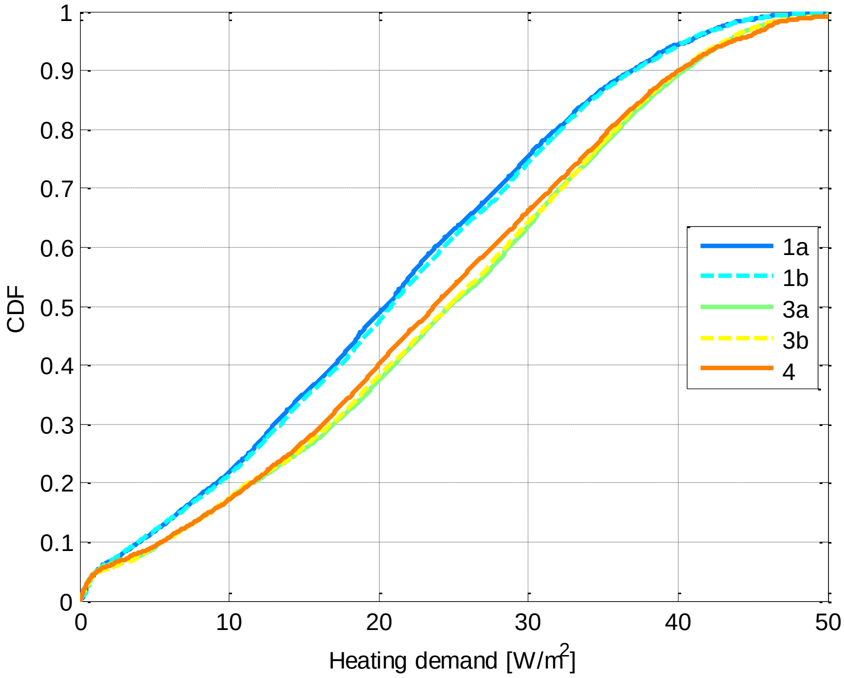

Figure 24: Cumulative Distribution of simulated heating loads [W.m-2] for models 1a, 1b, 3a, 3b, and 4

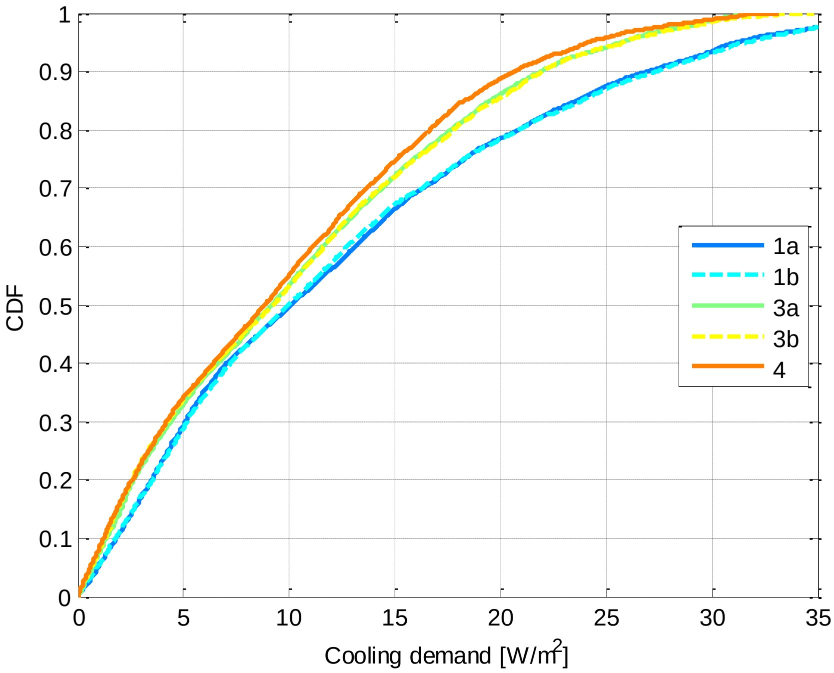

Figure 25: Cumulative Distribution of simulated cooling loads [W.m-2] for models 1a, 1b, 3a, 3b, and 4

4 DISCUSSION

4.1 Overview

Based on the former chapters, where the approaches and results of two case studies (Virtual and real office building) were separated as different sub-sections, in this chapter as well the discussion and interpretation of the results are divided in two parts, each explains one case study.

