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Occupancy and weather: How these influence robustness and building design

- Uncertainty study with stochastic building performance simulations

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Synopsis:

The aim of this thesis is to achieve better knowledge of how occupants and weather affect the predictions from building performance simulations. The influence of weather is evaluated based on robustness and design tendencies, while the occupancy modelling is evaluated on building performance and dimensional values. A series of weather files and methods to perform occupancy modelling are tested with factorial experiment. These are performed on either building performance simulation tool, Be15 and BSim, respectively.
Based on a fictional office building, stochastic simulations were carried out with two simulation methods. The whole building is simulated in Be15, where the influence from including multiple historic weather files are compared with results from Design Reference Year. The design solutions were evaluated in terms of their robustness level towards weather files and the most important input parameters were identified through sensitivity analyses. Additionally the design tendencies that grants a desired building performance are studied.
Furthermore, for a selected room modelled in BSim, the influence of using stochastically generated occupancy profiles were studied and compared to static occupancy profiles in terms of performance and system dimensioning. Tendencies that leads to deviations in the building performance and system dimensioning are outlined. Sensitivity analysis were conducted to identify the influence from variability of occupants and weather on the evaluated parameters.

Summary

Several studies have shown that there are many uncertainties when performing building performnce simulations. Occupants and weather are among the most important ones. When designing buildings, it is common to use static occupancy profiles which does not reflect the random nature of occupants. In terms of weather, building performance simulation modellers are typically using one weather file. The design weather file for the simulations does not necessary reflect the present weather or future weather for the respective building.

The aim and purpose of this thesis is to study these uncertainties by including stochastically generated occupancy profiles, various historic and future weather files along with a Design Reference Year weather file.

The abovementioned have been studied with stochastic building performance simulations with two different methods. Each of the methods are used on either building performance simulation software. A monthly quasi-steady calculation method and a sub-hourly dynamic calculation method with use of the building performance simulation programs Be15 and BSim, respectively. Various input parameters with suitable ranges and distributions were selected and afterwards implemented in a Monte Carlo Simulation process. The results were hereafter evaluated with sensitivity and robustness analyses where the ranking of the input parameters were identified alongside with determination of design tendencies. Furthermore, the energy performance were evaluated along with system dimensioning.

Since the monthly quasi-steady calculation method have limited options for occupancy inclusion, the part mainly focuses on the influence of using various historic weather files. Simulation results with the Design Reference Year weather file and the weather files it is based on showed significant differences in terms of total energy demand when studying the results for each weather file as individual groups. Comparing the individual design solutions, different results were observed when solely changing weather file.

Two sensitivity analysis methods determines window-to-facade ratio, mechanical ventilation and the U-value of the windows to be the most sensitive input parameters in terms of total energy demand. The ranking of these parameters are almost constant throughout the weather files. Some changes of the less influential input parameters were observed with the different weather files.

The design tendencies from the simulations showed some insignificant differences between the weather files. Specific fan power and infiltration proved a high correlation with the respective weather file's solar conditions.

In terms of getting high robustness the study concludes that the U-value of the windows, mechanical ventilation and window-to-facade ratio should be in the lower end of the selected ranges. Opposite, the g-value, specific fan power and internal heat load should be in the high end of the selected ranges.

Stochastically generated and static occupancy profiles were studied by a sub-hourly dynamic building performance simulation software with multiple weather files. In a preliminary study, variations from day to day proved to be insignificant on energy demand for cooling and heating, hours of excessive temperatures and energy demand for the fan. Variations on an hourly level turned out to produce different results.

The stochastic and the static occupancy profiles with same amount of occupants were compared in terms of energy performance and system dimensioning. The static occupancy profiles induce higher total energy demand compared to the stochastic occupancy profiles and the difference is more distinct

in the higher range of the total energy demand. The deviation was identified to be primarily caused by the energy demand for cooling, which is significantly higher for the static occupancy profiles. The static occupancy profiles also induce a higher amount of excessive temperatures, causing a higher fan energy demand.
In the study of system dimensioning with focus on an acceptable deviation of 3 %, similar results were obtain in terms of dimensional power. The results from the two occupancy profiles deviates from each other and the static occupancy profiles causes higher dimensional cooling power, higher dimensional fan power and lower dimensional heating power.
From the results it is evident that the yearly mean occupants present is affecting the cooling and heating demand for both models. Regarding the dimensional power, the yearly mean occupants present is primarily affecting the cooling power. On the other hand, varying the daily standard deviation of occupants present in the stochastic occupancy profiles is not affecting the cooling and heating demand nor the dimensional power of these.
Through a sensitivity analysis, the cooling power, mechanical ventilation and weather file proved to be the most sensitive parameters in terms of total energy demand and excessive temperatures. The window-to-facade ratio, weather and yearly mean of occupants present are the most sensitive parameters in terms of dimensioning of cooling and heating systems.
The future weather files used in the simulations causes both the cooling demand and cooling power to be higher and opposite for heating.

Keywords: Monte Carlo Simulations, stochastic occupancy profiles, multiple weather data sets, building performance, building robustness, sensitivity analysis, building design, uncertainty analysis

Preface

This Master thesis presents the work from a nine month long struggle with software problems and programming languages together with endless amounts of simulation data. This report can not express the amount of hours put down in data treatment and analysis, the optimism for good results, the joy for something to succeed, and the despair and sadness with each error and worthless result.

The work has been conducted during the period from September 2016 until June 2017 by two fellow students at the Master's programme *Indoor Environmental and Energy Engineering* at the Department of Civil Engineering at Aalborg University.

To broaden the knowledge regarding building performance simulations, this study investigates the uncertainties concerning occupancy and weather. Historic and future weather data and stochastically generated occupancy profiles will be investigated with a stochastic simulation process to examine their influence on building design, dimensional values, design choices and robustness.

Acknowledgements
We would like to thank our supervisors, Rasmus Lund Jensen, associate professor at Aalborg University and Torben Østergård, Industrial PhD student at MOE A/S.
Rasmus has through several years at Aalborg University been our supervisor and we are grateful for the knowledge and experience he has been sharing with us. Throughout this period, Rasmus has been very resourceful with insightful guidance and constructive feedback.
Torben introduced us to stochastic modelling and we got hooked after the very first lecture he gave us. Torben has given us valuable guidance with regards to the stochastic modelling and his experience from his workplace has provided us food for thought.

Furthermore we would like to thank PhD fellow Kim Trangbæk Jønsson and research assistant Frederik Søndergaard Mikkelsen for having patience with us and our questions in terms of programming complications. We would also like to thank William O'Brien and Burak Gunay from Carleton University for their clarifying answers regarding occupancy modelling.
Furthermore, we are grateful to Jørgen Rose at Sbi for his contribution by generating future weather data and Poul Svante Eriksen at the Department of Mathematical Sciences at Aalborg University for his guidance regarding statistical methods.
Additionally, we are grateful for the input regarding occupancy profiles used in the commercial sector from Steffen E. Maagaard and Mathias Villumsen from MOE A/S and Sweco Danmark A/S, respectively.

Finally, we must express our gratitude to our fellow students, Morten Hjalf Silkjær and Kasper Kingo Hansen, who have also been working on a Master thesis regarding stochastic modelling. They have successfully motivated us and brightened our days with laughter, joy and interesting discussions and conversations.

Reading guide
Throughout the report there will be references to sources which are all listed in the bibliography in the end of the report. The Harvard-method is used for references. The source will be referred to as either "[Surname/Organization, Year]" or "Surname/Organization [Year]" and when relevant also with a specific page or section in the source.

Webpages are listed with author, title, URL and date. Books are listed with author, title, publisher and version, so forth these are available.

The report contains figures and tables which are numbered in relation to the chapter they appear in. Thus, the first figure in chapter 1 will be named figure 1.1, the second figure 1.2 and so on.

In addition to the report there is also an appendix report. Throughout the report there will be references to the appendix, numbered with a letter and a number for parts of the appendix. E.g. appendix A.1, B.1 and so forth. For references to a whole chapter in the appendix only the letter is used. E.g. appendix A, D and so forth.
We advice the reader to use the appendix alongside the main report for supplementary details and results.

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1 Introduction

Focus on reducing the energy consumption for buildings to improve energy conservation and reduce the environmental impact has increased during the past decades. As a result the most important subjects in building design have been the focus on innovation in building materials and technological solutions to improve building performance. This had lead to optimization of building envelopes and the development of building management systems, which has contributed to a reduction of the energy consumption in buildings. However the predictions of a building's energy consumption and indoor environment using building performance simulations (BPS) is still not reflecting the actual conditions. This mismatch is often referred to as the "performance gap", and is provoked by various causes since many parameters are influential on the uncertainty of the BPS. These include weather conditions, building construction, material properties, presence and behaviour of occupants together with operational systems, [Zhao and Magoulès, 2012].

The design stage may cause performance discrepancies in the later stages as it includes important decision-making which is highly influential on a building's performance. Miscommunication between stakeholders about performance targets can be one of the first causes towards the performance gap. With stochastic modelling in the early design stage, guiding for decision-making may be given and the most influential parameters can be identified.

In terms of physical properties, the BPS tools are highly accurate, but due to complexity of a problem, they fail to predict energy consumption and indoor environment quality with accuracy.
Occupants and weather have significant impact on a building's indoor climate quality and energy consumption, [Calleja Rodríguez et al., 2013; Clevenger and Haymaker, 2006]. As a consequence of buildings getting more efficient and the climate is changing, the influence of occupants and weather is both increasing and changing. Meanwhile, these parameters behave stochastically and are difficult to predict and imply in simulations with the current simulation tools. To understand the random nature of occupants and weather and to implement them in the stochastic modelling might be the key to reduce the performance gap of buildings.

Hong et al. [2016] claims that the essential starting point of bridging the credibility gap is the integration of diverse occupant behaviour and stochastic nature, coupled with an extensive understanding of the methods and tools used regarding energy-efficient buildings.
Another contribution to decrease this gap is to increase the robustness of a building. A building with high robustness will handle uncertainties better than a building with low robustness, and the credibility gap will therefore be passively reduced.

Especially in office buildings, where the occupants are a significant part of the heat gains for the building, occupant behaviour is interesting to model. This might influence the design of HVAC systems and increase the building robustness towards the variability of occupants. Understanding the influence of occupancy and weather in an office building might yield design tendencies that decreases performance gap while sustaining the energy conservation and the quality of the indoor environment.

This thesis focuses on implementing multiple weather files and dynamic occupancy profiles to determine their influence on the building performance, robustness and system dimensioning. It is desired to couple the variability of these with the uncertainty of stochastic modelling for a global design space.

Literature Review 2

In this chapter, literature regarding stochastic building simulation is presented. Furthermore, literature concerning occupancy and weather in relation to building performance simulations are presented. At last, the review is recapitulated to define the gaps.

The aim of this chapter is to present knowledge from a series of studies in the field of research and determine some gaps and unanswered questions.

Stochastic modelling within BPS have gotten more attention during the past few years but the knowledge within the subject and level of detail have great potential of being explored further. In this review, some of the most relevant studies to date are addressed and outlined.

Many topics concerning occupant behaviour and weather in building simulations have been investigated to expand the knowledge within these subjects. Although the existing literature covers a vast variety of aspects and issues, this review will keep two major themes as focal points. These are the uncertainty related to the variability of occupants presence and weather in relation to building simulations and thereof the influence of these on building robustness towards occupants presence and weather.
The term robustness origins from statistics where it is described as a certain technique's ability to give precise results even when the underlying assumptions are violated, [Leyten and Kurvers, 2006]. Regarding buildings, it relates to a building's ability to perform as intended under realistic conditions, including climate changes. Furthermore, the robustness of a building can be broken down into multiple performance indicators and their sensitivity towards uncertainty, miscue or even faults in the underlying design assumptions.

In the research made by Calleja Rodríguez et al. [2013], three scenarios for both weather and occupancy behaviour were defined. Alongside with a series of other input parameters, the results showed that weather and occupancy behaviour are the most influential parameters on the building's yearly consumption to air-conditioning.
Similar conclusion have been drawn by Azar and Menassa [2012] in terms of energy demand while Brohus et al. [2010] concludes that occupancy is among the most substantial parameter to the total level of uncertainty.

This review is divided into three sections, covering studies regarding stochastic modelling and occupancy presence in terms of modelling methods, tools and case studies. Hereafter, the review presents studies regarding the uncertainty of weather conditions in BPS and lastly, recapitulated to define gaps in the current literature.

2.1 Stochastic modelling

Conventionally, BPS modellers use deterministic building simulations in their evaluation of design. This deterministic approach is giving very limited guidance when considering design improvements and is evaluating the design instead of proactively guiding the design, [Attia et al., 2012].
The introduction of stochastic modelling in BPS have opened up exploration of global design spaces meanwhile considering many performance outputs is very useful to optimize the design and hereof the performance of a building. This building design approach is especially useful in the early design

phase where the amount of uncertainties and large variability for various design parameters are not determined. Hence, this culminate into a large design space where it may be difficult to choose the optimal design without any guidance. [Østergård et al., 2017a].

The underlying reason to use a proactive method or approach is that engineers and other consultants are more involved from the very beginning of the design phase. This type of working process is called the Integrated Design Process (IDP) or Integrated Project Delivery (IPD). According to Aia [2007], the "Integrated Project Delivery (IPD) is a project delivery approach that integrates people, systems, business structures and practices into a process that collaboratively harnesses the talents and insights of all participants to optimize project results, increase value to the owner, reduce waste, and maximize efficiency through all phases of design, fabrication, and construction." The abovementioned advantages are resulted by a move of the main work effort to an earlier part of the project as illustrated in figure 2.1.

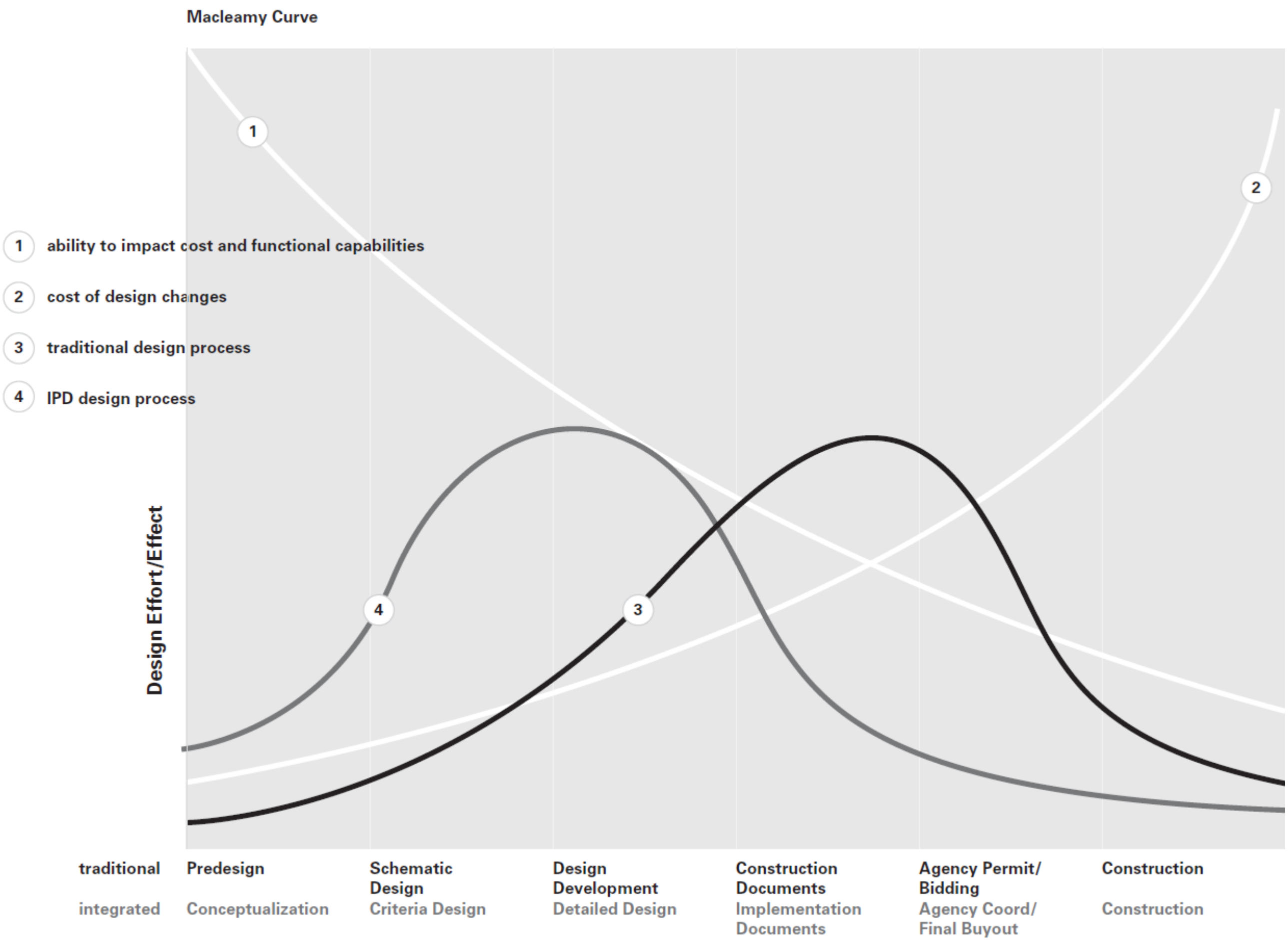


Figure 2.1. The MacLeamy curve showing the design effort versus the different stages in a building design project. [Aia, 2007].

While the IDP is fully developed, the practical use of it is faced by many challenges and to maximize the potential for the IDP, these challenges have to be solved. Among many, the challenges between architects, engineers and other contributors are among the most important ones. Kanters and Horvat [2012] reckons costs, competition, communication and actors versus activities as some of these challenges.

The use of a proactive approach along with the design settling was recognized by Petersen [2011].

Petersen [2011] developed a tool that may be supportive in the whole design process. With a reference value and two optional alternative values, the tool may simulate a building with the reference values, and two variations of each of the parameters that are varied with a one-at-the-time method. In three real building projects, the tool was used to investigate its usefulness. The three actors involved experienced useful aid when making design decisions when using the tool.
Another similar tool was developed by Ochoa and Capeluto [2009] to give aid and support when considering intelligent facades in the conceptual design stage. Based on energy codes, the tool suggests a range of facade solutions that may give a starting direction for the designer. The designer may with these solutions estimate the energy demand and visual comfort through BPS programs such as EnergyPlus.

Targeted towards net zero energy buildings, Attia et al. [2012] developed a tool for parametric analysis that with a small amount of iterations may support decision making. The tool is a prototype with an intuitive and easy to use interface, however usability testing revealed that the tool may be challenging to use without an expert knowing the tool. The prototype is also only limited to energy estimations.

The level of detail in the early design phase is low and the phase is typically characterized by large uncertainties and frequent design changes. Because of this, the simulations in this phase does not need to be overly detailed but rather fast and less detailed.
This is recognized by Østergård et al. [2017a] as the authors uses a simple, monthly calculation method provided by DS/EN ISO 13790 [2008]. Based on an industrial PhD project, Østergård et al. [2017a] proposes a methodology to improve the practice of BPS in the early design phase. Over a period of two years, a number of case studies were conducted as a part of the proposed methodology.
The proposed methodology is an iterative parametric method to explore a global design space with stochastic methods. A chart of the proposed workflow is presented in figure 2.2.

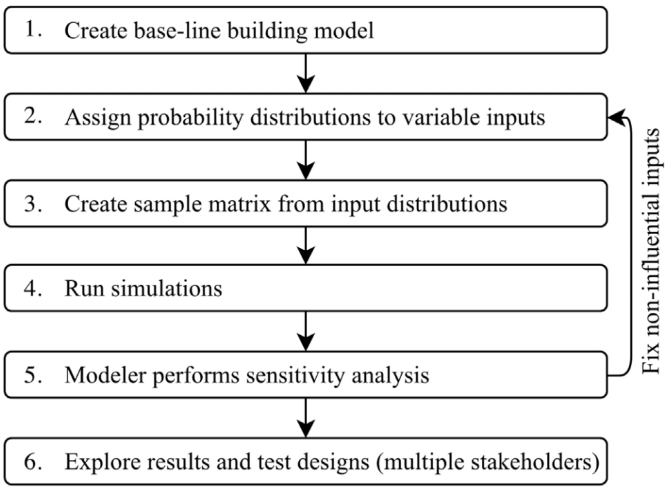


Figure 2.2. Proposed workflow from Østergård et al. [2017a] when exploring a global design space.

It is referred to Østergård et al. [2017a] for more elaborative descriptions of the six steps in the workflow.
When modelling stochastically, thousands of simulations are conducted and therefore the results may not be analysed nor visualized as commonly done with deterministic simulations. For stochastic simulations it have previously been shown that parallel coordinate plot (PCP) is a good visualisation tool, [Østergård et al., 2017a]. The tool may also be used in meetings between different stakeholders to aid decision making. To be able to visualise and see the different inputs and performance indicators

at the same time was recognized by Østergård et al. [2017a]. During these meetings between different stakeholders, supplementary models may be rapidly created by means of metamodels for exploration of design space, sensitivity analysis or optimisation. This have been exploited in several studies, [Asadi et al., 2014; Gelder et al., 2014; Geyer and Schlüter, 2014; Fumo and Biswas, 2015] as well as [Østergård et al., 2017a].

It may be difficult to address a building's energy demand, thermal comfort and daylight separately. These are closely correlated as changing one of them will probably change the other twos. To evaluate these performance indicators combined, Østergård et al. [2015] constructed a holistic scoring function to weight the energy demand, thermal comfort and daylight by 50, 25 and 25 % out of the total score. This scoring function were also included in the proposed methodology by Østergård et al. [2017a].

2.2 Occupancy presence

Janda [2011] address different challenges concerning integration of occupants in building performance. Janda [2011] argues in the article "Buildings don't use energy: People do" that "building users play a critical but poorly understood and overlooked role in the built environment."
In a comparison of building design, climate change and different occupant scenarios, Roetzel and Tsangrassoulis [2012] argues that the most important factor to optimize thermal comfort is building design and that the main factor to reduce energy consumption is occupant behaviour.
In another study, Silva and Ghisi [2014] concludes that occupancy behaviour in buildings have a significant effect on a building's demand for heating and cooling.

The thermal process in building simulations have over the last forty years been brought to perfection according to Degelman [1999]. Even though if this is true, the inputs related to occupants are highly uncertain and simplified. Because of this, occupants and their behaviour in terms of their presence and their actions, as well as interactions with systems, evidentially creates a discrepancy between the results from the simulations and the performance of the real building.

In building simulations today, modellers usually make assumptions about occupants that are much less complex than what is being observed in reality. Static occupancy profiles without any variation or random behaviour are commonly used and are in many cases overly optimistic which could lead to results in BPSs that are over-predicted. Brien et al. [2016] provides a selection of interesting findings in their international survey concerning approaches to occupant modelling in BPS today. The survey was sent to approximately 5000 engineers, researchers, educators and architects and obtained 274 valid responses. A couple of interesting findings from the survey in numbers are listed in the following:

- 75 % of the participants agrees, or somewhat agrees that more occupant modelling features should be included in BPSs.
- 76 % of the participants thinks that uncertainty should be addressed better in BPSs.
- 37 % of the participants stated however, that they would lose their client's confidence in BPSs if uncertainty were expressed explicitly.
- 74 % of the participants agrees, or somewhat agrees that the requirements to occupant modelling should be increased.

Opposite to Calleja Rodríguez et al. [2013], Wang et al. [2016] found out that occupant presence has no impact on direct and only a small impact on the indirect consumption compared to lighting and equipment. It has to be mentioned that this is evidence of one specific case only. Wang et al. [2016]

mentions that in consideration of thermal peaks, occupant variability is important as static profiles comes short in this matter.

Occupancy methods and models

Occupant behaviour is not deterministic but may be described by stochastic measures. Hong et al. [2016] describes occupant behaviour as diverse, stochastic, complex and that it includes interdisciplinary characteristics. Because of this stochastic nature, many researcher have proposed a number of models to describe occupancy behaviour. Among the first attempts was the LIGHTSWITCH model developed by Newsham et al. [1995]. The model is based on observed occupancy data for the purpose of creating realistic profiles for both occupancy and lighting. LIGHTSWITCH includes the probability of arrival and departure, intermediate arrivals and departures for the profile generation.
The model was further developed by Reinhart [2001] where the integration of inverse transform sampling made it possible to generate arrival and departure time samples and distributions for break lengths.
Based on analysed statistical properties of occupancy, Wang et al. [2005] proposed a probabilistic model that can anticipate the occupancy in single person offices.
It is important to remember that these models deterministically chooses how many breaks the occupants have during the day and in real life the number of breaks would probably vary more. The models also exclude any occupancy during weekends.

Page et al. [2008] - proposed a model, with a Markov chain to describe the occupant presence, that may create a time series of presence states in the two modes, presence or absent. Further details such as long periods of sickness, holiday, business trips, etc. were also included in their model. When compared to data from private offices, the occupancy model proved that it is capable of generating realistic key properties such as arrival and departure times, intermediate presence and absence and longer periods of absence.

As mentioned earlier, typically simplified and static profiles are used as input for the BPSs. The advantages of these static profiles are their ease of use and integration to BPS programs. These profiles may be incorporated by non-expert modellers and are not especially time consuming to generate.
However, there are some major drawbacks related to this modelling approach. The static profiles are periodically steady and have weaknesses concerning the diversity in occupant behaviour. In real life, there are few or no certainties that the occupants in a building will be present in a predefined space at rigid time steps. The random nature of occupants have lead to the integration of the abovementioned methods and models in BPS programs such as EnergyPlus and OpenStudio. [Hong et al., 2016].
A typical example of a static occupancy profiles is presented in figure 2.3 and compared to a stochastic generated occupancy profile.

Figure 2.3. Typical diversity profile from ASHRAE Standard 90.1-2004 representing the weekdays compared to a stochastic generated occupancy profile from Lawrence Berkeley National Laboratory. [Tianzhen Hong and Yixing Chen, 2016].

Agent-based modelling of occupancy behaviour is a relative new method within BPS which has been review by a number of sources. Agent-based modelling is in its simplicity a method to simulate both actions of autonomous agents and their interactions with other agents and environment. In an occupancy perspective, these agents are the occupants in a building which performs various actions based on their desire, intention and belief, [Andrews, 2016]. These actions are typical characterizations for humans process for decision making.

Chen et al. [2016] created an agent-based occupancy simulator as a web-based application for modellers to use. With a case study, they demonstrates that the simulator can replicate the diversity of occupancy behaviour while creating realistic schedules for occupancy for BPSs.
Similar work were conducted by Liao et al. [2012] that propose a stochastic agent-based model.

Another method to create occupancy behaviour for BPSs are the creation of synthetic data sets. These data sets are generated based on data sets collected from existing relevant buildings which often includes cross-sectional (data collection at a single point of time) and longitudinal data (data collection over a period of time).
Among the research with this approach for modelling occupancy behaviour, Andrews [2016] created a model which can be coupled with the BPS program EnergyPlus.

Occupancy tools and scripts
A selection of occupant behaviour modelling tools have in the recent years been developed and incorporated in to BPS programs. An example of this is an EMS script for EnergyPlus developed by Gunay et al. [2015]. They gathered theories and models from the literature and incorporated them into this EMS script which may model numerous actions and events that occupants perform. The work with this script continued by Gunay and O'Brien [2016] and was further developed into a "measure" (a scripting facility to automate tedious tasks) for the BPS program OpenStudio. With this measure a BPS modeller can easily include stochastic occupancy behaviour models in their simulations. However, the developed measure have been lacking robustness against updates in OpenStudio.

Another example of a tool to model occupancy behaviour is the web application made by Tianzhen Hong and Yixing Chen [2016]. This is an application which can simulate the movement of occupants in a building based on the Markov-chain model. The downside of this application is its limitation for new buildings since there are only a small number of template buildings to be used.

Simulations with occupancy behaviour models

The ultimate goal of the methods and models mentioned above is to produce predictions that are realistic for a building even before the building is built when the information regarding the occupants are limited. As a reason for this, the methods and models should be able to work totally independent of the individual buildings. [Andersen et al., 2016].

As a requirement for the methods and models to be used they need validation of its functionality and only a sparse number of the existing ones have been validated. [Andersen et al., 2016; Parys et al., 2011]

A comparison between stochastic generated occupancy behaviour and measured data from five apartments in Copenhagen were conducted by Andersen et al. [2016]. The authors implemented stochastic models for adjustments of heating set-point and window opening actions in to the BPS program IDA ICE. The results showed that the stochastic models may give realistic predictions considering that the simulated data were close and even within the range of the measured data. However, the authors emphasize that the results from the average predictions from the stochastic models did not give a good prediction of the indoor environmental conditions compared to the measured data.

The static profiles that most BPS modellers uses today are unable to create the thermal peaks that stochastic profiles can. Tahmasebi and Mahdavi [2015] investigated the implications regarding the use of different models for occupancy in BPSs. With a full-year observed occupancy from a building in Vienna, the authors compared the data with results from a number of Monte-Carlo simulations with stochastic occupancy profiles and a number of standard-diversity profiles such as those provided by ASHRAE, see the left illustration in figure 2.3.

Similar to other studies, the results indicates that stochastic profiles for occupancy is better to replicate occupant's presence when considering peak values and distribution.

As mentioned earlier, a building with high robustness will more easily handle uncertainties such as the occupants in a building. The robustness of a building towards occupant behaviour is investigated by Hoes et al. [2009] with two models for occupancy presence and interactions. The authors combined the User Simulation of Space Utilization model (USSU), [Tabak et al., 2006; Tabak, 2009], and the sub-hourly occpupancy-based control model (SHOCC), [Bourgeois et al., 2006]. The results from the study showed that there are no specific design concepts that can increase the robustness towards user behaviour without having systems that are vastly oversized.

In terms of energy usage, occupancy behaviour is an important uncertainty that may change a building's energy consumption both negatively and positively.

With various occupancy schedules, Clevenger and Haymaker [2006] studied the uncertainty regarding occupant behaviour in building simulations. The results showed that the predicted energy usage could differ more than 150 % when using all the minimized and maximized values for the related occupant inputs in their study.

2.3 Weather

Because building performance and weather conditions are closely connected, it is necessary to include weather data to choose design and estimate both energy performance and indoor climate conditions. The impact of the present and future climate have been investigated in several studies.
With the climate change the outdoor temperature is increasing constantly, [IPCC, 2014], hence, the energy balance for buildings will change alongside. It is therefore important to identify what impact this will have.
A building's energy performance is conventionally evaluated deterministically with the use of a single set of weather data, based on historical data. Because of this, the choices regarding design is only based on the energy demand and indoor climate estimated with the current weather conditions.
With the thought of building's lifespan should be from 50 to 100 years and that they should perform as intended through out it's life time it is obvious that a single current weather file is insufficient in building performance simulations.

Frank [2005] created a weather file for the time horizon 2050-2100 based on the temperature increase in the period 1961-1990. The BPSs results showed that the yearly heating demand for residential and office buildings in Switzerland will decrease by $33 - 44\,\%$ and $36 - 58\,\%$ respectively, for this future period. For office buildings with an internal heat load of $20 - 30\,\mathrm{W/m^2}$, the yearly cooling demand will increase by up to $1050\,\%$.
Similar results have also been observed by other studies. Some of these are presented in table 2.1.

Author	Location	Heating decrease	Cooling increase
Wan et al. [2011]	China	12 % - 15 %	7 % - 9 %
Wan et al. [2012]	China	14 % - 56 %	11 % - 24 %
Olonscheck et al. [2011]	Germany	44 % - 75 %	28 % - 59 %
Roetzel and Tsangrassoulis [2012]*	Greece	40 % - 100 %	30 % - 160 %
Asimakopoulos et al. [2012]	Greece	50 %	248 %

Table 2.1. Overview of studies concluding that heating and cooling demand will decrease and increase, respectively, with climate changes. *Peak demands.

As it can be observed in table 2.1, there are large variations in the results. These variations can be explained by the diverse choices of weather data, time periods, scenarios and buildings. Even though the results are varying the tendency of them all are the same.

Chan [2011] investigated the consequences of climate changes with six different future weather data sets in terms of air-conditioning consumption. With simulations of a residential apartment and a typical office building the authors observed that the energy consumption for air-conditioning can increase substantially. An increase of up to $24\,\%$ for the apartment and up to $14\,\%$ for the office building were observed.

Considering the weather's impact on total energy use, Shen [2017] simulated four different buildings in four different regions in the United States, in EnergyPlus. The observed results for the residential and office buildings revealed that the predicted annual energy use will change by $-1.64\,\%$ to $14.07\,\%$ and $-3.27\,\%$ to $-0.12\,\%$, respectively. Furthermore, the authors argues that the savings will be larger for office buildings located in cold climate regions than the ones located in hot climate regions.
Similar work were conducted by Yang et al. [2008], where energy simulations were conducted for an

office building in five different climate zones in China. The authors used historical weather data (1971-2000) and compared the results with a typical meteorological year (TMY) weather data file. The authors argues that the profiles for the monthly energy consumption from the TMY results followed the mean from the historical data pretty close with the root-mean-square errors ranging from 3 % to 5.4 %.

Results similar to the ones obtained by the studies above can be expected as the climate gets warmer and the demand for heating will decrease and the demand for cooling will increase. In this matter, the systems for cooling will either have to be oversized to compensate for the future increase in cooling demand or be upgraded along the way. Neither of these options are preferable and therefore the focus should be changed towards the robustness of a building.

In a recent paper, Chinazzo et al. [2015b] investigates the sensitivity of a building towards different weather files in terms of it's energy demand. The simulations revealed a clear connection and dependency between the weather files and the energy demand. The authors clearly points out that it is advisable to include multiple weather files in BPSs to achieve a range of possible outcomes instead of single values only.
Further work concerning this was conducted by the same authors in [Chinazzo et al., 2015a] where the same set of weather files were used in multiple simulations in the BPS program EnergyPlus. The simulations were used as a foundation for a methodology to determine the robustness of a building's performance with a probabilistic approach.

As a consequence of climate changes, possible precautions for the future may be needed. As discussed above, typical office buildings will in the future be in need of more cooling and less heating, but with buildings that are natural ventilated, the main concern is quite different. A study of a natural ventilated office tower in the UK were investigated by Jentsch et al. [2008] to demonstrate the effects. With measured data the authors compared results from simulations with present and future weather data. The study concludes that "free running buildings may be hard to keep comfortable without taking appropriate measures," [Jentsch et al., 2008].

2.4 Recapitulation and gap determination

The design phase of a building is characterized by frequent changes of design, vast variability of design parameters and many uncertainties. With stochastic modelling in BPSs, many of these challenges may be easier to handle by exploring a global design space. However, most of these studies are focusing on the design variability without investigating the influence due to occupants and weather on the design choices.

There is a vast amount of theories concerning modelling of occupants in BPSs but the knowledge is sparse when coupling it with design choices. The literature shows that occupancy may be modelled realistically and there is a tendency that BPS modellers want more occupant modelling features to be included in BPSs. Some tools and scripts have been developed but none have been included in any BPS software as a default feature. This shows that more user friendly implementations of occupancy behaviour in BPS software are needed.

Many studies have investigated different topics concerning weather in BPSs. Some showed a high dependency between energy demand and weather files while others investigated future weather climate to see what influence the climate changes have on cooling, heating and total energy demand. Similar to the studies regarding occupancy, studies investigating the influence of the uncertainty on the design choices are lacking.

This literature review reveals gaps in the field of research. Uncertainties concerning occupancy behaviour and weather conditions have not been investigated in terms of their influence on design choices with a stochastic approach. The number of occupants and their behaviour in the BPSs during the design phase may not be accurate of how it will be when the building is taken in use. Because of this uncertainty, design choices may be taken based on inaccurate or even wrong modelling inputs. Studies regarding the uncertainty of weather and its influence on design choices are limited. Especially future climate changes may have an impact on the design choices taken today. It is typical to only include one single weather file in BPSs, but this file does not necessary lead to the most ideal design or even accurate results.

Problem Description 3

Based on the literature review, the problem that forms the basis of the thesis is presented and described in this chapter. Furthermore, elaborative questions are presented to clarify the aim of the thesis even further and the delimitations of the project are described.

The background for this projects is, as concluded in chapter 2, that there is a lack of studies and knowledge regarding the influence of the uncertainties from the variability of occupants and weather on building design. These uncertainties have been proven to be highly influential on energy, heating and cooling demand in several studies. However, these have not been thoroughly investigated with a stochastic modelling approach and a global design space exploration. As a result, this thesis will be aimed to fill the abovementioned gap.

3.1 Problem definition

To broaden the knowledge within the topic of research, the following problem definition have been formed:

> *How does the uncertainties from the variability associated with occupants and weather influence building robustness and building design when performing stochastic building performance simulations?*

To support the problem definition, elaborative research questions with relation to building performance simulations are listed in the following:

- *How does the variability associated with occupants and weather influence building performance?*
- *In terms of robustness and building performance, what results does inclusion of multiple weather files provide compared to using the Danish Design Reference Year weather file?*
- *How does static occupancy profiles affect building performance and system dimensioning compared to dynamic stochastically generated profiles?*
- *How does inclusion of multiple weather files and dynamic occupancy modelling affect the ranking of the most sensitive inputs?*

3.2 Delimitations

As this thesis only may study the abovementioned problems to a certain extent with a limited level of detail, various delimitations are considered. These are as following:

- The weather files are limited to be for Danish climate only.
- The study is directed towards office buildings and not residential buildings.
- The occupancy behaviour modelling in this thesis is limited to the presence of the occupants, with equipment correlated with the occupancy profiles. Behaviour in terms of interactions with building systems, windows etc., are not included in this study.

4 Methodology

In this chapter, the method to answer the problem definition and the supporting elaborative questions is presented.

The underlying method for this thesis is the Monte Carlo method. The method seeks to obtain numerical results based on repeated random sampling and includes several steps to solve a problem. A typical and simplified approach for the method includes the following and is briefly described afterwards, [Wikipedia, 2017]:

1. Specify a domain of both possible and relevant inputs.
2. Randomly sample these inputs from probability distributions.
3. Execute deterministic computations based on the inputs.
4. Aggregate and analyse the results.

In the context of building projects, the domain is conventionally specified by a design team or a group of stakeholders. Distributions and ranges for the selected inputs are assigned and afterwards sampled with appropriate sampling techniques. The chosen sampling methods are crucial as they are decisive for how well the domain is represented. The methods for post-treatment of the data is dependent on the problem which is to be solved and the intent of the investigation.

Two methods are presented in this thesis. One implements weather files as an factorial experiment and the other implements occupancy modelling as an factorial experiment. Either methods are applied to two different BPS tools.

The occupancy model and weather is treated differently in terms of modelling and implementation in the BPS software. The possibility of implementing dynamic occupancy modelling is limited for the the monthly quasi-steady calculation method. Therefore it is implemented in a sub-hourly dynamic calculation method. Since the quasi-steady calculation method has a shorter simulation time, factorial experiments with large variance is an advantage compared to the other BPS method. This is the reason why the weather is studied by the quasi-steady calculation method.

For implementing weather files and studying their influence on robustness and building design, a building is simulated using Be15. The study of the influence of occupancy modelling on building performance and system dimensioning is implemented with BSim on a critical room.

Description of the BPS tools
Be15 is developed by the Danish Building Research Institute, [Statens Byggeforskningsinstitut, 2016], and is a tool that utilises monthly quasi-steady calculations and is based on the monthly balance of heat gains and losses. Since buildings includes a significant amount of dynamic effects, the method introduces correlation factors to take these into consideration, [DS/EN ISO 13790, 2008]. This enables multiple simulations to be performed quickly. Note that the tool is not developed for design buildings but rather for code compliance with the energy requirements.
Be15 is used since it is a fast normative model and it is interesting to investigate how occupancy modelling and weather affects the results and design choices with a simple calculation software.

BSim is also developed by the Danish Building Research Institute, [Statens Byggeforskningsinstitut, 2013], and is a program which utilize sub-hourly dynamic calculations. The tool can simulate and

calculate energy demand, thermal and atmospheric indoor climate, daylight conditions and installations such as heating, cooling, lighting and ventilation systems. This will be used to investigate the influence from occupants and weather on multiple output parameters from a more advanced model.
Be15 handles input parameters as macro-parameters, which means that the influence from e.g. solar shading is determined by one value. In BSim however there are e.g. more input parameters that affects the solar shading, such as the type of solar shading, properties, settings for the control and time schedules. When implying such in stochastic modelling, more influential parameters from solar shading than e.g. the shading coefficient might be revealed.
Since BSim is utilizing sub-hourly dynamic calculations, output parameters that requires hourly units may be evaluated, e.g. hours with excess temperature or hours with exceeding CO_2 concentrations.

Overview of the methods

Figure 4.1 presents an overview of the implementation of occupancy and weather in the two BPS tools.

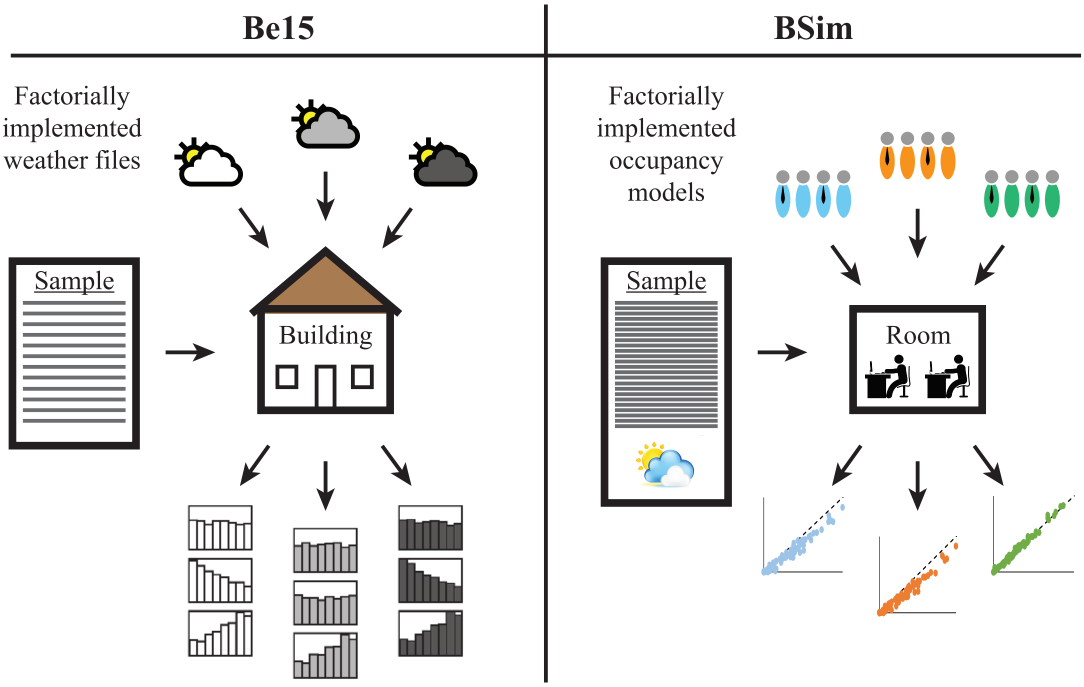


Figure 4.1. Overview of implementation of occupancy and weather in the building performance simulation process.

The difference between the methods consists of what is factorially implemented and therefore which results can be concluded based on the methods. Furthermore weather files are included as uniformly distributed discrete values in the sampling of inputs for BSim. More details about the stochastic modelling and the methods to obtain results are shown later in this chapter.

4.1 Implementation of weather files

The design reference year (DRY) weather file is based on historical data from 1975-1989 and are along with the underlying weather files inserted as a factorial experiment in the simulations. In total 16 weather files are inserted and the influence of these are studied.

4.2 Implementation of dynamic occupancy modelling

4.2.1 Occupancy

Conventional static occupancy profiles are not replicating the diversity in occupant behaviour, hence not replicating realistic profiles of presence. These will therefore be compared to stochastically generated occupancy profiles to determine whether it is necessary to use more complex occupancy models. The stochastic occupancy modelling is based on Reinhart [2001] that refined the model from Newsham et al. [1995].
Before doing this, a preliminary study of the detail level related to the stochastic occupancy models is conducted to investigate if simplified versions can provide similar results.

4.2.1.1 Preliminary study of detail level

Three stochastically generated occupancy models with different levels of detail are investigated in a preliminary study. Illustrations of these occupancy models are presented in figure 4.2. The occupancy profile models are denoted as DOMa, DOMb and DOMc.

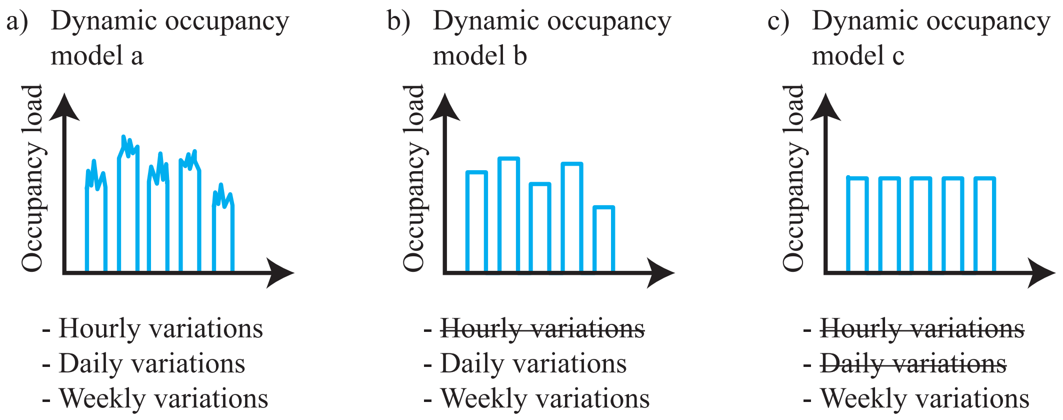


Figure 4.2. Examples of occupancy profiles for the weekdays with three different models.

These models will be investigated in a simulation process, similar to the workflow presented in figure 4.4. Afterwards, the results are aggregated and analysed to choose which model to be further investigated.