4.2 Virtual office building

As it is presented in the tables 5-7 and figure 26, the results obtained from different scenarios clearly show, in the Virtual office building, the deployment of the stochastic model for generating random occupancy profiles does not have a noticeable impact on computed values of the selected building performance indicators (Annual and peak heating and cooling demand).

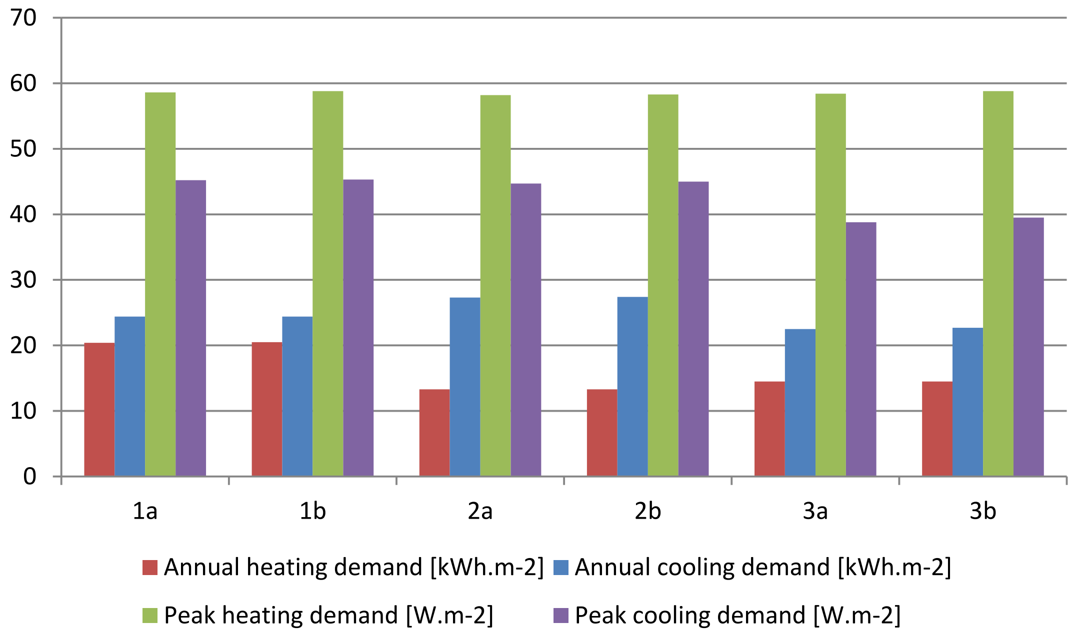

Figure 26: Annual and peak hourly heating and cooling demands per conditioned floor area

In fact, it is arguable that in first pair of scenario, only the "Passive" impact of occupants' presence is taken into account and therefore there is no difference observable in the simulation results. However, even in the next two scenario pairs (2a,2b and 3a,3b), where different operational processes such as ventilation and shading system were coupled to occupant's presence, a significant difference in results was not observable. The results are available in a precise resolution in the figure 15-18. Specifically in models 3a and 3b, where the presence level of occupants determines the magnitude of both the ventilation rates and the state of the blinds. Yet, even with regard to peak demands, simplified versus stochastic occupancy modeling alternatives do not result noteworthy differences (only 0.7% difference for peak heating load and 1.8% for peak cooling load).

Therefore, it can be concluded that as long as there is no reliable empirically-based and detailed (and diverse) occupancy data available, the mere randomization of average occupancy profiles does not appear to add any value to the building performance simulation effort; as it is also concluded in another research, exploring a case study regarding the sensitivity of simulation results to by occupancy modeling (Tahmasebi and Mahdavi 2015).