Beside the abovementioned variation, the average number of present occupants per year are varied. This is done by varying the mean and standard deviation of occupants present on a yearly and daily basis, respectively.

4.2.1.2 Occupancy profile models

In the primary simulations, two different occupancy models are investigated. The dynamic occupancy model 1 from the preliminary is compared to what is common to use when designing buildings, namely the aforementioned static profile.
After conversations with two engineers from the commercial sector, the following description of a static profile are typically used. A occupancy load of 100 % throughout the day and 50 % reduction in the hour between 12:00 and 13:00 because of lunch break. No other variations are used and the profile is therefore used for each work day during the year.

The method to generate the occupancy profiles stochastically for the dynamic occupancy model a includes coffee and lunch breaks, hence the yearly mean occupant presents drops as a consequence of this (see section 7.3 for details regarding this). It is therefore chosen to also include profiles that are adjusted up to the same level as the static ones. Furthermore, the static profile are adjusted to the same yearly occupancy load as the profiles for dynamic occupancy model a.
To clarify, figure 4.3 shows examples of the four different occupancy profile models that will be investigated. The occupancy profile models are denoted DOM1, DOM2, SOM1 and SOM2.

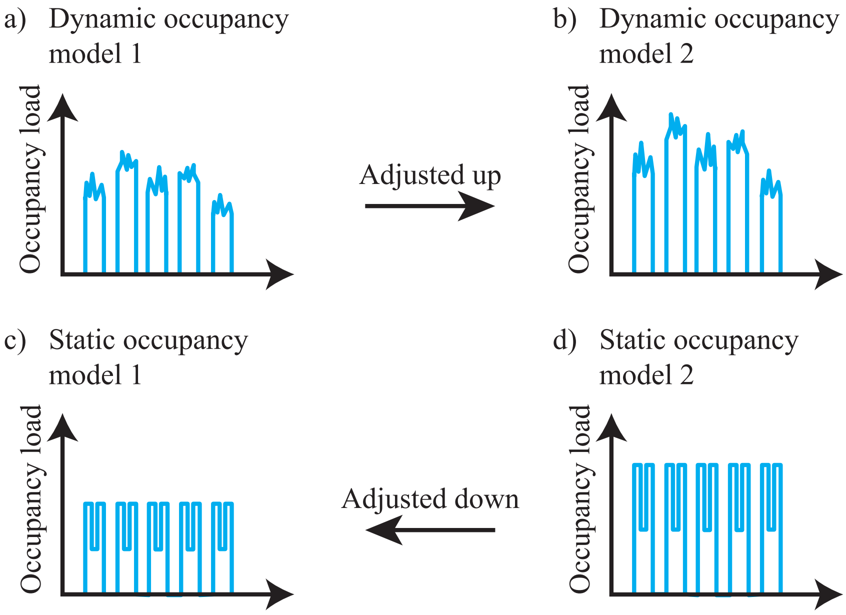


Figure 4.3. Examples of occupancy profiles for the weekdays for the four different occupancy profile models.

Figure 4.3 a) illustrates the dynamic occupancy model a from earlier, renamed to "dynamic occupancy model 1" for these simulations. The version that is adjusted up according to the static ones, is illustrated in figure 4.3 b).
In figure 4.3 d) and c), the static profiles is presented alongside the profile model which is adjusted down to match the one for dynamic occupancy model 1, respectively.

4.3 Performing the stochastic modelling

The overall method for the two simulation approaches, the quasi-steady state approach with Be15 and the dynamic hourly based approach with BSim is presented in figure 4.4 and elaborated further in the following subsections. The methods for the two approaches are combined in the same figure since the method is relatively similar, especially for the pre- and simulation-process. More details are provided for the post-process where the approach to obtain results are explained for each method.

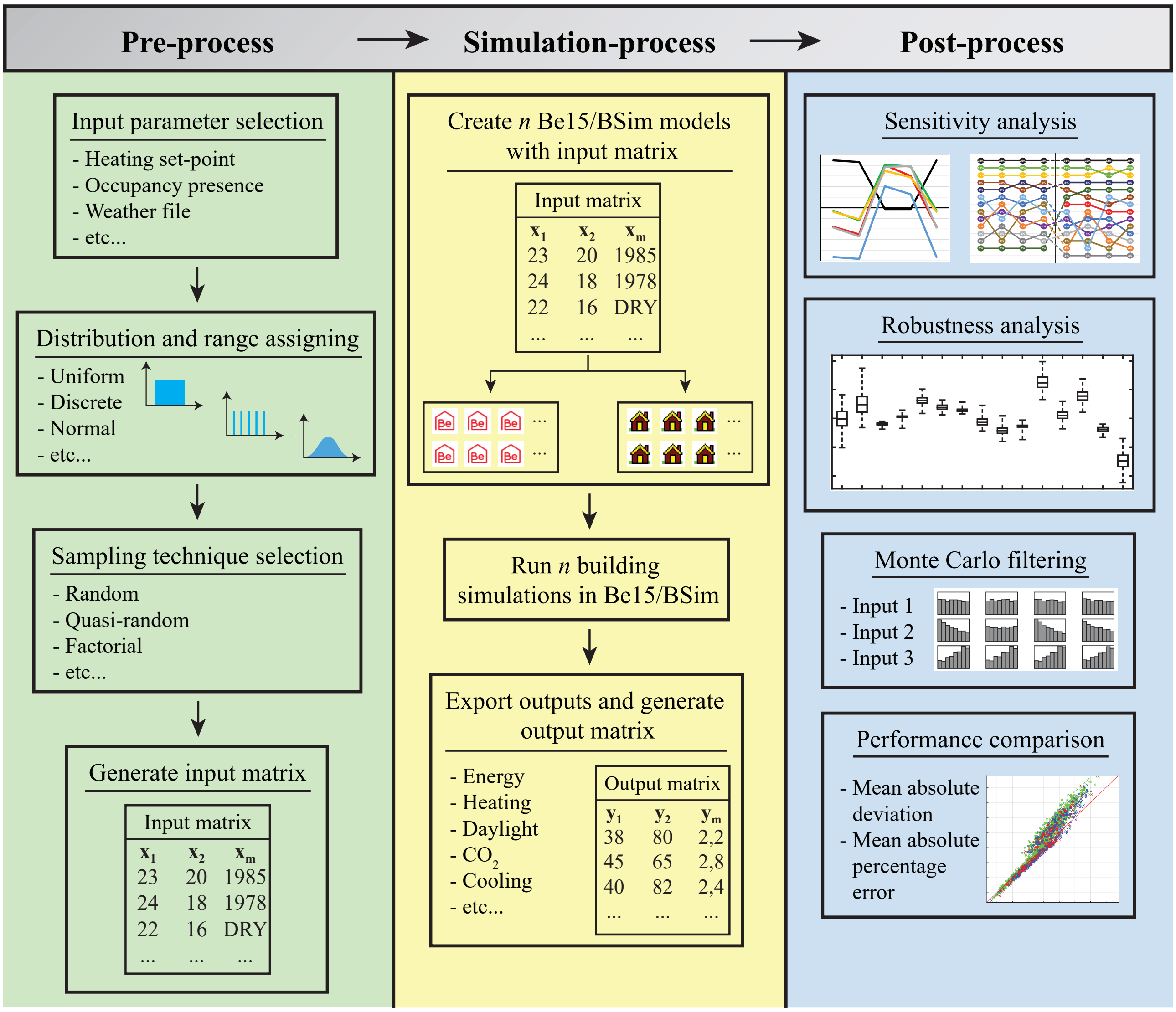


Figure 4.4. Flowchart of the overall method to perform the stochastic simulations. The red logos with the text "Be" in them illustrates Be15 models, while the logo with brown houses illustrates BSim models.

The method presented in figure 4.4 is described in appendix A along with a detailed flowchart of the BSim simulation framework in figure A.1. A brief summary of the method is presented in the following subsections.

4.3.1 Pre-process

For the Monte Carlo simulations, a baseline building model is required to perform the parameter variations on. This model is essential for the simulation results and the conclusion hereof. For both methods a baseline model is designed in such a way that the demand for cooling and heating is frequently shifting.

There is a significant amount of input parameters which may be included to explore the global design space. Inclusion, hence exploration of all input parameters is an immense and highly time-consuming process and is therefore reduced. A subjective sensitivity analysis is therefore conducted to choose a selection of parameters, [Hamby, 1994].

The selected input parameters are varied with appropriate distributions and ranges. The distribution types used in this thesis are variations of uniform and discrete.
The ranges and distributions for the selected input parameters for the two BPS calculation methods are specified in chapter 6 and 7.

To generate the values for the inputs with their respective distributions, appropriate sampling techniques are required to give a good representation of the domains. Figure 4.5 shows an example of sampling 100 points with two different sampling techniques, random and low-discrepancy.

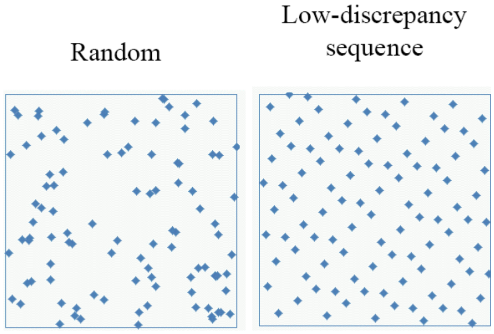


Figure 4.5. Comparison of random and low-discrepancy sampling technique of 100 points, ed., [Wikipedia, 2016].

For a random sampling technique, the sampling is without any consideration of covering the domain uniformly. The low-discrepancy sampling technique, also known as quasi-random sampling, divides the domain into squared subregions. Sampling in these results in more uniform coverage of the domain with the low-discrepancy sampling technique and the outcome is that lumps and holes are minimized. In this thesis, the samples of the input parameters are generated with SimLab 2.2.1, using the low-discrepancy sampling technique, Sobol sequence. By using this method, additional points or values for a sample may be generated by simply adding new unique values together with the existing ones. [Ratto et al., 2008].

4.3.2 Simulation-process

The input matrix created in the pre-process is used to create the Be15 and BSim models. In the BSim model creation process, the occupancy profiles are generated with inputs from the input matrix. If interested, an overview of the framework in the simulation process is presented in figure A.1 on page 85 in appendix A.

The simulation-process is time consuming and nearly impossible to carry out manually, which is why an automation-process is utilised. AutoIt is used to perform recorded or programmed actions through a script, [AutoIt Consulting Ltd, 2015]. This permits the creating of models and simulations to be performed automatically and gather results faster.

Afterwards the models are simulated in Be15/BSim and the results are aggregated into two output matrices for post-processing.

4.3.3 Post-process

The approach to obtain potential results are described for the two methods.

Influence of weather files

The simulation results are presented in box-plots and parallel coordinate plots. Box-plots are used to present and reveal the variance of results from several simulation sets while parallel coordinate plots (PCP) visualises correlations between between inputs and outputs.
Monte Carlo filtering is conducted on various output parameters to identify potential differences in terms of design recommendations between the simulations sets with different weather files or occupancy profile models.

To identify the influence of the inputs on the outputs and determine sensitive and insensitive parameters, two sensitivity analysis methods are conducted. These are the Pearson's r correlation and the TOM regionalized sensitivity analysis method. Studying the variation of the ranking will yield if multiple weather files should be used to identify all the highest ranked parameters for changing weather. Parameters ranked lower than the dummy are negligible for the output, since the dummy represents an input with no influence on the output, [Østergård et al., 2017b].

To analyse how the weather affects the output parameters for a solution, e.g. how robust a solution is towards weather, a robustness index (RI) is used. The RI is from Chinazzo et al. [2015a] and is in this thesis, implemented as a quantitative measure of the robustness and is used in the PCP as an output when designing buildings. This make it possible to compare the robustness of solutions and to include the robustness as a design evaluation when designing buildings in the early design phase. The RI is given as a number between 0 and 1, where values close to zero indicates low robustness and values close to 1 indicates high robustness. The RI for a given design solution is relative compared to another design solution. As a consequence hereof the robustness of a building design itself can be acceptable even though it has a low RI value. It is related to the robustness of the base case, which can be chosen as the building design with highest variation (lowest robustness) to ensure values between 0 and 1.
The RI is calculated based on the standard deviation and the interquartile range of a data set, thus the RI is measuring the absolute difference between the set, and not the relative. Thus the RI would yield the same value for the two given fictional data sets: {1 5 10} and {101 105 110}.
Description of the calculation of RI is shown in appendix A.4.3.

Due to the factorial experiment of implementing weather files in Be15, differences in results are only due to the impact of the weather files. With this approach, the RI can be used to evaluate the robustness towards weather. The RI can be implemented in the PCP to help decision makers evaluate building design in the early design phase.

To study the influence of the weather files on the building design, the RI is used as an output in the PCP. First meta models are used to generate additional simulation results, then Monte Carlo filtering is performed. By filtering the 10 % best performing solutions and showing the remaining inputs in histograms, differences in design tendencies when evaluating the RI, TED, and these combined can be revealed. The variation between the histograms for each input yield differences in design tendencies when including the RI instead of only the TED for the building performance evaluation.

Influence of occupancy models

Similarly to the implementation of weather in Be15, the different occupancy models are included as a factorial experiment in BSim. This enables comparison of results when only changing the occupancy model, thus how it influences the results for each building design. In this method, the weather files are sampled as uniform discrete values. This means that the different weather files are not used on the exact same building design. Hence, differences in results may be caused by other inputs. The implemented weather files are DRY, 3 historic weather files and 9 future weather files.

Scatter plots are used to plot an output for one occupancy model against another, to reveal how the output parameters are affected by the differences in occupancy models. Furthermore filtering by weather files in the scatter plots are conducted to determine the weather files influence on the uncertainty of the given output. To give a quantitative evaluation of the difference, the mean absolute deviation (MAD) and mean absolute percentage error (MAPE) are calculated for each output.
The abovementioned is both done for the building performance and the system dimensioning. The evaluated parameters are shown in table 4.1. For the dimensional values for the systems, values for acceptable deviations of 1, 3 and 5 % of the work hours are included.

Evaluated in Be15	Evaluated in BSim	
Building performance	Building performance	System dimensioning
TED & RI	TED	–
Cooling demand	Cooling demand	Cooling power
Heating demand	Heating demand	Heating power
Electricity demand	Fan energy demand	Fan power
–	Excessive temperatures	T_{op} mean & CO_2-level

Table 4.1. Evaluated parameters for each method. For the system dimensioning, all parameters are investigated by acceptable deviations of 1, 3 and 5 % of the work hours.

Sensitivity analysis is conducted to determine the influence of the variability of weather and mean internal heat load together with the daily variation on the uncertainty of both building performance and system dimensioning.

Case Description 5

In this chapter the case of the thesis is presented and described. The case building for the study is briefly described and a summary of the design conditions and criteria are presented.

5.1 Building description

For this thesis a fictional, mechanical ventilated office building has been modelled. The building is a two storey rectangular building with the dimensions 23 x 14 x 6.4 meters and a net internal floor area of 554 m^2 (613 m^2 gross floor area). Even though the exact location of the building is not chosen the setting of the building is chosen to be a scenery with scattered vegetation and windbreaks in Denmark.

To ease the process of collecting dimensions and areas for the simulation programs, a 3D building have been created in Autocad Revit. The 3D model is presented in figure 5.1 and 5.2.

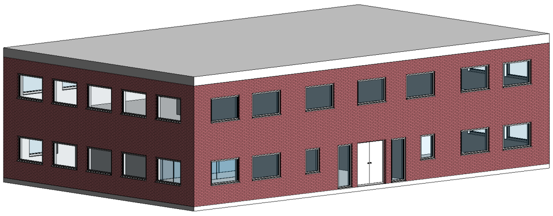


Figure 5.1. 3D model of the building presented from north-east.

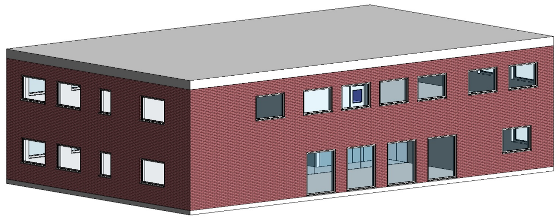


Figure 5.2. 3D model of the building presented from south-west.

The building is constructed as a "typical" office building, with reception, open office landscapes, cell offices, conference rooms etc.
The building is divided in to 15 rooms, with nine different room types. Plan view of the ground- and 1. floor are presented in figure 5.3 and 5.4, respectively.

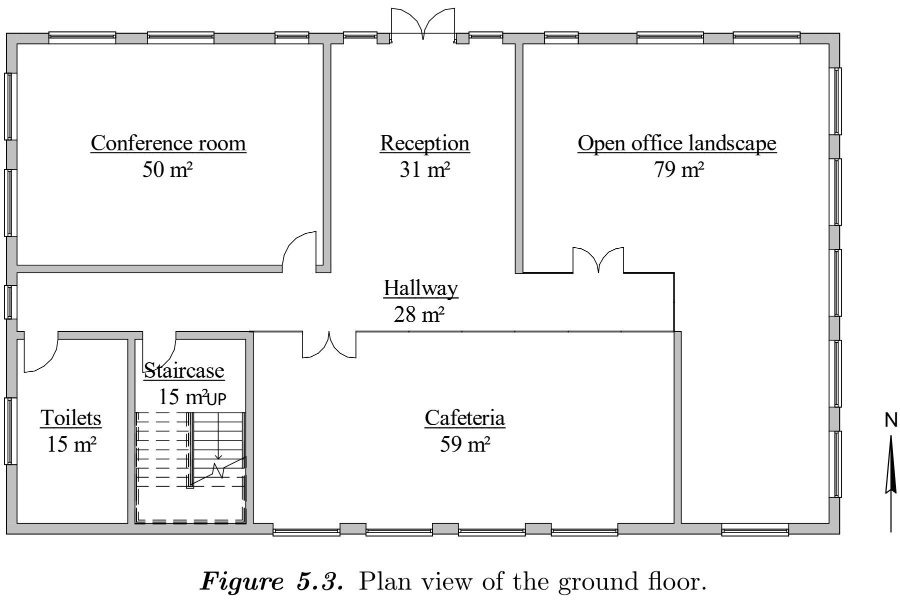


Figure 5.3. Plan view of the ground floor.

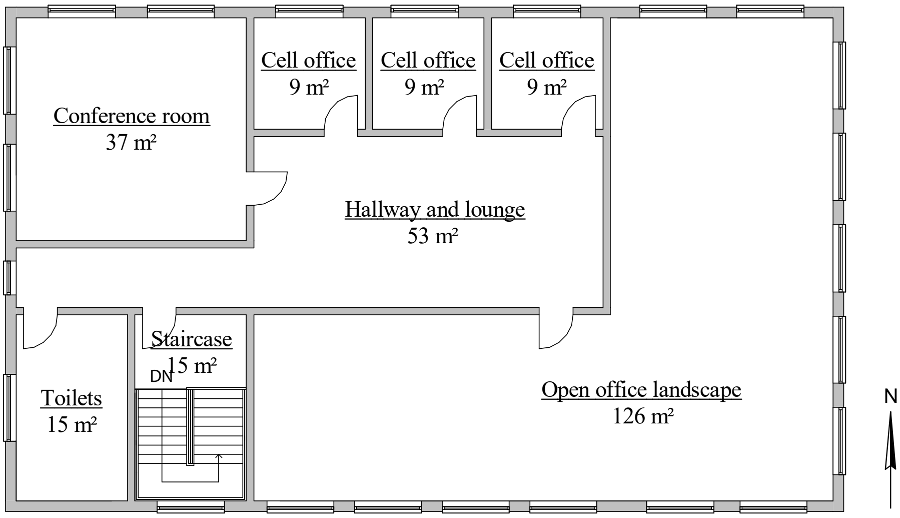


Figure 5.4. Plan view of the 1. floor.

Influence of Multiple Weather Files in Be15 6

The aim of this chapter is to evaluate the use of the DRY weather file and to state if changes in the current simulation approach is required. With a monthly quasi-steady state calculation approach, stochastic simulations are carried out with multiple weather files and results are presented and discussed.

In Denmark, it is a legal requirement that the energy demand of all new buildings shall fulfil the energy requirements for the Danish Building Regulations 2015 and this are to be done with the normative model Be15.

Be15 is based on DS/EN ISO 13790 [2008] and exploits macro-parameters, predefined settings and interpolation based on dynamic models. The macro-parameters and predefined settings allows the user to perform simulations without necessarily having taken any decisions upon the design yet.

In this chapter, multiple weather files are included by factorial experiments in stochastic simulations. The results are analysed with focus on comparing the variation in total energy demand (TED) for each weather file and the different design solutions. Furthermore, sensitivity analyses are performed to identify the influence of different weather parameters and to identify the most sensitive input parameters. At last, the robustness of the design solutions and the influence on building design due to simulation with these weather files are investigated.

6.1 Parameter selection

In table 6.1, the input parameters for the stochastic simulations, their representative ranges and distributions are presented. These parameters are chosen based on a subjective sensitivity analysis where parameters that normally are not important have been excluded.

	Parameter	Range	Unit	Distribution
Design	g-value, glass*	0.3 - 0.7	[–]	Continuous uniform
	Heat capacity*	60 - 140	[Wh/K m^2]	Continuous uniform
	Lighting (general installation)*	4 - 10	[W/m^2]	Continuous uniform
	Mechanical ventilation*	0.9 - 3.6	[l/s m^2]	Continuous uniform
	Overhang depth*	0 - 45	[°]	Continuous uniform
	Specific fan power* (SFP)	1.5 - 2.1	[kJ/m^3]	Continuous uniform
	Solar shading*	0.2 - 1.0	[–]	Continuous uniform
	U-value, external wall*	0.10 - 0.15	[W/m^2 K]	Continuous uniform
	U-value, windows*	1.0 - 1.6	[W/m^2 K]	Continuous uniform
	Window-to-facade ratio*	25 - 75	[%]	Continuous uniform
Uncertain	Equipment	8.2 - 12.2	[W/m^2]	Continuous uniform
	Heating set-point	21 - 24	[°C]	Continuous uniform
	Infiltration, working hours	0.07 - 0.13	[l/s m^2]	Continuous uniform
	Occupant load	8 - 12	[W/m^2]	Continuous uniform
	Weather file	DRY; 1975 - 1989	[–]	Discrete factorial

Table 6.1. Input parameters for the stochastic modelling in Be15 with their ranges and distributions. *Ranges are collected from Østergård et al. [2015].

The ranges for the inputs marked with a "*" in table 6.1 are collected from Østergård et al. [2015].

The mechanical ventilation is different for each of the rooms in the building. The ventilation rates for these are specified in table C.2 in appendix C. The values for mechanical ventilation in table 6.1 are therefore according to the floor area.

In terms of equipment, the range has been selected based on the assumption that each person in the offices has equipment of 150 W, corresponding to a desktop PC. In the conference rooms, equipment of 50 W per person is used, corresponding to a laptop, and it is assumed that there are no used equipment in the hallway, lounge, toilets, staircase or cafeteria.

The heating set-point range is set to 21−24 °C as a conjecture based on DS/EN 15251 [2007, Table A.3, page 33].

The range for the infiltration correspond to the requirements for renovation class 1 (BR10) and up to the requirement for Energy frame Buildings 2020, [Energistyrelsen, 2017, section 7.2.1, 7.2.4]. The infiltration requirements from [Energistyrelsen, 2017] are at 50 Pa pressure test which are recalculated with the expression from Aggerholm and Grau [2009, page 63]. With the infiltration during the working hours sampled, the infiltration outside of working hours are simply determined by subtracting 0.04 l/s m^2 from the infiltration during the working hours according to Aggerholm and Grau [2009, page 63].

The range for the occupant load is correlated what has been used in BSim, which is estimated based on the occupant density from [DS/EN 15251, 2007, Table B.2, page 34]. It has been assumed that each person releases 100 W each.

6.2 Comparing weather files

In this section, 16 selected weather files for the simulations and their characteristics are described and compared. This gives an overview of the weather files which later helps interpreting the results from the simulations. Afterwards, the TED from the simulations are compared. First as a group for each weather file and afterwards determining the difference of using the DRY weather file or the historic ones for each design solution. This is done to study if a design solution performs differently with other weather files than DRY.

6.2.1 Weather file characteristics

To study how the DRY weather file perform compared to multiple historic weather files, 16 weather file are included. DRY is a compiled weather data set including climate data for one year with hourly data for various weather parameters, [Statens Byggeforskningsinstitut, 2017]. The weather file is a generated data set, based on thoroughly selected historic data from the time period between 1975 and 1989. Both the DRY weather file and the historic ones are included in this investigation.
Furthermore, it is interesting to compare the results from the DRY weather file and the weather files it is based on to validate if it represents its sources sufficiently.
For details regarding the weather file, see Statens Byggeforskningsinstitut [2017] and Jensen and Lund [1995].

To understand the behaviour of the models and what causes the variation in the results, the characteristics of the weather files are presented in table 6.2.

Weather file	Outdoor temperature			Solar conditions		
	Mean [°C]	OHS [°C]	HS [°C]	Global [W/m^2]	Direct [W/m^2]	Sunshine hours [h >120 W/m^2]
DRY	7.8	14.3	3.1	214	291	2018
1989	9.1	14.4	5.3	213	241	2100
1975	8.9	15.3	4.3	239	287	2288
1983	8.6	15.0	4.0	225	256	2022
1982	8.5	15.2	3.6	237	298	2150
1988	8.3	14.5	3.7	212	246	1978
1984	8.0	13.8	3.8	206	224	1821
1977	8.0	13.9	3.7	221	250	1919
1981	7.6	14.8	2.5	218	224	2033
1976	7.6	14.6	2.6	245	284	2221
1978	7.5	13.8	3.0	232	256	1974
1980	7.3	14.2	2.4	214	220	1862
1979	6.9	13.9	1.9	220	227	1920
1986	6.9	13.4	2.1	214	255	1981
1987	6.6	13.2	1.8	207	248	1932
1985	6.4	13.7	1.1	206	242	1713
Mean, historic	7.8	14.3	3.1	221	251	1994

Table 6.2. Annual mean outdoor air temperature, global and direct solar radiation for the 16 weather files. Outside of heating season (OHS) is defined as the time period from May up to and including September, while the heating season (HS) is from October up to and including April. Solar radiations are mean values of the hours within a year given a radiation above 0 W/m^2. The table is sorted after the annual mean outdoor temperature in descending order. If interested, see appendix D for monthly averaged outdoor temperatures for each weather file.

The coldest and warmest years in terms of annual mean outdoor temperature, 1985 and 1989, is 2.4 °C colder and 1.3 °C warmer than the mean of the historic. It is clear that the difference is mainly due to the difference in outdoor temperature during the heating season and the amount of sunshine hours.

The weather files 1975, 1976 and 1982 have higher direct and global radiation, and a higher amount of sunshine hours. The sunshine hours for the weather files varies between 1713 to 2288 hours, which equals $20 - 26$ % of the year.

In figure 6.1, the data of the mean outdoor temperature is presented for each month during the year along with the hourly minimum and maximum for each month.

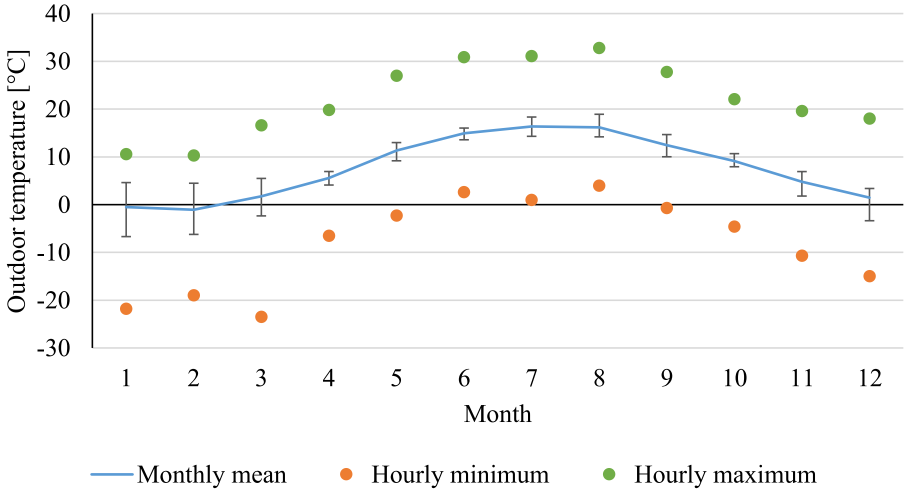


Figure 6.1. Annual outdoor air temperature variation of the 16 weather files. The whiskers represents the minimum and maximum monthly mean outdoor temperature.

Alongside with table 6.2, figure 6.1 indicates that the largest outdoor temperature variations are occurring during the months outside the heating season.

6.2.2 Variation in total energy demand

The TED is presented for each simulation set of different weather files and analysed based on the characteristics of the weather files.

Box and whisker plots for the TED for each weather file is presented in figure 6.2. The boxes represents the 25 % and 75 % quartile with the line in the middle representing the median. The whiskers show the minimum and maximum observed value within each group. Box-plots of the heating demand is presented in appendix F along with box-plots for cooling and electricity.

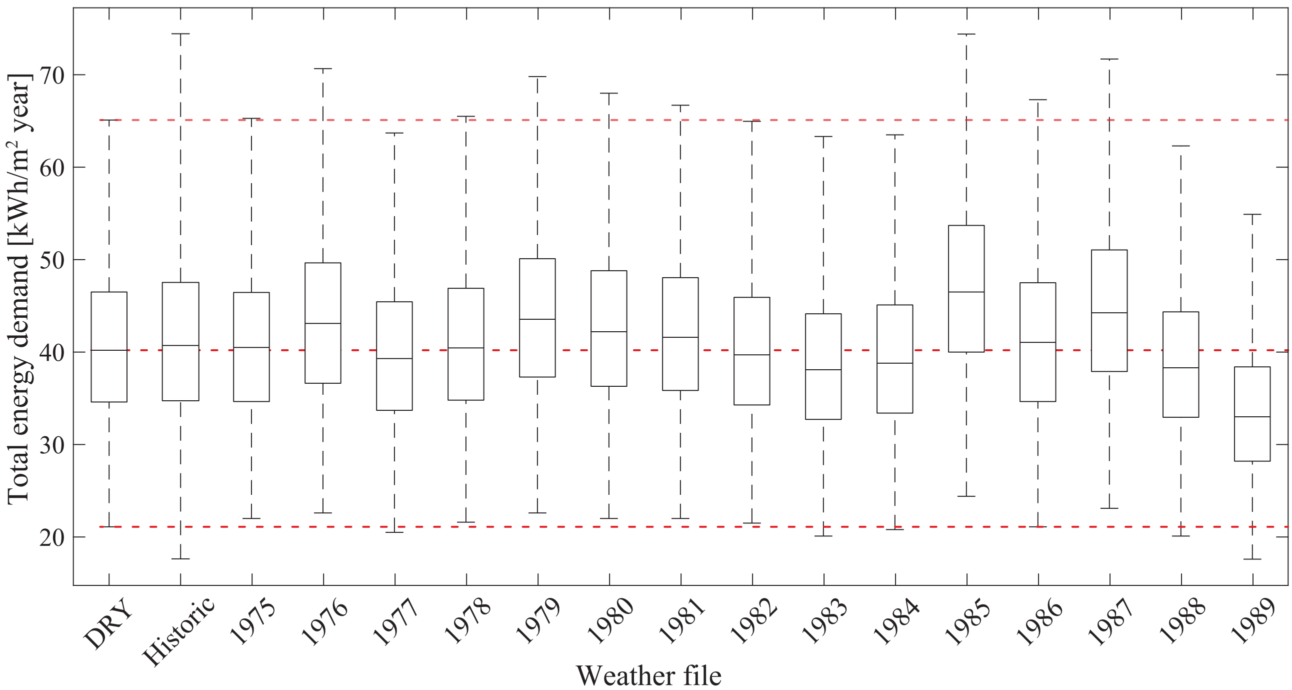


Figure 6.2. Box-plots showing the TED from the stochastic modelling with Be15 for 512 simulations for each weather file. The red dashed lines indicates DRY's minimum, maximum and median.

From the figure it is shown that the TED calculated from Be15 varies when changing weather files. Some weather files induces significant higher or lower energy demand, both for the medians and the minimum and maximum values.

The TED is somewhat constant considering the size of the interquartile range and the length of the whiskers, though with varying medians.
Comparing the box-plots with the mean temperatures during the heating season of the weather files from table 6.2, a correlation is noticeable. The year with the warmest temperatures during the heating season has the lowest TED (1989), and the year with the coldest temperatures during the heating seasons has the highest TED (1985). This applies for all the design solutions simulated with these weather files. This also complies with the fact that most of the variation in the TED between the weather files is due to the heating demand for the models, as presented in table 6.3. The mean of the difference from TED for the given weather file and DRY is shown as the dif. TED.

Weather file	TED	Heating	Cooling	EL	Dif. TED
DRY	41.1	28.1	0.5	12.8	0.0
1975	41.0	26.1	1.9	14.1	-0.1
1976	43.6	28.9	1.8	14.0	2.5
1977	40.1	27.2	0.4	12.7	-1.0
1978	41.4	28.4	0.5	12.7	0.2
1979	44.3	31.5	0.3	12.7	3.1
1980	43.0	30.2	0.3	12.7	1.9
1981	42.5	29.5	0.4	12.8	1.4
1982	40.6	26.9	1.8	13.0	-0.6
1983	39.0	25.4	1.9	12.8	-2.1
1984	39.7	26.9	0.3	12.7	-1.4
1985	**47.4**	**34.7**	**0.2**	**12.6**	**6.3**
1986	41.7	28.9	0.3	12.6	0.6
1987	45.0	32.4	0.2	12.6	3.9
1988	39.2	26.3	0.5	12.7	-1.9
1989	**33.7**	**20.7**	**0.6**	**12.8**	**-7.4**
Mean, historic	41.5	28.3	0.8	12.9	0.4

Table 6.3. Results from the simulations. Dif. TED is the mean of the difference in TED from each simulation. The weather files resulting with highest and lowest TED are marked with red and green, respectively. The results are without primary energy factors and are given in kWh/m^2 year.

When comparing the results from DRY, 1975 and 1978 in the box-plots for the TED as shown in figure 6.2, the results do not seem significant different from each other. In fact when performing an analysis of variance (ANOVA) test, they are with a significance level of 5 % statistically from the same mean value. This implies that DRY is covering the other two weather files as a group, but when studying the individual design solutions this is not the case as presented in the following section.
The results from the ANOVA test also shows that the amount of simulations within the requirement for DRY is 8.2 % where the mean for the historic weather files is 8.7 %. The DRY weather file is therefore a well representation of the mean compared to using weather files from the 15 historical years, even though it does not include the variation and extrema for these years. The foundation for

this is that buildings are not being designed after all extrema, which applies to energy performance, system dimensioning and indoor climate.
A table containing the results from the ANOVA test is presented in table F.4 in appendix F along with percentage of design solutions that meets the BR15 requirement.

A sensitivity analysis is performed on the parameters listed in table 6.2, with addition to the standard deviation of the temperature. The sensitivity analysis is conducted for the mean value of each output for the simulations with each weather file. Pearson's r correlation is evaluated and the results are presented in figure 6.3. "Dif. TED" refers to the mean of the difference in TED between a weather file and DRY for each simulations.

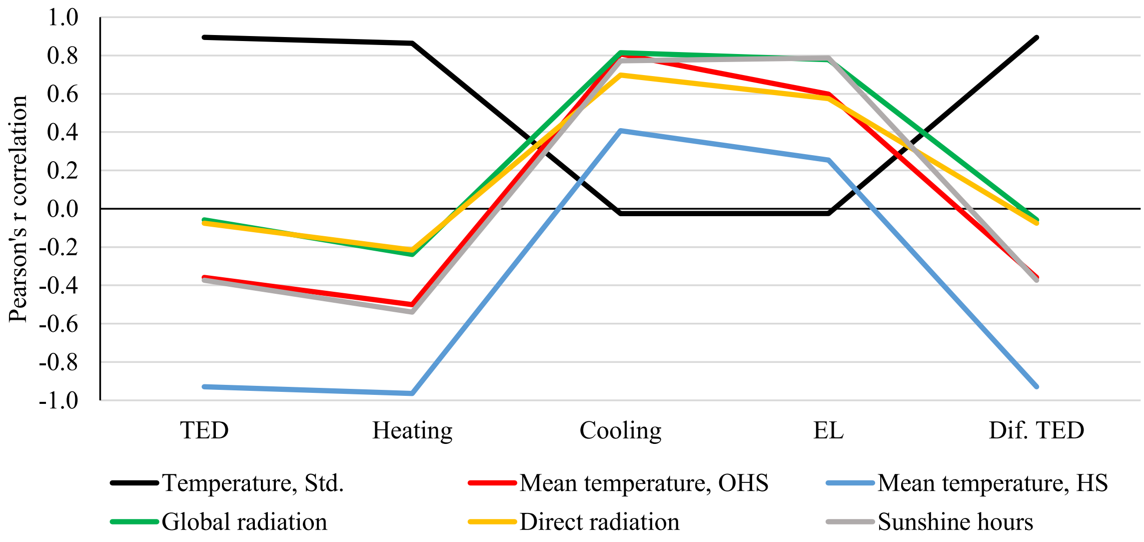


Figure 6.3. Sensitivity analysis of weather data's influence on the output parameters.

From the figure it is noticeable that the mean temperature during the HS and the standard deviation of the temperature has largest impact on the TED, heating and difference in the TED, Dif. TED. Dif. TED is an indicator of robustness, since it represents the mean of the change from each simulation due to the weather files.
The direct and global radiation as well as the sunshine hours reveals similar tendencies along with the mean temperature OHS. Solar conditions have highest impact on the cooling and electricity consumption, as a effect of increased ventilation and cooling demand outside the heating season.
The mean OHS temperature has little or no effect on the difference among the TED. This is also expected since the variation is small compared to the variation of the heating season temperatures and because the variation in TED is mostly due to the variation in the heating consumption.

6.3 Robustness analysis

To investigate how the performance of the design solutions of the case building varies for each weather data, a robustness analysis is performed. A RI and its use in the early design phase is introduced and sensitivity analyses are conducted to identify the most sensitive parameters. To evaluate the effect of running simulations with multiple weather files, the design tendencies are investigated for the given weather files with Monte Carlo filtering.

6.3.1 Robustness of design solutions

According to the ANOVA test, it is showed that the DRY weather file is a good representation of seven of the underlying weather files. However this does not state how well the individual design solutions perform when changing weather files, nor how robust the solutions are to weather changes. This is analysed with the RI, calculated for the TED for each design solution of the model. Before presenting the results for the RI, the necessity of it is emphasized.
The box-plots in figure 6.4 presents the actual difference in TED of the design solutions of the historic weather files compared to the same solutions simulated with the DRY weather file.

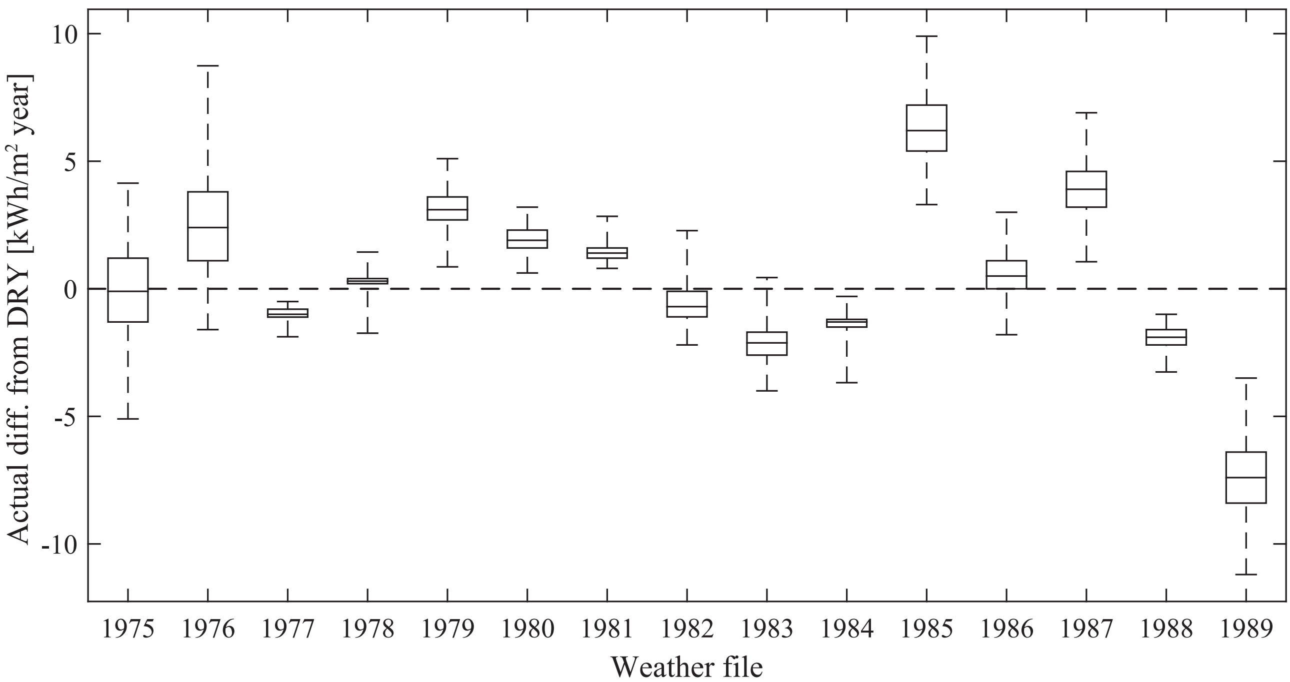


Figure 6.4. Box-plots presenting the actual difference in TED from DRY for each design solution.

From the previous results it is shown that DRY, 1975 and 1978 produces similar results for all the simulations as groups. However this does not show how the individual design solution is affected by the changing weather file. The variation of the actual difference between the results from DRY and 1975 for the individual design solutions is significant. The box-plot for the actual difference from DRY for the 1975 weather file in figure 6.4 indicates that almost half of the design solutions have higher energy demand, and the other half have lower. This supports the fact that only comparing the TED, as presented in figure 6.2, is not sufficient to conclude how the models behave as a group when changing weather files.

The weather file of 1978 yields almost the same results as the DRY file, indicating that 1978 and DRY is similar. Similar to figure 6.2, the 1985 and 1989 weather files provides the most different results compared to DRY.

A performance gap for a building might result in unsatisfied building owners, which is why low variation in the results is preferable alongside with low energy consumption. The RI can help the building designers to obtain these properties. As presented above, the very same design solution may produce different results when changing weather file. The effect of using different weather files for the design tendencies are presented in the following section.

6.3.2 Robustness of design tendencies

Design tendencies is referred to as noticeable tendencies for histograms of the input parameters when applying Monte Carlo filtering on an output, e.g if an output has more solutions in a specific range. Furthermore, the ranking of sensitive input parameters plays an important role considering a building's robustness.

In this subsection, results for the DRY, 1975, 1985 and 1989 weather file are presented. Most of the weather files show same tendencies when applying a filter to them, hence not all are presented.
The reason for presenting the abovementioned weather files are:

- DRY: To compare results with the historic weather files and evaluate whether or not to design with multiple weather files.
- 1975: Relatively high solar condition measures and is the second warmest weather file in terms of mean annual outdoor temperature.
- 1985: Highest mean annual outdoor temperature and TED.
- 1989: Lowest mean annual outdoor temperature and TED.

Simulation results for all weather files are presented in section F.3 and F.4 in appendix.

6.3.2.1 Sensitivity analysis

Two sensitivity analysis methods are conducted, the Pearson's r correlation and the TOM regionalized sensitivity analysis.

The ranking of the input parameters based on their influence on the TED along with their sensitivity measure (percentage inside of the dots) are presented in figure 6.5 for the two sensitivity analysis methods.

It should be noted that the conversion of the weather files is imprecise regarding the solar shading. All weather files have been converted with this process, hence the error is the same for every weather file. Furthermore the daylight factor inserted in the simulations is 3 % for all rooms and not variated as a function of the window-facade ratio. This will have an impact on sensitivity for the g-value, solar shading, window-to-facade ratio and lighting.