It should be noted that in the virtual office case study, only one typical occupancy schedule was used. In other words, by using an average presence profile, the diversity among occupants was neglected. To address this issue, in the next case study a real office building is simulated, for which high-resolution monitored data is available.

4.3 Real office building

Since the results of simulations for the real office building are presented regarding two point of view, the analysis and discussion is also attained in two vantage points, which would make the interpretation more logical and accurate. Yet the interpretation of these two points of view are connected and effected by each other, this section of thesis opposed to last chapters, is not divided into two separated part, rather both aspects are discussed successively.

As it is mentioned before a high-resolution monitored data was available for the real office building and based on this fact, the results are evaluated according to the model 4, which is formed by applying the whole-year real monitored data and is named as “reality benchmark”. From the occupants’ presence prediction point of view, the accuracy of the simulation result is discussed according to the precision of the predicted patterns of occupants’ presence. And for the building performance indicators four selected indicators (Annual and peak heating and cooling demands) are taken into consideration.

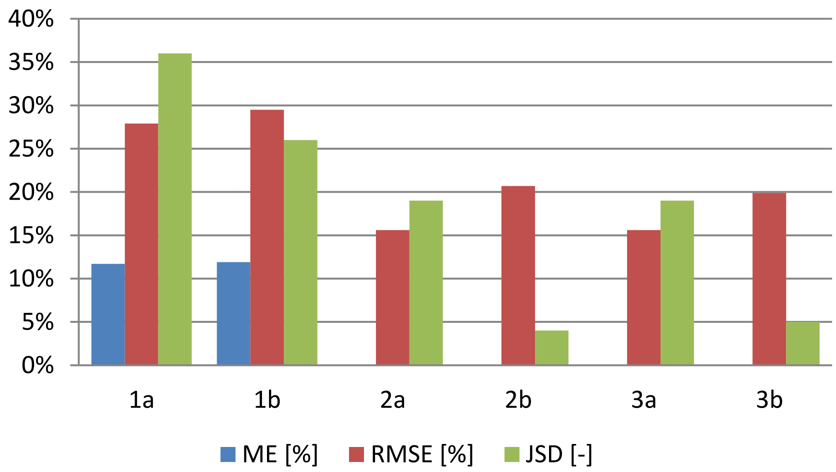

Figure 27: ME, RMSE and JSD values based on model 4

Based on the results represented in the figure 19, which illustrates the distribution of occupants' presence level predicted by different models for the real office and also considering the values obtained from Jensen-Shannon Distance (JSD), represented in figure 27 (obtained from table 8), it can be argued that randomization of occupants' presence patterns reduces the distance between the predicted and actual distributions of occupancy levels.

However considering Mean Error (ME) presented in the same figure, the first two models (1a, 1b) clearly overestimate the occupants' presence level, which leads also to lower heating demand (see figure 24) and systematically higher cooling demand (Figure 25).

In view of building performance indicators, the stochastic occupants' presence profiles, which are applied in model 1b, 2b and 3b, do not produce more accurate results (figure 29). More importantly, concerning the results yielded by each pair of scenarios represented in figure 28 (achieved from table 9) and also the relative error displayed in figure 29 (obtained from table 12), it is obvious that models 1a and 1b provide fairly comparable results, as do models 2a and 2b, and models 3a and 3b. As a result the divergence of the simulation results for different models is not mainly due to the nature of occupants' presence models (i.e. stochastic versus non-stochastic); Rather, the significant difference is between generic (standard-based) assumptions used in first pair (1a, 1b) and assumptions based on actual occupancy information applied in 2a, 2b, 3a, 3b, 4.

In other words despite the fact that the distribution of stochastic occupants' presence predictions is closer to the actual occupancy level distribution, concerning building performance indicators (e.g. building annual and peak heating and cooling demands) using stochastic presence patterns per se does not insure any closer value to the reality than the values obtained from non- probabilistic occupancy patterns.