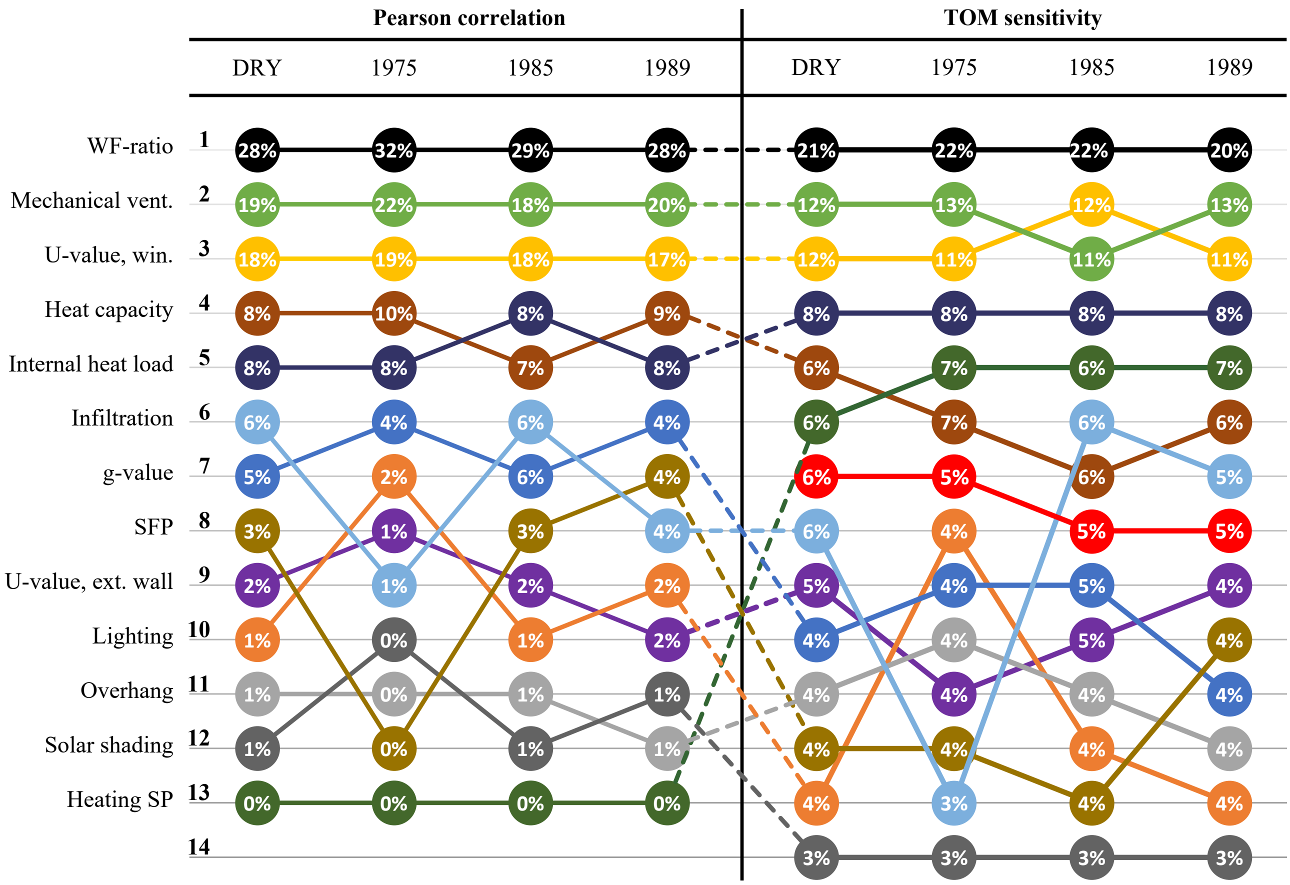


Figure 6.5. Rank and sensitivity measure (percentage inside of the dots) of the input parameters for the two sensitivity analysis methods in terms of TED. The inputs on the left are sorted after their rank from the Pearson correlation based on the simulations with the DRY weather file. The dashed lines couples the parameters rank in each of the sensitivity analysis methods. The red dots in the right hand side is the dummy parameter for the TOM correlation method.

As mentioned in chapter 4, input parameters with lower rank than the dummy parameter in the TOM sensitivity analysis method are considered to be non-influential.
From figure 6.5 it may be observed that each sensitivity analysis method yields almost the same ranking for the three highest ranked input parameters.

Differences may be observed in terms of the rank and the sensitivity measure of the heating set-point. This parameter's rank and sensitivity measure is significantly different in the two sensitivity analysis methods. The difference is probably caused by the fact that TOM can handle non-linear correlations, while Pearson does only handle linear effects.

Comparing the sensitivity of the inputs of the different weather files within each sensitivity method, no significant changes are observed. The ranking of the parameters are changing between the weather files, but the sensitivity measure are almost constant for each parameter for the four weather files. The only input parameters that deviates from the rest is the infiltration and the SFP. Their sensitivity measure is mainly lower for 1975 than for the rest. This applies for both sensitivity analysis methods and is due to the weather file's characteristics, see table 6.2.
The 1975 weather file is the second warmest weather file in terms of mean annual outdoor temperature, with high mean temperatures outside and during the heating season. Furthermore, the solar conditions in the weather file are in the high end of all 16 weather files.

A sensitivity analysis is also performed on the TED together with the RI as outputs to identify which parameters that has the overall highest influence on these two inputs combined. The TOM regionalized sensitivity analysis method is used as it can handle multiple output parameters and the results are presented in figure 6.6.

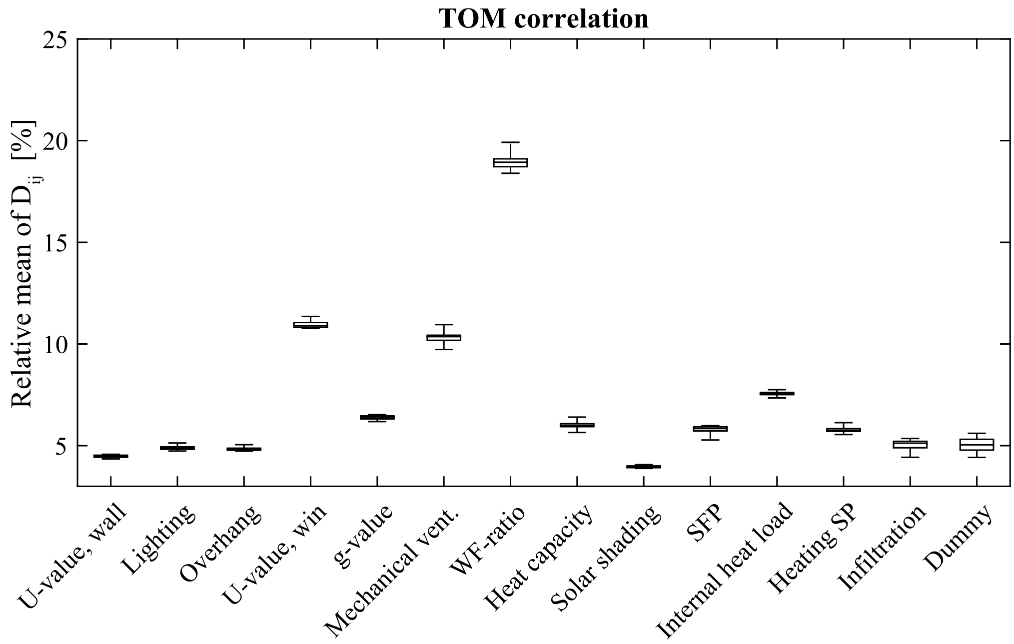


Figure 6.6. Results from the sensitivity analysis using TOM when the TED and the RI are evaluated parameters.

The results shows similar tendencies as for those presented above. Window-to-facade ratio is the most sensitive and the U-value of the windows ranks now slightly higher than the mechanical ventilation. This is because the U-value of the windows has even more influence on the robustness of the building than the TED. The g-value of the window is the 5th most sensitive parameter, more sensitive than the dummy. This result is significant different from what is shown earlier, where it was ranked 10, below the dummy. Other than that the changes in sensitivity are insignificant, which indicates a correlation between the TED and RI.

6.3.2.2 Monte Carlo filtering

Monte Carlo filtering are applied for both the TED and the RI. Since the input parameters are uniformly distributed, potential changes in the histograms are recognisable. Inputs that are affected by the filtering will deviate from the uniform distribution to different extent and shape, for example skewed to either sides of the initial sampling range. The design tendencies shows which spans of the input parameters that are recommended in order to reduce the TED or to increase the robustness. All results from the Monte Carlo filtering are based on the results from the neural network, which is used to generate 10 000 simulations for each weather file.

Filtering for total energy demand

To investigate if there are differences in the design tendencies when using different weather files, histograms of the 10 % best performing solution in terms of TED are presented, compared and discussed. The histograms of the input parameters for the four weather files are presented in figure 6.7. The spans and tendencies of the presented histograms are correlated with what was presented in

figure 6.5 for the sensitivity of the input parameters.
An advantage of utilizing Monte Carlo filtering is to identify what range of the input parameters are recommended to achieve a low TED. The most varying histograms compared to the uniform distributions are strongly correlated with the most sensitive parameters as described earlier. Knowing which parameters are most sensitive and their recommended spans are useful in design situations but is not further described in this section since the aim is for the robustness of the design tendencies when changing weather files.

	Parameter	Range	Unit	Weather file DRY	1975	1985	1989
Design	g-value, glass	0.3 - 0.7	[–]				
	Heat capacity	60 - 140	[Wh/K m^2]				
	Lighting (general installation)	4 - 10	[W/m^2]				
	Mechanical ventilation	0.9 - 3.6	[l/s m^2]				
	Overhang depth	0 - 45	[^{o}]				
	Specific fan power (SFP)	1.5 - 2.1	[kJ/m^3]				
	Solar shading	0.2 - 1.0	[–]				
	U-value, external wall	0.10 - 0.15	[W/m^2 K]				
	U-value, windows	1.0 - 1.6	[W/m^2 K]				
	Window-to-facade ratio	25 - 75	[%]				
Uncertain	Heating set-point	21 - 24	[^{o}C]				
	Infiltration	0.07 - 0.13	[l/s m^2]				
	Internal heat load	16 - 24	[W/m^2]				

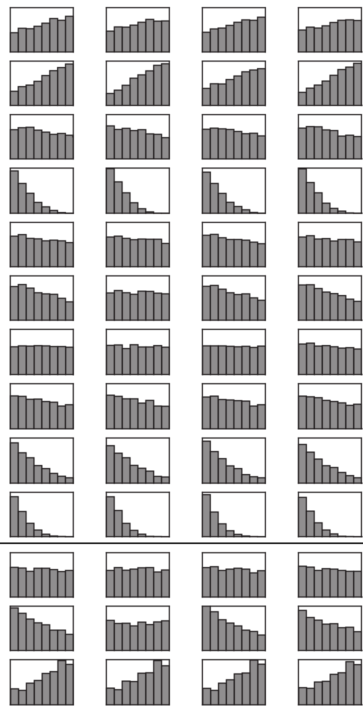


Figure 6.7. Histograms of the top 10 % best performing solutions in terms of TED alongside with the initial range of the input parameters.

From the histograms in figure 6.7, very few differences may be observed. In general, only four parameters show different tendencies when using different weather files.

In terms of the g-value for the glass, a small tendency of lower g-value for the weather file 1975 and 1989 may be observed. In terms of the g-value for the glass, a small tendency of decreased g-value for the weather file 1975 and 1989 may be observed. This difference is minimal and it was expected to obtain larger variation of this parameter between the weather files. The tendency is probably caused by the weather files' higher solar condition measures.

The histogram for heat capacity for the simulations with the 1985 weather file sticks a bit out from the rest. While the other weather files strongly indicate that a high heat capacity is preferred, the histogram for 1985 is more flat. This design tendency difference is minimal but noticeable. The 1985 weather file is the coldest weather file with the least amount of sunshine hours above 120 W/m^2. This might be why an increased thermal mass it not recommended, since the cooling demand is lower compared to the other weather files.

The histograms of the SFP and the infiltration indicates the lower end is more preferable for all weather files, except for 1975 as these are more even. This is correlated with the sensitivity measure of the SFP and infiltration presented in figure 6.5 for the Pearson's r correlation. These differences might be due to that the weather file in average is warmer than the others and have higher solar condition measures.

Filtering for the RI

When designing buildings, design teams are probably not interested in various box-plots with the detail level as presented earlier. Instead, the RI introduced in section 4.3 can be included in the PCP as an indicator for the design solutions' robustness. The RI tracks the variation when applying different weather files for each model configuration. The lower the variation is due to changing weather file, the higher the value of the RI gets, hence more preferable. This enables a quantitative measure of the robustness for each solution and enables the users to evaluate building design from another perspective.

To show how the RI may be used in the PCP, two PCPs are presented in figure 6.8 and 6.9. Both PCPs are first filtered after 35 kWh/m^2 per year and down for the TED and afterwards for the 10 % highest and lowest in the RI output. Recall that a high RI is preferable to reduce the influence of weather. The plots are furthermore reduced in terms of number of inputs. The seven most sensitive input parameters based on the sensitivity analysis conducted for the TED and the RI combined, presented in figure F.15 in appendix F.3, are included.

The following output parameters are added to give an example of the usage in a design situation. These output parameters are calculated based on the results for the historic weather files only.

- Mean Dif [%] - The relative mean difference of TED.
- Mean TED [kWh/m^2 year] - The mean TED.
- Max Dif [%] - The relative maximum/minimum difference of TED.
- Max TED [kWh/m^2 year] - The maximum/minimum observed TED.

These parameters can help the design team to evaluate how much the TED is varying in average with the historic weather files, both as a relative measure but also as an absolute value. Furthermore the absolute value of the maximum or minimum value is shown for the TED and the relative change compared to the TED from DRY.

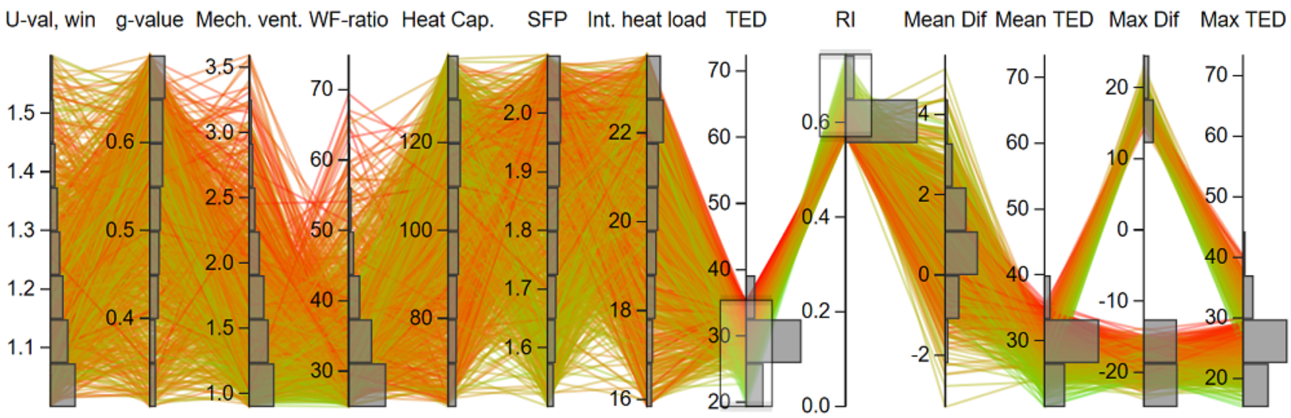


Figure 6.8. PCP presenting 1000 simulations. First filtered after 35 kWh/m^2 per year and down for the TED and afterwards for the 10 % highest in the RI output. The colour scale is sorted after the TED. Created with the interactive PCP from MOE A/S [2016].

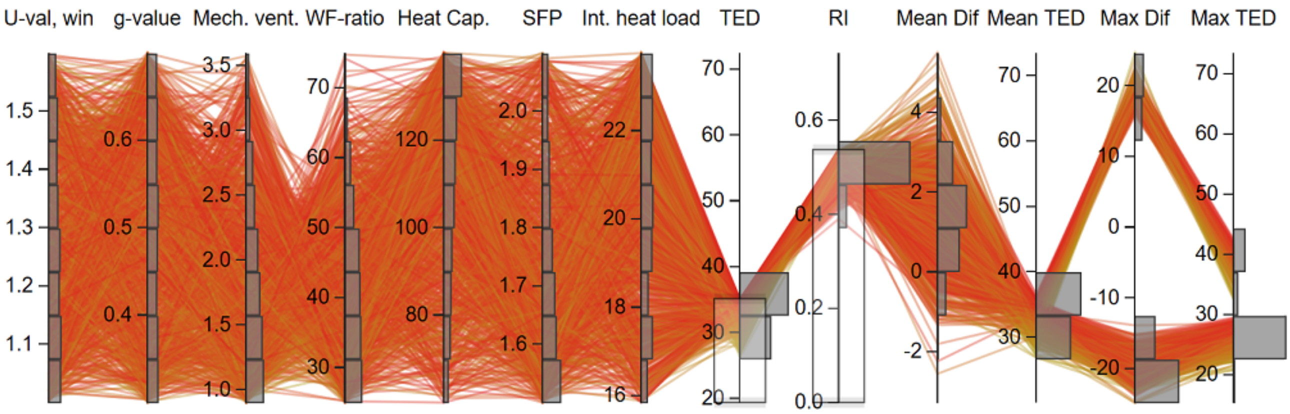


Figure 6.9. PCP presenting 1000 simulations. First filtered after 35 kWh/m^2 per year and down for the TED and afterwards for the 10 % lowest in the RI output. The colour scale is sorted after the TED. Created with the interactive PCP from MOE A/S [2016].

As per the histograms of the TED, most solutions in figure 6.9 are in the higher end of the filtering, indicating a correlation between the TED and the RI output. The histograms of the TED is changing as the filter of RI changes, with more solutions in the higher end of TED when RI decreases and vice versa. To show the correlation, the RI is plotted against the TED in figure 6.10.
What may also be observed is that when changing the RI from the highest 10 % of the design solutions to the lowest 10 %, the histograms for the input parameters changes as well. The tendencies are most visible for the 10 % highest RI.
The most distinct change is for the SFP input, which changes from one end of the range to the other. For the window-to-facade ratio, a clear connection can be observed with the RI output.

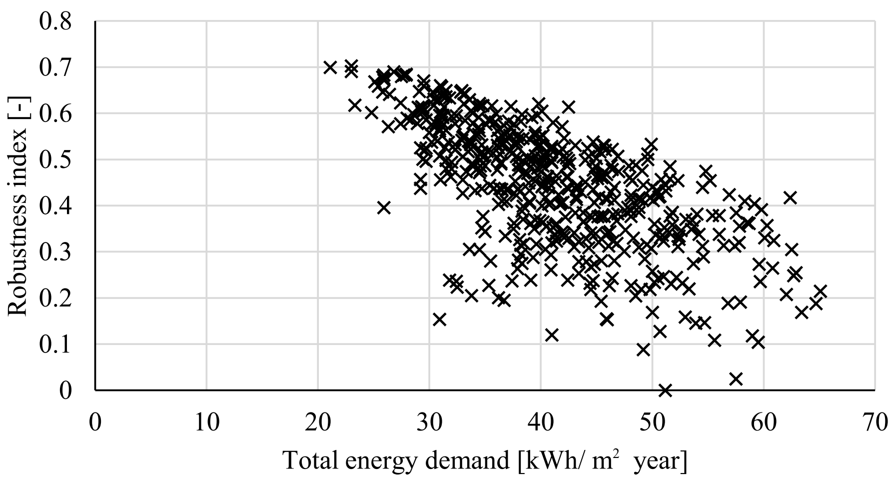


Figure 6.10. Scatter plot showing the RI plotted against the TED for simulations performed with DRY.

There is a correlation between the RI and TED. This is because a low TED reflects a building that is protected from the outdoor conditions, therefore yielding a high RI for these solutions. Recall that the RI is based on absolute difference between solutions from each weather file and not the relative difference. The Pearson's r correlation between TED and RI is -0.66.

Figure 6.11 and 6.12 presents the design solutions, filtered after the highest and lowest 5 % in the RI output, respectively. These shows how to use the RI alone in a PCP, and to determine how the other inputs and outputs vary by solely changing the filter of RI.

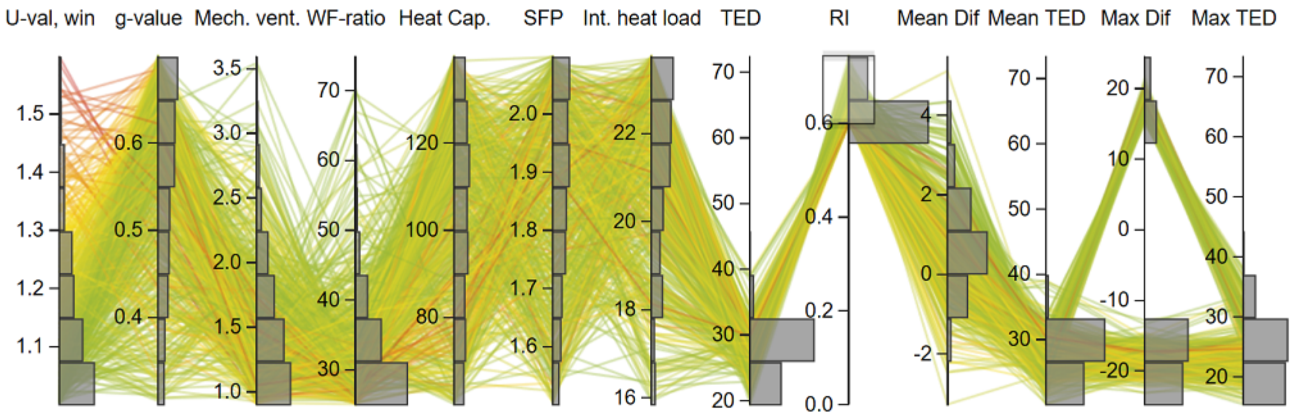


Figure 6.11. Parallel coordinate plot, filtered after the highest 5 % in the RI output. The colour scale is sorted after the TED. Created with the interactive PCP from MOE A/S [2016].

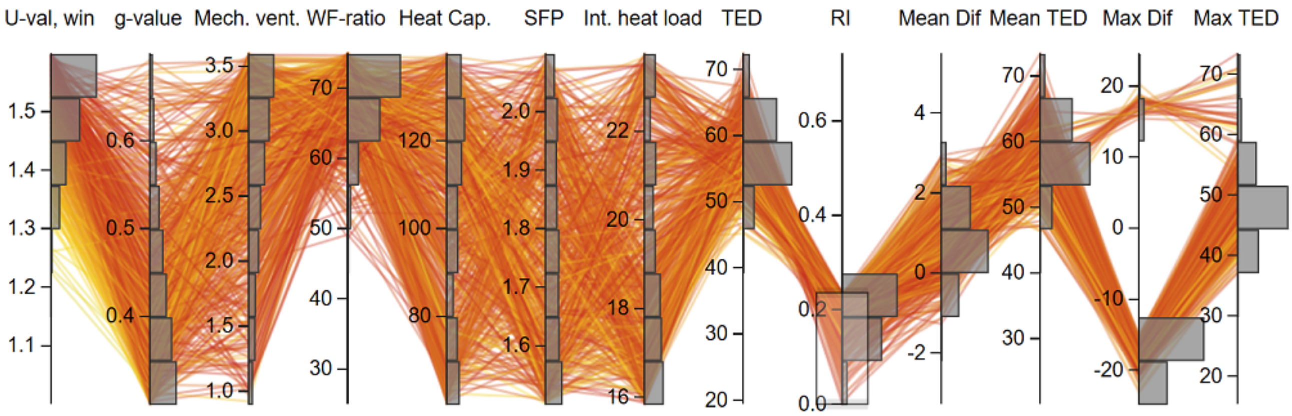


Figure 6.12. Parallel coordinate plot, filtered after the lowest 5 % in the RI output. The colour scale is sorted after the TED. Created with the interactive PCP from MOE A/S [2016].

Based on the PCPs above, to achieve high robustness towards weather, the following is recommended after altering the RI output alone:

- g-value in the high end of the range. (Original range: 0.3 – 0.7)
- Mechanical ventilation in the low end of the range. (Original range: 0.9 – 3.6 l/s m^2)
- U-value of the windows in the low end of the range. (Original range: 1.0 – 1.6 W/m^2 K)
- Window-to-facade ratio in the low end of the range. (Original range: 25 – 75 %)
- SFP and internal heat load in the high end of the range, though not that distinct. (Original ranges: 1.5 – 2.1 kJ/m^3 and 16 – 24 W/m^2)

While the PCP is an intuitive method of presenting the data and to identify design trends, histograms eases the comparison of several filtering settings.
In figure 6.13, two individual sets of the 10 % best performing solutions in terms of TED and RI are compared with a combined filtering for the TED and RI. The latter filtering is made by first filtering for the lowest 3000 simulations in terms of TED and afterwards for the 1000 solutions with highest RI. A total of 1000 simulations are presented for each filtering.
The RI is a value based on the effects from all weather files, while the TED is only from the simulations with the DRY weather file. This is because the RI is a single value for each design solution, representing the variation in TED from changing weather file.

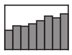
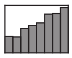
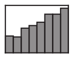
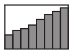
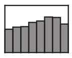
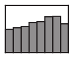
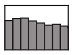
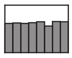
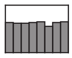
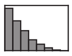
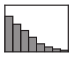
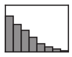
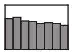
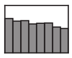
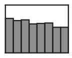
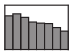
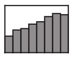
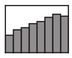
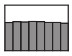
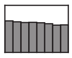
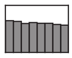
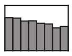
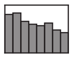
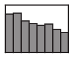
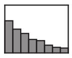
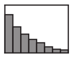
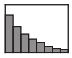
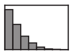
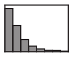
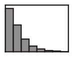
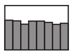
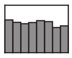
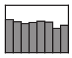
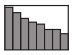
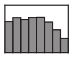
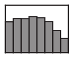
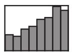
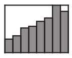
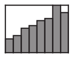
	Parameter	Range	Unit	TED	RI	TED+RI
Design	g-value, glass	0.3 - 0.7	[–]			
	Heat capacity	60 - 140	[Wh/K m^2]			
	Lighting (general installation)	4 - 10	[W/m^2]			
	Mechanical ventilation	0.9 - 3.6	[l/s m^2]			
	Overhang depth	0 - 45	[°]			
	Specific fan power (SFP)	1.5 - 2.1	[kJ/m^3]			
	Solar shading	0.2 - 1.0	[–]			
	U-value, external wall	0.10 - 0.15	[W/m^2 K]			
	U-value, windows	1.0 - 1.6	[W/m^2 K]			
	Window-to-facade ratio	25 - 75	[%]			
Uncertain	Heating set-point	21 - 24	[°C]			
	Infiltration	0.07 - 0.13	[l/s m^2]			
	Internal heat load	16 - 24	[W/m^2]			

Figure 6.13. Histograms of the top 10 % best performing solutions in terms of TED and RI alongside with histograms combining TED and RI. The latter filtering is first filtered for the lowest 3000 simulations in terms of TED and afterwards for the 1000 highest RI solutions. Each histogram includes 1000 simulations with DRY as weather file.

As shown earlier the correlation between RI and TED is strong. This is the reason why the histograms when filtering for RI and TED respectively, are similar for most parameters.

The histograms in figure 6.13 shows some interesting tendencies.
For the g-value, the RI indicates that a high g-value for glass is preferable to gain high robustness. This is similar to what is observed in the PCP in figure 6.11.

For TED there is a clear tendency towards the high range of the heat capacity, while the tendency for the RI is more neutral. This is because the heat capacity has influence on the TED, but not the variation between the weather files with monthly quasi-state calculations.
This is also shown in table F.5 in appendix F.3, where the standard deviation is almost equal when sorting the 10 % solutions with highest and lowest heat capacity. The mean difference in TED for the weather files is 5.0 kWh/m^2 year between high and low heat capacity, which support the observations from the results presented above.

The histograms for the SFP are contradicting. For low TED, the SFP should be in the low end, leading to less energy consumption from the ventilation system. For the RI, the opposite is observable, indicating that a high SFP is preferable.

Observing the infiltration histograms, differences between the TED and RI are noted. For TED, the infiltration should be in the low end because this will reduce the energy loss through infiltration. In terms of the RI, the infiltration is more flat.

6.4 Recapitulation

From this study it has been proven that the DRY weather file and the weather files it is based on may produce different results in terms of the TED when studying the total variation of the simulations. Though are the number of design solutions that complies with the BR15 requirement 8.2 % and 8.7 % when simulating with DRY and the historic weather files, respectively. This indicates that the DRY weather file is a well representation of the mean compared to using the historic weather files, even though it does not include the variation and extrema for these files.

When comparing each single design solution, different TEDs were observed when solely changing the weather file. This means that if conducting deterministic BPS, one may end up with different results the very same design solution, depending on the weather file used for the simulations.

From the sensitivity analyses it may be concluded that the sensitivity of the input parameters on the output parameter, TED, are not changing significantly with different weather files. The analyses agreed that window-to-facade ratio, mechanical ventilation and the U-value of the windows are the most influential input parameters in terms of TED. The ranking of these parameter are almost constant throughout the weather files. Some changes of the less influential input parameters were observed with the different weather files with the Pearson's r correlation. In terms of the TOM sensitivity, parameter ranking below the dummy are not accurate.

Sensitivity analyses of RI and TED and RI combined showed similar results as mentioned above. The window-to-facade ratio is the most sensitive parameters in both of these analyses. The U-value for the windows are the second most sensitive parameter followed by the mechanical ventilation and internal heat load.

The design tendencies from the simulations showed some differences between the weather files. The input parameters specific fan power and infiltration showed a high correlation with the respective weather file's solar conditions.
In terms of achieving high robustness, even with different weather files, the results indicates that the U-value of the windows, mechanical ventilation and window-to-facade ratio should be in the lower end of the selected ranges. Opposite, the g-value, specific fan power and internal heat load should be in the high end of the selected ranges.

Considering the design tendencies when evaluating the RI, the histograms for SFP and infiltration deviates. While the specific fan power should be in the low end concerning TED, the RI indicates a high SFP is preferable.
In terms of infiltration, the histograms for the TED are right-skewed, indicating that the infiltration shall be low. For the RI, the tendency for the infiltration is more flat, while lowering in the higher end.

7 Influence of Stochastic Occupancy Modelling in BSim

The aim of this chapter is to evaluate the use of static occupancy profiles compared to stochastically generated occupancy profiles to determine if static occupancy profiles induce inadequate results and system dimensions. With a calculation approach that utilize sub-hourly dynamic calculations, stochastic simulations are carried out with different occupancy profile models. The performance of the occupancy models are compared and differences in building performance and dimensional values are determined. Furthermore, sensitivity analyses are carried out to identify the most sensitive parameters on multiple indicators.

It is common to use BSim with a deterministic approach with the DRY-file and a simple model for the occupants. BSim grants possibilities to perform simulations with more advanced occupant profiles. It is therefore interesting to investigate if the deterministic approach for occupancy profiles are sufficient when performing stochastic modelling, hence the influence on building performance and dimensional values. For the stochastic modelling in BSim presented in this thesis, four occupancy models are included by factorial experiment. The occupancy profiles are generated with stochastic methods which changes the occupancy profiles for each simulation. A range of the mean value of the present occupants added with the daily variation is also included for the simulations.
Furthermore, weather files are included to estimate the influence of the variability of weather on relevant outputs. This is done by performing a sensitivity analysis.

An open office landscape on the 1. floor of the building is selected to perform the simulations for. The room has a net internal floor area of $126\,\mathrm{m}^2$ and is highlighted with blue in figure 7.1 with a plan view of room in figure 7.3.
The open office landscape is an L-shaped room, with large window areas facing south and east, and a smaller area facing north. The windows facing north does not have solar shading, as it is unlikely occupants have the need to use solar shading in this direction.

With a floor area of $7.5\,\mathrm{m}^2$ per occupant the room is occupied by 17 persons at a normal scenario. It is typical for an open office landscape that not every occupant are present in the room at all time. Therefore the variability of occupants is implemented stochastically in the dynamic occupancy models. This is described further in section 7.3 and additionally in appendix E.
Furthermore, depending on the owner, the occupant level in such office may differ from year to year.

Figure 7.2 presents the simulation model in BSim.

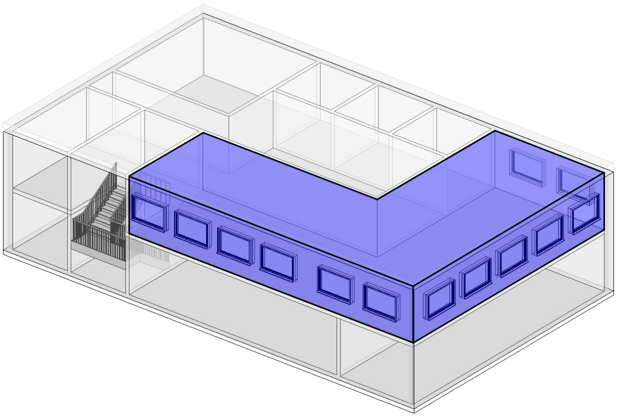


Figure 7.1. Selected room for the BSim simulations highlighted with blue.

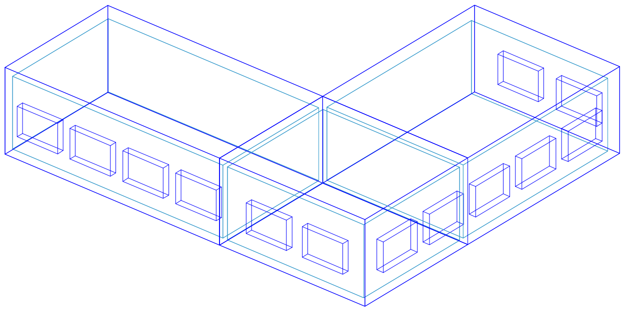


Figure 7.2. Model of the open office landscape as modelled in BSim.

The BSim model presented in figure 7.2 represents the base model which the stochastic parametric analysis is based on.
The selected room is assumed to be the critical room in the building, mainly because the room has multiple windows facing south and east and will be occupied during almost all working hours.

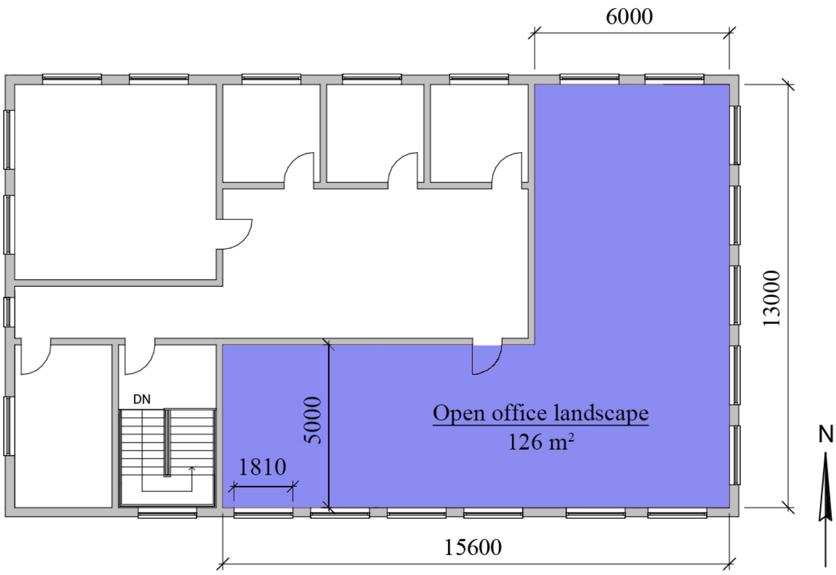


Figure 7.3. Plan view of the open office landscape. Dimensions in millimetres.

Since the BSim simulations only are conducted for this single room, the results will reflect this. The occupants in the room are modelled to leave the room when having breaks and will therefore most certainly be present in the cafeteria on the ground floor during these breaks.

7.1 Parameter selection

A selection of 18 input parameters are chosen to be varied and are presented in table 7.1 with their respective range and distribution. These parameters are selected based on a subjective sensitivity analysis and considerations along the project period. The table is sorted into two categories, design and uncertain parameters.

	Parameter	Range	Unit	Distribution
Design	Cooling power	0; 20; 40; 60; 80; 100	[W/m^2]	Discrete
Design	Exterior wall type	1; 2; 3; 4; 5	[–]	Discrete uniform
Design	External wall construction	Light/heavy	[–]	Discrete uniform
Design	Lighting (effect)	2 - 8	[W/m^2]	Discrete uniform
Design	Mechanical ventilation	0.5 - 2.0	[l/s m^2]	Continuous uniform
Design	Overhang	0; 20; 40; 60	[°]	Discrete uniform
Design	Shading on	25 - 100	[kLux]	Continuous uniform
Design	Shading off	Shading on minus 20 kLux	[kLux]	–
Design	Solar shading coefficient	0.2 - 1.0	[–]	Continuous uniform
Design	VAV factor	4	[–]	Constant
Design	Window type	1; 2; 3; 4; 5; 6; 7	[–]	Discrete uniform
Design	Window-to-facade ratio	30 - 84	[%]	Continuous uniform
Uncertain	Cooling SP, work. hours	25	[°C]	Constant
Uncertain	Equipment	15 - 23	[W/m^2]	Following occupants
Uncertain	Equipment, base load	2	[W/m^2]	Constant
Uncertain	Heating SP, work. hours	21 - 24	[°C]	Continuous uniform
Uncertain	Heating SP, outside work. hours	18	[°C]	Constant
Uncertain	Infiltration, work. hours	0.07; 0.10; 0.13	[l/s m^2]	Discrete uniform
Uncertain	Infiltration, outside work. hours	0.03; 0.06; 0.09	[l/s m^2]	Discrete uniform
Uncertain	Occupants, yearly mean load	80 - 120	[%]	Continuous uniform
Uncertain	Occupants, daily std.dev.	0 - 20	[%]	Continuous uniform
Uncertain	Weather file*	DRY; 1978; 1985; 1989; 2030; 2050; 2070	[–]	Discrete uniform

Table 7.1. Input and uncertain parameters for the stochastic modelling in BSim with their ranges and distributions. SP and std.dev. are abbreviations for set-point and standard deviation, respectively. *For the future weather files, three scenarios are applied, described further in section 7.2.

A brief summary of the selected inputs and their ranges are presented in the following and further described in appendix C. The cooling power is varied between between 0 and 100 W/m^2 in steps of 20 W/m^2, with half of the models without cooling. The reason for this is that it is interesting to investigate solutions with different cooling power as well as solutions without.

The external wall are varied between five different types with two different construction types (light and heavy). The U-value of the walls varies from 0.12 W/m^2 K and up to 0.20 W/m^2 K with steps of 0.02 W/m^2 K. The thickness of the walls decreases with increasing U-values, from 19 cm and up to 31.5 cm.

A VAV ventilation system is used to have the possibility to change the air flow according to level of occupancy and therefore ensure sufficient ventilation. A VAV-factor of 4 is used as constant for the simulations while the basic air change (minimum air flow) is varied from 0.5 to 2.0 l/s m^2.

The solar shading for the windows is controlled by the illuminance on the facades. There are no shading attached to the windows facing north, and for simplification, the set-point for the required illuminance to activate and deactivate the shading is the same for the south and east facing windows. The shading is deactivated when the illuminance level is 20 kLux under the limit for activated shading.

Seven predefined windows are chosen with U-value from 0.8 to 1.1 W/m^2 K, g-value from 0.25 to 0.63 and light transmittance from 0.46 to 0.80.

The cooling set point during the working hours is set constant to 25 °C as a conjecture. The set point for the heating system is varied in the range of 21 to 24 °C as a conjecture based on DS/EN 15251 [2007, Table A.3, page 33].

The number of occupants in the room and the occupancy profiles are varied with two parameters, the yearly mean load and the daily standard deviation. The yearly mean load is a percentage of how many occupants there are in the building in average per year. While 100 % corresponds to 17 persons, the low and high end of the range from table 7.1, 80 % and 120 %, corresponds to approximately 14 and 20 persons, respectively.
The standard deviation, given in percentage, describes the variation which may occur from day to day. Note that this is constant for each simulation.
The equipment load in the room is divided into two parts. The first part correlates to the occupancy profiles since most of the equipment in the room is handled by the occupants. The second part is a base load which represent equipment that is not dependent on the occupant, for example printers or other equipment on stand-by.

The range for the infiltration correspond to the requirements for renovation class 1 (BR10) and up to the requirement for Energy frame Buildings 2020, [Energistyrelsen, 2017, section 7.2.1, 7.2.4]. The infiltration requirements from [Energistyrelsen, 2017] are at 50 Pa pressure test which are recalculated with the expression from Aggerholm and Grau [2009, page 63]. With the infiltration during the working hours sampled, the infiltration outside of working hours are simply determined by subtracting 0.04 l/s m^2 from the infiltration during the working hours according to Aggerholm and Grau [2009, page 63].

7.2 Comparing weather files

The weather files used in the BSim simulations differ from those used for the Be15 simulations. In the BSim simulations, weather files for the future are also included as well as the DRY weather file and three of the historic weather files. The weather files for the future are created with the climatological database software Meteonorm [Meteonorm, 2017]. Since the future includes many uncertainties, the Intergovernmental Panel on Climate Change, IPCC, has developed a series of scenarios of future emissions scenarios. These scenarios takes population and economic growth, behaviour and lifestyle changes, changes associated with land and energy use, and policies regarding technology and climate into account, [IPCC, 2014].
In this study, the years 2030, 2050 and 2070, including three scenarios (B1, A1B and A2), are chosen as future weather files. Description of the different scenarios is presented in section D.2.1 in appendix D.

The three selected historic weather files are the warmest (1989), the coldest (1985) and a weather file that is similar to the DRY file (1978). Characteristic of the 13 weather files are presented in table 7.2. Solar radiations are mean values of the hours within a year given a radiation above 0 W/m^2. The sunshine hours are evaluated as hours with a direct solar radiation exceeding 120 W/m^2 during a year, [WMO, 2008]. For outdoor temperatures for each weather file on a monthly basis, see appendix D.

Weather file	Outdoor temperature Mean [°C]	OHS [°C]	HS [°C]	Solar conditions Global [W/m^2]	Direct [W/m^2]	Sunshine hours [h >120 W/m^2]
DRY	7.8	14.3	3.1	214	291	2018
1978	7.5	13.8	3.0	232	256	1974
1985	6.4	13.7	1.1	206	242	1713
1989	9.1	14.4	5.3	213	241	2100
Mean, historic	7.7	14.0	3.1	217	246	1929
2030B1	9.6	15.2	5.5	224	320	2094
2030A1B	9.7	15.4	5.6	224	324	2060
2030A2	9.6	15.3	5.4	221	320	1999
2050B1	10.0	15.7	5.9	227	345	2159
2050A1B	10.4	16.0	6.3	224	333	2099
2050A2	10.2	15.9	6.1	222	337	2063
2070B1	10.3	15.9	6.2	227	332	2172
2070A1B	10.9	16.5	6.9	225	360	2150
2070A2	11.0	16.6	6.9	221	347	2065
Mean, future	10.2	15.8	6.1	224	335	2096

Table 7.2. Annual mean outdoor air temperature, global and direct solar radiation of the DRY, the three selected historic and the nine future weather files. OHS is defined as the time period from May up to and including September, while the HS is from October up to and including April.

The future weather files includes warmer outdoor temperature within the data. These temperatures are also increasing further out the century. In terms of the solar conditions, the only parameter that is changing significantly is the direct radiation. The direct radiation in the future weather files are significantly higher than what is evident for the others.

In figure 7.4, the annual variation of the weather files' outdoor air temperature is presented.

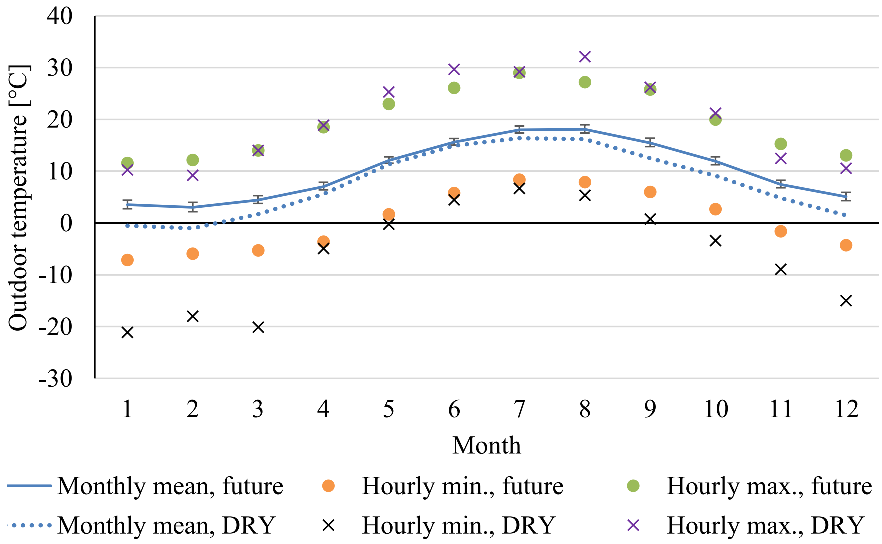


Figure 7.4. Annual outdoor temperature variation of DRY and the nine future weather files. The whiskers represents the minimum and maximum monthly mean outdoor temperature of the future weather files.

The deviation of the monthly mean is significant smaller for the future weather data than what is evident for the historic weather data, presented in figure 6.1 on page 28. Because of this, extreme temperatures such as those from the DRY weather data (x'es in figure 7.4) are not occurring in the future weather data (dots in figure 7.4). For example, the DRY weather data includes temperatures of down to about $-21\,^{\circ}\mathrm{C}$ in January while the future weather data only drops down to $-7\,^{\circ}\mathrm{C}$. The differences in extreme temperatures are mostly evident during the heating season.
The monthly mean for both the future weather data and the DRY weather data are almost parallel through out the year, except for the months of April up to and including July. In this time period, the two means are almost the same.

7.3 Occupancy modelling and preliminary study

As mentioned earlier, the occupancy profiles that are typically used in practice are static and simple. These will be compared to dynamic occupancy profiles (stochastically generated occupancy profiles) to study any potential differences in relation to building performance and system dimensioning.

Before comparing the static occupancy profiles with the dynamic ones, a preliminary investigation is conducted to determine what level of detail the dynamic occupancy profiles is advised to be modelled. Three models are investigated and the results are compared at last in this section. Note that the examples of weekly occupancy profiles presented in this section are all illustrating the same week.

128 simulations are performed for each occupancy model with a Sobol sequence sampling with the parameters and ranges described in section 7.1.

7.3.1 Static occupancy model

The static occupancy model (SOM) profiles are modelled as presented in figure 7.5. The occupancy level is at 100 % from 08:00 until 12:00, 50 % from 12:00 until 13:00 because of lunch break, and afterwards 100 % until 18:00.

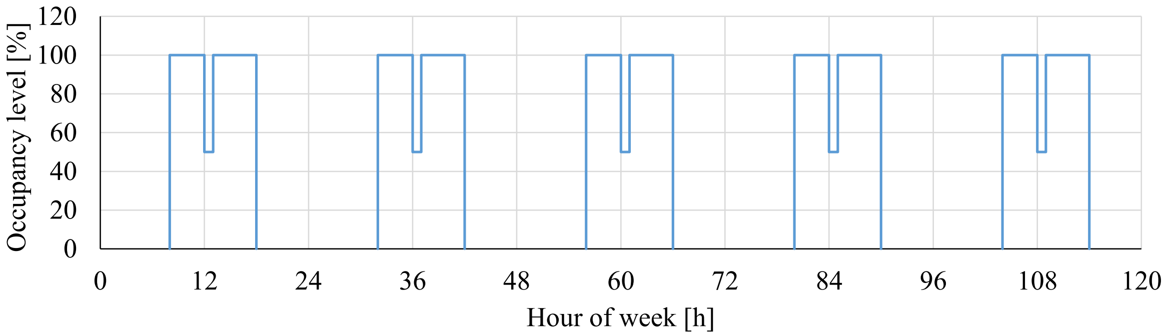


Figure 7.5. Example of a static occupancy profile. The model is without hourly, daily or weekly variations except for the lunch break, where the occupancy level is reduced to 50 %.