Therefore, possessing reliable estimations of actual occupancy levels is much more important than applying probabilistic or non-probabilistic presence profiles in order to achieve high-fidelity simulation results, (Tahmasebi and Mahdavi 2015) at least concerning building-level performance indicators such as heating and cooling annual and peak demands.

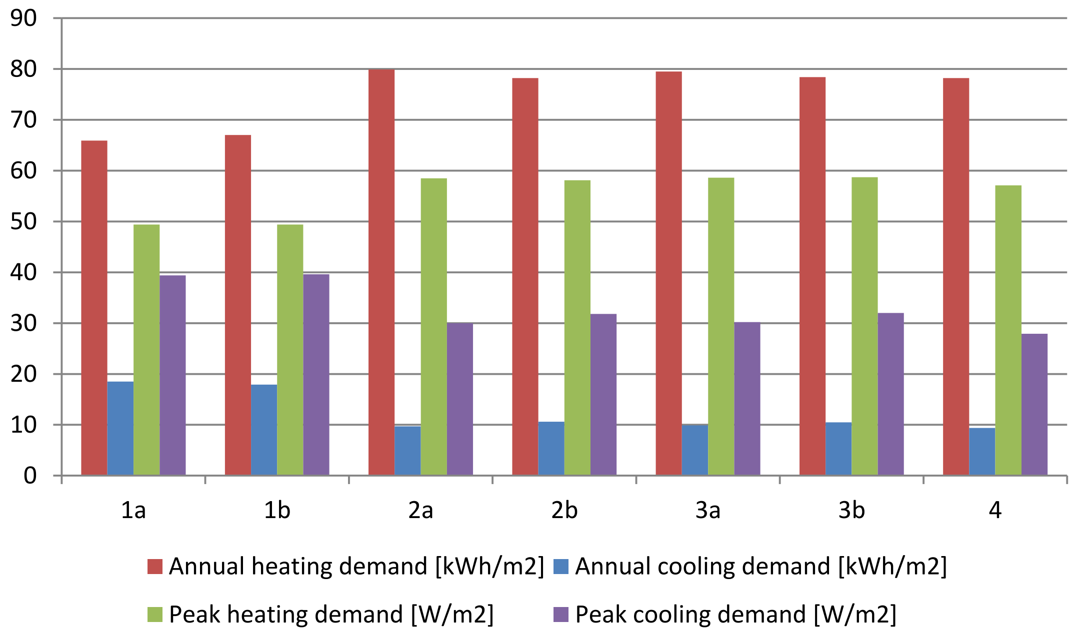

Figure 28: Annual and peak heating and cooling demands per conditioned floor area-Real Building