7.3.2 Dynamic occupancy model a

The first dynamic occupancy model (DOM) includes both hourly and daily variations and is created with a method that Reinhart [2001] refined from Newsham et al. [1995].
The method implies that each occupant has its own mean value for each event (both start and duration), which is stochastically generated based on the normal distribution for the entire population. The population is in this context referred to as all the occupants in the room.

This grants each occupant a unique normal distribution, from which their behaviour can vary throughout a year on an hourly level. Therefore, e.g. occupant 1 has a mean value of meeting at the office at 8:00 but throughout the year there is a probability that this person will arrive earlier or later based on the random number generated for this person for this event each day. It should be noted that the standard deviation is identical for each occupant and the entire population. However it could be a possibility to vary this as well, but for simplicity this is not done in this project.

The algorithm in the method creates occupancy profiles based on five different events during a workday, see table 7.3.

Event	Mean start	Standard deviation	Event interval
Arrival	08:00	15 minutes	07:00 - 09:00
Coffee break	10:00	15 minutes	09:00 - 11:00
Lunch break	12:00	30 minutes	11:00 - 13:00
Coffee break	15:00	15 minutes	14:00 - 16:00
Departure	18:00	15 minutes	17:00 - 19:00

Table 7.3. Events during each day with mean start, standard deviation of the start and the time interval for the events, [Reinhart, 2001], [Newsham et al., 1995]. The mean and standard deviation is valid for the whole population.

The "event interval" in the last column of table 7.3 indicates the time interval when an event is probable to take place, hence an event may not start or continue outside of these hours.
As presented in chapter 5, the building has its own cafeteria, therefore the occupants will leave their workspace, hence the room during lunch and coffee breaks. The durations of these breaks are presented in table 7.4.

Event	Mean duration	Standard deviation
Coffee break	15 minutes	6 minutes
Lunch break	60 (30) minutes	15 (6) minutes

Table 7.4. Event durations during a day with mean duration and standard deviation of the duration, [Reinhart, 2001], [Newsham et al., 1995]. For the duration and standard deviation of the lunch breaks, the values given in the parentheses are the values used in this thesis.

The data from table 7.3 and 7.4 is then used to create cumulative distribution functions (CDF). With the CDFs it is possible to stochastically generate occupancy profiles with the inverse transform sampling (ITS) method. The ITS method uses a randomly generated number from a uniform distribution, between 0 and 1, and then computes the corresponding value from the CDF. With this value as a new mean value, the process is repeated. A new random number between 0 and 1 is generated and with ITS, a new corresponding value is computed from the CDF.
By setting up the occupancy model with these settings, a probable variance of the occupants can be generated and simulated.

An Excel spreadsheet has been developed to generate these stochastic occupancy profiles and an overview of the method is presented in appendix E along with an example. Beside this, details concerning coding for implementing the occupancy profiles in BSim are presented.

In figure 7.6, an example of an occupancy profile for DOMa is presented for a selected week during the year.

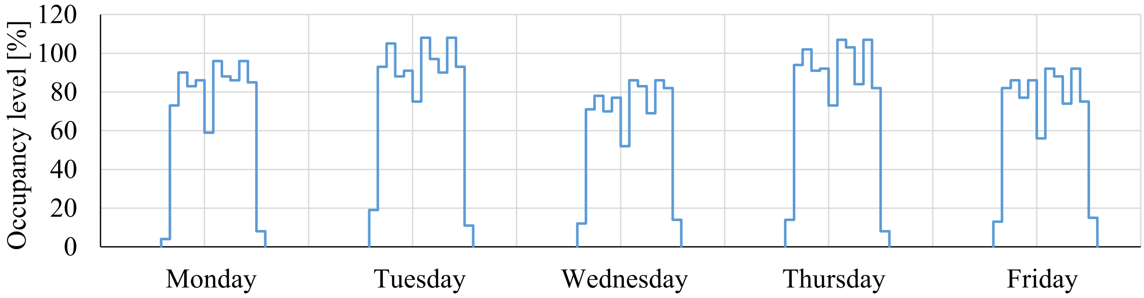


Figure 7.6. Example of an occupancy profile for DOMa for a selected week during the year. The occupancy model includes hourly and daily variations.

7.3.3 Dynamic occupancy model b and c

DOMb and DOMc are simplifications of the first with different level of variation.
The second occupancy model averages the hourly values from the first model to generate even daily occupancy profiles. An example of such occupancy profile is presented in figure 7.7.

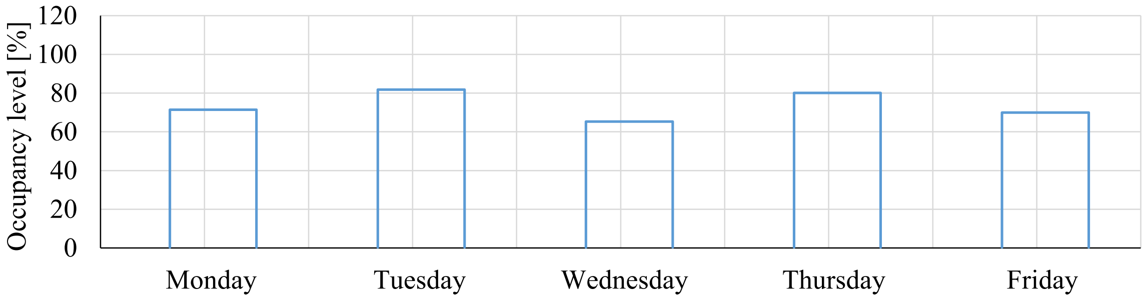


Figure 7.7. Example of an occupancy profile for DOMb of the same week as DOMa. The occupancy model includes daily variations but not hourly.

The third occupancy model is simplified even further. The occupancy model averages both the hourly and daily variations to generate even weekly occupancy levels. An example of this is presented in figure 7.8.

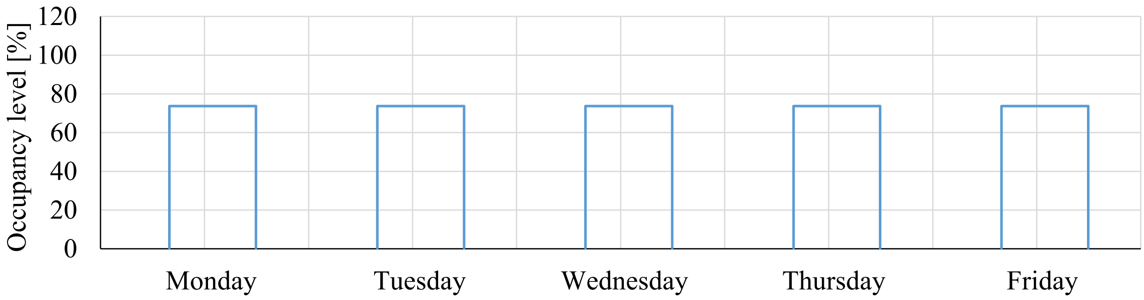


Figure 7.8. Example of an occupancy profile for DOMc of the same week as the two to other occupancy models. The occupancy does not include hourly and daily variations.

Examples of the weekly variations, which all three occupancy models includes, caused by the variations of the yearly mean and the daily standard deviation are presented in appendix E. These examples presents the effects of changing the yearly mean and the daily standard deviation.

7.3.4 Preliminary study

The three different occupancy models are evaluated on their performance in four different output parameters. These are energy demand for cooling and heating, hours of excessive temperatures above 26 °C and the fan power demand which is the TED for motors, ventilators and transmission in the mechanical ventilation system.
Overall, the differences between the models are small but showing that DOMa demands more energy for cooling, which is reasoned by a higher amount of hours with excessive temperatures. The comparison for the cooling demand is shown in figure 7.9. DOMa is in general yielding higher operative temperatures, which is evident from the heating demand. The heating demand is lower for DOMa than for the two others. In terms of fan power demand, DOMa requires more mechanical ventilation as a reason of the higher temperatures and higher cooling demand as shown in figure 7.10. The results for DOMb and DOMc are similar throughout the four outputs. It may therefore be concluded that there is no difference in the results when modelling accordingly to DOMb or DOMc.

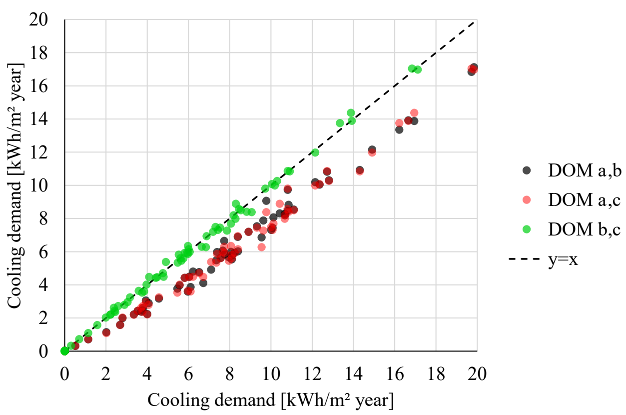


Figure 7.9. Scatter plot comparing the cooling demand of the three occupancy models. The numbers in the legend after "DOM" corresponds to the x- and the y-axis.

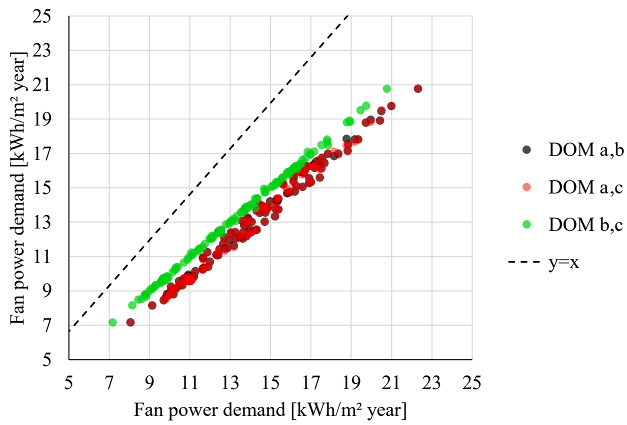


Figure 7.10. Scatter plot comparing the power demand for the ventilation fan of the three occupancy models. The numbers in the legend after "DOM" corresponds to the x- and the y-axis.

With this preliminary study of the detail level of the occupancy profiles, it is chosen to continue with DOMa, which is the most detailed one, since it deviates from the other two. In the next part of the thesis, further simulations are carried out with this model and the results are compared with results from simulations with commonly used static occupancy profiles. The documentation for the chosen dynamic occupancy model is shown in appendix, section G.

7.3.5 Additional occupancy profile models

As a consequence of the events occurring during the day (table 7.3), the yearly number of occupants present in DOMa is reduced. The number of occupancy profile models is then increased from two to four, see figure 4.3 on page 18 for clarification.

In the following sections, results from the simulations with these four occupancy models and the different sets of weather files are presented. In the main report, the focus is towards the differences in results between DOM1 and SOM2. Results for the rest of the occupancy models are presented in appendix G.

7.4 Energy performance

The energy performance of the models are in this section presented for the TED, cooling and heating demand to evaluate any potential differences between the occupancy models. The results are presented with scatter plots and evaluated with the Mean Absolute Deviation (MAD) measure, which describes the mean difference between two data sets. Along with the MAD, the Mean Absolute Percentage Error (MAPE) is also evaluated.
The colouring used in the scatter plots are indicating results from the simulations with different weather files (DRY, historic and future). Because of the amount of data in the scatter plots, some results are located on top of others. Since there are more results for the future weather files, these are placed in the bottom layer of the plots followed by the historic and DRY on top.
Since the aim of this thesis is to compare the typically used static profiles described earlier in this chapter with the stochastically generated occupancy profiles, the presented results in this section are for DOM1 and SOM2. Scatter plots comparing DOM1 with SOM1 and DOM2 with SOM2 are presented in appendix G.2.

The TED, cooling and heating demand for DOM1 and SOM2 is presented in figure 7.11, 7.12 and 7.13. Figure 7.14, 7.15 and 7.16 presents the fan power and excessive temperatures above 26 and 27 °C, respectively. In table 7.5, the MAD for the occupancy models are presented.

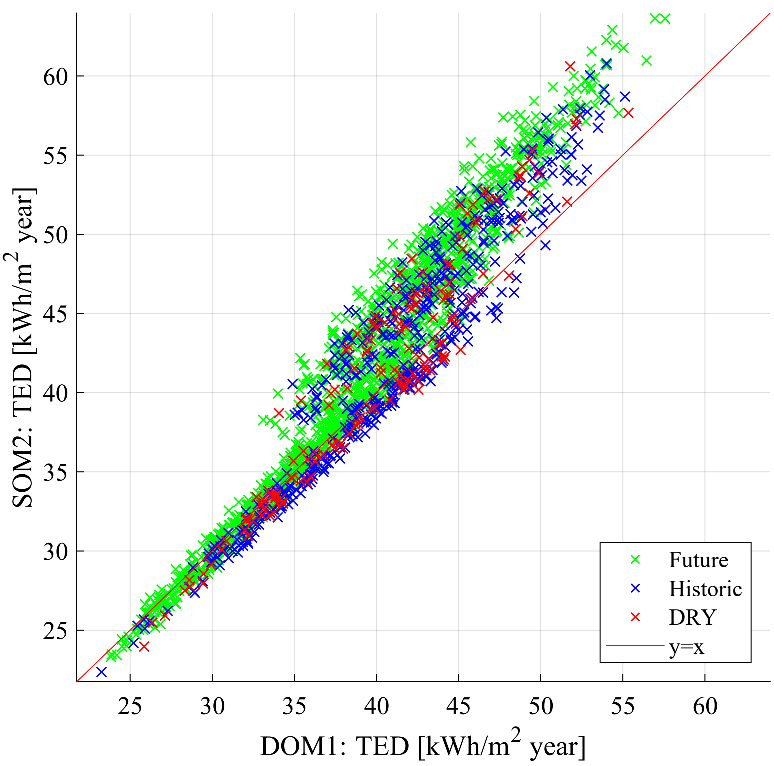


Figure 7.11. Scatter plot presenting the TED for occupancy model DOM1 and SOM2. The red dashed lines splits the data set into two parts, above and below 40 kWh/m^2 year.

The TED for the two models are rather similar until about 40 kWh/m^2 year. A change is observable from this point, where the TED for SOM2 deviates more from DOM1. The difference is higher above 40 kWh/m^2 year than below. From this it is clear that the uncertainty related to modelling of occupants has larger impact on the building's TED when the TED is above 40 kWh/m^2 year. The MAD for the TED is 2.7 kWh/m^2 year.

In terms of the weather files, no significant observations are made other than the DRY weather file seems to induce more similar results for the two occupancy models.

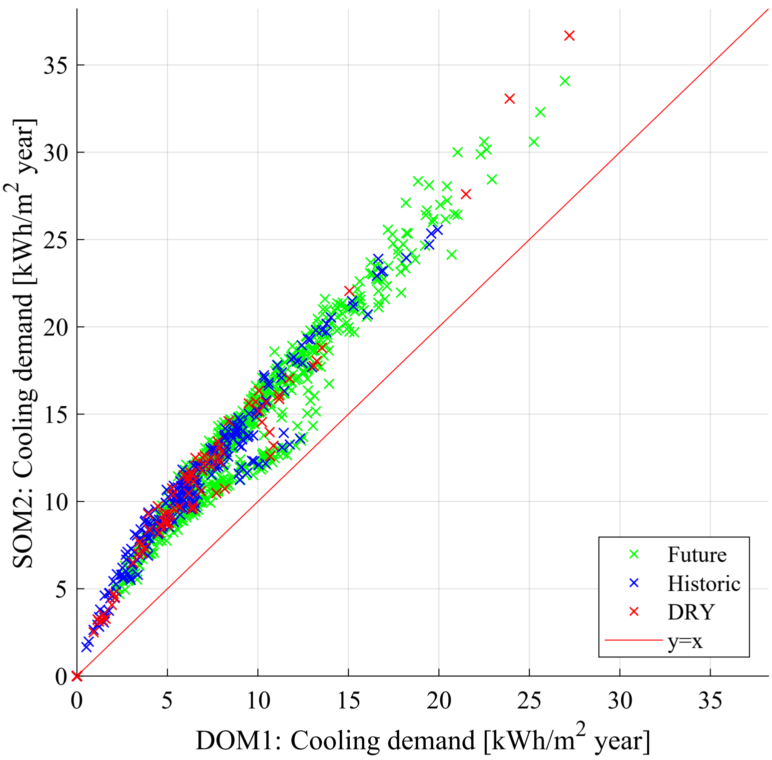


Figure 7.12. Scatter plot presenting the cooling demand DOM1 and SOM2.

From figure 7.12 it can be observed that the cooling demand is higher for SOM2 as expected. The MAD is calculated to 4.7 kWh/m^2 year for all the data, which gives the magnitude of the difference between the two occupancy models. This means that when using static occupancy profiles, with the same amount of occupants as the dynamic ones, the total cooling demand is higher. This is due to the reduction of the occupancy presence because of breaks during the day. It has to be noted that the occupants does not leave the building during these breaks, thus the heat emission from the occupants is still released inside the building and might cause cooling in another room.
It may be observed that the future weather files cause higher cooling demand as the weather data is warmer.

Opposite to the cooling demand, the heating demand is higher for DOM1 than SOM2, figure 7.13. This is also expected as the occupancy load in average is higher for SOM2. The MAD for the heating demand is 3.2 kWh/m^2 year, which indicates that the difference between the occupancy models is smaller than for cooling.
The future weather files seems to induce less difference between the occupancy models, especially from 11-12 kWh/m^2 year and above on the x-axis. The results for the DRY weather file is fairly spread out.

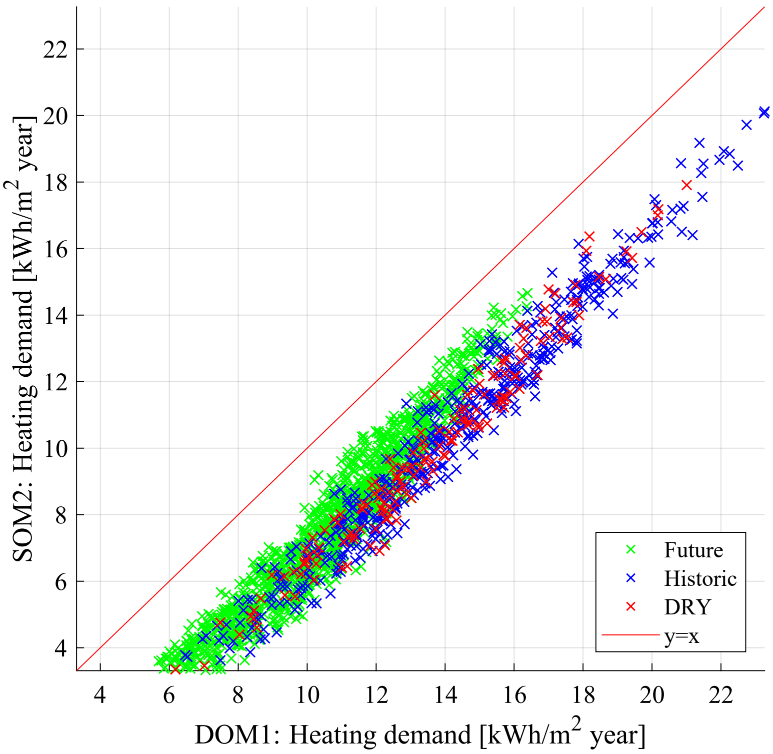


Figure 7.13. Scatter plot presenting the heating demand for DOM1 and SOM2.

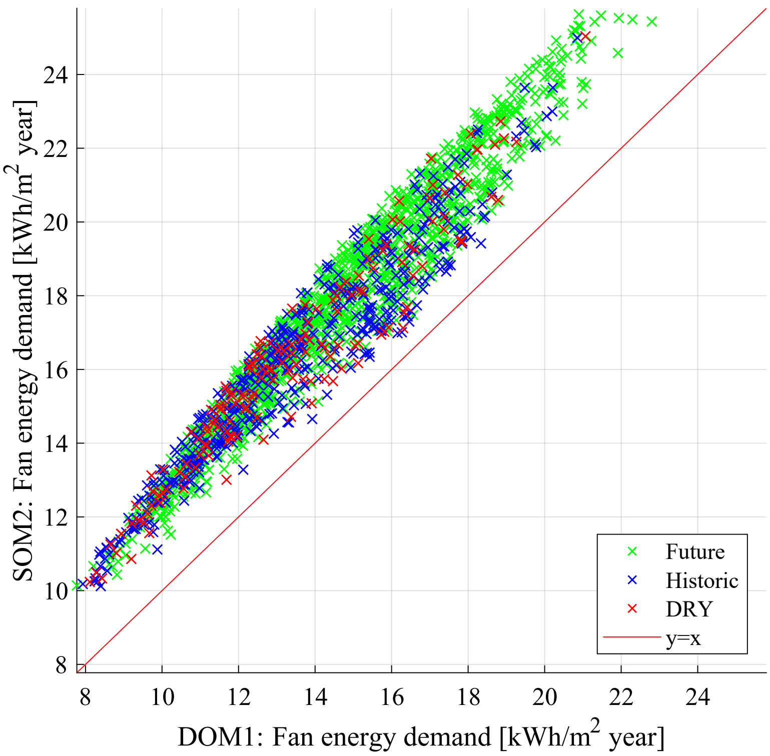


Figure 7.14. Scatter plot presenting the yearly fan energy demand for DOM1 and SOM2.

The energy demand for the fan is higher for SOM2 which is caused by the higher amount of occupants present. The future weather files causes higher fan energy demand than the other weather files.

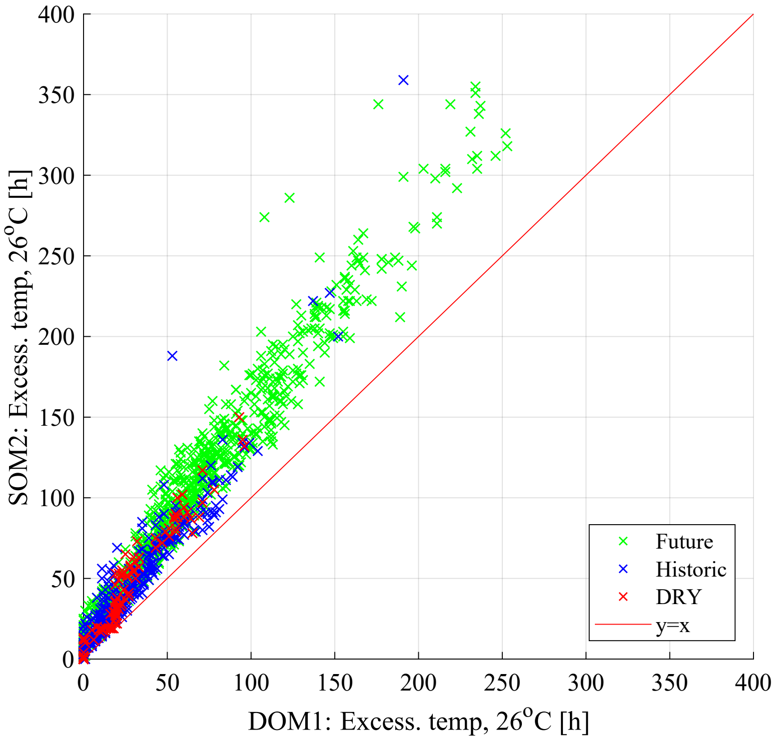


Figure 7.15. Scatter plot presenting excessive temperatures above 26 °C for each building design for DOM1 and SOM2.

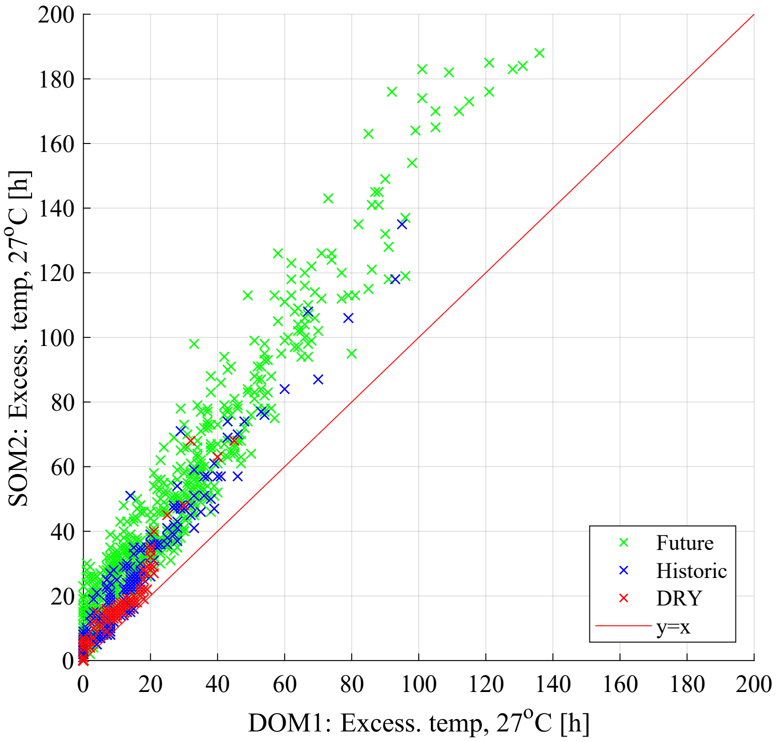


Figure 7.16. Scatter plot presenting excessive temperatures above 27 °C for each building design for DOM1 and SOM2.

The scatter plots in figure 7.15 and 7.16 indicates that when using SOM2, the excessive temperatures are higher. The future weather files induces more hours of excessive temperature than the other weather files.

Model comparison	TED [kWh/m^2 year]		Cooling [kWh/m^2 year]		Heating [kWh/m^2 year]		Fan power [kWh/m^2 year]		$T_{op,26°C}$ [h]		$T_{op,27°C}$ [h]	
DOM1 & SOM2	2.7	6%	4.7	37%	3.2	30%	3.0	18%	22	–	10	31%
DOM1 & SOM1	0.2	1%	0.2	3%	0.1	1%	0.1	1%	2	6%	1	8%
DOM2 & SOM2	0.8	2%	0.3	3%	0.3	9%	0.3	2%	3	7%	2	9%

Table 7.5. Mean absolute deviation (MAD) of occupancy model comparisons for the building performance. The gray values are the mean absolute percentage error (MAPE) for DOM as the predicted value.

According to table 7.5, the MAD for the TED is approximately 2,5 and 1.9 kWh/m^2 year lower for the comparison of the DOM1 with SOM1 and DOM2 with SOM2, than for DOM1 and SOM2. This indicates that differences between two occupancy models (static and dynamic) with the same yearly average number of present occupants are small, compared to the result of two models with different yearly average number of present occupants, such as DOM1 and SOM2. This also applies to the other performance indicators presented from the table.
It is noticeable that the heating and fan power is higher for SOM2 than for DOM1 for all building designs.

In table 7.6, results from a more comprehensive study for the comparison between DOM1 and SOM2 are presented. Included filtering displays if there are any difference in applying the two models for the three sets of weather data and all models with or without cooling. The minimum and maximum of the absolute deviation (AD) and the percentage deviation (PD) are not necessarily for the same building design.

	Filter	TED [kWh/m^2 year]		Cooling [kWh/m^2 year]		Heating [kWh/m^2 year]		Fan power [kWh/m^2 year]		$T_{op,26°C}$ [h]		$T_{op,27°C}$ [h]	
Min	**All**	**0.0**	**0%**	**0.0**	**0%**	**1.1**	**8%**	**0.7**	**4%**	**0**	**0%**	**0**	**0%**
	DRY	0.0	0%	0.0	0%	1.8	10%	0.8	5%	0	0%	0	0%
	Historic	0.0	0%	0.0	0%	1.5	10%	0.7	4%	0	0%	0	0%
	Future	0.0	0%	0.0	0%	1.1	8%	0.9	5%	0	0%	0	0%
	W/ cooling	0.1	0%	1.0	8%	1.1	8%	0.7	4%	0	0%	0	0%
	W/o cooling	0.0	0%	0.0	–	1.2	9%	1.1	6%	2	9%	0	0%
Mean	**All**	**2.7**	**6%**	**4.7**	**37%**	**3.2**	**30%**	**3.0**	**18%**	**22**	–	**10**	**31%**
	DRY	2.3	5%	4.4	41%	3.6	28%	2.9	18%	13	29%	4	27%
	Historic	2.3	5%	4.4	43%	3.6	28%	2.8	17%	12	–	5	27%
	Future	2.8	6%	4.9	35%	2.9	31%	3.2	18%	27	30%	12	32%
	W/ cooling	4.6	9%	4.7	37%	3.2	30%	3.0	18%	5	–	2	13%
	W/o cooling	0.7	2%	0.0	0%	3.1	29%	3.0	17%	39	39%	18	49%
Max	**All**	**14.0**	**20%**	**13.9**	**68%**	**5.2**	**66%**	**5.1**	**26%**	**310**	–	**219**	**100%**
	DRY	8.9	15%	9.5	65%	5.2	63%	4.7	26%	57	100%	36	100%
	Historic	7.6	15%	7.2	68%	5.2	61%	4.7	25%	168	–	42	100%
	Future	14.0	20%	13.9	58%	5.1	66%	5.1	25%	310	100%	219	100%
	W/ cooling	14.0	20%	13.9	68%	5.2	62%	4.9	26%	80	–	56	100%
	W/o cooling	2.6	8%	0.0	–	5.2	66%	5.1	24%	310	100%	219	100%

Table 7.6. Minimum, mean and maximum of both absolute deviation and percentage deviation for different filters of each output. The compared models are DOM1 and SOM2.

From the table it can be concluded that the minimum AD for TED, cooling and excessive temperature are close to zero. The PD is high compared to the AD, but this is caused due to high relative differences for the low absolute values. Likewise when filtering building design with a cooling system, the minimal AD is 1 kWh/m^2 year for the cooling demand.

For the mean of the AD and PD, the values do not differ significantly when applying filters. The most significant difference is for the models with cooling, where the mean TED is almost a factor 2 higher than all models compared. For the excessive temperatures, the highest AD and PD are for the filtering of models with future weather file and without cooling. Note that the excessive temperatures are accurate with cooling enabled, while the opposite applies without cooling.

The maximum AD is high for TED and cooling for the future weather files. Furthermore, the PD are high for cooling and heating demand.

7.4.1 Influence of mean and standard deviation of occupants present

The effect of varying the number of present occupants in the models with the yearly mean and the daily standard deviation is studied.
The heating and cooling demand for DOM1 and SOM2 for different settings for the yearly mean are presented in figure 7.17 and 7.18, respectively. Figure 7.19 presents the effect of altering the daily standard deviation of occupants presents for DOM1.

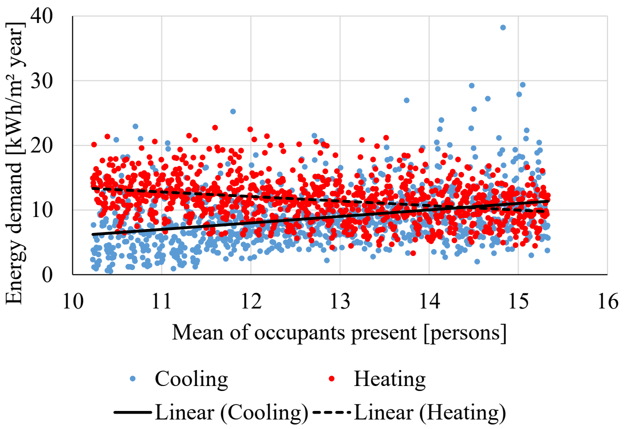


Figure 7.17. Cooling and heating demand for DOM1 with changing yearly mean of occupants present in the room.

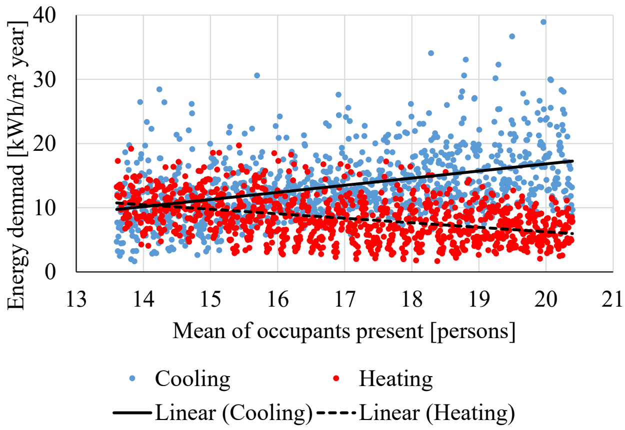


Figure 7.18. Cooling and heating demand for SOM2 with changing yearly mean of occupants present in the room.

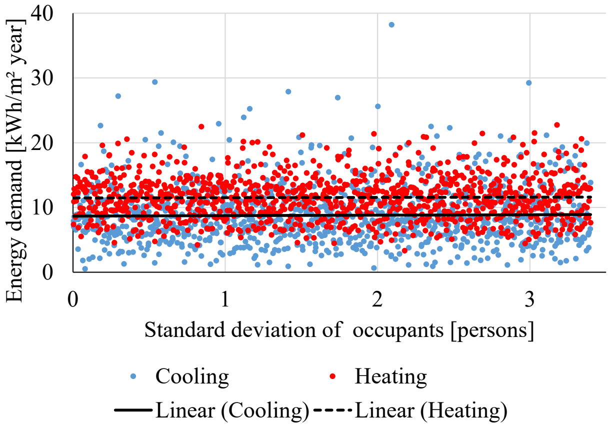


Figure 7.19. Cooling and heating demand for DOM1 with changing daily standard deviation of occupants present in the room.

Evident from the results, the yearly mean of occupants present are significantly more influential on the cooling and heating demand than the standard deviation. The trendlines for the standard deviation indicates that the are no need of varying the numbers of occupants present from day to day.
According to the trendlines, the cooling and heating demand are equal with 14-15 occupants present in average per year. The results shows that with more than 14-15 occupants present in average per year, the cooling demand will be higher than the heating demand. This applies to both occupancy models.

7.4.2 Sensitivity analysis

The sensitivity analysis ranks and gives a quantitative measure of how much a parameter influences the variation in the outputs. In this way the influence of the variability of occupants and weather can be determined on the given evaluated parameters for the building design.
The results for the sensitivity analysis for the energy performance are presented in table 7.7.

Input	TED, T_{26}, T_{27}				TED				T_{26}, T_{27}				Cooling				Heating			
	DOM1		SOM2		DOM1		SOM2		DOM1		SOM2		DOM1		SOM2		DOM1		SOM2	
Cooling power	1	25%	1	28%	1	20%	1	31%	1	34%	1	34%	11	4%	3	11%	16	1%	17	2%
Mech. vent.	2	12%	2	12%	2	17%	2	14%	4	6%	4	7%	3	10%	4	9%	1	23%	1	25%
Weather file	3	10%	3	10%	10	4%	7	4%	2	13%	2	13%	4	10%	5	9%	2	15%	3	11%
WF-ratio	4	9%	4	8%	3	8%	4	8%	3	11%	3	9%	1	16%	2	12%	10	4%	6	6%
IHL, mean	5	6%	5	7%	4	8%	3	9%	6	5%	5	6%	2	11%	1	12%	3	10%	2	13%
Window	6	5%	6	5%	6	5%	6	5%	5	5%	6	5%	5	10%	6	8%	5	8%	4	7%
Lighting	7	5%	7	4%	5	7%	5	5%	15	2%	15	2%	10	4%	12	4%	11	3%	9	4%
Shading south	8	4%	9	4%	8	4%	9	3%	7	4%	7	3%	6	5%	7	5%	6	5%	8	4%
Heating SP	9	4%	11	3%	7	5%	8	4%	13	2%	12	2%	15	3%	15	2%	4	9%	5	6%
Shading east	10	4%	10	3%	9	4%	10	3%	9	3%	9	3%	7	5%	8	5%	7	5%	11	3%
Dummy	11	3%	8	4%	11	4%	12	2%	8	3%	8	3%	12	3%	10	4%	12	3%	13	3%
Overhang	12	3%	12	2%	13	3%	13	2%	10	3%	11	3%	8	5%	9	4%	9	4%	10	3%
IHL, variation	13	3%	13	2%	15	2%	15	2%	14	2%	13	2%	14	3%	13	4%	14	2%	16	2%
Shading coeff.	14	3%	14	2%	17	2%	17	1%	12	2%	14	2%	13	3%	14	3%	13	2%	15	2%
Light/heavy	15	2%	15	2%	12	3%	11	3%	11	3%	10	3%	9	4%	11	4%	17	1%	14	2%
U-value wall	16	2%	16	2%	16	2%	14	2%	16	1%	16	1%	16	2%	17	1%	15	2%	12	3%
Infiltration	17	2%	17	2%	14	2%	16	1%	17	1%	17	1%	17	2%	16	2%	8	4%	7	4%

Table 7.7. Rank and sensitivity measure of the input parameters for the building performance with TOM sensitivity. IHL is an abbreviation for internal heat load.

The most sensitive parameter for the TED and excessive temperatures is the cooling power. This means

that if the cooling power is dimensioned poorly in terms of robustness, the variability of weather and occupancy presence will greatly affect the performance of the building.
The weather file and window-to-facade ratio are also significant sensitive parameters, which indicates that the weather has a great influence on the exceeding temperatures. This supports the results from figure 7.15, where it is evident that the future weather files are causing most of the exceeding temperatures above 100 hours.
In terms of TED, the weather file only ranks 10, while the second most sensitive parameter is mechanical ventilation, followed by the window-to-facade ratio. The mean of the internal heat load, occupants and equipment, is the fourth most sensitive parameter.

Considering the cooling, window-to-facade ratio, mean of internal heat load and mechanical ventilation ranks in the top of the most sensitive parameters. What is interesting is that the cooling power is ranked 3 for SOM2 but only 11 for DOM1. This is also the parameter which is deviating the most in terms of MAD, presented earlier.
Parameters that protects the building from outdoor conditions have slightly less influence for SOM2. This is because the mean IHL is a factor 1,3 higher, thus the balance of heat gain is different.
The mean IHL and weather is ranked 2 and 4, respectively. This means that the predicted cooling demand will change depending on the variability of weather and occupancy, thus promote the performance gap.

According to the sensitivity analysis, the input rankings are deviating the most between DOM1 and SOM2 for heating and cooling demand.
The fact that the heating demand is most influence by the mechanical ventilation means that the heat loss from ventilation is greater than from transmission and infiltration for the open landscape office. The uncertainty coupled with the amount of ventilation impacts the prediction of heating demand for the building. An accurate estimation of the mean IHL and using various weather files means that the calculated heating demand will reflect the uncertainty of actual heating used, thus reducing the performance gap.

Generally, the sensitivity analysis shows that the sensitivity of the inputs for the two occupancy models are rather similar throughout the performance indicators.
The ranks of the weather and mean IHL are in average 4,4 and 3,3 respectively, which emphasize the importance of study the uncertainty associated with them.

7.5 System dimensioning

HVAC systems are typically dimensioned based on simulations conducted in BSim, without being able to handle peak power demands. Since the simulations provide hourly results, a helpful method is to use a duration curve. With this, the dimensional values can be determined based on a desired acceptable deviation. The acceptable deviation used in this study is 1 %, 3 % and 5 % of the working hours. Results for the 3 % acceptable deviation are presented, while the others are show in appendix H. The term acceptable deviation refers to the percentage of time which is not covered by the systems, for example that 3 % of the time the operative temperature exceeds the given value. This allows a margin for the dimensioning of systems which is also used in practice.

The dimensional cooling and heating power for DOM1 and SOM2 with an acceptable deviation of 3 % is presented in figure 7.20 and 7.21. Figure 7.22, 7.23 and 7.24 presents the dimensional fan power, mean operative temperature and CO_2-levels for DOM1 and SOM2 with an acceptable deviation of

3 %. Scatter plots comparing DOM1 with SOM1 and DOM2 with SOM2 are presented in appendix G.2.

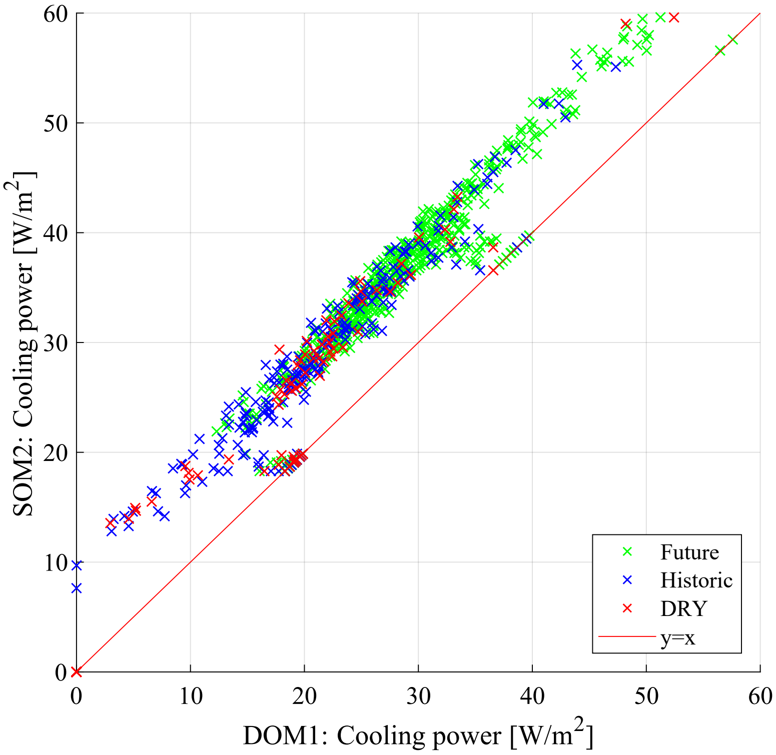


Figure 7.20. Scatter plot presenting the dimensional cooling power for DOM1 and SOM2 with an acceptable deviation of 3 %.

From figure 7.20 it is evident that when using SOM2, the cooling system requires higher cooling power than for DOM1. This is also supported by the MAD presented in table 7.8 which is 6.5 kWh/m^2 year. The cluster at 20 W/m^2 are building designs that have reached their maximum cooling power, as these are sampled to from 20−100 kWh/m^2 year with 20 kWh/m^2 year steps. Overall, the deviation between the models seems constant as most of the results are located parallel to the y=x line.
The future weather files are generally increasing the dimensional cooling power because of the warmer weather data included in these.

In terms of the heating demand in figure 7.21, using the DOM1 will result in choosing a system with higher heating power than SOM2. This is expected as DOM1 has a lower mean of occupants present through the year. The difference is small as the MAD is only 0.9 kWh/m^2 year. The differences between the two occupancy models are larger in the low end of the required heating power where DOM1 requires higher heating power than SOM2.
The dimensional heating power is changing more for SOM2 than for DOM1, which is clearly visible for the future weather files. A possible contribution to this is the combination of the time-schedules for the heating systems and the occupants. In SOM2, all occupants arrive at 08:00, and leave at 18:00. In DOM1, some of the occupants are also arriving before 08:00, and some leave after 18:00. This means that the hours 07:00−18:00 and 18:00−19:00 includes heat release from occupants, which decreases the required heating power for these hours. Within these hours, the heating system will try to reach the set-point. What is also visible in figure 7.21 is that results for the DRY weather file are fairly concentrated in the middle. The reason for this is that the future weather files along with the weather file for 1989 are warmer than DRY. The results for the historic weather file in the high end of the plot

are from the 1985 weather file, which is the coldest of the ones included in the simulations.

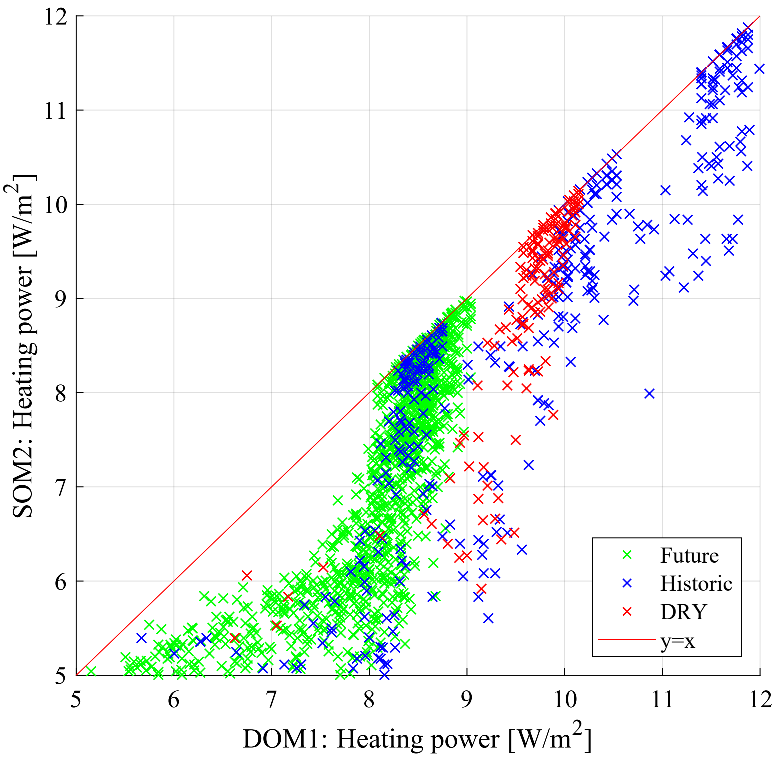


Figure 7.21. Scatter plot presenting the dimensional heating power for DOM1 and SOM2 with an acceptable deviation of 3 %.

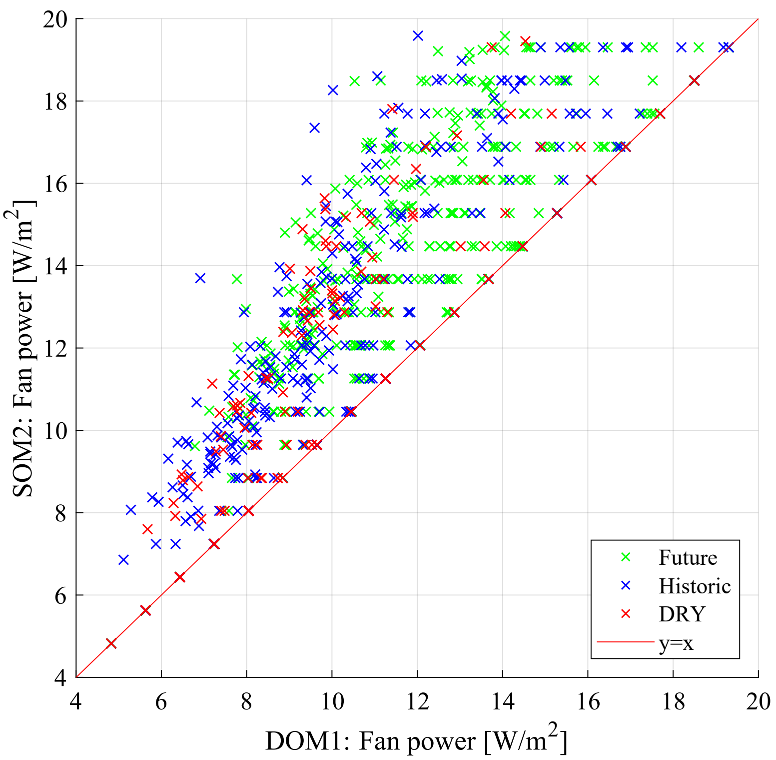


Figure 7.22. Scatter plot presenting the dimensional fan power for DOM1 and SOM1 with an acceptable deviation of 3 %

The results for the dimensional fan power in figure 7.22 indicates that the fan shall have more power if

using SOM2. What may also be observed are solutions located on the horizontal lines and on the y=x line, divided in to 20 steps. Since the mechanical ventilation has been implemented with continuous uniform values, the odd tendency could be due to a stepwise regulation of the fan power. The horizontal lines are therefore showing design solutions where the maximum available fan power is used. Thus, results located in between these lines are not using the maximum available fan power.
Considering the different weather data, no tendencies are observed.

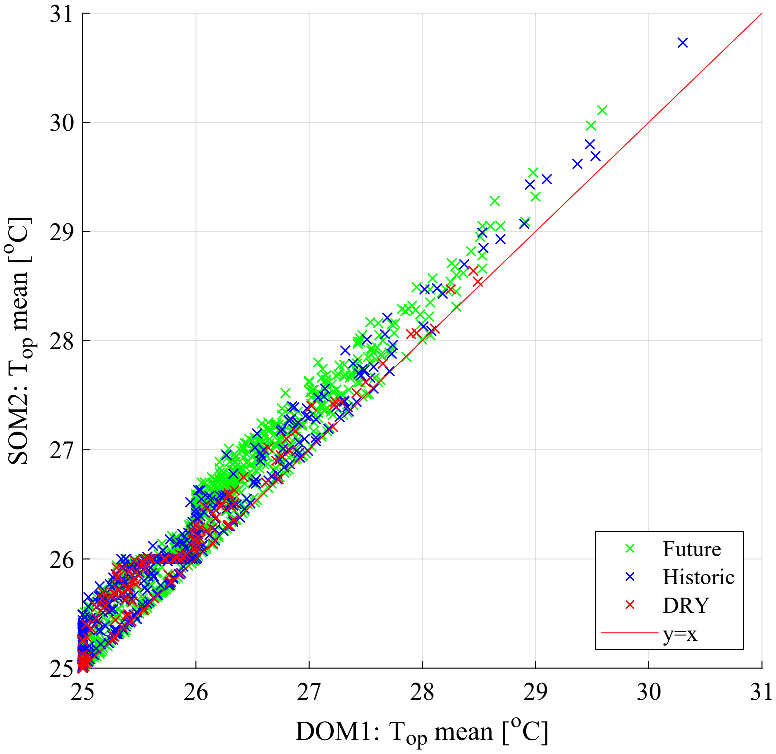


Figure 7.23. Scatter plot presenting the mean operative temperature for occupancy model DOM1 and SOM2 with an acceptable deviation of 3 %.

Considering the mean operative temperature, using SOM2 will in average result in slightly higher temperatures. Recall that the set-point for the cooling system is at 25 °C and that 50 % of the design solutions are without cooling. This means that all the solutions presented in the figure either do not have enough cooling power, or are without cooling.
What is interesting is an L-shape at 26 °C. The solutions creating this shape are solutions where the cooling of the mechanical ventilation system has contributed to keep it at 26 °C.
The future weather files are causing higher temperatures in the room as a reason of the warmer weather data.

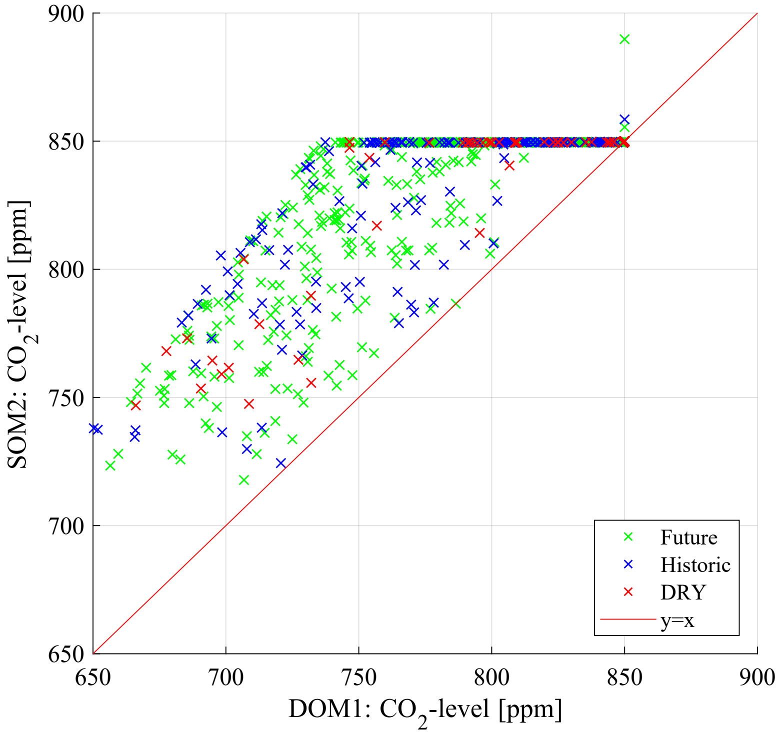


Figure 7.24. Scatter plot presenting the CO_2-levels for occupancy model DOM1 and SOM2 with an acceptable deviation of 3 %.

The CO_2-levels are in average higher for SOM2 with a MAD of 20.3 ppm. What is interesting is the horizontal line at 850 ppm on the y-axis. 850 ppm has been set to the CO_2-level limit in the room which is why there are many results located at this level. The mechanical ventilation system is therefore keeping the CO_2-level at this very point.

AD [%]	Model comparison	Cooling [W/m^2]		Heating [W/m^2]		Fan power [W/m^2]		TopMean [°C]		CO_2 [ppm]	
1	DOM1 & SOM2	5.7	14%	0.7	9%	0.1	1%	0.3	1%	14.3	2%
3	DOM1 & SOM2	6.5	20%	0.9	14%	1.1	8%	0.2	1%	20.3	2%
5	DOM1 & SOM2	7.0	25%	0.9	16%	1.5	13%	0.2	1%	24.8	3%
1	DOM1 & SOM1	0.8	3%	0.1	1%	0.0	0%	0.0	0%	22.3	3%
3	DOM1 & SOM1	0.6	3%	0.1	1%	0.1	1%	0.0	0%	16.2	2%
5	DOM1 & SOM1	0.5	6%	0.1	1%	0.1	1%	0.0	0%	12.2	2%
1	DOM2 & SOM2	1.0	3%	0.8	9%	0.0	0%	0.0	0%	7.3	1%
3	DOM2 & SOM2	0.7	2%	0.6	8%	0.1	1%	0.0	0%	5.3	1%
5	DOM2 & SOM2	0.5	2%	0.5	7%	0.1	1%	0.0	0%	4.2	1%

Table 7.8. Mean absolute deviation of occupancy model comparisons for the dimensional values. The gray values are the mean absolute percentage error for DOM as the predicted value. AD is the acceptable deviation.

Similar to the energy performance, the largest variations in MADs is between DOM1 and SOM2, which is expected. It is evident from the results that the MAD is largest for the dimensional cooling power. For heating and fan power, the MADs are almost negligible.
From table 7.8 it is noticeable that the influence of not using the same yearly mean of occupants

present is decisive. The MAD results for the other two comparisons (DOM1 with SOM1 and DOM2 with DOM2) reveals smaller differences.

7.5.1 Influence of mean and standard deviation of occupants present

The dimensional heating and cooling power for DOM1 and SOM2 for different settings for the yearly mean are presented in figure 7.25 and 7.26, respectively. Figure 7.27 presents the effect of altering the daily standard deviation of occupants presents for DOM1.

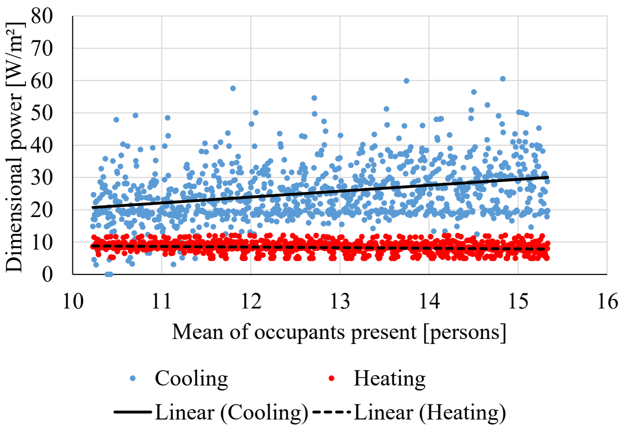


Figure 7.25. Dimensional heating and cooling power for DOM1 with changing yearly mean of occupants present in the room.

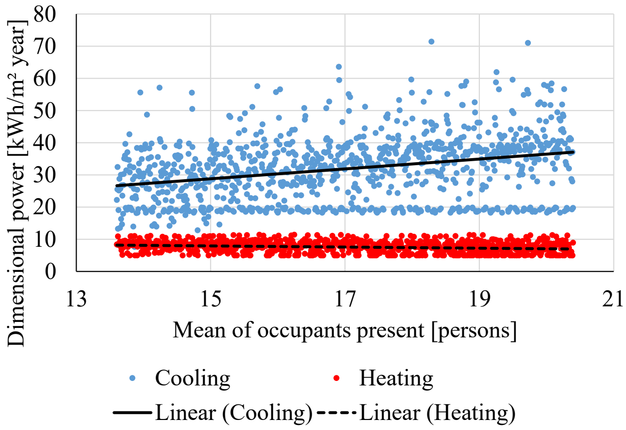


Figure 7.26. Dimensional heating and cooling power for DOM1 with changing daily standard deviation of occupants present in the room.

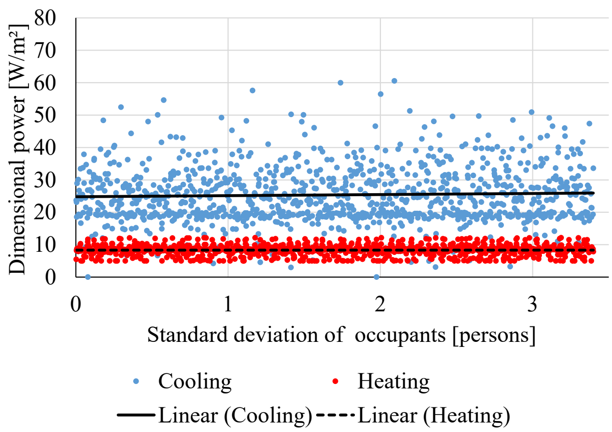


Figure 7.27. Dimensional heating and cooling power for SOM2 with changing daily standard deviation of occupants present in the room.

From figure 7.25 and 7.26 it is evident that the yearly mean of occupants presents almost have not influence on the dimensional heating power. This is probably because the main part of the heating occurs outside of the working hours. On the other hand, the dimensional power for cooling is affected by the yearly mean of occupants present. With increasing number of occupants, the dimensional cooling power increases.

A series of solutions are located along 20 W/m^2, mostly evident in figure 7.26. This is the minimum cooling power used in the simulations, and these solutions are therefore using the maximal cooling power available.

Again, there are evidence of the unimportance of including the daily standard deviation in the occupancy modelling. The trendlines are almost not affected by the standard deviation for either of the occupancy models.

7.5.2 Sensitivity analysis

The results from the TOM sensitivity analysis are presented for cooling, heating, operative temperature and CO_2 in table 7.9, 7.10, 7.11 and 7.12, respectively.
For results regarding cooling, only the models with cooling system are evaluated (1024 out of 2048). For the other outputs, all 2048 building models are included.

Input	Cooling			
	DOM1		SOM2	
Cooling power	1	19%	1	19%
WF-ratio	2	13%	2	14%
Weather file	3	9%	4	10%
IHL, mean	4	8%	3	12%
Window	5	8%	5	8%
Mech. vent.	6	6%	8	5%
Dummy	7	5%	11	3%
Shading east	8	5%	7	5%
Shading south	9	5%	6	5%
Light/heavy	10	4%	9	4%
Overhang	11	4%	10	3%
Lighting	12	3%	12	3%
IHL, variation	13	3%	15	2%
Heating SP	14	3%	14	2%
Shading coeff.	15	3%	13	2%
U-value wall	16	2%	16	2%
Infiltration	17	1%	17	1%

Table 7.9. Ranking and relative sensitivity of the cooling power for the dimensional values with a 3 % acceptable deviation using TOM sensitivity. IHL is internal heat load.

Input	Heating			
	DOM1		SOM2	
Weather file	1	23%	1	19%
WF-ratio	2	13%	3	13%
Heating SP	3	12%	2	17%
Mech. vent.	4	9%	5	9%
IHL, mean	5	8%	4	10%
Light/heavy	6	7%	7	4%
U-value wall	7	5%	12	3%
Infiltration	8	5%	6	5%
Shading south	9	4%	8	4%
Lighting	10	3%	9	3%
Window	11	3%	10	3%
Dummy	12	3%	11	3%
Shading east	13	2%	14	2%
Shading coeff.	14	2%	13	2%
IHL, variation	15	2%	15	2%
Overhang	16	1%	16	2%
Cooling power	17	1%	17	1%

Table 7.10. Ranking and relative sensitivity of the heating power for the dimensional values with a 3 % acceptable deviation using TOM sensitivity. IHL is internal heat load.

Input	T_{op} mean			
	DOM1		SOM2	
Cooling power	1	26%	1	28%
WF-ratio	2	17%	2	14%
Window	3	11%	4	9%
Weather file	4	9%	3	9%
Mech. vent.	5	6%	5	7%
IHL, mean	6	5%	6	6%
Overhang	7	4%	8	4%
Light/heavy	8	4%	9	3%
Dummy	9	3%	7	5%
Shading south	10	2%	10	3%
Shading east	11	2%	11	3%
Heating SP	12	2%	13	2%
Shading coeff.	13	2%	15	2%
IHL, variation	14	2%	12	2%
Lighting	15	2%	14	2%
U-value wall	16	2%	16	1%
Infiltration	17	1%	17	1%

Table 7.11. Ranking and relative sensitivity of the mean operative temperature that is exceeded 3 % of the working hours using TOM sensitivity. IHL is internal heat load.

Input	CO_2			
	DOM1		SOM2	
Mech. vent.	1	53%	1	60%
IHL, mean	2	14%	2	12%
IHL, variation	3	7%	13	1%
Dummy	4	4%	3	4%
Heating SP	5	3%	6	3%
Shading south	6	2%	8	2%
Shading east	7	2%	10	2%
Light/heavy	8	2%	4	3%
WF-ratio	9	2%	7	2%
Weather file	10	2%	14	1%
Window	11	2%	16	1%
Lighting	12	1%	12	2%
Shading coeff.	13	1%	15	1%
U-value wall	14	1%	5	3%
Cooling power	15	1%	11	2%
Infiltration	16	1%	9	2%
Overhang	17	1%	17	1%

Table 7.12. Ranking and relative sensitivity of the CO_2-levels that is exceeded 3 % of the working hours. IHL is internal heat load.

The results shows that the most sensitive design parameters are somewhat constant when changing the occupancy models between DOM1 and SOM2. Only small variations are shown for the rankings, as a result of input parameters with equal magnitudes of the relative sensitivity. This means that the ranking of inputs for system dimensioning are not affected by the dynamic or static occupancy profiles. The variability of the mean for the IHL has a high influence on dimensioning of cooling and heating system. It is also a sensitive parameter in terms of CO_2-levels. It is therefore recommended to user multiple user profiles and weather files for the dimensioning of the cooling system. If logged data of the occupants presence are available and a distribution can be well fitted to the data, it is a possibility to give a confidence interval for the cooling system, that it will meet the requirements for multiple occupancy levels. This will ensure robustness towards occupants. The mean of the IHL is ranked between 6 and 2 in the performance indicators. Naturally there is a difference in the relative sensitivity for mean of IHL, since the range and mean value are higher for SOM2 than DOM1. The variation of the IHL is only among the most sensitive parameters for the CO_2. This performance indicator is also dominated by the sensitivity of the mechanical ventilation.

The sensitivity of the weather file are ranked between 10 and 1 throughout the analyses with highest sensitivity for the heating dimensioning. The high sensitivity of the weather files on the heating dimensioning shows that the size of heating systems are highly dependent on the weather file used. This is also shown previously in the scatter plot for the heating power in figure 7.21. However, the uncertainty of the heating power is from 5-12 W/m^2 which is a small absolute variation compared to the range of 0-60 W/m^2 for the cooling power. A modeller are therefore not required to dimensioning the heating system by stochastic modelling with included variability of weather and occupants.

For the operative temperature the cooling power is the most influential. Therefore if the cooling system is dimensioned poorly due to variability of occupants and weather, it might results in exceeding temperatures, which will not satisfy the building owner. Therefore it is recommended to perform stochastic modelling of occupants and weather to check the robustness of the chosen building design.

7.6 Recapitulation

Energy performance
In terms of energy performance, using SOM2 induce higher TED, with a MAD of 2.7 kWh/m^2 year, than DOM1. The difference in TED is mainly present after approximately 40 kWh/m^2 year and is primarily caused by the deviation in cooling demand. The cooling demand is higher for SOM2 than for DOM1. For heating, the opposite is evident. SOM2 demands more energy for the ventilation fan and the hours of excessive temperatures are significantly higher.
In the comparisons of dynamic and static occupancy profiles with the same yearly mean occupants present, the differences are significant smaller. The MAD for the TED for the comparisons DOM1 with SOM1, and DOM2 with SOM2, are 0.2 and 0.8 kWh/m^2 year, respectively. The other evaluated output parameters are also deviating less than the comparison between DOM1 and SOM2.

The MAD for all the weather files for cooling demand, heating demand and fan power demand are 4.7 kWh/m^2 year, 3.2 kWh/m^2 year and 3.0 kWh/m^2 year, respectively. The largest mean variation is therefore induced by the cooling demand. Solutions with cooling have a high cooling demand with almost no hours with excessive temperatures while the solutions without cooling induce several hours. The MAD for these are 39 h and 18 h for 26 °C and 27 °C, respectively.
The future weather file causes the highest maximum ADs for TED (14.0 kWh/m^2 year), cooling (13.9 kWh/m^2 year) and fan power (5.1 kWh/m^2 year). The maximum AD for cooling is similar for both the DRY weather file and the historic weather files. The maximum AD for these are 5.2 kWh/m^2 year.
Considering the maximum ADs for the excessive temperatures, it is evident that these are caused by the future weather files as these are the warmest ones.

System dimensioning
In the study of system dimensioning, similar results were obtained in terms of dimensional power. SOM2 causes higher dimensional cooling power and lower dimensional heating power when using an acceptable deviation of 3 %. These deviations are mainly present for the cooling power and only minor for the heating power as the MADs are 5.7 kWh/m^2 year and 0.7 kWh/m^2 year, respectively.
Similarly to the results for the energy performance, the differences between the models are smaller when having the same yearly mean occupants present.

Influence of mean and standard deviation of occupants present
The variation of the yearly mean occupants present is affecting the cooling and heating demand for both occupancy models. Regarding the dimensional power, the yearly mean occupants present is primarily affecting the cooling power. The dimensional power for the heating system is almost not affected by this variation.
Varying the daily standard deviation of occupants present are not affecting the cooling and heating demand nor the dimensional power of these.

Sensitivity analysis
The most sensitive parameters for the TED and excessive temperatures combined are cooling power, mechanical ventilation and weather files. Generally, the sensitivity analyses shows that the sensitivity of the inputs for the two occupancy models are rather similar throughout the performance indicators. The mean of the IHL ranks at the 4th most important parameters in terms of TED, which emphasize the importance of the occupants.

The sensitivity analysis for the dimensional cooling power, heating power and operative temperature shows that the weather file is ranked as 3, 1 and 4, respectively. The high ranking is mainly caused by the future weather files as these have higher mean temperatures than the other weather files. The mean of the IHL ranks between 6 and 2 for the dimensional parameters.

Weather impact
The future weather files used in the simulations causes both the cooling demand and cooling power to be higher and opposite for heating. This is because the future weather files are warmer than the historic and DRY.

Conclusion 8

The thesis and its provided investigations in form of stochastic simulations have been based on the following problem definition:

> *How does the uncertainties from the variability associated with occupants and weather influence building robustness and building design when performing stochastic building performance simulations?*

The problem definition has been supported by the following elaborative research questions:

- *How does the variability associated with occupants and weather influence building performance?*
- *In terms of robustness and building performance, what results does inclusion of multiple weather files provide compared to using the Danish Design Reference Year weather file?*
- *How does static occupancy profiles affect building performance and system dimensioning compared to dynamic stochastically generated profiles?*
- *How does inclusion of multiple weather files and dynamic occupancy modelling affect the ranking of the most sensitive inputs?*

To answer these questions, stochastic simulations have been carried out with different weather files and various stochastically generated occupancy profile models.

Study of influence from weather files
With stochastic simulations for the whole building in Be15, the results showed that inclusion of multiple weather files results in varying total energy demand. From the results it was evident that the outdoor temperature during the heating season (October up to and including April) is decisive for the difference.

Considering the accuracy of the DRY weather file, the total energy demand for the groups of data were compared to the energy frame BR 2015. With the DRY weather file, 8.2 % of the simulations complied, while the historic overall complied with 8.7 % of the building designs. It is therefore concluded that the DRY weather file is representing the historic weather files for groups of data.

With a sensitivity analysis of the input parameters' influence on the total energy demand, the ranks of input parameters are almost consistent with the different weather files. The most sensitive parameters are the window-to-facade ratio, air flow from mechanical ventilation and the U-value of the windows, respectively. This also applies when combining the robustness index and total energy demand, though the U-value has increased rank over mechanical ventilation.
The ranking of the inputs are overall more or less consistent with the different weather files. The DRY weather file is therefore representing the rankings from the other weather files.

Results shows that design solutions with low total energy demand are correlated with having high robustness towards weather. To achieve a high robustness towards weather, the U-value of the windows, mechanical ventilation and window-to-facade ratio should be in the lower end of the selected ranges. This also applies for the total energy demand. Opposite, the g-value, specific fan power and internal heat load shows tendencies towards the high end of the selected ranges, when evaluating the robustness index.

The studied design tendencies are based on histograms for inputs when filtering the 10 % best performing design solutions. For total energy demand, more or less the same tendencies are observed for all of the included weather files. Exceptions are weather files with higher direct solar radiation and more sunshine hours where the tendencies differs for the specific fan power and the infiltration.
For robustness the tendencies for specific fan power and infiltration deviates by being opposite and divergent, respectively. While results for total energy demand indicates a tendency of low specific fan power, the tendencies for the robustness index indicates a high specific fan power. Regarding infiltration, it is preferable to be in the lower end of the selected range when considering the total energy demand while it is more even for the robustness index.

By sensitivity analysis on the results from BSim it is shown that the weather file is ranked 3, 1 and 4 for dimensional cooling power, heating power and operative temperature, respectively. The high rank is caused by the future weather files, which have higher mean temperatures. For the building performance, the weather file is ranked 3 for total energy demand combined with exceeding temperatures. This means that the variability in weather has great impact on the uncertainty of the results.

When filtering the dimensional heating power based on the weather files, it is evident that the future weather files causes reduced required heating power. Furthermore it is shown that DRY is positioned between the warmest (1989) and coldest (1985) year of the historic weather files, and close to year 1978, which from the results in Be15 showed to produce similar results as DRY.

Dynamic and static occupancy modelling
8192 simulations were conducted in total with four occupancy profile models. In terms of energy performance, the typical static occupancy profile used in the commercial sector induces in average 2.7 kWh/m^2 year or 6 % higher total energy demand than the stochastic occupancy profile. The maximum observed difference due to variation in building design is 14 kWh/m^2 year or 20 %.
The results showed a 4.7 kWh/m^2 year or 37 % increase in cooling demand and a 3.2 kWh/m^2 year or 30 % decrease in heating demand for the static occupancy profile. The maximum obtained difference is 13.9 kWh/m^2 year or 68 % increase and 5.2 kWh/m^2 year or 66 % decrease for the same performance indicators, respectively.
It is noteworthy that the difference is mainly caused by the modelled breaks in the stochastic occupancy profile models, reducing the mean of the occupant load for the dynamic occupancy models. The mean of the dynamic occupancy profiles are a factor 1.33 lower due to the abovementioned breaks.
The differences in building performance are negligible when comparing dynamic and static occupancy profiles with the same yearly mean occupants present.

As a consequence of using dynamic occupancy modelling, the capacity of the cooling system can be decreased for design criteria of acceptable hourly deviations of 1, 3 and 5 % of the work time. The reduction of dimensional cooling power is varying for each building design and is in average 20 % or 6.5 W/m^2. For the fan power, a reduction of the dimensional power is shown for 3 and 5 % by 10 % or 1.3 W/m^2 in average. These decrease of required system sizes are due to the reduction of occupants present caused by modelled breaks.

The comparison of occupancy profiles with the same yearly mean occupants present yields that the only noticeable differences are for the cooling power and the dimensional CO_2-level. This means that variation from day to day has an impact on these. The mean absolute percentage deviation is 3 % for the dimensional cooling power and 2 % for the dimensional CO_2-level. These results are averaged for acceptable deviations from 1,3 and 5 % of the design criteria.

From the study it is evident that a variation of the mean of occupants present during a year has impact on the total cooling and heating demand. In terms of system dimensioning with an acceptable deviation of 3 %, cooling power is affected by this variation while the heating power is not. Varying the number of occupants present per day does not have any influence on neither energy performance or system dimensioning for the design solutions evaluated.

Discussion and Future Work 9

This chapter presents a discussion of the results and limitations of the current study. Furthermore, directions for future work are outlined based on the acquired knowledge.

In this thesis, several weather files and occupancy models have been studied in terms of their influence on building robustness and building design. With the conducted simulations, a large amount of knowledge has been acquired in terms of implementation of the occupancy and weather in the simulation process and the influence of these on the robustness and building design.

Method evaluation

The method implied for running simulations based on monthly calculations is fast for handling multiple weather files with a factorial sampling, since the simulation time is short. For the sub-hourly simulations the required simulation time on an average PC is a factor 30 higher for the same amount of simulations (512). It is learned that the methods provided in this thesis allows comparison of weather files in Be15, but not in BSim. In order to compare weather files in BSim, it is suggested to perform multiple stochastic simulations as a factorial experiment for DRY, historic and future weather files. The focus should be on multiple factorial experiment with a low amount of building designs, to keep the overall simulation time low. This will permit comparison between DRY, the historic and the future weather files by the same method for Be15, which yielded to be efficient when applying the robustness index for a design situation.
By including future weather files with the abovementioned method, the influence of the different emission scenarios can be studied. With this, a recommendation of the building design could be altered depending on how the climate changes will develop in the future.

The study with BSim has been performed on a selected room in the office building which means that some results may have been different if they were based on the whole building. This might be the case for the observed deviation between the static and dynamic occupancy models. During the time where the occupants are absent from the room, most of them will most likely be present other places in the building. This means that e.g the cooling energy is consumed in another zone than the one modelled.

Influence of weather files

A new version of DRY could include higher mean temperatures to prepare the building designer for warmer climates, depending on the life expectancy of building envelope and systems. Another option is to make a DRY file for future scenarios to prepare likely climate changes. To force the inclusion of these weather files and therefore a small robustness check, it is requested to investigate the need of an energy requirement for each weather file. This will ensure building robustness towards future climate and might yield different design strategies that might guide the innovation within the building industry.

In this thesis, the included weather files are either historic data or generated future data for Denmark. The results are therefore reflecting this and it could be interesting to broaden the knowledge of weather's influence on building robustness and building design with weather data from other climates.

A valuable discovery from the monthly quasi-steady simulations is that low total energy demand leads to high robustness towards weather changes. This means that designing based on DRY alone is well representing high robustness, and that DRY therefore is sufficient to use. Before adapting to this conclusion it is important to verify if the same correlation is revealed by a dynamic sub-hourly calculation method. Furthermore it can have interest to test the design tendencies for DRY compared to future weather files.

Some design tendencies when including multiple weather files might be different when using a sub-hourly dynamic building simulation tool instead of the monthly quasi steady based tool.

The DRY used in this thesis is not the current DRY to use for BPS in Denmark. It would be interesting to examine if similar results can be proved for the current DRY weather file.

Influence of dynamic occupancy modelling

The occupancy behaviour modelling in this thesis has been delimited to the presence of occupants and their equipment usage, hence the occupancy profiles. This has given valuable results but the influence of their interaction with a building needs to be further investigated. It is suggested that more advanced occupancy behaviour should be studied with similar focus on building robustness and building design. More advanced occupancy behaviour could be inclusion of the occupant's actions on control of window, artificial lighting, thermal environment, shading control etc. In some of the literature, models of the occupant's actions are included but their realism not yet verified.

The focus of the study concerning occupancy presence was to include a dynamic occupancy model and to compare it with a static model as used in the commercial sector. The results for the energy performance and system dimensioning showed that there are no need for daily variations within the occupancy profiles. However the results showed that the reduction of occupancy presence due to breaks in the dynamic occupancy modelling influenced both the energy performance and system dimensioning. Reducing the mean of the occupancy presence by a factor (1.33 in our case, based on the literature), might be a solution to implement the dynamic behaviour of occupancy presence.
This reduction factor means that the size of cooling systems and ventilation system can be reduced. Note that the factor depends on the assumptions for the dynamic occupancy modelling. If a building owner has logged data available for occupancy presence of his own building, the real variation of occupancy could be used to generate a reduction factor. This would reduce the required cooling and ventilation capacity, thus save resources for the operation and acquisition.

In an investigation of occupancy profile detail level, hourly variations are evidentially leading to different results compared to dynamic profiles with only daily or weekly variations. The latter two yields similar results in terms of cooling and heating demand, excessive temperatures and fan power consumption for mechanical ventilation. By varying the occupancy profiles on an hourly basis, a higher cooling demand and fan power demand is a consequence of higher internal heat peak loads. On the other hand, less heating is required.

Since the mean of the occupancy presence has an impact on multiple outputs by the sensitivity analysis, the next step should be to check the robustness of building design with varying occupants as a factorial experiment. This could reflect a situation where a building owner moves into a building along with an occupancy load below the dimensional one and occupies it until it matches and exceeds it.

The method to create stochastic occupancy profiles in this thesis is based on measurements in an office building in Canada. The working hours of this model has been locked to 08:00 until 18:00, and this is not the normal amount of working hours for offices in Denmark. For offices in Denmark, the normal amount of working hours is 35 hours per week (5 hours per day), [Det Nationale Forskningscenter for Velfærd, 2009, Table 2.13, page 50]. It would therefore be interesting to develop a dynamic occupancy model which is based on Danish or Scandinavian office buildings to improve the knowledge.

Stochastic modelling in BPS
Due to the complexity of the sub-hourly dynamic calculations, there is a higher risk of running simulations providing results with errors than with the monthly quasi-steady state calculation approach. It is experienced that these errors occur during model setup, processing the sampled values to readable values in the BPS, using third party software to automate the stochastic modelling process, and as a reason of the complexity of the dynamic occupancy models. These errors are faster to discover when using Be15, as the simulation process is shorter and the amount of data is smaller for each simulation, compared to data produced with BSim.

The implementation of the dynamic occupancy model in a deterministic BPS is fairly simple. With just a number of occupants and details regarding their habits in terms of arrival, breaks and departure, the spreadsheet will generate values that are ready to be inserted in the BSim model file (.disxml), given that the required id's in the code are known. The benefits of this should be to generate an occupancy model that fits to logged data for a building or room.

Reflectance on the simulation process has given thoughts about the simulation strategy. It is recommended to run a fewer number of simulations to perform a fault localisation procedure before running the desired number of simulations required for the study. This would contribute to a reduction of time spend before detecting errors.
In general the implementation of stochastic modelling in BPS can be improved. By including the sample generating within the BPS tool will reduce the time spend on manual tasks of processing the sample file. The BPS tool OpenStudio 2.0.0 may do this and due to the complexity of stochastic modelling in BPS, it requires great knowledge and experience to detect potential errors. An error test that suggest possible errors due to model setup will help the users to focus on discovering results rather then fault detection.

Future Work
Based on the results provided in this thesis, the following research tasks will help clarify the influence of occupants and weather on robustness and building design:

- Perform factorial experiment of mean occupancy presence to study the robustness for building performance and dimensional values.
- Measure the occupancy presence of an open landscape office and compare it to the dimensional occupancy load to determine a reduction coefficient for the observation.
- Implement occupancy behaviour that enable users to interact with the building they occupy.
- Investigate the opportunities, benefits and drawbacks of including statistics from future weather files in a DRY weather file.
- Conclude if the current DRY is representing its historic weather files and in general analyse the building design and robustness when varying them (for the same building designs as presented in this thesis).

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Appendix

Methodology A

In this appendix, the method to answer the problem definition and the underlying elaborative questions is thoroughly presented. First, the technical framework of the methodology is presented, and then the process is described.

A.1 Framework of the methodology

Additionally to the method presented in figure 4.4 on page 19 and above, a flowchart of the simulation process is presented in figure A.1. This figure presents an overview of the software that are used in the method and a framework of the process.

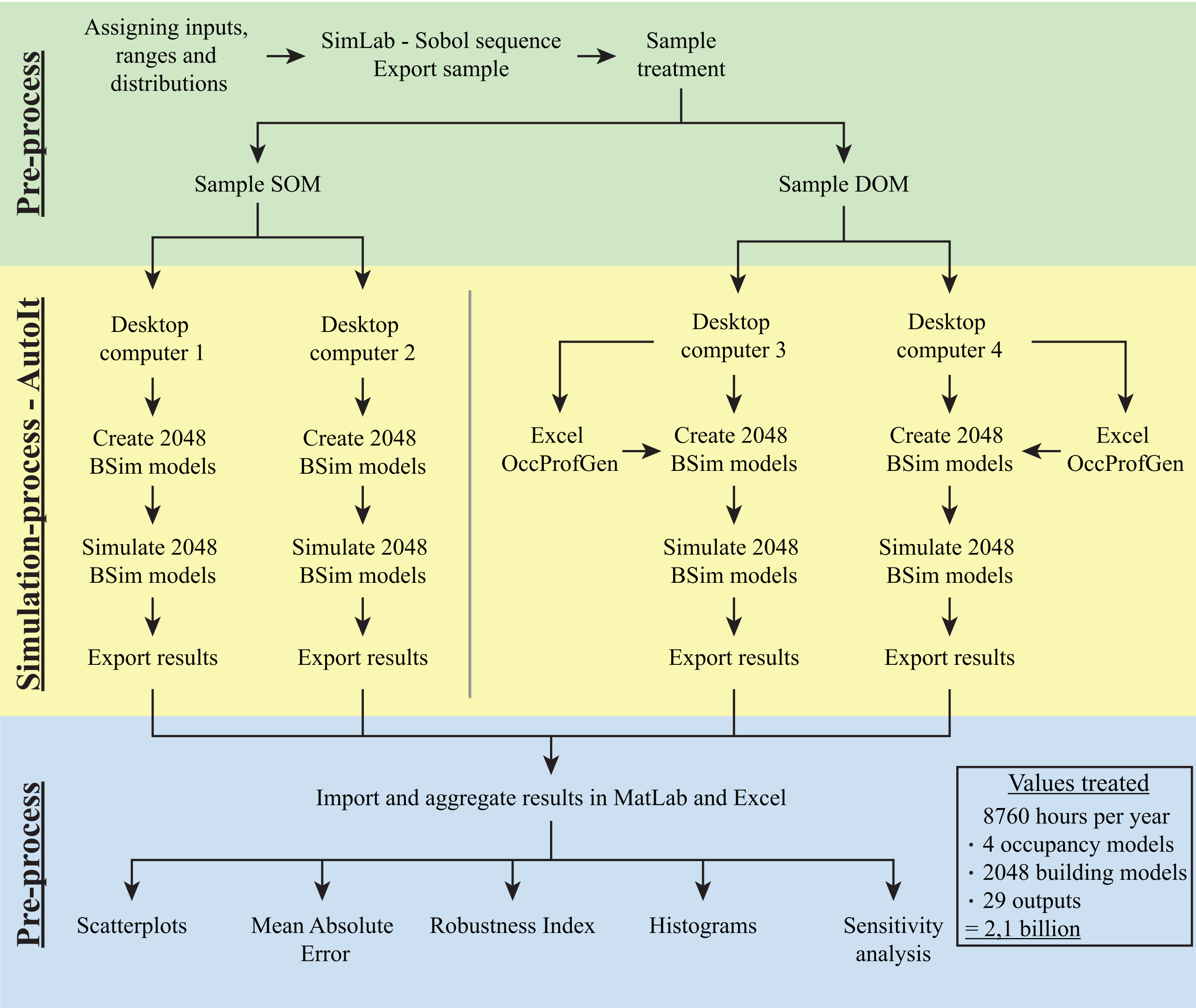


Figure A.1. Elaborative flowchart of the method used for BSim showing an overview of the software used and framework of the process. SOM and DOM indicates the sample for static and dynamic occupancy model. ExcelProfGen refers to an Excel spreadsheet, developed to generate stochastic occupancy profiles, see section 7.3.

The method includes many steps such as sample treatment where the sample file are tweaked in Excel for correct input to BSim. An example of this is the weather files, that are sampled from 1 to 13, and afterwards changed to DRY and 1975 – 1989.
Four desktop computers are used for faster simulations, where each computer has simulates 2048 BSim models.
In the pre-process, MatLab is the main tool aggregate data and to create graphs and analyses.

A.2 Pre-process

The pre-process consists of four main parts which leads to an input matrix for the simulation-process to use.

A.2.1 Input parameters

There is a significant amount of input parameters which may be included to explore the global design space. Inclusion, hence exploration of all input parameters is an immense and highly time-consuming process and is therefore reduced. It will therefore be chosen a selection of parameters to be varied based on subjective sensitivity analysis, [Hamby, 1994].

A.2.2 Distributions and ranges

The selected input parameters are varied with appropriate distributions and ranges. There is a vast amount of different probability distributions to choose from but for building simulations, four types are typically used, presented in figure A.2 and briefly described below.

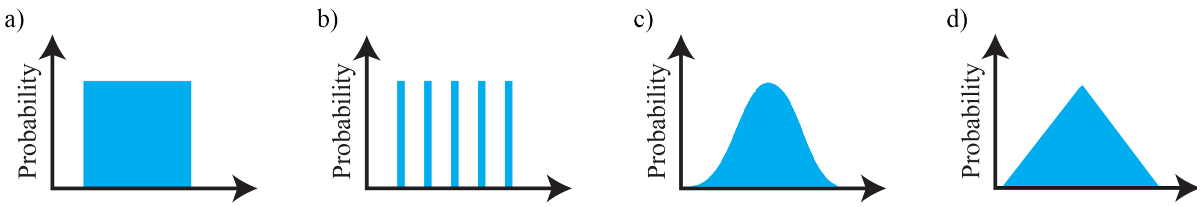


Figure A.2. Examples of probability distribution types. a) uniform, b) discrete, c) normal, d) triangular.

- Uniform
  - A distribution with constant probability for a infinite (in theory) number of values in a selected range.
- Discrete
  - A distribution with finite number of values to be observed.
- Normal
  - A probability distribution which is symmetric around its mean and with decreasing probability to each of its tails.
- Triangular
  - A continuous probability distribution defined by a range and a peak value.

These probability distribution types may vary in appearance. For example, a discrete distribution may have a normal or triangular shape, or a triangular shape may be skewed in any direction.

A.2.3 Sampling techniques

To generate the values for the inputs with their respective distributions, different sampling techniques may be used. To represent the different domains as best as possible, appropriate sampling techniques needs to be chosen. Figure A.3 shows two different sampling techniques, random and low-discrepancy.

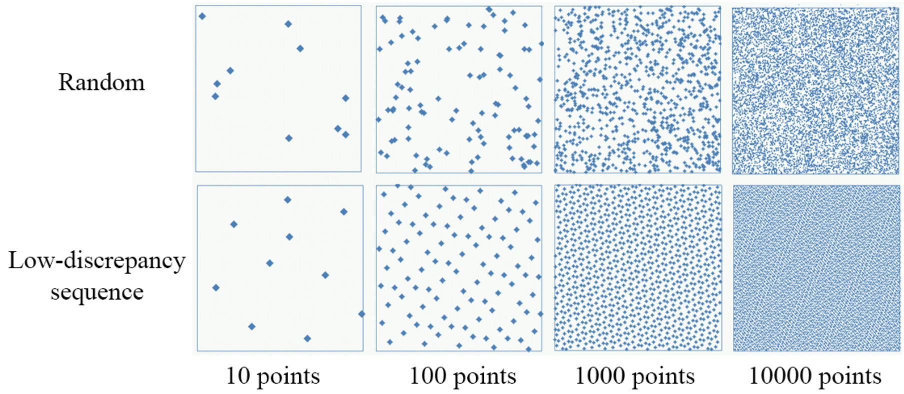


Figure A.3. Comparison of random and low-discrepancy sampling technique, ed., [Wikipedia, 2016].

A random sampling technique will randomly choose locations in the domain without any consideration of covering the domain uniformly. The low-discrepancy sampling technique, also known as quasi-random sampling, divides the domain into squared subregions. The technique seeks to fill these subregions uniformly by increasing the distance between the points in all dimensions with roughly the same amount of points in each subregion. Hence the low-discrepancy sampling technique is faster to converge than random sampling since the domain is covered faster.

From figure A.3 it may be observed that the low-discrepancy sequence covers the domain more uniformly than the random sampling and lumps and holes are minimized.
The samples of the input parameters are generated with SimLab 2.2.1, using Sobol sequence, also known as LP_τ, which is a quasi-random low-discrepancy sequence. Another advantage of using this sampling method is that the size of the sample may be increased by simply adding new unique values together with the existing ones. This relates to the quasi-random term where new points are biased based on the old ones. [Ratto et al., 2008].

Another sampling method is the factorial sampling method where all possible combinations are sampled. According to MacDonald [2002], this sampling method are suitable for BPS because of its ability to assess the uncertainty of the model outputs and the robustness of the method. With this method, the only difference between to models may be one parameter only, for example the weather files applied in this thesis.

A.3 Simulation-process

The input matrix created in the pre-process is used to create the Be15 and BSim models.
Afterwards the models are simulated in Be15/BSim and the results are aggregated in to an output matrix for post-processing.

The whole simulation-process is automated in which creation of Be15 and BSim models, simulations and export of data is performed with a script in the automation software AutoIt, [AutoIt Consulting Ltd, 2015].

A.4 Post-process

To be able to answer the problem definition in this thesis, the post-process of the method is essential regarding methods for data treatment treatment and visualisation.

A.4.1 Sensitivity analysis

Sensitivity analysis is a process where the influence of the inputs on the outputs may be identified with various methods. According to [Hamby, 1994], sensitivity analysis may be used for number of different reasons such as identifying which parameters that are insignificant and therefore be excluded. Furthermore, identifying which parameters that are affecting the output variability the most and identifying correlations between the inputs and the outputs to determine consequences of changing a parameter.

Many popular methods of performing sensitivity analysis exists and among these are the Morris method, the Pearson's r correlation, standardized regression coefficients and the Sobol method.

The Pearson's r correlation is a simple correlation measure that returns a number for the linear correlation between two variable, for example an input and an output.
Another method is the novel sensitivity analysis method, TOM regionalized sensitivity analysis developed by Torben Østergård. The method is denoted TOM (Torben Østergård Multiple) and is based on Komogorov-Smirnov test of two distributions. The method may rank the influence of the inputs, opposite to other sensitivity analysis methods, on multiple outputs. This is essential when considering multiple outputs at the same time. The TOM sensitivity analysis method includes a "dummy" input, which is an input that does not affect the output. Input parameters which have lower rank than this input may be considered to be non-influential. [Østergård et al., 2017b]

A.4.2 Parallel coordinate plot and Monte Carlo filtering

Parallel coordinate plot (PCP) is a powerful visualisation technique when it comes to high-dimensional data such as data from BPSs. The tool may visualise inputs and outputs of the BPSs in a structured matter with the opportunity of observing correlations between parameters and finding optimal design solutions. An example of such a plot is presented in figure A.4.