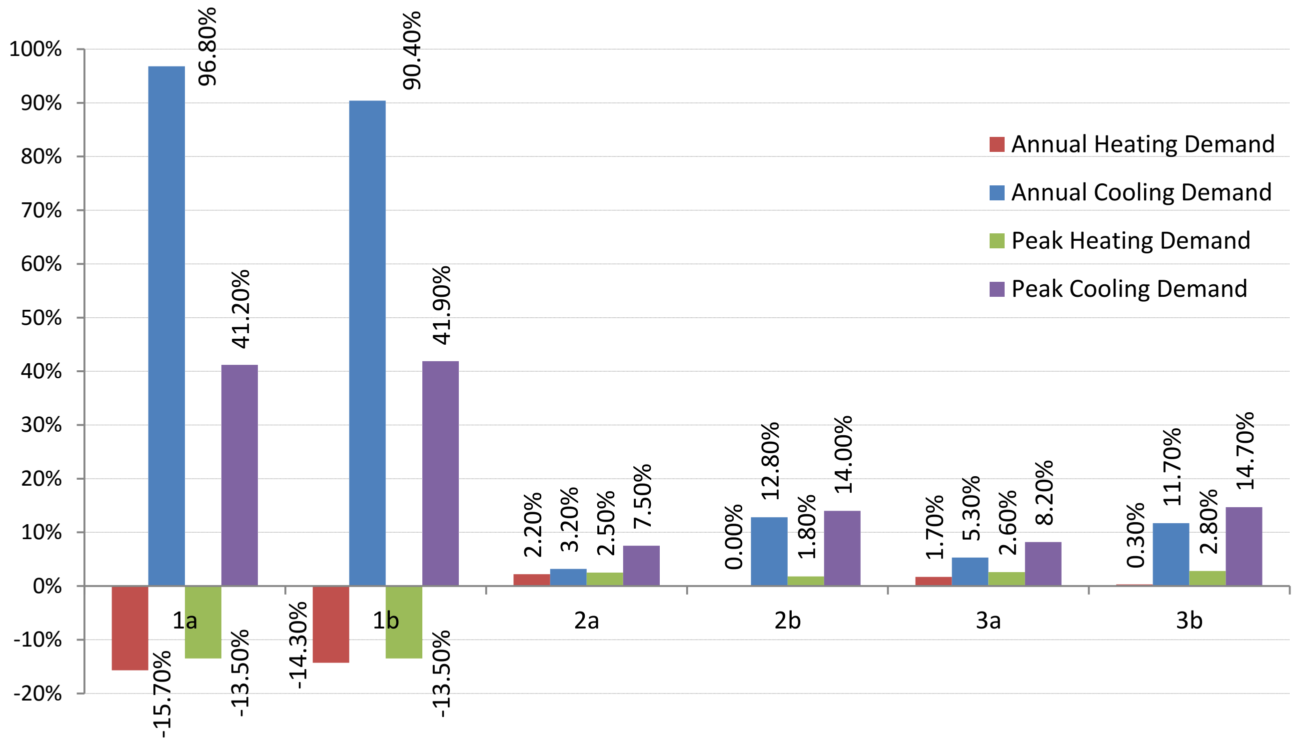

Figure 29: Relative Error of performance indicators in reference to model 4

At this point it is necessary to mention that the present study focused on the implications of occupants' presence models and not occupant behavior models for simulation results. The modeling approaches which are used in this study represent the occupants with a set of three schedules for presence, lighting, and equipment (either in a fixed or stochastic manner, either for an average person or for individuals). This means the occupants' presence is applied relevant to the equipment and light usage, but the corresponding relationship is assumed as simple as possible. These type of schedule sets are used fairly common by the building performance simulation community to represent occupants in the simulation models, which indicates the importance of the current study, as an initial step in exploring and assessing the influence of different occupancy modeling assumptions on building performance simulation results.

5 CONCLUSION

Along with trends in defining more accurate and realistic occupancy presence profiles and considering the passive and active influence of the building users on simulation result and respectively energy demand of a building, this thesis was intended to explore the influence of different occupancy modeling assumptions regarding thermal performance simulations. This assessment is done based on four building performance indicators which have been used fairly common in building simulation community; heating and cooling annual demands and peak loads.

The simulations were conducted on two types of office building, a virtual and a real office building and each building was simulated through different scenarios each formed by two occupancy modeling assumption, conventional diversity profiles and stochastic models of occupancy.

In the virtual case study, different levels of occupants' interactions with building system (HVAC and shading) were deployed to the ASHRAE profiles. The results achieved from virtual office building shows that, when the information on occupancy is limited to typical presence and equipment use profiles, the deployment of stochastic models does not have a noticeable impact on the annual, monthly and peak heating and cooling demands, even when different levels of occupants' interactions with building systems are considered.

In the real case study due to the availability of high-resolution monitored data, it was possible to evaluate the accuracy of the obtained building performance indicators from the simulation models. The fixed and randomized profiles were created using three different profiles; ASHRAE profiles (the same used in virtual office), monitored data assumed as one average diversity profile and then monitored data as 8 individual diversity profiles for occupancy, lights & plug loads profiles. Based on the obtained results from different scenarios it can be concluded that although the distribution of stochastic occupancy presence predictions is closer to the actual occupancy level distribution, concerning building performance indicators (e.g. building annual and peak heating and cooling demands) use of stochastic presence patterns by itself does not provide any closer value to the reality than the values obtained from non-probabilistic occupancy patterns.