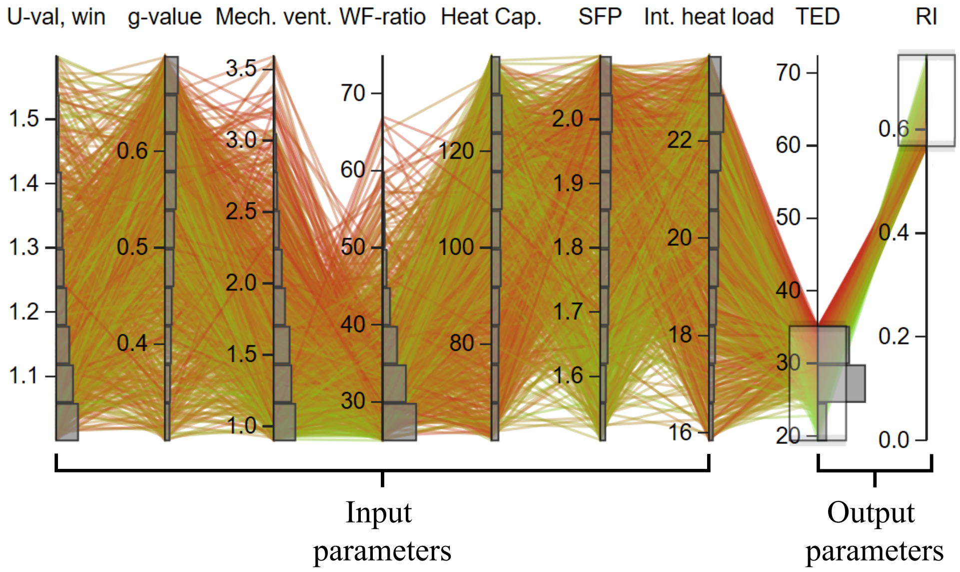


Figure A.4. Parallel coordinate plot visualisation technique of design solutions with corresponding values for input and output parameters. Each of the coloured lines represents an unique design solution with intersections on the vertical axes representing a solution's corresponding values for input and output parameters. Created with the interactive PCP from MOE A/S [2016].

This visualisation technique allows a designer to identify both ranges and distinct values of the variables which leads to the best design solutions.
Another useful feature of the PCP is that Monte Carlo filtering may be conducted for the parameters (transparent boxes on the output parameters in figure A.4). Monte Carlo filtering is a method to determine "acceptable" and "not acceptable" results according to one or more criteria. Both of the output parameters are filtered in the PCP above and solutions fulfilling the criteria are left in the plot. With the filtering, histograms of the different parameters may give valuable information in terms of preferable spans or differences between simulations sets, for example different weather files.

A.4.3 Robustness index

To analyse how the weather affects the output parameters for a solution, e.g. how robust a solution is, a robustness index (RI) is required. In this thesis, the RI is implemented as a quantitative measure of the robustness and is used in the PCP as an output when designing buildings. This makes it possible to include the robustness as a design evaluation when designing buildings in the early design phase.

For each solution, multiple instances with different weather files are composed. The aggregated results of these instances determines the robustness of a solution.

Chinazzo et al. [2015a] introduced a robustness index which includes two expressions. First a comparison number (ω) is calculated for each solution (S_i) based on its instances and for the base case (BC) with the following equation:

$$\omega = 0{,}3 \cdot IQR + 0{,}7 \cdot \sigma \tag{A.1}$$

The comparison numbers is calculated by a weighted sum of the interquartile range (IQR) and the standard deviation (σ) of the data from the instances. Then the RI is calculated based on the solutions and a base case:

$$RI = 1 - \frac{\omega_{S_i}}{\omega_{BC}} \tag{A.2}$$

With this RI, different design solutions may be compared in terms of their robustness towards weather. Based on these expressions, a positive RI means that the design solution is less robust than the base case, and vice versa with a negative RI.
To grant a quantitative range for the RI which is persistent for any simulation, it is advised to choose the least robust solution as the base case. This ensures the robustness index to be a number between 0 and 1, where values close to zero indicates low robustness and values close to 1 indicates high robustness. Note that the RI is relative, which means that the robustness itself can be acceptable even though it is the lowest in a set of data. For example, a solution may meet the energy use requirement even with low robustness, and vice versa.

Design Conditions and Criteria B

This chapter presents the design conditions and criteria for the project.

B.1 Internal loads

The internal loads in a building includes occupants, equipment and lighting. The distribution between these vary from building to building and will therefore be described in the following. Since this thesis focuses on stochastic modelling, which includes parametric variations, the following data are specified for the baseline model of the building.

The building is designed for a total of 62 persons and their working hours are from 08:00 until 18:00. It is assumed that the occupants in the office building only will work during the weekdays. Accumulated this results in a total of approximately 2600 working hours per year.
The occupants in the building are assumed to have a sedentary activity, which corresponds to a metabolic rate of 1.2 met and a heat release of approximately 100 W/person, [DS/EN 15251, 2007].

In terms of equipment in the building, several consideration are made. There are several different types of rooms in the building, hence the amount of equipment vary. It is assumed that four of the nine room types have equipment. These rooms and their equipment load are as following:

- Open office landscapes: 150 W/person.
- Cell offices: 150 W/person.
- Conference rooms: 50 W/person.
- Reception: 150 W/person.

150 W/person corresponds to approximately one desktop computer with one or two monitors, depending on the performance of the computer. In the conference rooms it is assumed that the occupants uses laptops, corresponding to approximately 50 W/person.
Beside this, a part of the total equipment load is always active during the working hours, illustrating standby-modes, printers and so on. Outside of the working hours, all equipment are assumed turned off.

The lighting system in the building is daylight controlled meaning that the system always corrects after the available daylight in the rooms. This is individually controlled in each room.
Since Be15 and BSim adjusts this differently, the complexity of these controls are different in the two BPS software.

B.2 Energy demand

The evaluation of the energy demand is performed in accordance to the classification from Energistyrelsen [2017]. This classification includes energy use to heating, cooling, lighting, ventilation and domestic hot water per square meter heated floor area per year. It is chosen to evaluate the solutions according to “energy frame BR 2015”, which is calculated with the following expression:

$$\text{Energy frame BR 2015} = 41.0\,\text{kWh/year} + \frac{1000\,\text{kWh/m}^2}{A} \tag{B.1}$$

where

A	is the heated floor area [m^2]

Since the heated floor area of the building is $613\,m^2$, the energy frame BR 2015 is $42.6\,kWh/m^2$ per year.

B.3 Atmospheric indoor climate

In terms of atmospheric indoor climate there are some requirements regarding ventilation rates and CO_2-concentration that must be satisfied.

When considering ICC II, the required ventilation rate due to emissions from occupants is $7.0\,l/s$ per person, [DS/EN 15251, 2007, table B.1]. Beside emissions from occupants, the building itself is also polluting which requires an additional ventilation rate of $0.7\,l/s/m^2$ floor area with the assumption of a low polluting building [DS/EN 15251, 2007, page 33].

Regarding CO_2-concentrations, DS/EN 15251 [2007] recommends that the concentrations should not exceed 500 PPM above outdoors when considering ICC II. Accordingly, Energistyrelsen [2017] requires that the CO_2-concentration for longer periods must not exceed $0.1\,\%$ CO_2.

Input and Output Parameters C

In this appendix, details regarding the selected range of the input parameters are presented. Furthermore, modelling considerations are discussed and presented. At last, considerations related to the output parameters are presented.

Considerations related to the design input parameters for Be15 are not presented. As specified in table 6.1 on page 25, these are collected from Østergård et al. [2015]. T. Østergård has valuable experience from the commercial sector and it has been chosen to follow these ranges. Regarding the uncertain parameters, considerations are described for both BPS softwares.

C.1 Design parameters

C.1.1 Cooling power

BSim

Cooling power is included as discrete values for the sampling with a probability distribution as presented in figure C.1. The figure shows that the probability of not having any cooling power is equal to the combined probability of having a system with either 20, 40, 60, 80 or 100 W/m^2 cooling power. The reason for this sampling method is that it is interesting to investigate solutions with different cooling power as well as solutions without. [1]

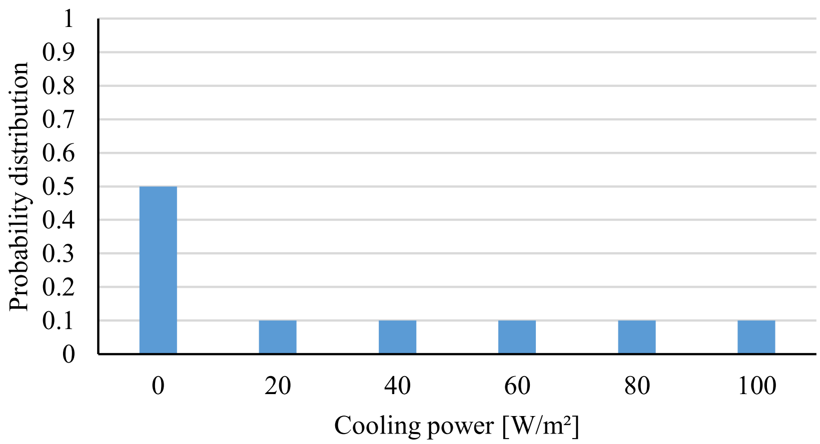


Figure C.1. The discrete distribution of the cooling power used for the simulations.

C.1.2 External wall

BSim

In table 7.1, it was presented that the simulations will vary between five different exterior wall types and between two different construction types. For each of the five different U-values, there is modelled a light and a heavy construction of the wall. This is done to examine if the thermal mass of the exterior wall has influence on the robustness of the model. The light wall are constructed by a wooden skeleton and the heavy is constructed by bricks and or light concrete according to ISOVER [2017b] and ISOVER [2017a] respectively. Both construction types includes different thickness of insulation.

[1] FiXme Note: SHM:fix discrete sampling

Wall	U-value [W/m^2 K]	t_L [m]	t_H [m]
1	0.12	0.315	0.300
2	0.14	0.290	0.250
3	0.16	0.240	0.220
4	0.18	0.215	0.190
5	0.20	0.190	0.150

Table C.1. Specifications for the walls used in the simulations. t_L and t_H are the thickness of the wall when a light or heavy construction is used, respectively.

C.1.3 Lighting

BSim

Collected from Østergård et al. [2015].

C.1.4 Mechanical ventilation

Be15

As mentioned in chapter 6 each of the rooms in the building need different ventilation rates. The ventilation rates for the different rooms are presented in table C.2.

Room type	Occupancy density [m^2/person]	Floor area [m^2]	Ventilation [l/s m^2]	Air flow [l/s]
Single offices	10.0	33	1.4	442
Landscape offices	7.5	260	1.7	32
Conference rooms	2.0	98	4.2	205
Canteen	1.5	64	5.6	71
Toilets	-	36	2.0	71
Hallways, lounge, staircases	-	124	0.7	87
Total		613		908

Table C.2. Mechanical ventilation rates for the room types of the building for the base case. Floor areas are given as gross area.

The average ventilation for the building is 1.48 l/s m^2 for the base case. By multiplying a factor, f_m, with the amount of ventilation for each zone, the total ventilation for the building can be adjusted in a range from 0.9 to 3.6. Hence, the f_m factor are varied between 0.39 and 1.56 to obtain the desired range. This factor is sampled and multiplied with the ventilation for each zone.

BSim

In most offices the preferred mechanical ventilation system is a VAV system. This grants the possibilities to change the air flow according to level of occupancy and therefore ensure sufficient ventilation. A VAV-factor of 4 is used as constant for the simulations while the basic air change (or the minimum air flow) is varied from 0.5 l/s m^2 to 2.0 l/s m^2.

C.1.5 Overhang

BSim
The overhang above the windows are sampled as an angle from the center of the windows, though the input to BSim is the depth. The reason of this is because the depth is relative compared to the window height, whereas overhang angle is a relation between the depth of the overhang and the window height. For example, a window with a height of 0.5 m with an overhang of 0.3 m will be relatively well covered. On the other hand, a window with a height of 2 m with the same overhang will be less covered. To take this into account the depth is calculated based on the overhang angle and the window height for each model.

C.1.6 Solar shading

BSim
The solar shading for the windows are controlled by the illuminance on the facades. There are no shading attached to the windows facing north, and for simplification, the set-point for the required illuminance to activate and deactivate the shading is the same for the south and east facing windows.

An idea was to sample the solar shading with discrete uniform values from 0-10-20-30-40-50 % active hours within working hours. This could grant confusion for the decision-makers as these ratios might not be consistent when changing weather files. Therefore it was decided to include continuous uniform distributed illuminance levels for activating the shading and a corresponding illuminance level of 20 kLux lower than the activation to deactivate the shading. A span from 25 kLux to 100 kLux is chosen. This span yields a maximum shading usage of 40 % for east and 49 % for south. The shading usage is used when evaluating how often shading is activated in each model, and the parameter can be displayed in the PCP.

C.1.7 Windows

BSim
The seven different windows types to be altered have different properties. These windows have different U-value, g-values and light transmittance, LT_g, and are seven windows that are on the market to date (1st of March 2017).
The properties of the windows are presented in table C.3.

Window	U-value [W/m^2 K]	g-value [–]	LT_g [–]
1	0.8	0.25	0.46
2	0.8	0.32	0.60
3	0.8	0.37	0.66
4	1.1	0.43	0.71
5	0.8	0.50	0.71
6	0.8	0.57	0.73
7	1.0	0.63	0.80

Table C.3. Properties of the windows used for the simulations. All windows has a frame with a thickness of 0.05 m and U-value of 1.3 W/m^2 K, [Energimærkningsordningen, 2017].

C.1.8 Window-to-facade ratio

BSim

To vary the window to facade ratio, the window height is altered. When the window to facade ratio increases, the windows are first expanded upwards until they are 10 cm below the ceiling. With further increase of window sizes, the windows are expanded downwards until a distance of 5 cm from the floor is achieved.
Applying limits to the window size as described above without altering the width, grants the window-to-facade ratio a range of $30 - 83.5\,\%$. The low end of the range corresponds to a window height of 0.44 m, while the high end results in a window height of 2.63 m.

C.2 Uncertain parameters

C.2.1 Cooling set-point

BSim

The cooling in the BSim model is constantly set to 25 °C during the working hours. The cooling system inactive outside of working hours.

C.2.2 Heating set-point

Be15 and BSim

For both Be15 and BSim it chosen to use a range of $21 - 24\,°\mathrm{C}$ for the heating set-point.
In BSim, this set-point is reduced to 18 °C outside of the working hours.

C.2.3 Internal heat loads

C.2.3.1 Occupants

Be15

The heat gain from occupant load is set to vary between $8 - 12\,\mathrm{W/m^2}$ with an uniform distribution. This corresponds to the range of the yearly average used for simulations of an open office landscape provided in chapter 7.

BSim

The number of occupants in the building and the occupancy profiles are varied with two parameters, the yearly mean load and the daily standard deviation. The yearly mean load is a percentage of how many occupants there are in the building in average per year. While 100 % corresponds to 17 persons, the low and high end of the range from table 7.1, 80 % and 120 %, corresponds to approximately 14 and 20 persons, respectively.
The standard deviation, given in percentage, describes the variation which may occur from day to day. Note that this is constant for each year.

C.2.3.2 Equipment

Be15

The heat contribution from the equipment is set to follow the heat release from the people load by a coefficient of 1,5 for the offices and the reception and 0,5 for the conference rooms. This represents the occupants having a desktop PC at the work desk and a laptop at the conference room. Furthermore, it is assumed that there are no equipment in the hallway, lounge, toilets, staircases and cafeteria. Thus the total equipment load from the building is $10.2\,\mathrm{W/m^2}$.

BSim
The equipment load in the room is divided into two parts. The first part correlates to the occupancy profiles since most of the equipment in the room is handled by the occupants. The second part is a base load which represent equipment that is not dependent on the occupant, for example printers or other equipment on stand-by.

C.2.4 Infiltration

The range selected for infiltration for both Be15 and BSim is in compliance with the three energy classes from Danish Building Regulations 2015, renovation class 1 (BR10), Energy frame BR 2015 and Energy frame Buildings 2020, [Energistyrelsen, 2017, section 7.2.1, 7.2.4].
The infiltration requirements from [Energistyrelsen, 2017] are at 50 Pa pressure test and are recalculated with the expressions from Aggerholm and Grau [2009, page 63].

The infiltration is modelled as a constant air flow.

C.2.5 Weather file

Be15
The weather files are sampled factorial, which means that the simulation models are identical in terms of building design for the simulation sets with different weather files. A total of 16 weather files are included in the study. The Danmark v2 DRY and the 15 weather files it is based on.

BSim
The weather files are implemented the same way as the other input parameters, with a discrete uniform distribution. This allows the weather files to be incorporated in the PCP and to be included in meta modelling. The weather files included in the BSim simulations are three of the historic weather files, DRY and three future weather scenarios for each of the years 2030, 2050 and 2070.
The three historic weather files are chosen to be the weather files with the highest mean temperature, lowest mean temperature and a year with nearly the same mean as the DRY file.
Further explanation of the weather files are presented in section 7.2.

C.3 Output parameters

C.3.1 Daylight

BSim
Calculations of daylight in the room are conducted in three reference points, one for each of the three parts of the room that is constructed in BSim. The reference points are located as presented in figure C.2, in the middle of each part of the room.

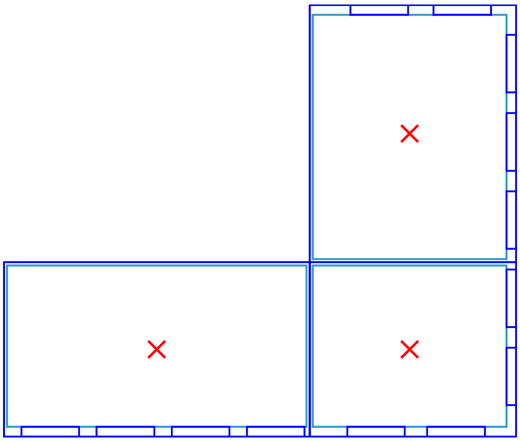


Figure C.2. Reference points, marked with red crosses, for daylight calculations in BSim.

Weather Files D

This appendix presents monthly mean outdoor temperatures of the used weather files along with description of the emissions scenarios for the future weather files. Furthermore, the method used for converting the weather files for Be15 and BSim is presented.

D.1 Outdoor temperatures for the weather files used in the Be15 simulations

Weather files	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
DRY	-0.5	-1.0	1.7	5.6	11.3	15.0	16.4	16.2	12.5	9.1	4.8	1.5
1975	4.6	0.9	2.5	5.3	11.1	14.4	17.5	18.9	14.7	8.7	4.2	3.4
1976	-0.4	-0.3	-0.5	5.5	10.9	15.0	17.8	17.0	12.1	8.9	4.9	-0.2
1977	-0.1	0.1	3.5	4.6	11.2	15.7	15.7	15.3	11.6	10.0	5.3	2.5
1978	1.0	-2.6	2.3	4.8	11.8	15.2	14.9	15.7	11.4	9.4	6.9	-1.1
1979	-3.3	-3.9	1.0	5.0	11.3	15.9	14.3	15.4	12.6	7.9	4.3	1.8
1980	-2.3	-1.7	0.3	5.9	10.2	15.3	16.6	15.6	13.4	8.1	3.9	2.3
1981	-1.1	0.4	2.8	6.0	13.0	14.5	16.3	16.2	13.9	8.0	4.7	-3.4
1982	-3.9	-1.3	3.5	6.7	11.3	15.0	18.3	17.5	14.0	10.6	6.4	2.7
1983	4.4	-0.8	3.6	6.6	11.1	14.8	18.1	17.7	13.5	9.2	3.6	1.0
1984	0.9	-0.1	0.6	6.4	11.4	13.7	15.5	16.8	11.4	10.7	6.0	2.1
1985	-5.8	-5.9	0.7	4.7	11.9	13.6	15.9	15.6	11.6	9.2	1.8	2.4
1986	-1.6	-6.2	0.9	4.1	11.6	14.8	16.2	14.5	10.0	8.6	6.7	1.9
1987	-6.7	-1.3	-2.4	5.9	9.2	15.1	15.8	14.2	11.9	9.4	5.1	2.4
1988	3.3	2.1	1.3	5.3	11.7	16.0	16.5	15.4	13.0	8.1	3.9	2.1
1989	3.6	4.5	5.5	6.9	12.2	15.2	15.9	16.8	11.7	9.8	4.2	2.3
Mean, historic	-0.5	-1.1	1.7	5.6	11.3	14.9	16.4	16.2	12.5	9.1	4.8	1.5

Table D.1. Overview of the mean outdoor air temperature for each month for the 15 historic weather files and the DRY file.

D.2 Weather files used in the BSim simulations

D.2.1 Future weather files

As a consequence of continuous greenhouse gas emissions, the global climate system becomes warmer. Based on models for climate changes, projected warming of the global surface have been developed. Figure D.1 presents this projected warming for the three abovementioned scenarios until the year of 2100.

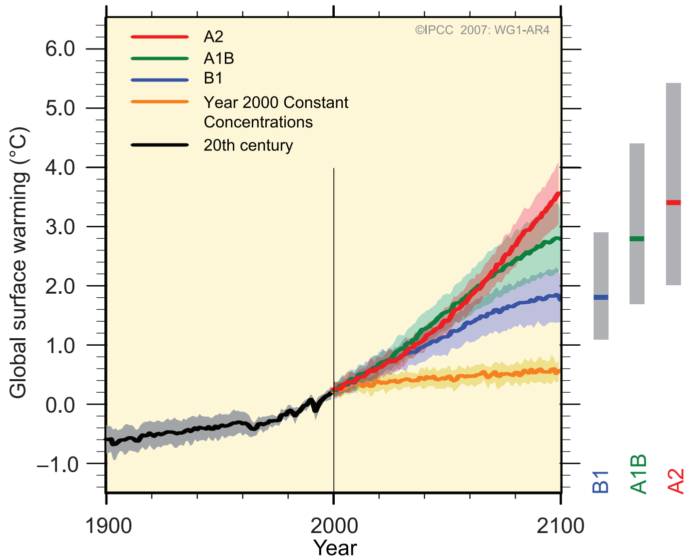


Figure D.1. Projected global surface warming for the three scenarios relative to 1980-1999. The solid lines in the graph presents the average global surface warming with a standard deviation range of ±1, indicated with shading. The grey bars with solid lines outside the graph, denotes the likely range and best estimate, respectively. Ed., [Solomon, S. et al., 2007].

An oversimplified illustration of the connections in the scenarios are presented in figure D.2. The figure illustrates four different scenario families and how these are oriented towards economic and environment, and regional and global development.

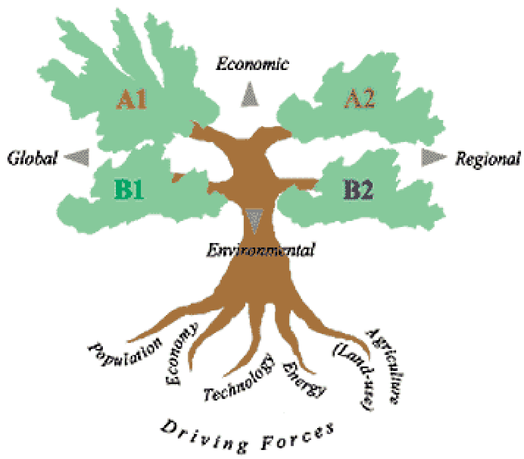


Figure D.2. Illustration of the four scenario families by the IPCC, their driving forces and the different orientations of development. [IPCC, 2017]

IPCC [2017] describes the three different scenarios as follow:

- **B1** - low emission case:
  A convergent world with emphasis on global solutions to social and environmental sustainability, economic and improved equity.
- **A1B** - medium emission case:
  A world with rapid growth in economics and efficient technologies. Increased social and cultural interactions, convergence among regions and more even income per capita. The A1B refers to a scenario with balanced technological emphasis across all energy sources.
- **A2** - high emission case:
  A very heterogeneous world with emphasis on self-reliance and increasing global population. The scenario includes regional economic development and fragmented and slow technological change.

D.2.2 Outdoor temperatures for the weather files used in the simulations

Weather file	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
DRY	-0.5	-1.0	1.7	5.6	11.3	15.0	16.4	16.2	12.5	9.1	4.8	1.5
1978	1.0	-2.6	2.3	4.8	11.8	15.2	14.9	15.7	11.4	9.4	6.9	-1.1
1985	-5.8	-5.9	0.7	4.7	11.9	13.6	15.9	15.6	11.6	9.2	1.8	2.4
1989	3.6	4.5	5.5	6.9	12.2	15.2	15.9	16.8	11.7	9.8	4.2	2.3
Mean, historic	-0.4	-1.4	2.8	5.5	12.0	14.6	15.6	16.1	11.6	9.5	4.3	1.2
2030B1	2.9	2.4	3.8	6.4	11.5	15.0	17.5	17.4	14.8	11.3	6.8	4.3
2030A1B	2.9	2.4	3.9	6.6	11.7	15.1	17.5	17.6	15.0	11.4	6.9	4.5
2030A2	2.8	2.2	3.8	6.4	11.6	15.1	17.4	17.5	14.9	11.3	6.9	4.4
2050B1	3.5	2.9	4.2	6.9	11.8	15.4	18.0	17.9	15.3	11.7	7.2	4.9
2050A1B	3.8	3.3	4.7	7.2	12.2	15.7	18.2	18.3	15.5	12.1	7.5	5.3
2050A2	3.4	3.1	4.4	7.1	12.1	15.7	17.9	18.2	15.6	12.0	7.5	5.0
2070B1	3.7	3.2	4.5	7.1	12.1	15.6	18.2	18.2	15.5	12.0	7.5	5.3
2070A1B	4.4	4.0	5.3	7.7	12.8	16.2	18.7	18.8	16.1	12.6	8.1	5.9
2070A2	4.3	3.9	5.2	7.9	12.8	16.3	18.6	19.0	16.4	12.8	8.2	5.8
Mean, future	3.5	3.0	4.4	7.0	12.1	15.6	18.0	18.1	15.4	11.9	7.4	5.0

Table D.2. Overview of the mean outdoor air temperature for each month for the 9 future weather files, the DRY file and the three selected historic weather files.

D.3 Conversion of weather files

The weather files for 1975 until 1989 are in a different format than what Be15 and BSim may read. It is therefore needed to convert these into format that may be read by the softwares. Figure D.3 presents the workflow used to convert the weather files and is afterwards described, step by step.

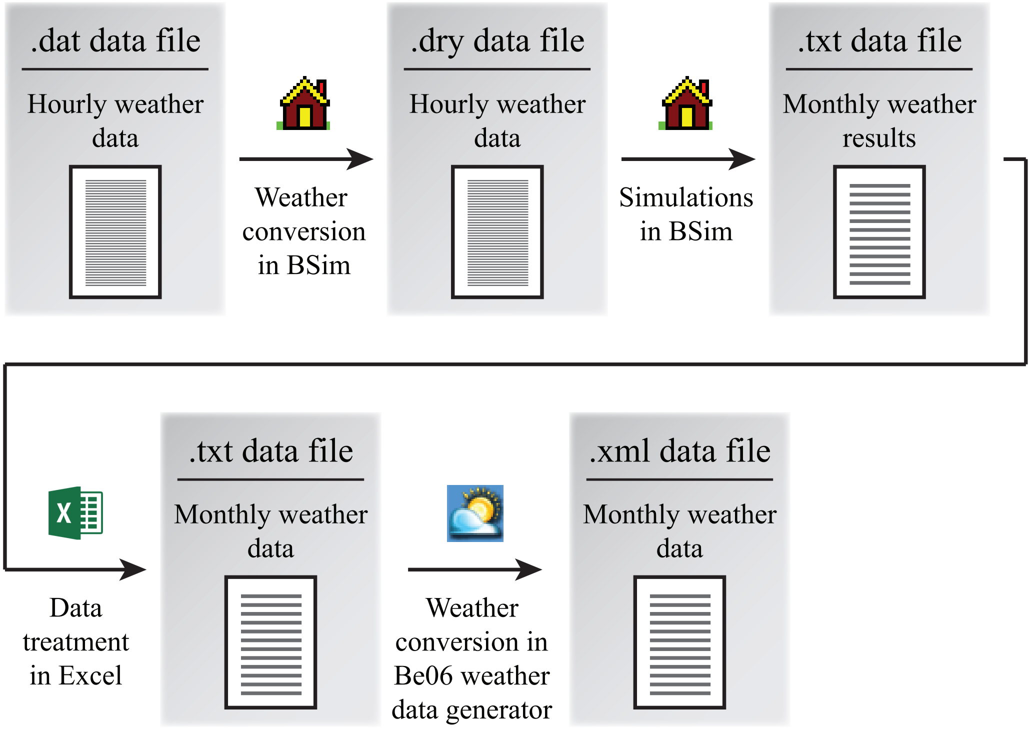


Figure D.3. Workflow of the weather file conversion process.

The acquired weather files are in a .dat data file format. These are imported into the weather data conversion function in BSim and then converted into .dry weather files. These .dry files includes hourly weather data and may be used in BSim.

For Be15 to be able reading the weather files, further conversion is needed. With a set of "pre-set" buildings created in BSim, simulations are carried out with each weather file. Afterwards, the results are extracted from BSim into a .txt data file. The extracted data in this step is monthly averaged climate data for outdoor temperature and various solar radiation parameters.

The data is then treated in an Excel spreadsheet, developed by Jørgen Rose at the Danish Building Research Institute. With this spreadsheet, the data gets treated and additional parameters are calculated and added to the existing data set. Shadowfactors based on specifications concerning overhang, horizon and window recess are calculated. The data is afterwards sorted and set up in the appropriate format for export to a .txt data file.

At last, the .txt data file is imported into Be06 weather data generator which converts the data file into an .xml file for Be15 to read as weather file.

It has to be noted that there are no data for ground temperature in the weather files. These are therefore set to the outdoor air temperature.

Occupancy Profile Generation and BSim Implementation E

In this appendix, details regarding the generation of the stochastic (dynamic) occupancy profiles are presented and discussed. Furthermore, a brief description of how to implement them into BSim is presented. An example of stochastically generate an event start and duration is presented along with examples of the included weekly variation.

The overall method used for creating the stochastic occupancy profiles in the developed spreadsheet is presented in figure E.1.

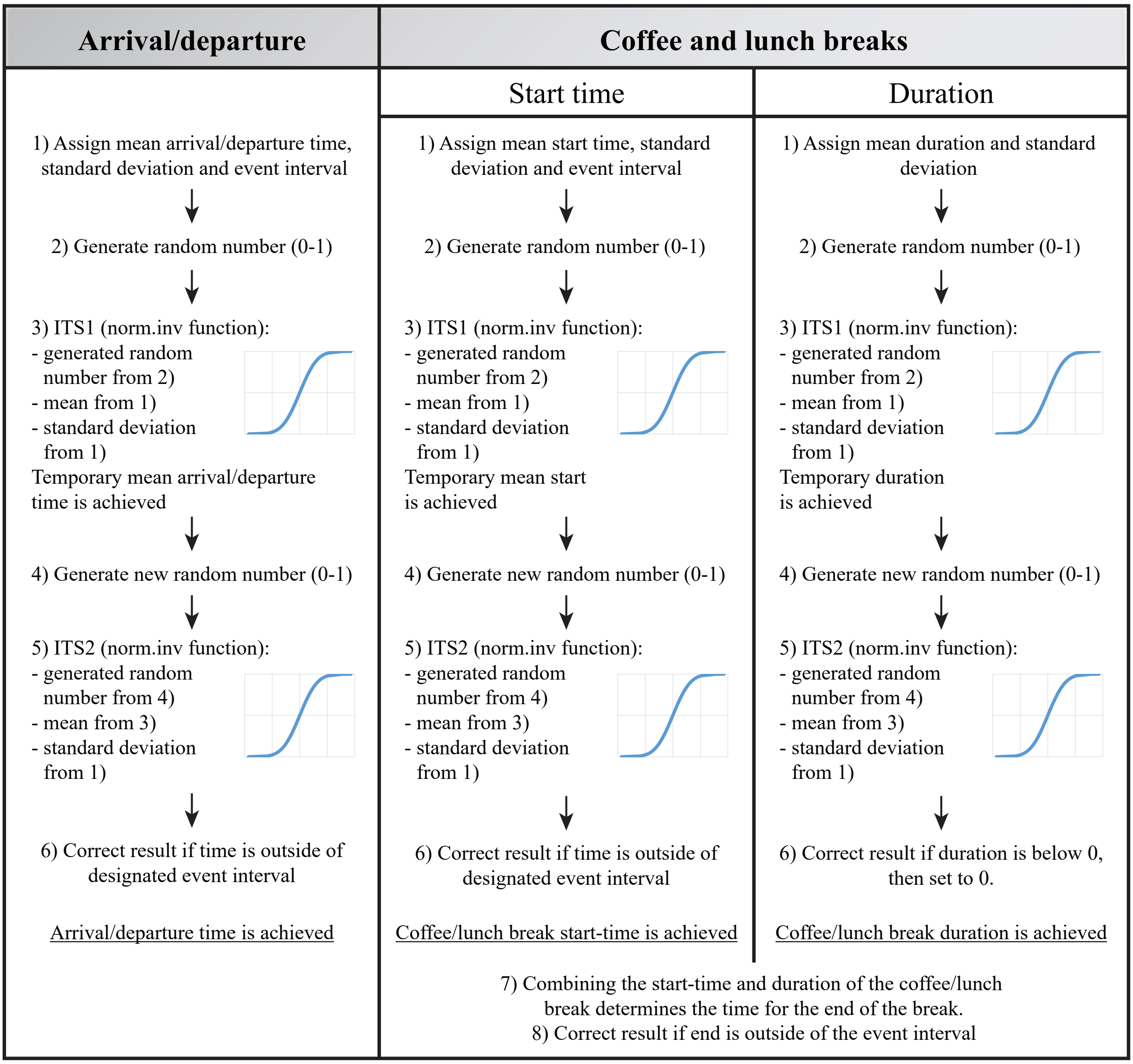


Figure E.1. Workflow of generating the stochastic occupancy profiles.

Since the occupancy profile generation process includes an immense amount of calculations, aggregation

of the data is required. For a scenario with 17 occupants, a total of 123 000 values are used to create one set of occupancy profiles for a year.
BSim may only include one number for the occupancy level per hour, hence the values related to the events needs to be aggregated into one number for every hour.
For example, if 8 of the occupants arrives before 08:00, and their average arrival time is 07:54, the occupancy load for the hours between 07:00 and 08:00 is calculated to:

$$\text{Occupancy level from 07:00 to 08:00} = \frac{\Big(8 \cdot (\text{08:00 - 07:54})\Big) \cdot 17}{100\,\%} = 4.7\,\% \tag{E.1}$$

This calculation is conducted for each of the 12 hours per day (07:00 - 19:00 since occupants are also arriving before 08:00 and departing after 18:00).
Some of the hours requires additional calculations. For example incidents where occupants starts their break before, for example 10:00, and end their brake after 10:00, is adjusted for.

E.1 BSim implementation and coding

Furthermore, for the data to work in BSim, a series of codes in the BSim model file (.disxml file) needs to be removed and replaced. But before this, a "PeopleLoad-system" needs to be established in the BSim software. This is done to create the connections needed for the occupancy system in the coding. The process is as following:

- First, the "PeopleLoad" system needs to be activated in the "ThermalZone Property" window.
- Secondly, the double amount of occupants in the room for "normal scenario" (basecase) needs to be inserted in the "PeopleLoad" tab in the "PeopleLoad" window.
  - This is done because BSim can not handle occupancy loads higher than 100 % in the "DayProfile" control system and since the occupancy load are varying by also increasing the amount of presence, this eases the coding.
- Establish "PeopleLoad" schedule by :
  - Adding a schedule in the "Schedule" tab
  - Adding a day profile in the "DayProfile" tab
  - Adding a time profile in the "Time" tab

E.1.1 Codelines to be removed

With this established, two codelines are to be removed from the .disxml file of the model. This is done because the new schedules created with the Excel spreadsheet are to be attached to the systems. The codes to be removed are:

"PeopleLoad" system which attaches to schedules:

```
<SYSTEM rid="#497"><id>PeopleLoad</id><active>1</active><has_component>#512</has_component>
<has_schedule>#513</has_schedule><system_type>.PEOP_SYS.</system_type></SYSTEM>
```

"Equipment" system which attaches to schedules:

```
<SYSTEM rid="#493"><id>Equipment</id><active>1</active><has_component>#520</has_component>
<has_schedule>#521</has_schedule><system_type>.EQUIP_SYS.</system_type></SYSTEM>
```

What is going to be changed in the two codes above are the numbers in the red squares. These numbers are to be replaced with schedules for each working day of the year.

E.1.2 Codelines to identify

There are also two codelines which needs to be identified to get the “rid” number:

“People type” (“PeopleLoad” tab in BSim):

```
<PEOPLE rid="#594"><id>Personer</id><person_heat>0.1</person_heat><person_moist>0.06
</person_moist><protect>0</protect></PEOPLE>
```

The rid (#594) is to be coupled with the following codeline.

“Total load” (“PeopleLoad” tab in BSim):

```
<PEOPLE_LOAD rid="#595"><id>Personer</id><number_of_people>34</number_of_people>
<people_type>#594</people_type></PEOPLE_LOAD>
```

The rid (#595) is to be coupled further down in the code.

E.1.3 Codelines to insert

Examples of the codes to be inserted are presented in the following.

New time profiles (“Time” tab in BSim):

```
<TIME_DEFINITION rid="#2502"><id>5</id><hour>8-19</hour><day>1</day><week>2</week>
<month></month><tariff_class>0</tariff_class><protect>0</protect></TIME_DEFINITION>
```

There is 1 of these lines for each day throughout the year. The codeline determines states the day and time.

New day profiles (“DayProfile” tab in BSim):

```
<DAY_PROFILE rid="#2002"><id>1</id><hour>6% 8    48% 9    50% 10    43% 11    50% 12    33% 13
54% 14    46% 15    48% 16    54% 17    48% 18    8% 19 </hour><percent>0</percent><protect>1
</protect></DAY_PROFILE>
```

There is 1 of these lines for each day throughout the year. The codeline determines the occupancy load during the day.

The two previous codelines are connected with the following “Schedule”:

```
<SCHEDULE rid="#3002"><id></id><has_control>#2002</has_control><has_time_definition>#2502
</has_time_definition></SCHEDULE>
```

There is 1 of these lines for each day to couple the time and day profiles.

Coupling of schedules to “PeopleLoad”:

```
<SYSTEM rid="#497"><id>PeopleLoad</id><active>1</active><has_component>#595</has_component>
<has_schedule>#3001 #3002 #.......</has_schedule><system_type>.PEOP_SYS.</system_type></SYSTEM>
```

There is only 1 of this codeline, coupling the schedules to the “PeopleLoad”. As seen in the code, multiple (all) schedules are to be included in this codeline.

Coupling of schedules to “Equipment”:

```
<SYSTEM rid="#493"><id>Equipment</id><active>1</active><has_component>#520</has_component>
<has_schedule>#3001 #3002 #...</has_schedule><system_type>.EQUIP_SYS.</system_type></SYSTEM>
```

There is only 1 of this codeline, coupling the schedules to the “Equipment”. As seen in the code, multiple (all) schedules are to be included in this codeline.

Note that rid numbers in the presented codelines vary from model to model, which is why it is important to use unique rids for the codelines which are added to the model. This is done in the codelines presented above, where the time profiles starts from 2500, day profiles starts from 2000 and the schedules starts from 3000.

E.2 Example of generated coffee breaks

The example presents one of the many generations of coffee breaks. Figure E.2 and E.3 illustrates two CDFs used for generation of the start time for the coffee break in the morning in this example.
The CDF in figure E.2 represents the probability distribution for the start time for the coffee break with a mean value of 10 h, and a standard deviation of 0.25 h (15 minutes). This CDF is for the entire population, and based on the random number generated a new mean value for the first occupant is generated.

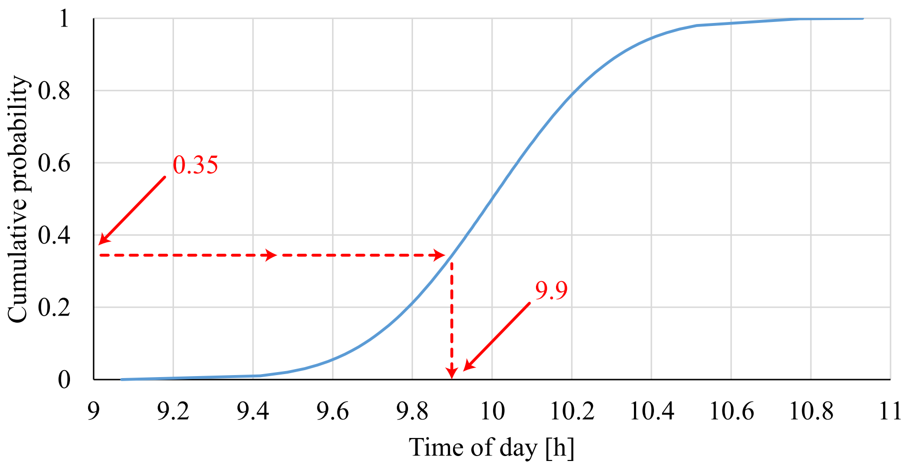


Figure E.2. First ITS of the CDF to generate the start time for the coffee break. This CDF represents the normal distribution for the population.

With a randomly generated number, in this example 0,35, the corresponding value from the CDF is 9.9 h. This value is then used to create a new CDF for the first occupant with 9.9 h as mean value, see figure E.3.

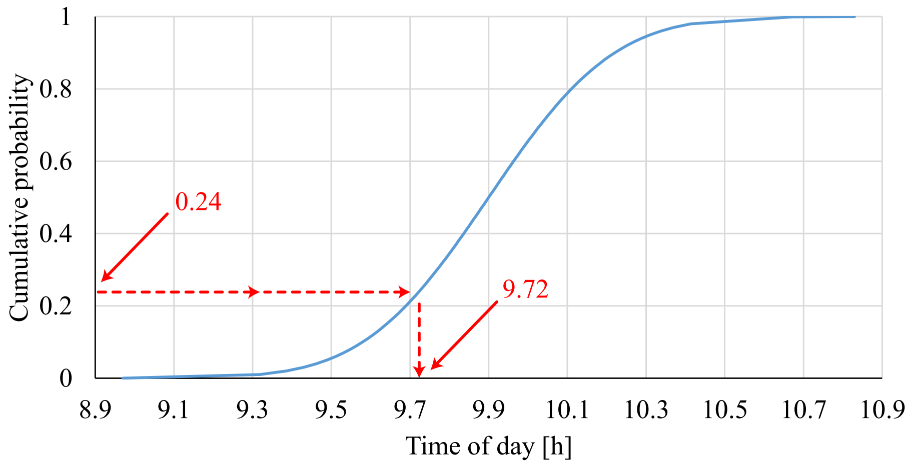


Figure E.3. Second ITS of the CDF to generate the start time for the coffee break. This CDF represents the normal distribution for the first occupant.

A new random number, 0.24, is generated and the start time for the coffee break in this example is 9.72 h, or 09:43. The generation of the coffee break duration is conducted with the same process, and with the corresponding mean and standard deviation. The two ITS of the two CDFs are presented in figure E.4 and E.5.

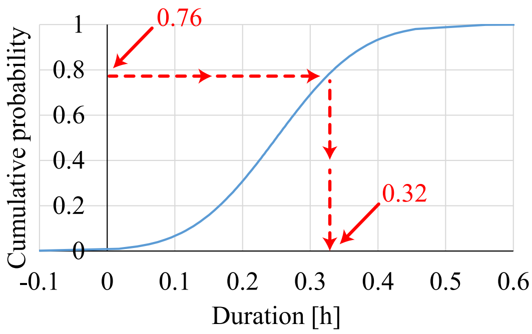


Figure E.4. First ITS of the CDF to generate the duration for the coffee break.

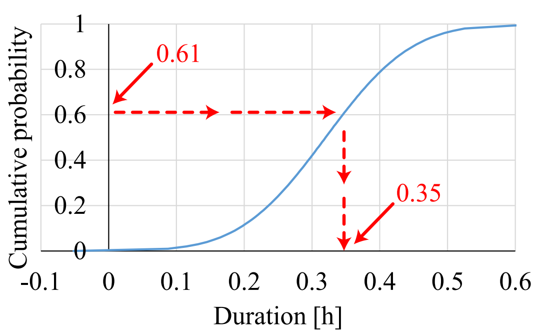


Figure E.5. Second ITS of the CDF to generate the duration for the coffee break.

The duration of this coffee break is 0.35 h, or 21 minutes. In this example, the occupant will start the coffee break at 09:43, and continue until 10:04.
This process is repeated for each of the five different events with the corresponding values for mean start and standard deviation. Obviously, arrival and departure does not have any duration and will therefore not be generated for these events.
In generations where the value for a break duration becomes negative, a duration time of 0 minutes is used instead, thus the occupant is modelled without break.

E.3 Examples of weekly variation

Variations of yearly and daily character may occur in offices and may be caused by sick leaves, holidays, change of building ownership and so on.
The yearly mean number of occupants and the daily standard deviation of the occupants in the building are varied from building model to building model, see table 7.1. To vary the number of occupants in the open office landscape from day to day, a similar process as presented above is used. With a CDF

including a generated yearly mean and yearly standard deviation, ITS is used to generate the number of present occupants each day.
Examples of this variation on a weekly basis is presented in figure E.6, E.7, E.8 and E.9. The effect from changing the yearly mean value and daily standard deviation for the normal distributions for the population is visible in the graphs.

The profiles for DOMc does not include the daily variation, but the variation caused by the daily standard deviation is included by averaging the daily values.

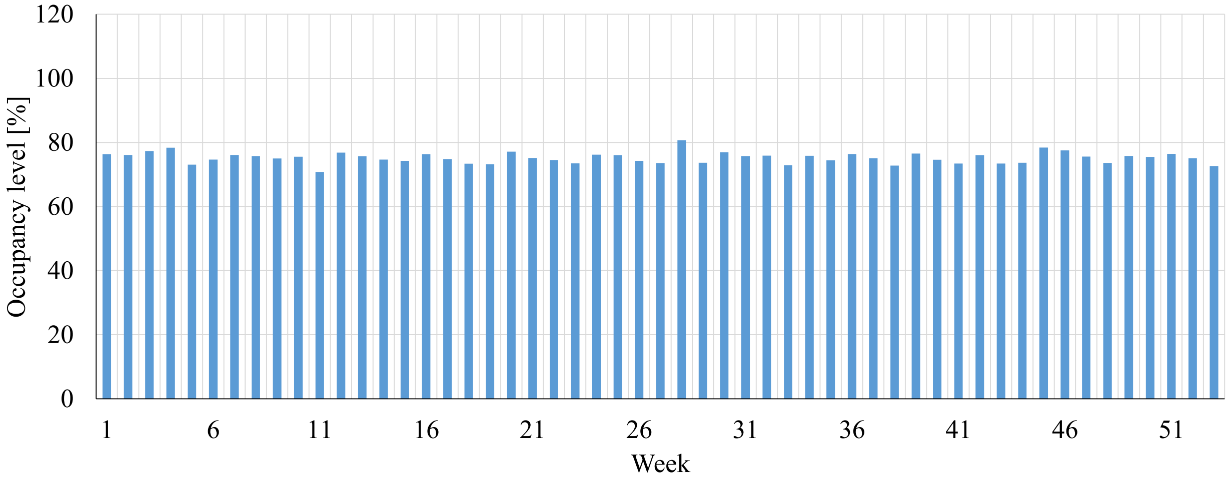


Figure E.6. Occupancy profile for a year with stochastic generated variations. Yearly mean is 100 % and standard deviation is 5 %.

As it may be observed in figure E.6, the different weeks are not concentrated around 100 % occupancy level. This is reasoned by the daily variations caused by the five different events, hence the occupants are not continuously present in the room during the working hours.

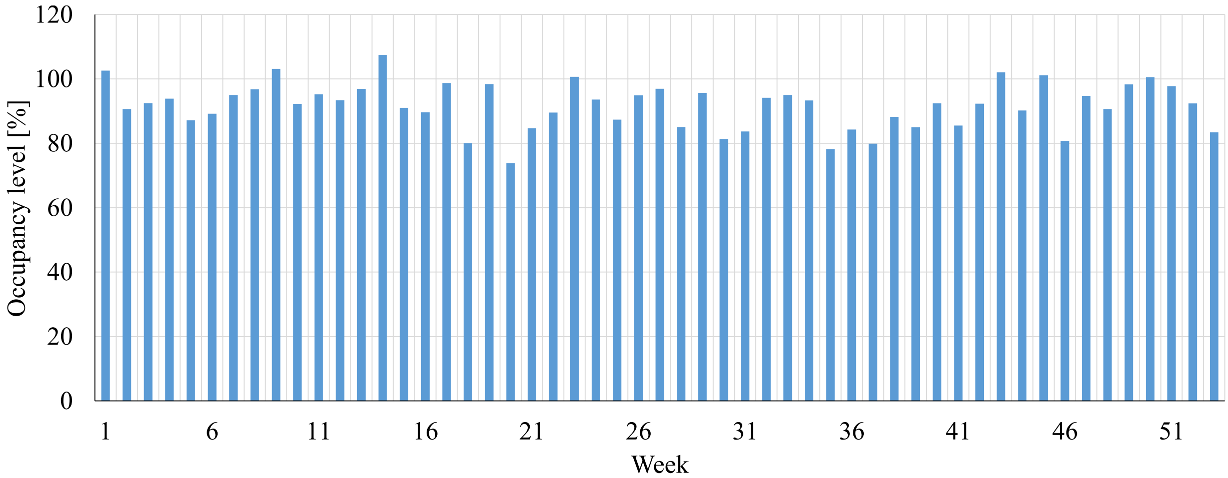


Figure E.7. Occupancy profile for a year with stochastic generated variations. Yearly mean is 120 % and standard deviation is 20 %.

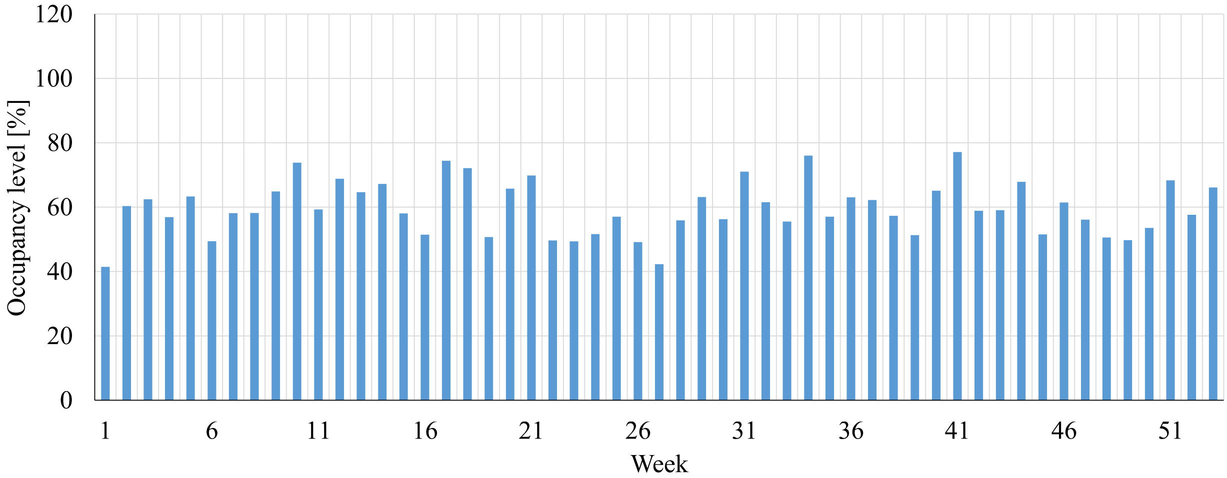


Figure E.8. Occupancy profile for a year with stochastic generated variations. Yearly mean is 80 % and standard deviation is 20 %.

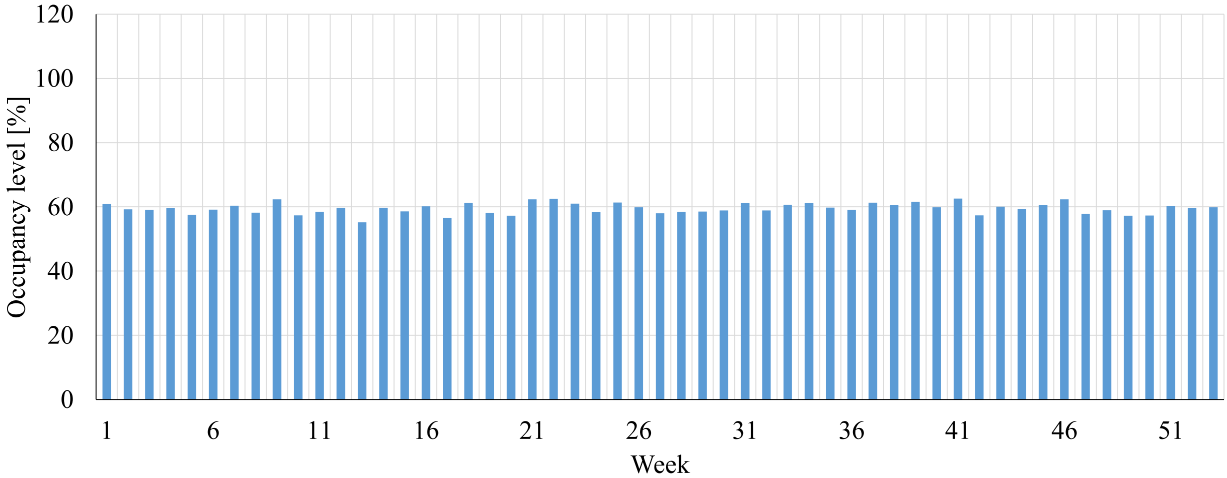


Figure E.9. Occupancy profile for a year with stochastic generated variations. Yearly mean is 80 % and standard deviation is 5 %.

Be15 Simulations F

This appendix presents details concerning the number of simulations for convergence in Be15. Furthermore, various simulation results are presented in detail.

F.1 Number of simulations

The convergence of the results from the simulations are dependent on the number of simulations that are conducted and hereof sample size. Furthermore, the regression from the neural network is dependent on the number of simulations as well as the sensitivity analysis method used in this thesis. To prove that the simulations are trustworthy a convergence analysis is performed.

In figure F.1, box-plots of the TED for DRY with varying number of simulations are shown. From the box-plots the number of simulations can qualitatively be assessed.

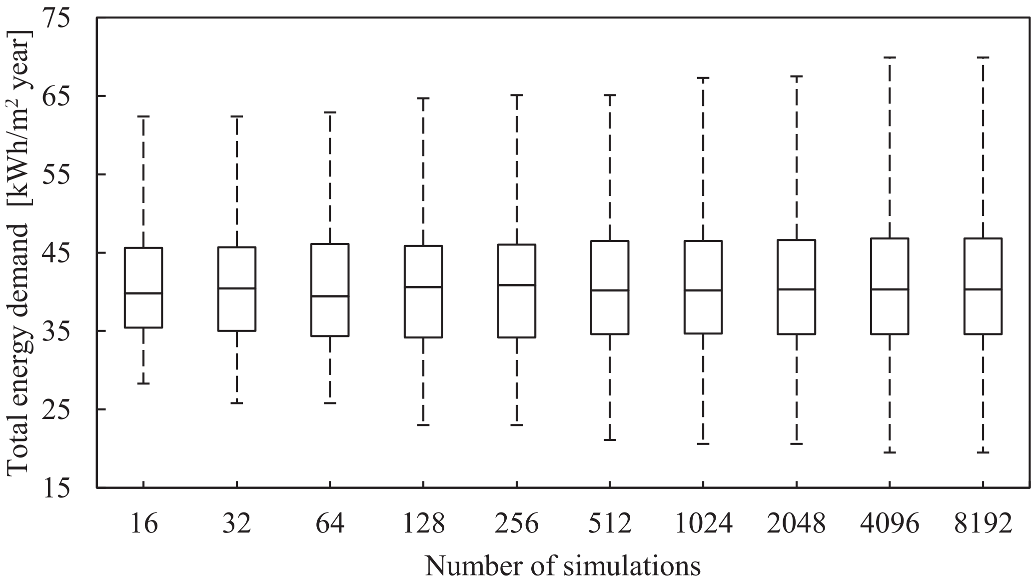


Figure F.1. box-plots showing the number of simulations and their distribution of TED for DRY.

From the figure it can be concluded that the range of the TED is enlarging as the number of simulations increases. Furthermore the data becomes close to normal distributed as the simulation number exceeds 256. It is therefore chosen to use at least 256 simulations based on the box-plots.

To quantitatively estimate the necessary number of simulations a statistical test is performed. The result is satisfying when the TED is within the 95 % confidence interval of both mean and standard deviation of the reference. The reference is 8192 simulations.

With the function "CONFIDENCE.NORM" in Excel, the confidence interval for the mean (μ) is calculated for the 8192 simulations. With a mean TED of 54.9 kWh/m^2 year for the 8192 simulations, the 95 % confidence interval is 54,9 $\pm$ 0.2 kWh/m^2 year. This means that the mean of the other simulation groups shall be within 54,7 – 55.1 kWh/m^2 year to be statistically significantly equal.

The confidence interval for the standard deviation (s) is calculated based on the chi-square distribution which is not symmetrical, thus granting an interval that is not centred around the mean.

The equation used for the confidence interval is shown in equation (F.1), [Ayyub and McCuen, 2003, section 11.3.3].

$$\sqrt{\frac{(n-1)\cdot s^2}{\chi^2_{\alpha/2}}} < \sigma < \sqrt{\frac{(n-1)\cdot s^2}{\chi^2_{1-\alpha/2}}} \tag{F.1}$$

where

σ	is standard deviation for the population [−]
n	is the number of simulations [−]
s	is the standard deviation for the group [−]
χ^2	is the critical value for the chi-squared distribution [−]
α	is the significance level [−]

By inserting the standard deviation of the group of 9,4, the confidence interval for the population is calculated to:

$$\sqrt{\frac{(8192-1)\cdot 9{,}4^2}{\chi^2_{0{,}05/2}}} < \sigma < \sqrt{\frac{(8192-1)\cdot 9{,}4^2}{\chi^2_{1-0{,}05/2}}} \tag{F.2}$$

$$9{,}26 < \sigma < 9{,}55$$

The distributions of the TED that are within the confidence interval for both the mean and the standard deviation are from the same population with a 5 % significance level. Therefore these groups are statistically significantly equal based on the mean and standard deviation.

The results are presented in table F.1.

Number of simulations	μ	s	$54{,}7 < \mu < 55{,}1$	$9{,}26 < s < 9{,}55$
16	54,8	9,36	✓	✓
32	55,3	9,43	X	✓
64	54,8	9,18	✓	X
128	54,8	9,26	✓	X
256	54,8	9,24	✓	X
512	54,9	9,39	✓	✓
1024	54,9	9,34	✓	✓
2048	54,9	9,38	✓	✓
4096	54,9	9,40	✓	✓
8192	54,9	9,40	✓	✓

Table F.1. Mean, standard deviation and a check if these are within the confidence interval of the reference (8192 simulations). Note that 128 simulations is not within the interval for the standard deviation. It may seem to be within, but this is reasoned by rounding.

To save simulation time, 512 simulations are chosen since they have proven to be adequate for the convergence for the model. The results from the 16 simulations are inside the 95 % confidence interval. That might be coursed by a coincidence, since the next acceptable number of simulations are 512. As presented in table F.1, the 128 simulation may seem to be within the interval for the standard deviation. This is not the case as its standard deviation is rounded up to 9,26.

The sensitivity analysis method developed by Østergård et al. [2017b] is also affected by the number of simulations, especially when the number of outputs increases.

For the simulations with Be15 only one output parameter is evaluated. In figure F.2 the relative sensitivity of the input parameters on the TED is shown for each group of simulations quantity.

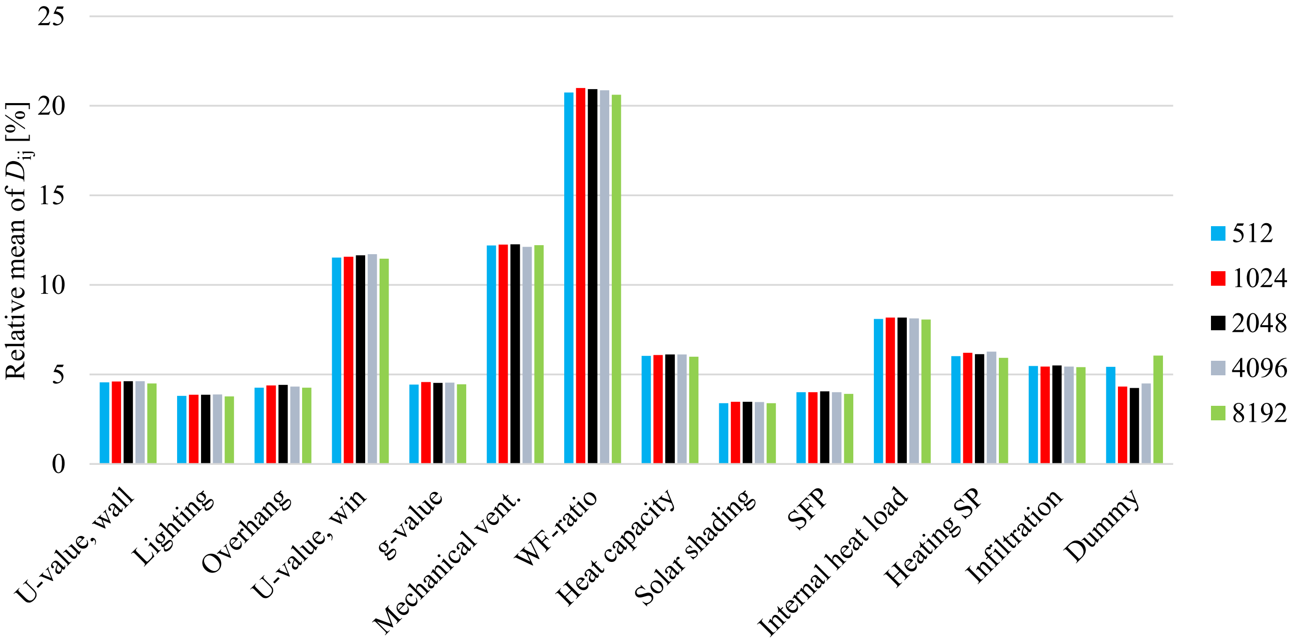


Figure F.2. Relative sensitivity of the input parameters on the output parameter, TED, for each group of simulation quantity.

The bar charts presented above shows that there is little difference in sensitivity when altering the number of simulations in the presented range from table 6.1.

The neural network is used to create more simulations fast which may used in the visualisation in the PCP for design purposes. The number of simulations applied in the neural network have an influence on how well the meta model represents the real models. To estimate how many simulations that are required for creating the meta models, the meta models are plotted against the real models and a linear regression is performed.

The linear regression of the TED for both the simulations and the neural network is presented in table F.2.

Train size	R^2
512	0.9985
1024	0.9973
2048	0.9965
4096	0.9959
8192	0.9959

Table F.2. Train size for the neural network and coefficient of determination, R^2, for the TED for both the simulations and the neural network.

As shown in the table, the neural network is a well estimate of the real models, since R^2 is above 0.99 for each case.

F.2 Robustness analysis

In table F.3 the mean values of the TED and the energy consumptions it consists of are shown. The biggest variation in the TED is due to the heating consumption.

Excessive temperature removal is the equivalent electricity needed to remove excessive temperatures with a standard mechanical cooling unit, [Aggerholm and Grau, 2016]. In the results presented it is named cooling as there are no cooling system inserted in the models.

Weather file	TED	Heating	Cooling	EL	Dif. TED
DRY	41.1	28.1	0.5	12.8	0.0
1975	41.0	26.1	1.9	14.1	-0.1
1976	43.6	28.9	1.8	14.0	2.5
1977	40.1	27.2	0.4	12.7	-1.0
1978	41.4	28.4	0.5	12.7	0.2
1979	44.3	31.5	0.3	12.7	3.1
1980	43.0	30.2	0.3	12.7	1.9
1981	42.5	29.5	0.4	12.8	1.4
1982	40.6	26.9	1.8	13.0	-0.6
1983	39.0	25.4	1.9	12.8	-2.1
1984	39.7	26.9	0.3	12.7	-1.4
1985	**47.4**	**34.7**	**0.2**	**12.6**	**6.3**
1986	41.7	28.9	0.3	12.6	0.6
1987	45.0	32.4	0.2	12.6	3.9
1988	39.2	26.3	0.5	12.7	-1.9
1989	**33.7**	**20.7**	**0.6**	**12.8**	**-7.4**
Mean, historic	41.5	28.3	0.8	12.9	0.4

Table F.3. Results from the simulations. Dif. TED is the mean of the difference in TED from each simulation. The weather files resulting with highest and lowest TED are marked with red and green, respectively. The results are without primary energy factors and are given in kWh/m^2 year.

The number of design solutions that meets the BR15 requirement is shown in table F.4 for each weather file. In the table, these are shown in the column denoted "Within BR15" as given as percentage out of 512 simulations.

A one-way ANOVA test is performed to identify if the TED from the simulations with statistically significance can be said to come from the same mean as DRY. In table F.4 the results are presented. The check marks indicates that distribution of the TED for the weather files with statistically significance belongs to the same mean value as DRY. The significance level is 5 %.

Weather file	TED [kWh/m^2 year]	σ [kWh/m^2 year]	Within BR15 [%]	ANOVA [–]
DRY	41.1	8.6	8.2	–
1975	41.0	8.1	4.5	✓
1976	43.6	9.1	4.5	X
1977	40.1	8.4	10.5	✓
1978	41.4	8.7	7.8	✓
1979	44.3	9.2	5.1	X
1980	43.0	9.0	6.4	X
1981	42.5	8.7	6.8	✓
1982	40.6	8.4	7.4	✓
1983	39.0	8.3	12.1	X
1984	39.7	8.4	12.1	✓
1985	47.4	9.8	2.9	X
1986	41.7	9.1	8.4	✓
1987	45.0	9.5	4.7	X
1988	39.2	8.2	12.9	X
1989	33.7	7.3	23.8	X
Mean, historic	41.5	8.7	8.7	

Table F.4. Results from the ANOVA test and amount of simulations within the BR15 requirements. The weather files with check marks can with statistical significance be said to come from the same mean value as DRY. The standard error for the calculations is 0.38 kWh/m^2 year.

The mean value of the TED and number of simulations within BR15 are well represented by DRY. Naturally the standard deviation are not equal, since more spread data i included due to the variation from the weather files.

The distribution of the outputs for the simulations are shown as box-plots for the given weather file. The box-plots contains TED, heating, cooling and electricity in figures F.3 through F.6 respectively.

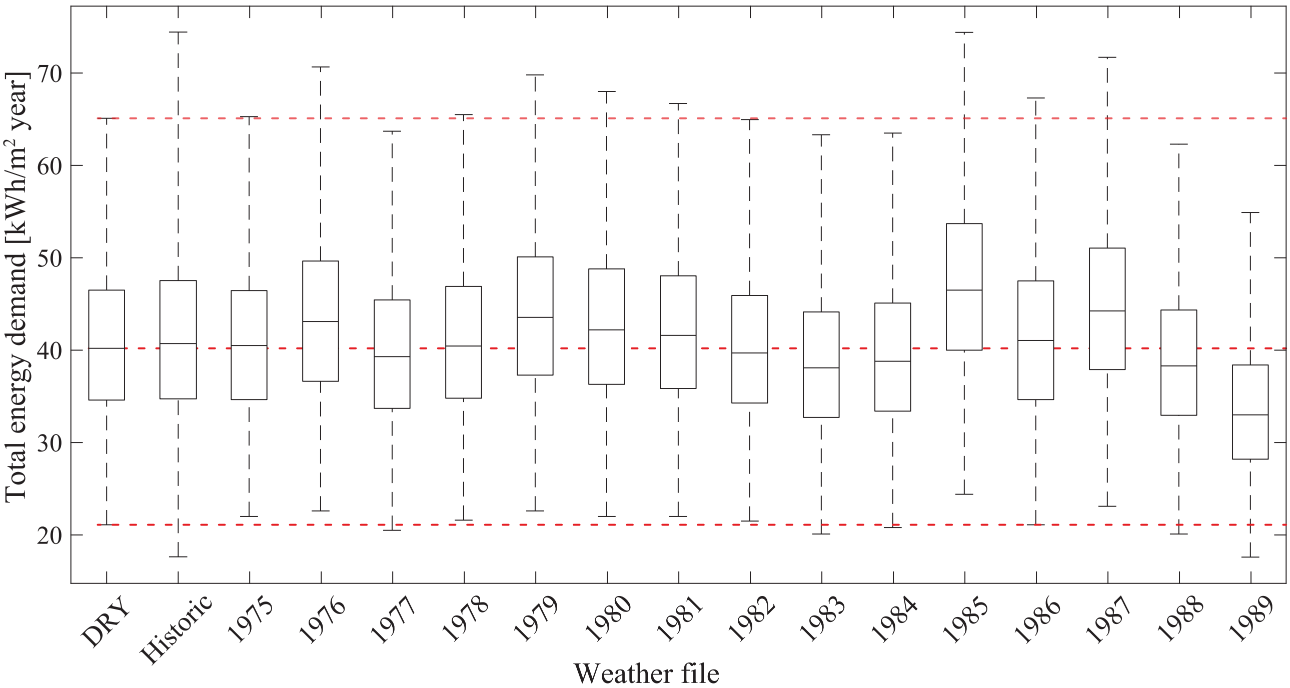


Figure F.3. The distribution of the TED from the stochastic modelling with Be15 for 512 simulations for each weather file.

The figure shows the variation for all of the simulations. It is obvious that weather file 1989 has the lowest TED, while 1985 has the highest. The span of the simulations are nearly the same, and the data is assumed to follow a normal distribution for each weather file.

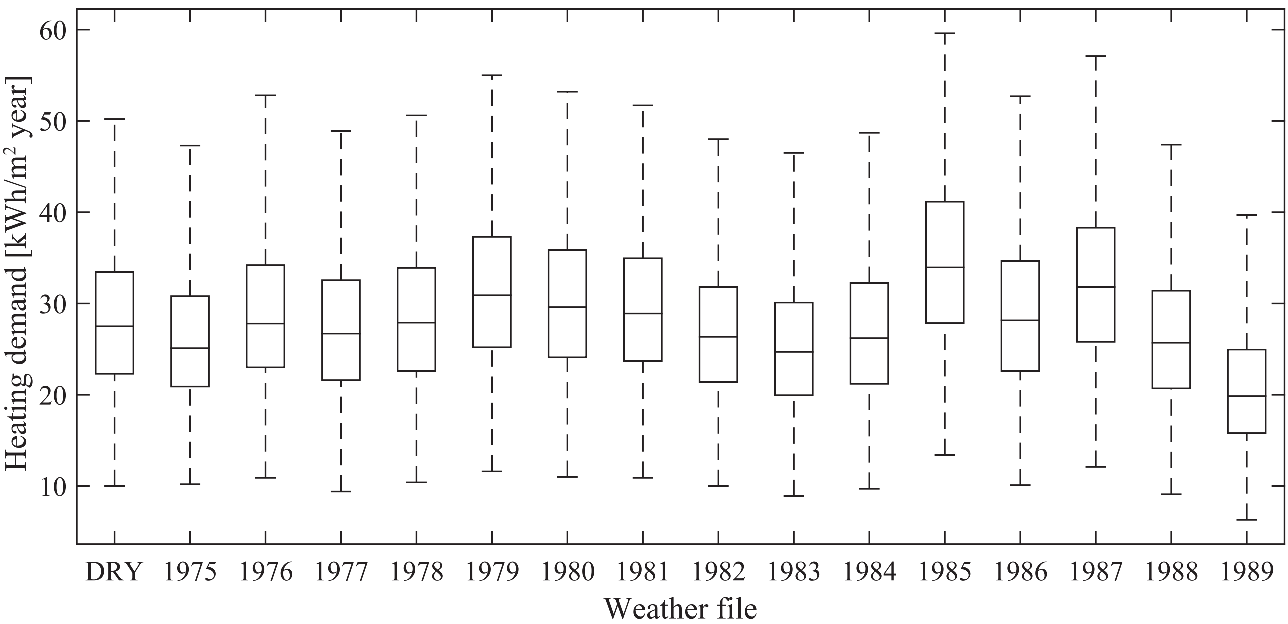


Figure F.4. Heating demand for each weather file calculated with Be15 presented in box-plots.

The tendency of the heating demand is somewhat following the tendencies of the TED. It is also evident from figure F.4 that the heating demand is the highest contributor to the TED when not including the primary energy factors.

In figure F.5 the variation of cooling given as the penalty for exceeding temperatures is shown. The figure reveals that there is a higher cooling demand for 1975, 1976, 1982 and 1983. The characteristics for these weather files is that the sunshine hours are relative high while the mean temperature outside heating season are higher than for the other weather files.

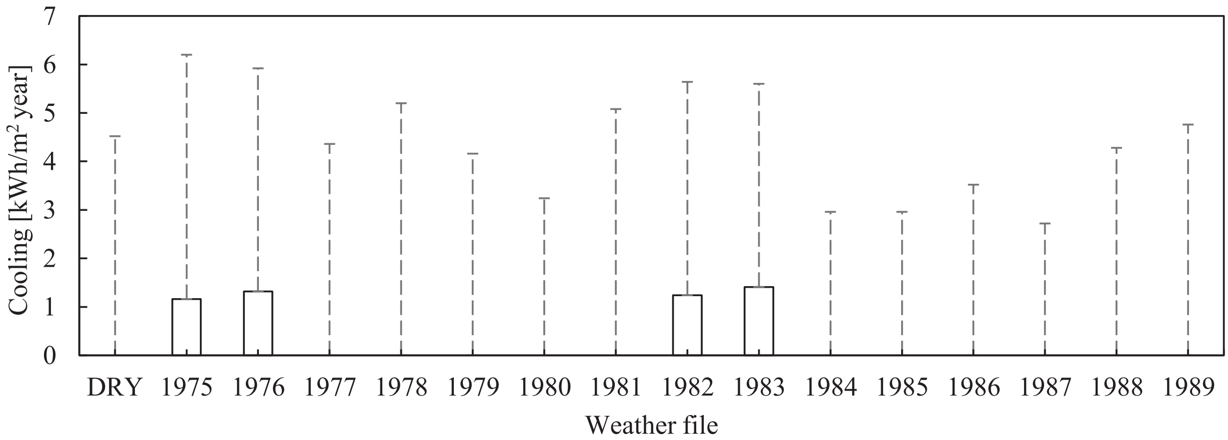


Figure F.5. Box-plots of the cooling for the simulations with each weather file.

In figure F.6 the distribution of the electricity consumption for each weather file is shown in box-plots. A visible difference is observed for the years 1975 and 1976, where the electricity consumption is raised due to increased ventilation demand. This is a result of the higher solar radiation outside the heating season for these years.

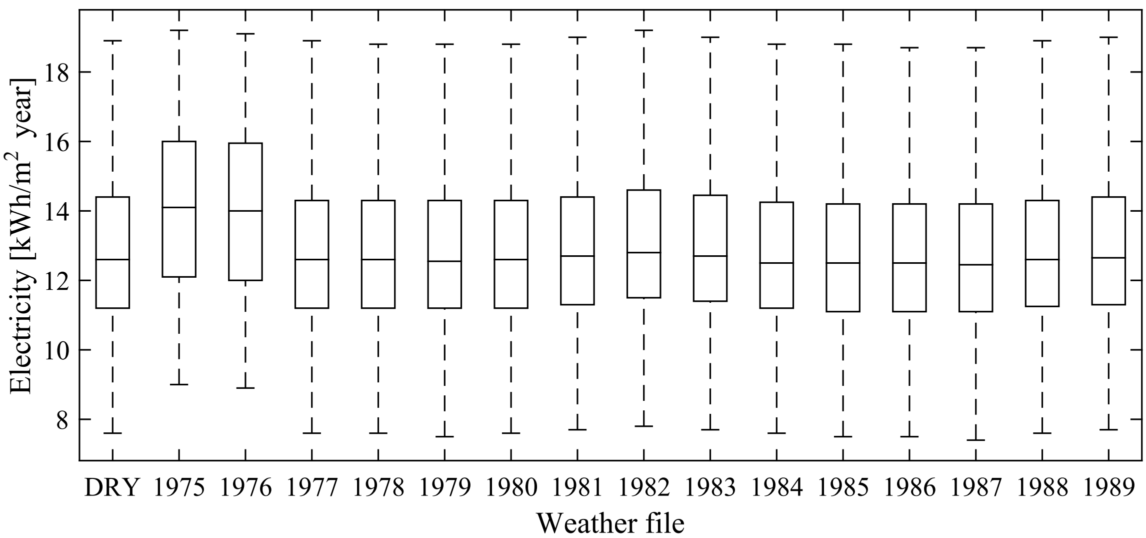


Figure F.6. The variation of electricity for each weather file shown in box-plots.

F.2.1 Parallel coordinate plots

Figure F.7 and F.8 presents the design solutions, filtered after the highest and lowest 5 % in the RI output, respectively.

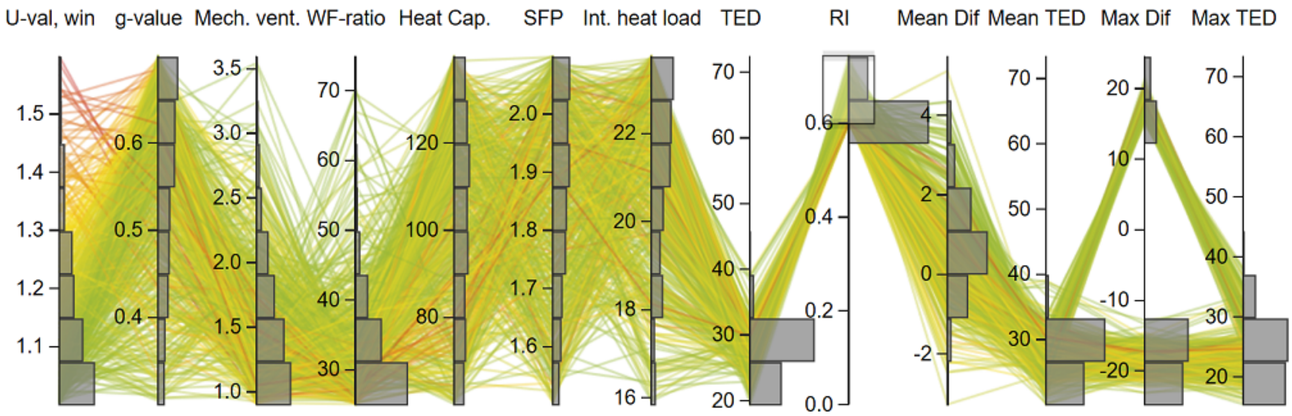


Figure F.7. Parallel coordinate plot, filtered after the highest 5 % in the RI output. The colour scale is sorted after the TED. Created with the interactive PCP from MOE A/S [2016].

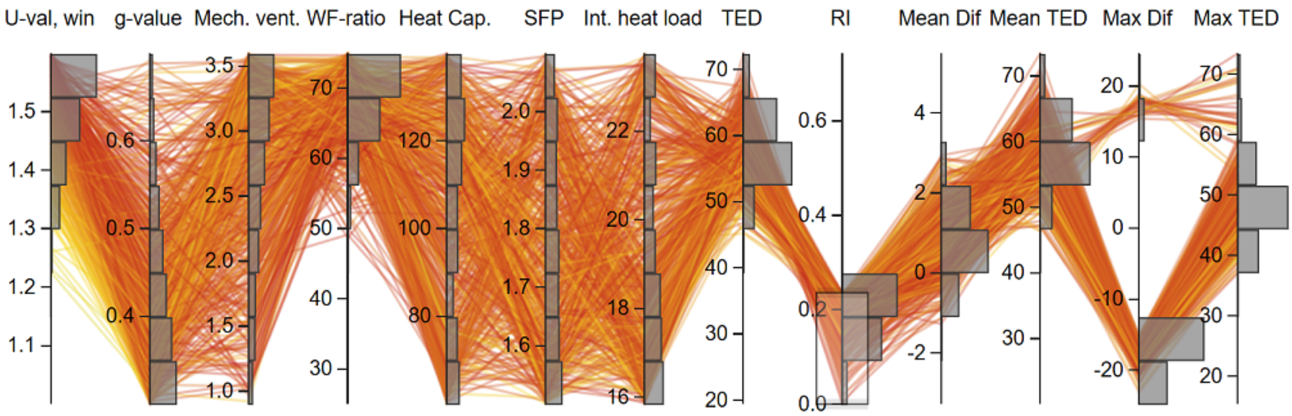


Figure F.8. Parallel coordinate plot, filtered after the lowest 5 % in the RI output. The colour scale is sorted after the TED. Created with the interactive PCP from MOE A/S [2016].

From figure 6.11 and 6.12 it may concluded that the robustness of the building is affected by some of the input parameters. The most significant ones are window-to-facade ratio, U-value for the windows and mechanical ventilation.

F.3 Sensitivity analysis

F.3.1 Influence of design inputs

The influence of design inputs is evaluated for different outputs. One analysis is performed for the TED while two others are performed on the RI and the TED combined with the RI.

F.3.1.1 Total energy demand

Two sensitivity analysis methods are applied. The results are presented in figure F.9 and F.10 for the relative mean of D_{ij} and the relative Pearson's correlation. This enables to compare the two sensitivity methods.

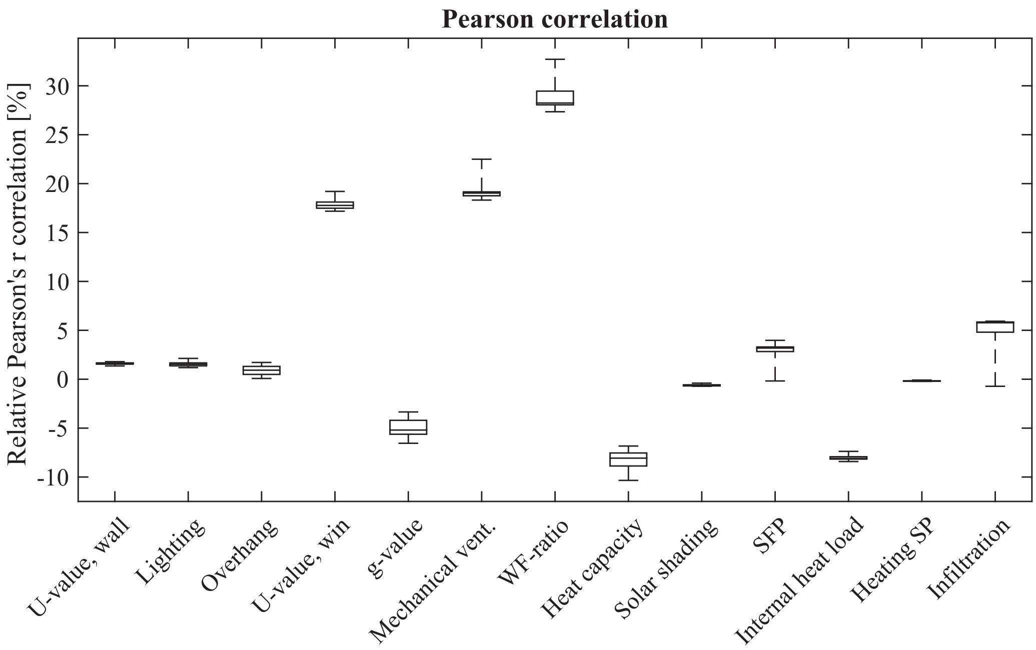


Figure F.9. Result from the sensitivity analysis for Be15 using Pearson correlation coefficient.

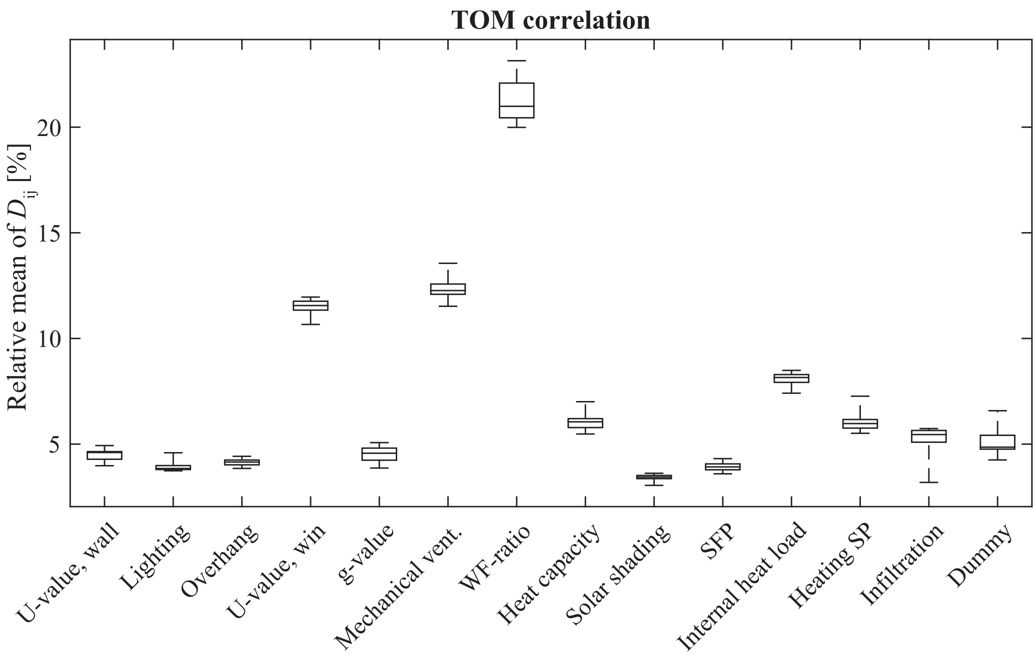


Figure F.10. Result from the sensitivity analysis for Be15 using TOM.

Both methods reveals a relatively high sensitivity for window-to-facade ratio, mechanical ventilation and the U-value for the windows. Other sensitive parameters are the internal heat load, heat capacity, heating set-point and infiltration. Within these parameters, both methods shows similar tendencies. The sensitivity for the window-to-facade ratio and infiltration yields great spans as effect of changing weather files. This is because the effect on the TED from this parameters are influenced by the weather conditions.

In figures F.11 and F.12, the sensitivity ranking of the inputs are presented for each weather file.

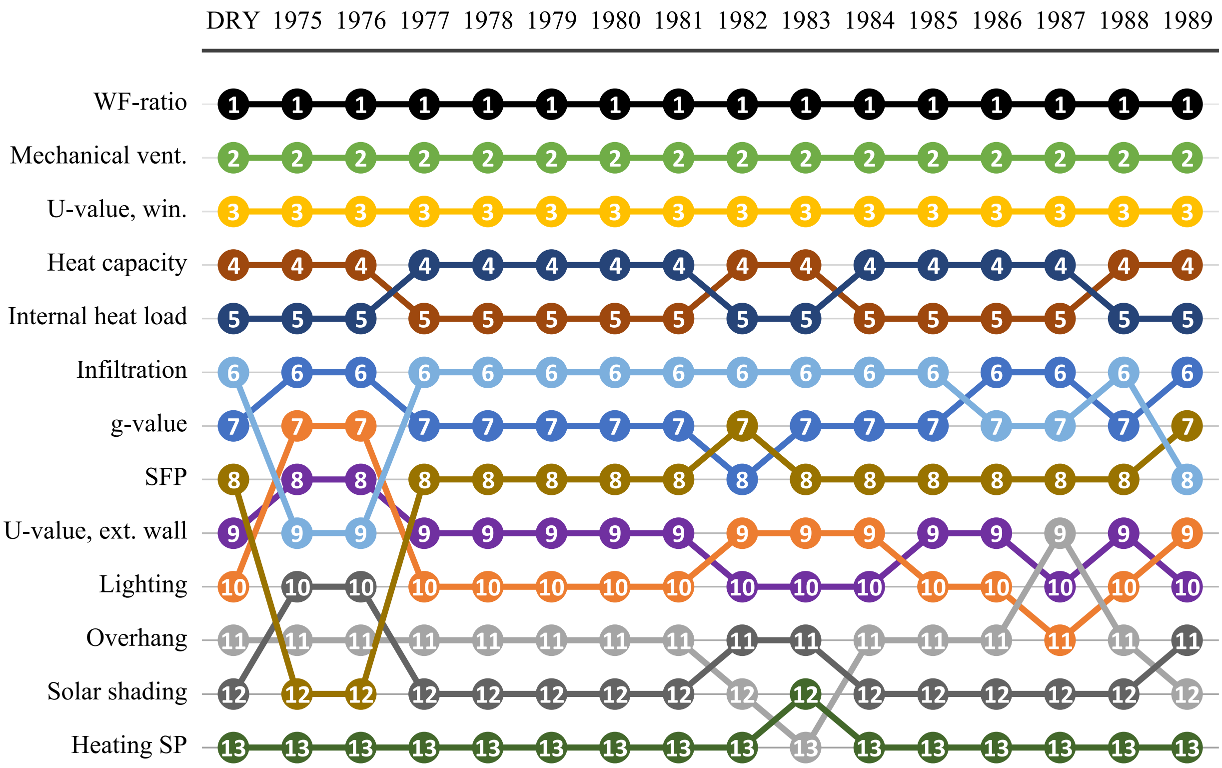


Figure F.11. Ranking of input parameter when using Pearson's r correlation as sensitivity measure. The inputs on the left are sorted after their rank, based on the simulations with the DRY weather file.

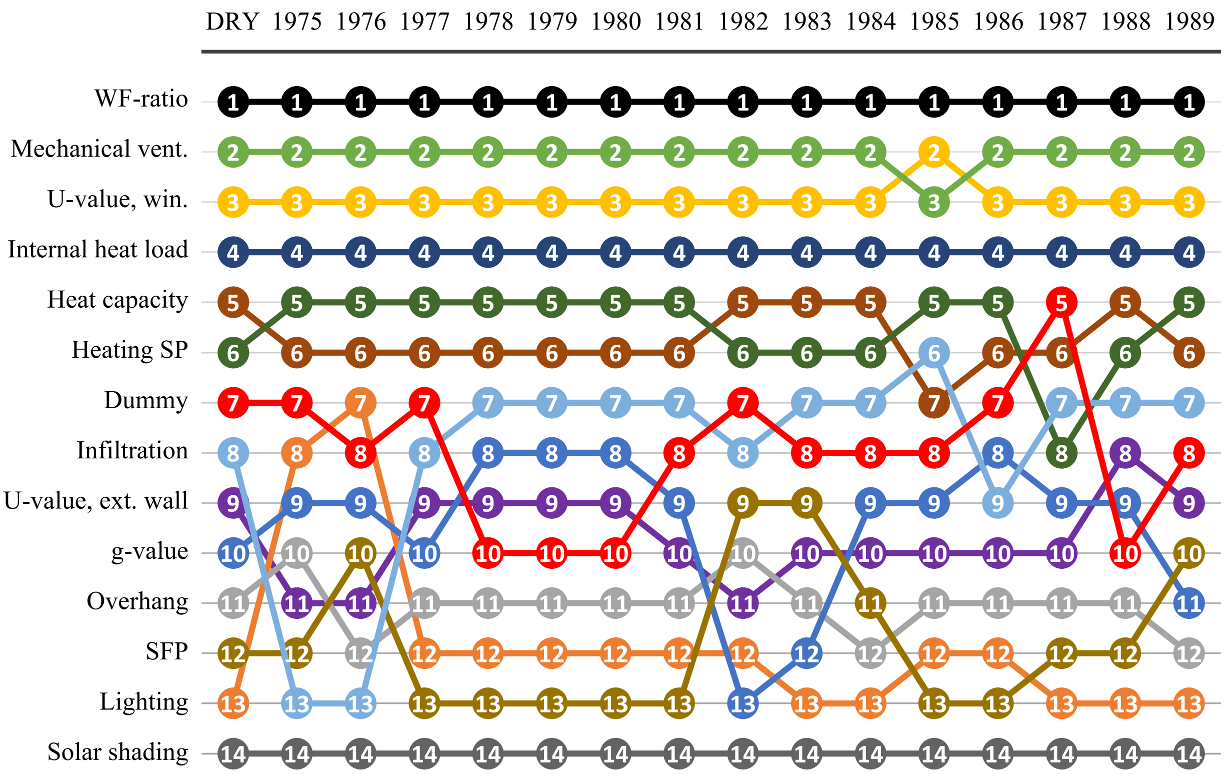


Figure F.12. Ranking of input parameters using TOM. Input parameters ranked lower than "Dummy" suggests no significant influence on the TED. The inputs on the left are sorted after their rank based on the simulations with the DRY weather file.