As it has been suggested in recent studies (Tahmasebi and Mahdavi 2015), to assess the occupancy models in a comprehensive manner it is required that the occupancy-related models be assessed by considering different building types, different zonal destinations, different phases of the building delivery process, different queries and so on, which all produces a great number of simulation scenarios. Hence no single occupancy modeling approach can contain all together and accordingly further studies are required to explore and declare the effects of different occupancy modeling assumption on the accuracy of occupancy prediction and the building performance simulation results.

6 INDEX

6.1 List of Figures

6.2 List of Tables

6.3 List of Formulas

7 REFRENCES

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APPENDIX

MATLAB Code;

To change the format of the monitored data which were exported as excel files to the text file according to EnergyPlus input categories.

The initialization part was defined separately for each set of sensors; occupancy, light and plug loads, i.e. for the creation of occupancy files the initialization part contained just "% Occupancy" and the number of excel input files was equal to the number of the sensors in that set and obviously the name of the created file depended on the intended sensor.

After creating all the text files, they were put together as a unique text file and easily addable to the EnergyPlus text file.

Definitely there are codes which could write all these data once in a time in a unique file, but I found this code much simpler and quicker to write and use.

%initialization

```
% Occupancy

file_name='Occ 1.txt';

col_number=2;

files=cell(3,2);

files{1,1}=['Occ_WD.csv'];

files{1,2}=['Weekdays'];

files{2,1}=['Plug_SAT.csv'];

files{2,2}=['Saturdays'];

files{3,1}=['Plug_SUN.csv'];

files{3,2}=['Allotherdays'];


% Light Loads

file_name=Light 1.txt';

col_number=2;

files=cell(3,2);

files{1,1}=['Plug_WD.csv'];
```

```
    files{1,2}=['Weekdays'];
    files{2,1}=['Plug_SAT.csv'];
    files{2,2}=['Saturdays'];
    files{3,1}=['Plug_SUN.csv'];
    files{3,2}=['Allotherdays'];

    % Plug Loads
    file_name='….txt';
    col_number=2;
    files=cell(3,2);
    files{1,1}=['Plug_WD.csv'];
    files{1,2}=['Weekdays'];
    files{2,1}=['Plug_SAT.csv'];
    files{2,2}=['Saturdays'];
    files{3,1}=['Plug_SUN.csv'];
    files{3,2}=['Allotherdays'];
```

% header text

```
    ftemp = fopen(file_name, 'W');

    fprintf (ftemp, 'Schedule:Compact,\r\n');
    fprintf (ftemp, 'OCC_WD, Name\r\n');
    fprintf (ftemp, 'Fraction, Schedule Type Limits Name\r\n');
    fprintf (ftemp, 'Through: 12/31, Field 1\r\n');
```

% let's go!

```
    seq=1;
    seq_name='Field ';
    for i=1:size(files,1)
```

```
seq=seq+1;
if (seq==151)
   seq_name='A';
   seq=seq+2;
end;
file=files(i,:);
list=load(file{1});

fprintf (ftemp, '    For: %s,          !- %s%i\r\n', file{2}, seq_name, seq);

minute=0;
hour=0;
for j=1:size(list)
   minute=minute+15;
   if ( minute==60)
      minute=0;
   end;
   if ( mod(j,4)==0)
      hour=hour+1;
   end;

   value=list(j,col_number);
   seq=seq+1;
   if (seq==151)
      seq_name='A';
      seq=seq+2;
   end;

   fprintf (ftemp, 'Until: %02d:%02d, %s%i\r\n', hour, minute, seq_name, seq);
```

```
        seq=seq+1;
        if (seq==151)
          seq_name='A';
          seq=seq+2;
        end;

        if (j==size(list,1)) && (i==size(files,1))
          fprintf (ftemp, '    %f;               !- %s%i\r\n', value, seq_name, seq);
        else
          fprintf (ftemp, '    %f,               !- %s%i\r\n', value, seq_name, seq);
        end;
    end;
end;
fclose(ftemp);
```