For both methods the most sensitive parameters are consistently window-to-facade ratio, mechanical ventilation and U-value for the windows. These are followed by the internal heat load and heat capacity of the building.

From Pearson, the heating set-point has no influence on the TED, but for TOM it is ranked as 5 and 6 throughout the weather files consistently. For Pearson, the ranking of the inputs between 6 and 12 changes significantly for 1975 and 1976. This is due to increased sunshine hours and direct radiation compared to the other weather files.

F.3.1.2 Robustness index

The sensitivity analysis when including the RI is based on the TOM sensitivity analysis method. TOM is able to handle multiple outputs when performing a sensitivity analysis.

In figure F.13 the sensitivity analysis is presented for the RI as the only evaluated parameter.
Sensitivity analysis according to the TED and the RI as outputs combined is presented in figure F.14.

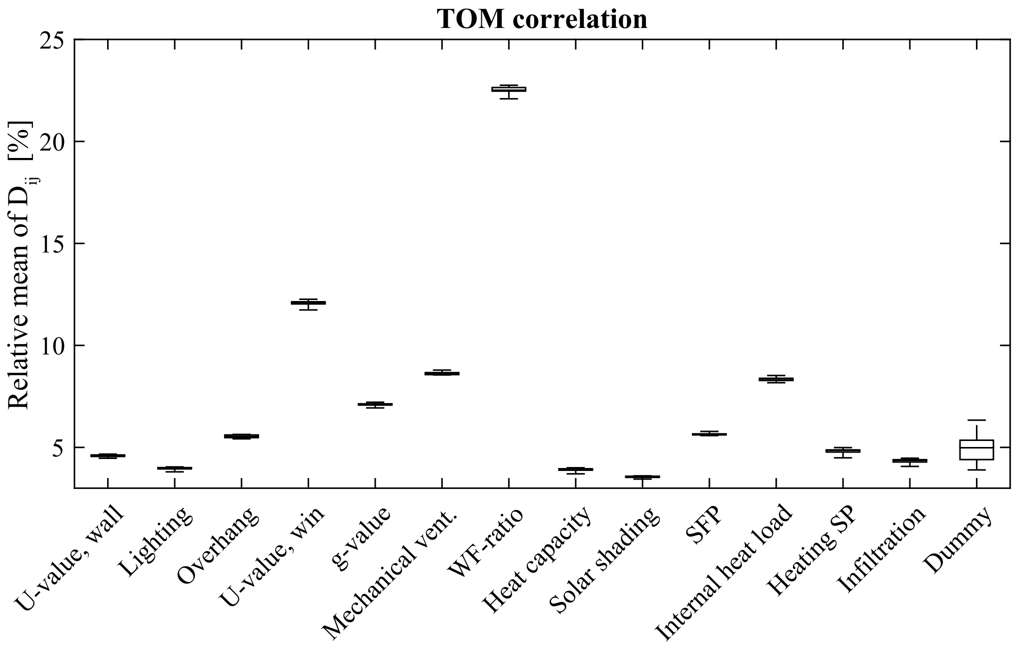


Figure F.13. Results from the sensitivity analysis using TOM when the RI is the evaluated parameter.

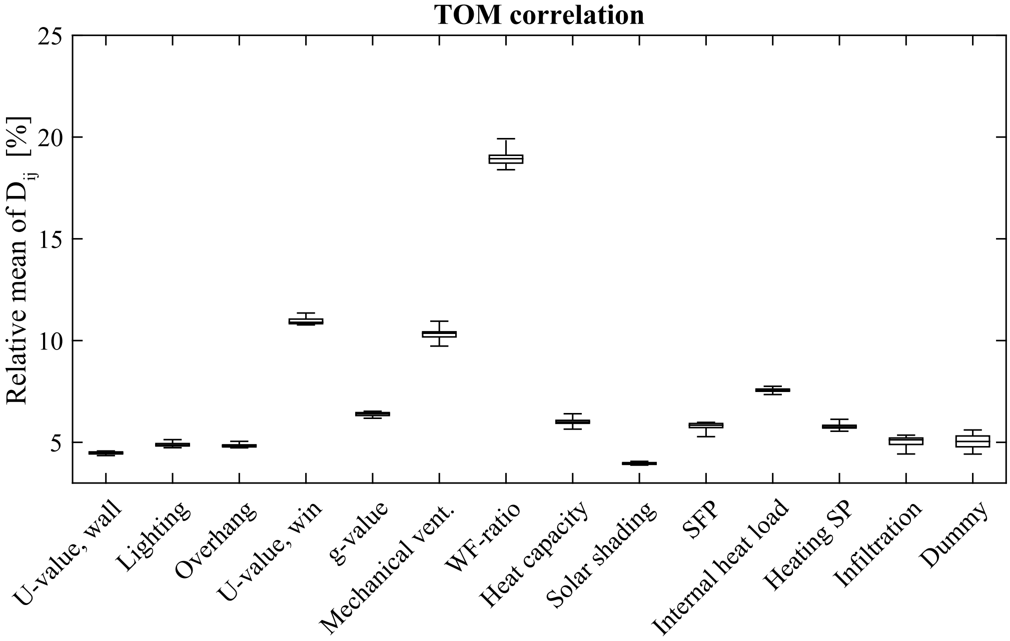


Figure F.14. Results from the sensitivity analysis using TOM when the TED and the RI are evaluated parameters.

From the figures it can be concluded that the window-to-facade ratio has the highest sensitivity on the outputs. Furthermore the mechanical ventilations indicates a lower sensitivity when considering the RI and the TED and the RI combined, compared to the results from using the TED as singular output parameter, see figure F.10. The sensitivity of the U-value for the windows is somewhat consistent in the three sensitivity analyses. The four most sensitive parameters are the same for all 3 figures (F.10, F.13 and F.14), which indicates a correlation between the TED and RI.

The ranks from the sensitivity analysis using TOM for the RI and the TED combined are presented in figure F.15.

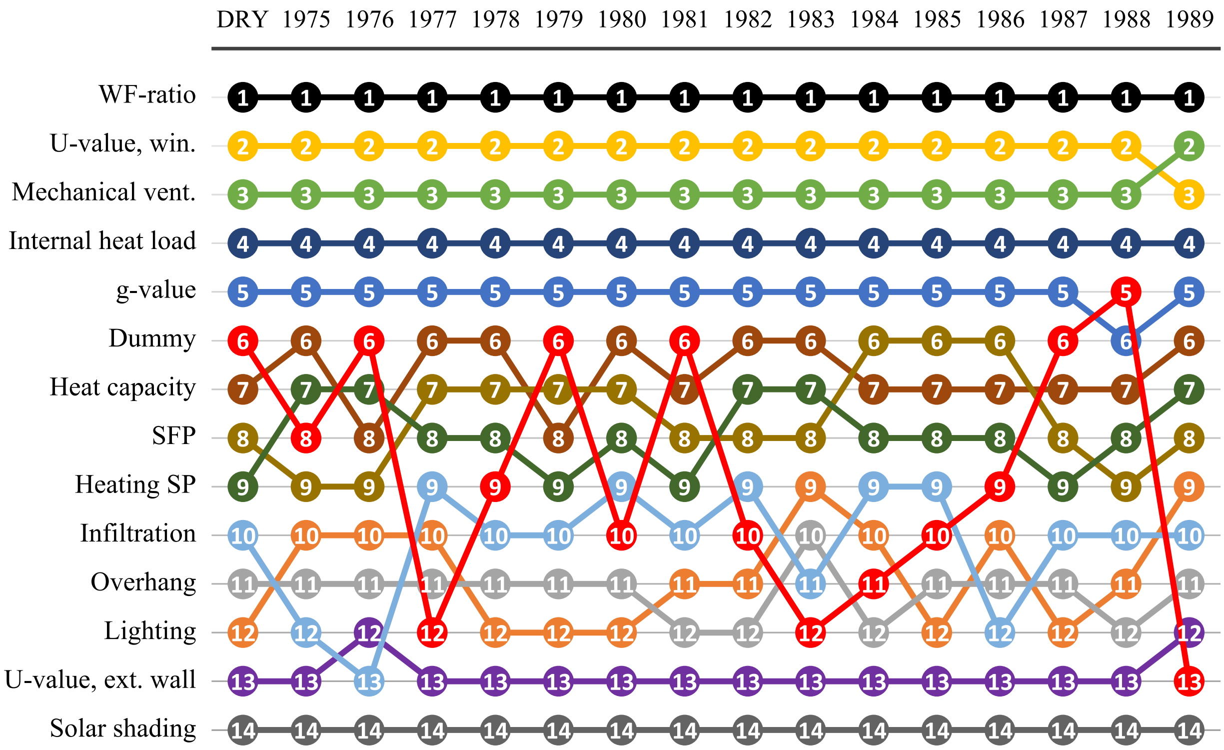


Figure F.15. Rankings of the sensitivity when applying the TED and the RI as outputs. The sensitivity measure is based on TOM correlation. Input parameters ranked lower than “Dummy” suggests no significant influence on the TED and RI combined. The input names on the left are sorted according to their rank based on the simulations with the DRY weather file.

When observing the sensitivity of the TED and the RI combined as outputs, it can be concluded that the parameters that are significantly changing ranks, compared to the sensitivity for TED only, are the U- and g-value for the windows. Note that both parameters describes how well the building is protected from outdoor conditions.
The U-value for the external wall is moved in the opposite way, being a less sensitive parameter when applying the TED and the RI combined as outputs. It has lower ranking compared to the results from figure F.10.
Note that for both sensitivity analyses the U-value for the external wall is below the dummy for multiple weather files.
Heating set-point and heat capacity are in several weather files below the dummy, which indicates that these parameters are non-influential for the given weather files.

In table F.5, the mean TED is shown for a filtering of the 10 % highest and lowest heat capacities for each weather file. This is done to show that the heat capacity has no significant impact on the RI but has an impact on the TED. The STD and IQR are shown to verify this assumption.

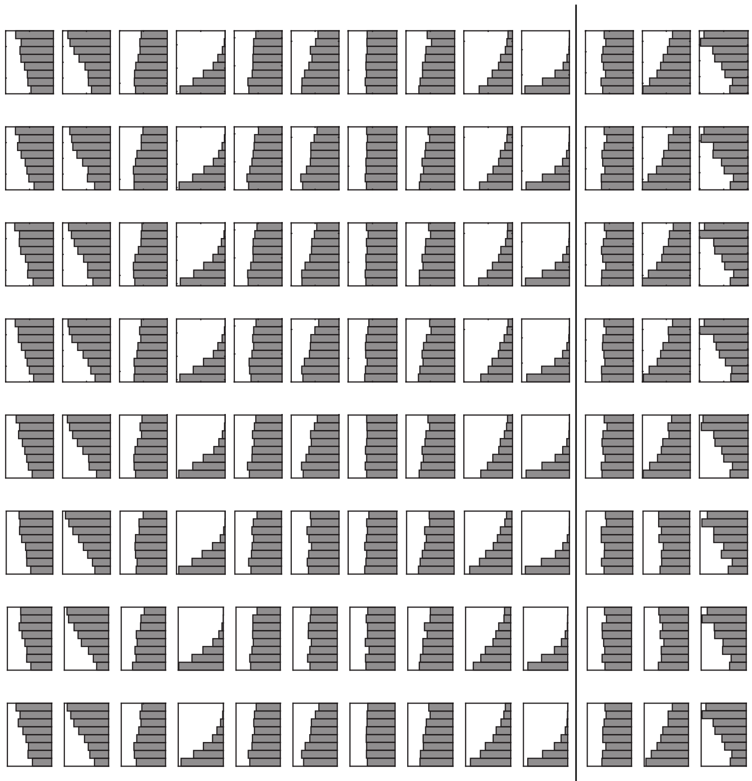
Weather file	TED HC_{high} [kWh/m^2 years]	TED HC_{low} [kWh/m^2 years]
DRY	38.9	43.8
1975	38.3	43.7
1976	41.2	46.6
1977	38.0	42.8
1978	39.2	44.1
1979	42.1	46.9
1980	40.8	45.7
1981	40.6	45.1
1982	38.4	43.3
1983	36.6	42.0
1984	37.3	42.1
1985	45.3	49.8
1986	39.4	44.4
1987	42.8	47.9
1988	37.0	41.9
1989	31.6	36.3
Mean, historic	39.2	44.2
STD	3.1	3.1
IQR	3.8	3.4

Table F.5. Mean TED for the weather files when filtering for the 10 % highest and lowest heat capacities, denoted HC_{high} and HC_{low} respectively. STD and IQR are denotations for the standard deviation and the interquartile range.

The table shows differences in the mean TED but almost no differences for the standard deviation and the interquartile range. This indicate that the heat capacity has influence on the TED but not the RI.

F.4 Histograms of design tendencies

Histograms of the input parameters for the 10 % best performing solution in terms of TED are presented in table F.6 and F.7 for all 16 weather files.



	Parameter	Range	Unit	DRY	1975	1976	1977	1978	1979	1980	1981
Design	g-value, glass	0.3 - 0.7	[–]								
	Heat capacity	60 - 140	[Wh/K m^2]								
	Lighting (general installation)	4 - 10	[W/m^2]								
	Mechanical ventilation	0.9 - 3.6	[l/s m^2]								
	Overhang depth	0 - 45	[°]								
	Specific fan power (SFP)	1.5 - 2.1	[kJ/m^3]								
	Solar shading	0.2 - 1.0	[–]								
	U-value, external wall	0.10 - 0.15	[W/m^2 K]								
	U-value, windows	1.0 - 1.6	[W/m^2 K]								
	Window-to-facade ratio	25 - 75	[%]								
Uncertain	Heating set-point	21 - 24	[°C]								
	Infiltration	0.07 - 0.13	[l/s m^2]								
	Internal heat load	16 - 24	[W/m^2]								

Table F.6. Histograms of the top 10 % best performing solutions in terms of TED alongside with the initial range of the input parameters. Presented results are for the DRY and the 1975-1981 weather files.

	Parameter	Range	Unit	1982	1983	1984	1985	1986	1987	1988	1989
Design	g-value, glass	0.3 - 0.7	[−]								
	Heat capacity	60 - 140	[Wh/K m^2]								
	Lighting (general installation)	4 - 10	[W/m^2]								
	Mechanical ventilation	0.9 - 3.6	[l/s m^2]								
	Overhang depth	0 - 45	[°]								
	Specific fan power (SFP)	1.5 - 2.1	[kJ/m^3]								
	Solar shading	0.2 - 1.0	[−]								
	U-value, external wall	0.10 - 0.15	[W/m^2 K]								
	U-value, windows	1.0 - 1.6	[W/m^2 K]								
	Window-to-facade ratio	25 - 75	[%]								
Uncertain	Heating set-point	21 - 24	[°C]								
	Infiltration	0.07 - 0.13	[l/s m^2]								
	Internal heat load	16 - 24	[W/m^2]								

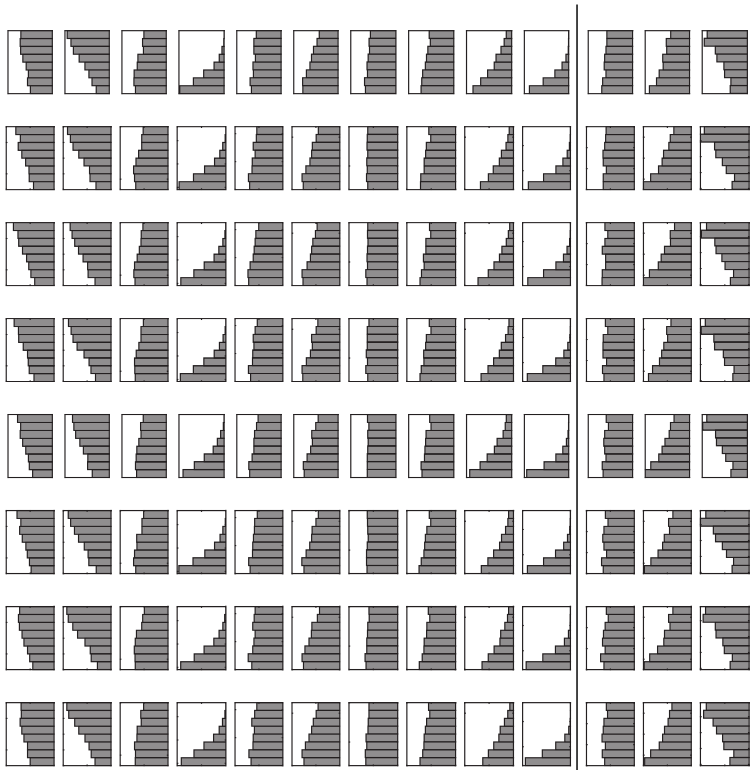


Table F.7. Histograms of the top 10 % best performing solutions in terms of TED alongside with the initial range of the input parameters. Presented results are for the the 1982-1989 weather files.

BSim Simulations G

Supplementary results of the BSim simulations are presented in this chapter.

G.1 Preliminary investigation of occupancy modelling

The results from the preliminary investigation is presented and discussed in this section. The three different occupancy models are evaluated on their performance in four different output parameters, cooling, heating, excessive temperatures and fan power demand. These are evaluated on an annual basis, by comparing the designs solutions with each other for each occupancy model.
The scatter plots presented in section are presenting and comparing the three occupancy models by plotting the simulation results for each design solution against each other. For example, when the legend says “DOM a,c”, the results from the simulations with DOMa and DOMb are presented along the x- and the y-axis. By doing this, there will be a line crossing the plot, where the value of the x-axis is equal to the y-axis. This is indicated with a dashed line, denoted “y=x” in the legends. There is therefore no difference in the respective output parameter for simulations results occurring on this line.

G.1.1 Cooling

The cooling in the room, adjusts the cooling performance to keep the indoor air temperature at the set-point. The results for the cooling demand is presented with a histogram and a scatter plot in figure G.1 and G.2, respectively.

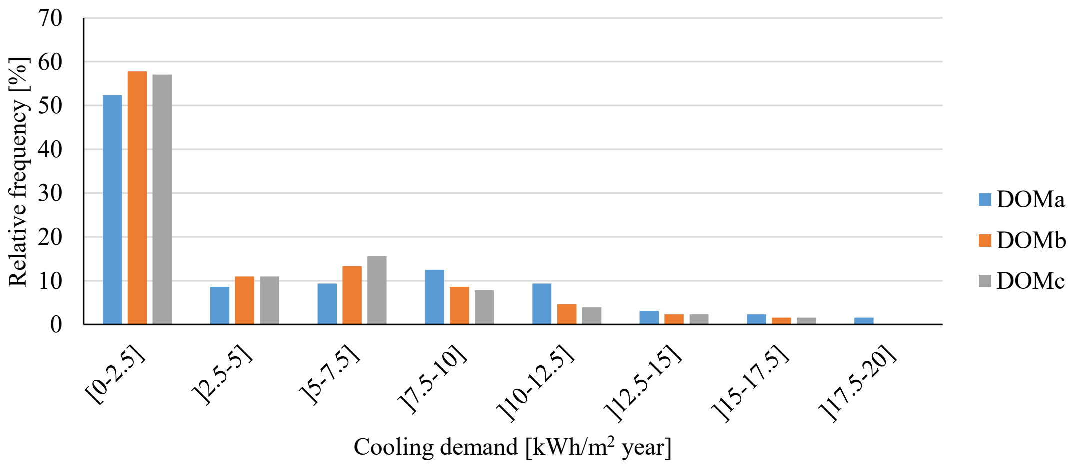


Figure G.1. Histogram presenting the relative frequency of the cooling demand for the three occupancy models.

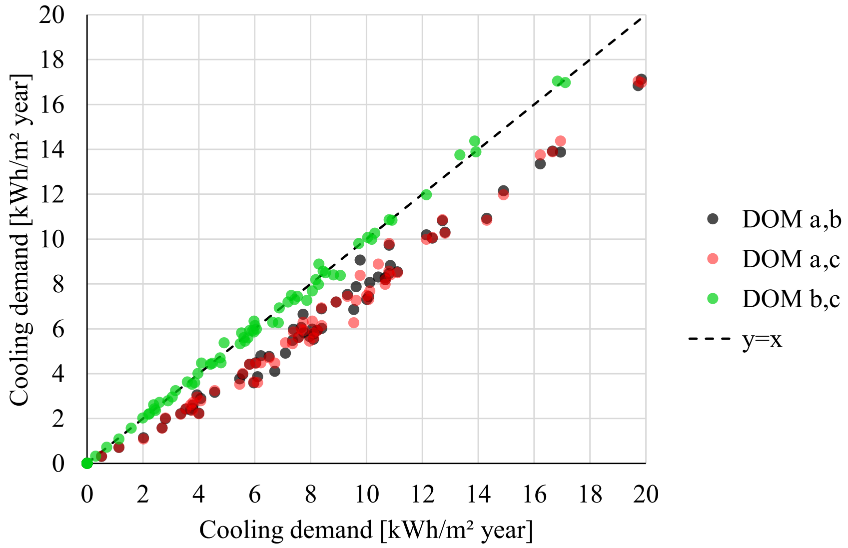


Figure G.2. Scatter plot comparing the cooling demand of the three occupancy models. The numbers in the legend after "DOM" corresponds to the x- and the y-axis.

Figure G.1 and G.2 shows interesting results in terms of the differences between the occupancy models. Comparing DOMa with both DOMb and DOMc, the results indicate that model a demands more cooling than the two others. Furthermore, DOMb and DOMc deliver similar results as the results in the plot are concentrated along the dashed line.

G.1.2 Heating

The heating output is energy demand to heat sources such as radiators to keep the indoor air temperature at the set-point. The results for the heating demand is presented with a histogram and a scatter plot in figure G.3 and G.4, respectively.

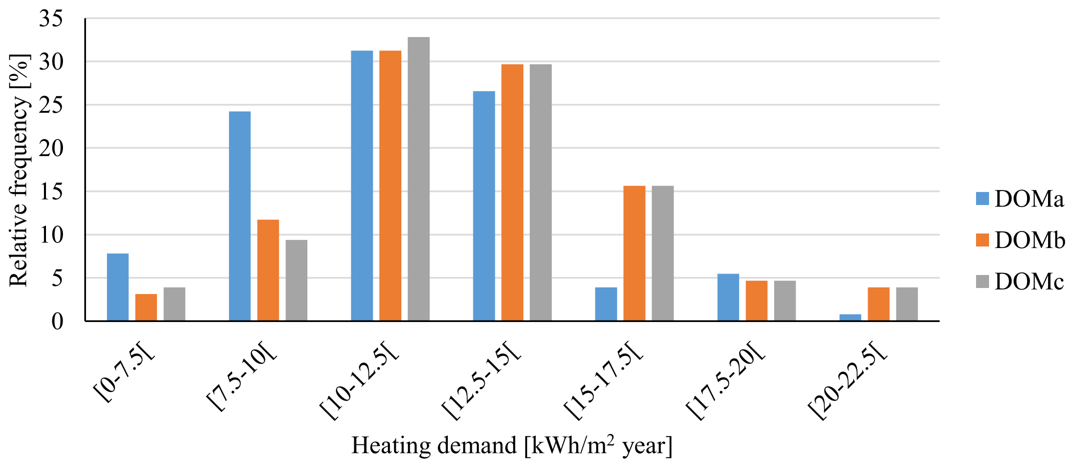


Figure G.3. Histogram presenting the relative frequency of the heating demand for the three occupancy models.

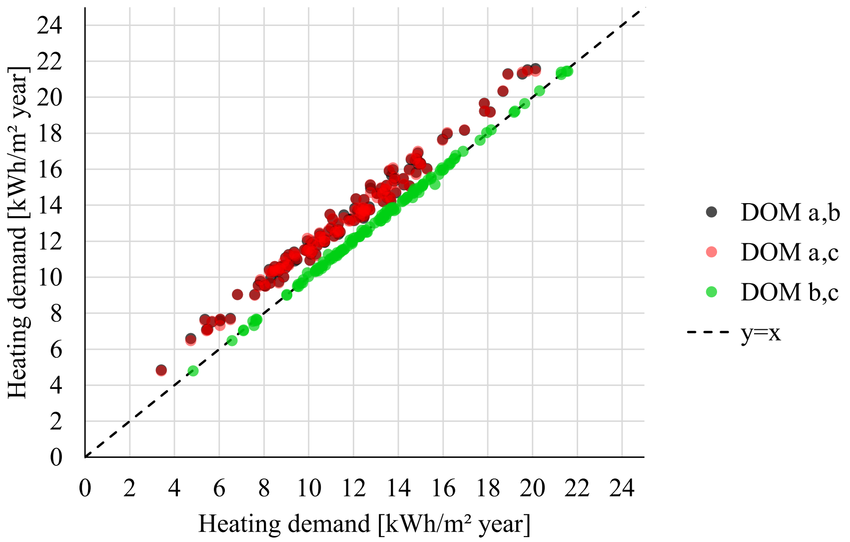


Figure G.4. Scatter plot comparing the heating demand of the three occupancy models. The numbers in the legend after "DOM" corresponds to the x- and the y-axis.

The results in figure G.3 and G.4 indicates that DOMa needs less heating than the two other models. As for the cooling demand, DOMb and DOMc are delivering similar results.

G.1.3 Excessive temperatures

To evaluate the thermal indoor climate, excessive temperatures are evaluated in terms of hours with indoor air temperature above 26 °C. The results for the excessive temperatures are presented with a histogram and a scatter plot in figure G.5 and G.6, respectively.

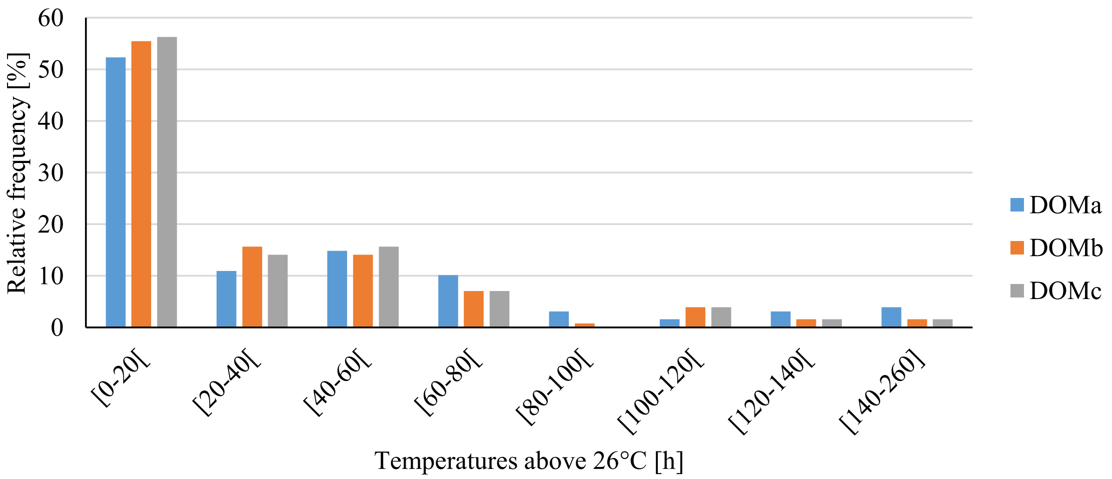


Figure G.5. Histogram presenting the relative frequency of hours with indoor air temperatures above 26 °C for the three occupancy models.

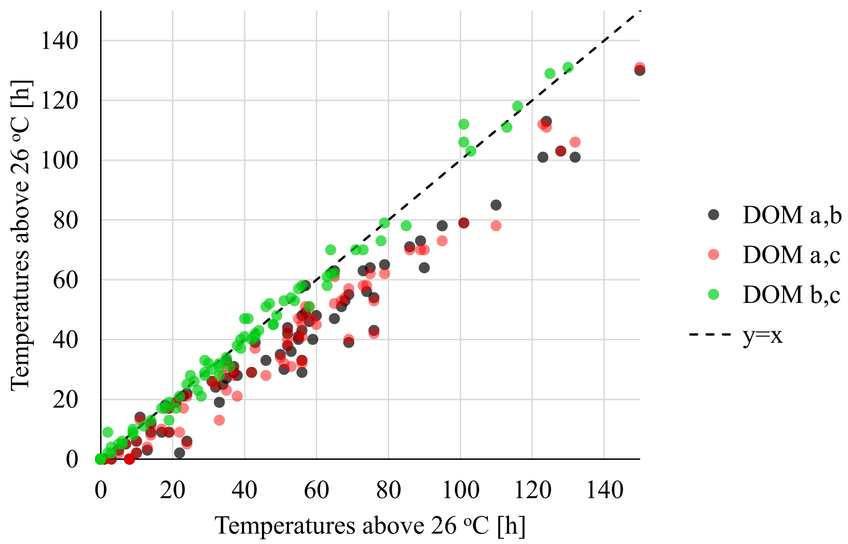


Figure G.6. Scatter plot comparing hours of indoor air temperatures above 26 °C of the three occupancy models. The numbers in the legend after "DOM" corresponds to the x- and the y-axis.

Figure G.5 and G.6 indicates that the amount of hours above 26 °C is higher for DOMa compared to the two others. DOMb and DOMc gives similar results.

G.1.4 Fan power

To evaluate the energy demand for mechanical ventilation for the three different occupancy models, the fan power demand is chosen as evaluation output. This output is the TED for motors, ventilators and transmission. A scatter plot of the results for the fan power demand is presented in figure G.7.

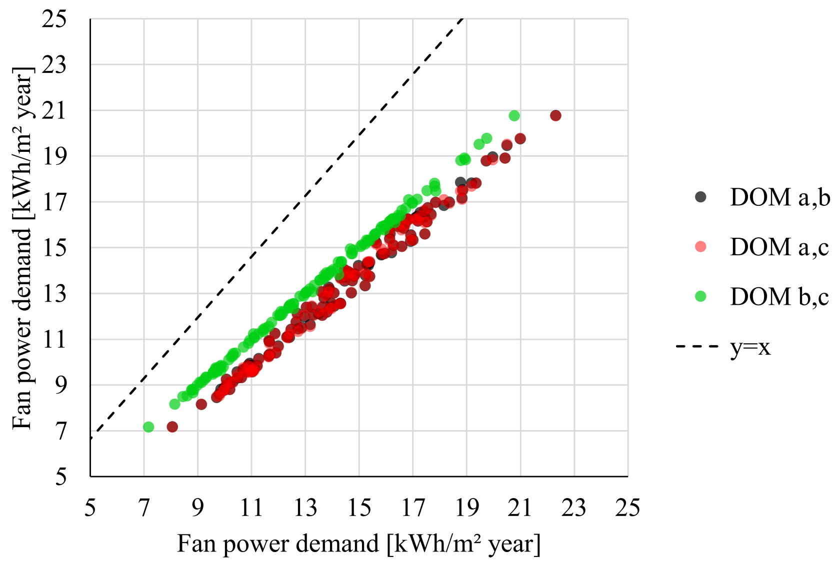


Figure G.7. Scatter plot comparing the power demand for the ventilation fan of the three occupancy models. The numbers in the legend after "DOM" corresponds to the x- and the y-axis.

Observing figure G.7, the results are again showing differences for DOMa. This model demands more energy for the fan than the two other models. DOMb and DOMc yields similar results.

G.2 Comparison of the occupancy models

The comparison of the occupancy models is shown as scatter plots and as a quantitative value. The quantitative value is the absolute mean deviation (MAD), which describes how different the models are in average.

The evaluated performance parameters are TED, cooling, heating, fan power, exceeding temperatures. For the dimensional values, the cooling, heating, fan power, operative temperature and CO_2-levels.

G.2.1 Energy and thermal performance

G.2.1.1 Comparison of DOM1 and SOM1

Scatter plots of the energy and thermal performance for DOM1 and SOM1 are presented in figure G.8, G.9, G.10, G.11, G.12 and G.13.

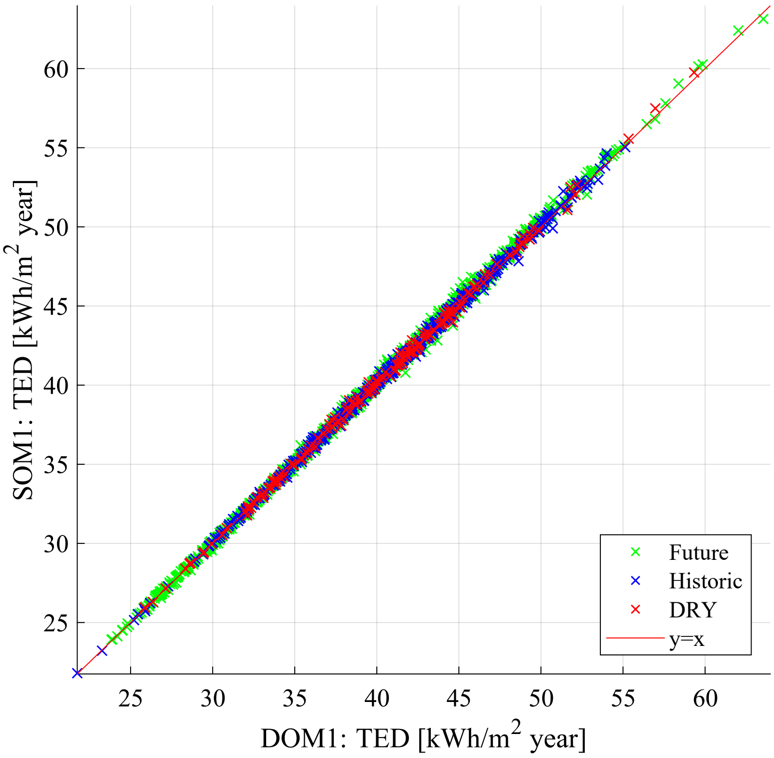


Figure G.8. Scatter plot presenting the TED for DOM1 and SOM1.

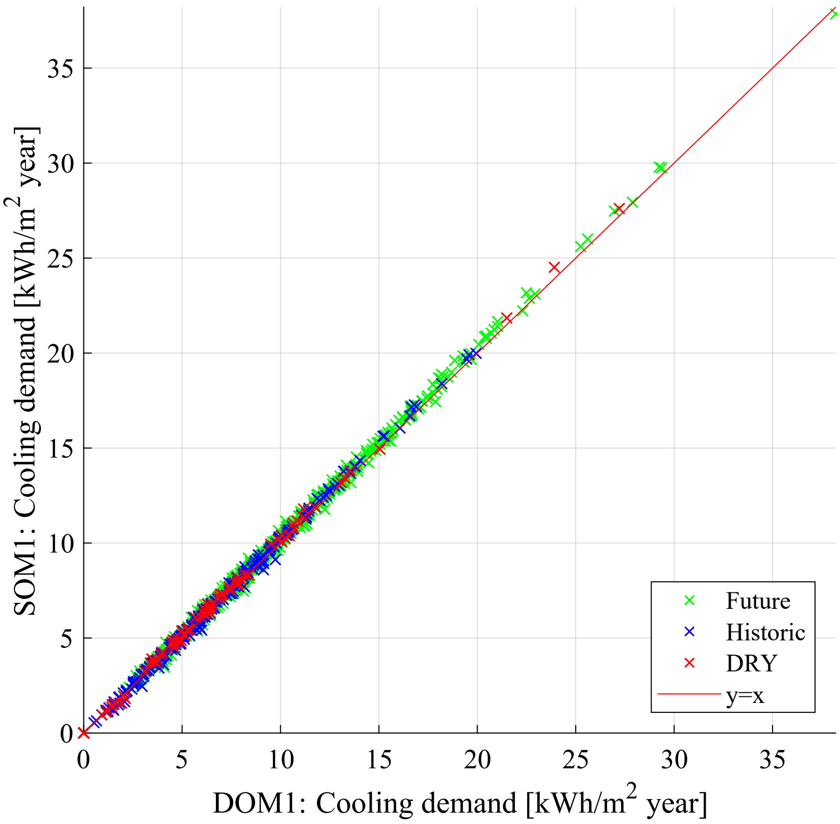


Figure G.9. Scatter plot presenting the cooling demand for DOM1 and SOM1.

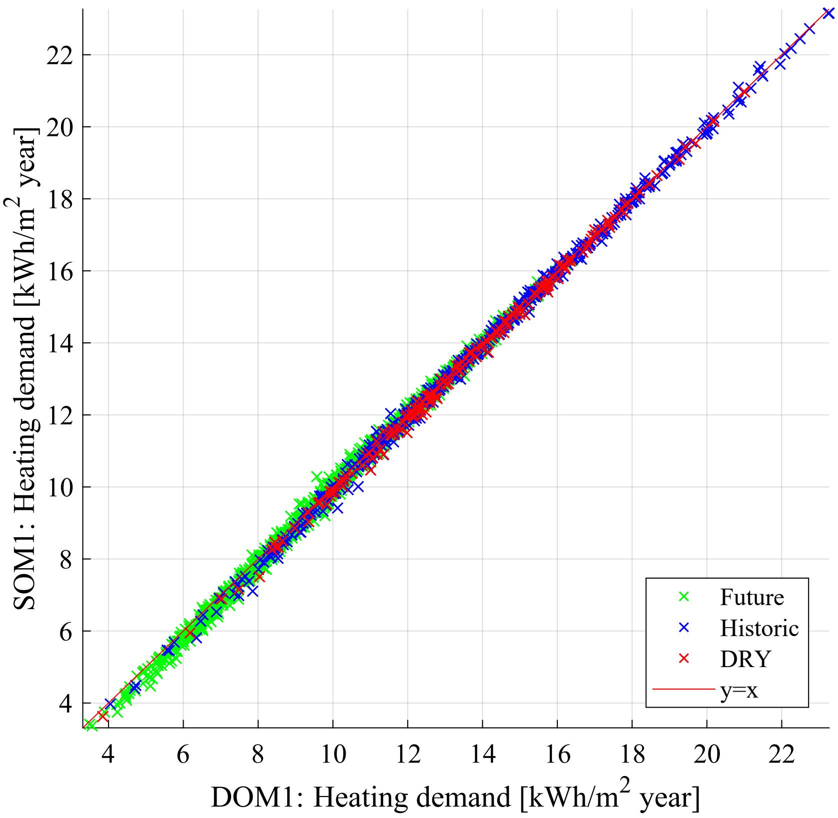


Figure G.10. Scatter plot presenting the heating demand for DOM1 and SOM1.

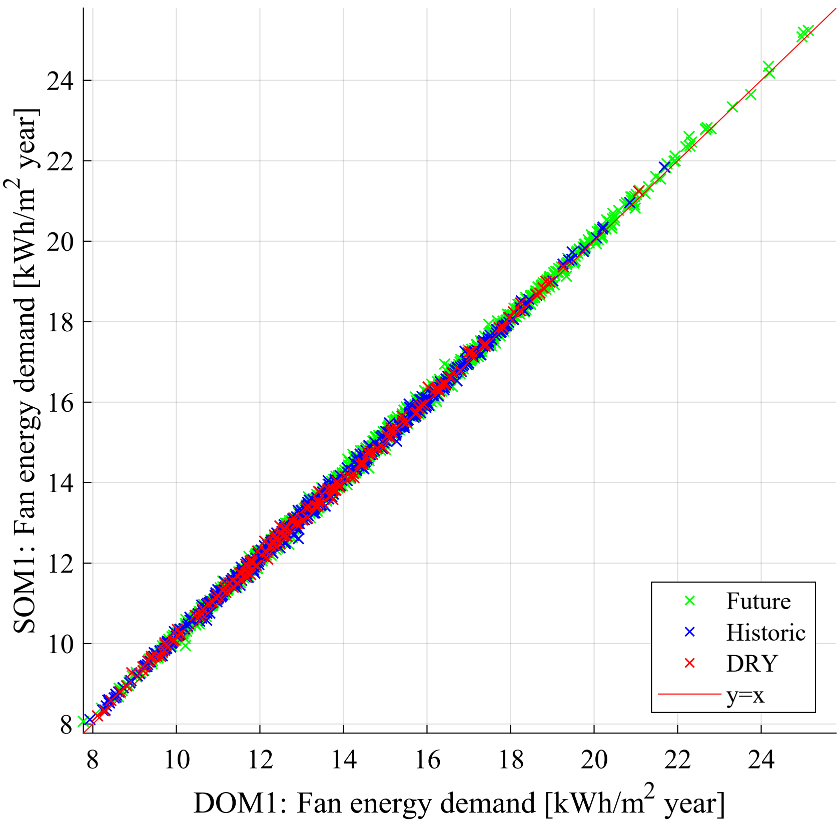


Figure G.11. Scatter plot presenting the yearly fan energy demand for DOM1 and SOM1.

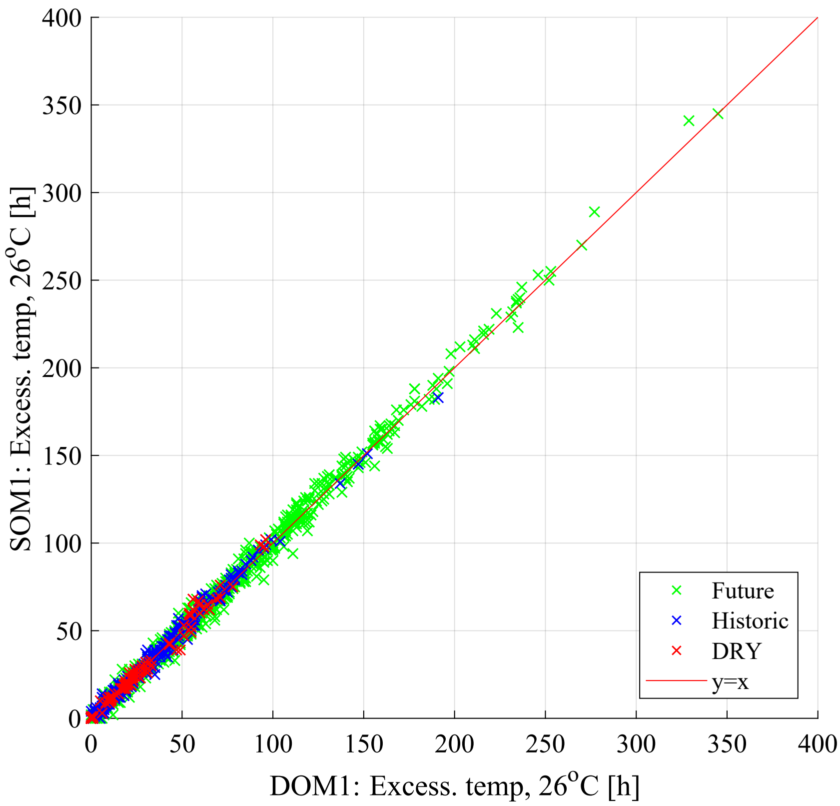


Figure G.12. Scatter plot presenting the exceeding temperatures above 26 °C for DOM1 and SOM1.

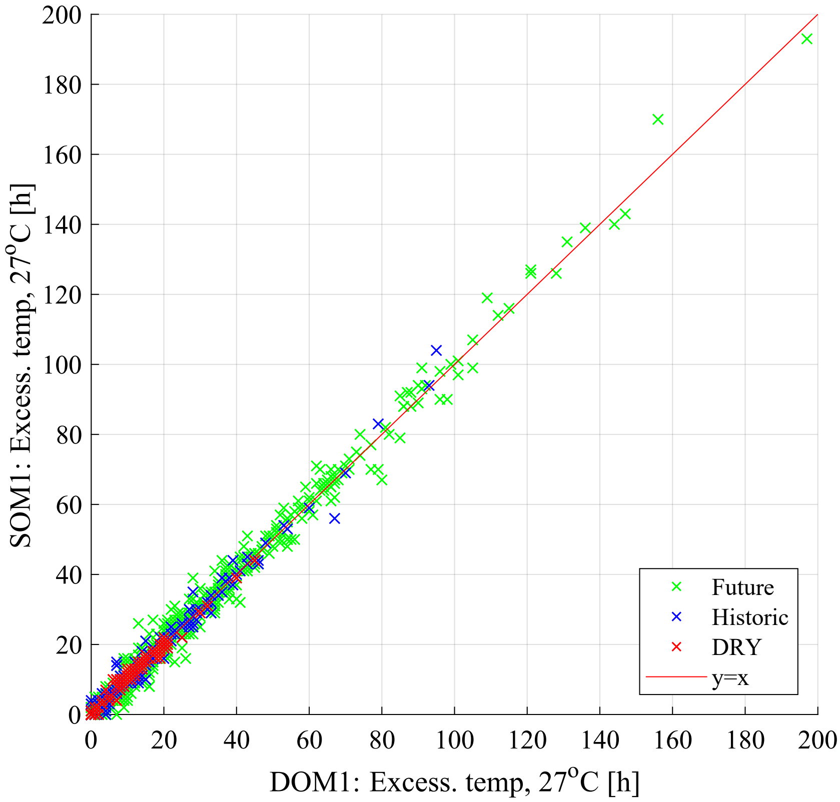


Figure G.13. Scatter plot presenting the exceeding temperatures above 27 °C for DOM1 and SOM1.

G.2.1.2 Comparison of DOM2 and SOM2

Scatter plots of the energy and thermal performance for DOM2 and SOM2 are presented in figure G.14, G.15, G.16, G.17, G.18 and G.19.

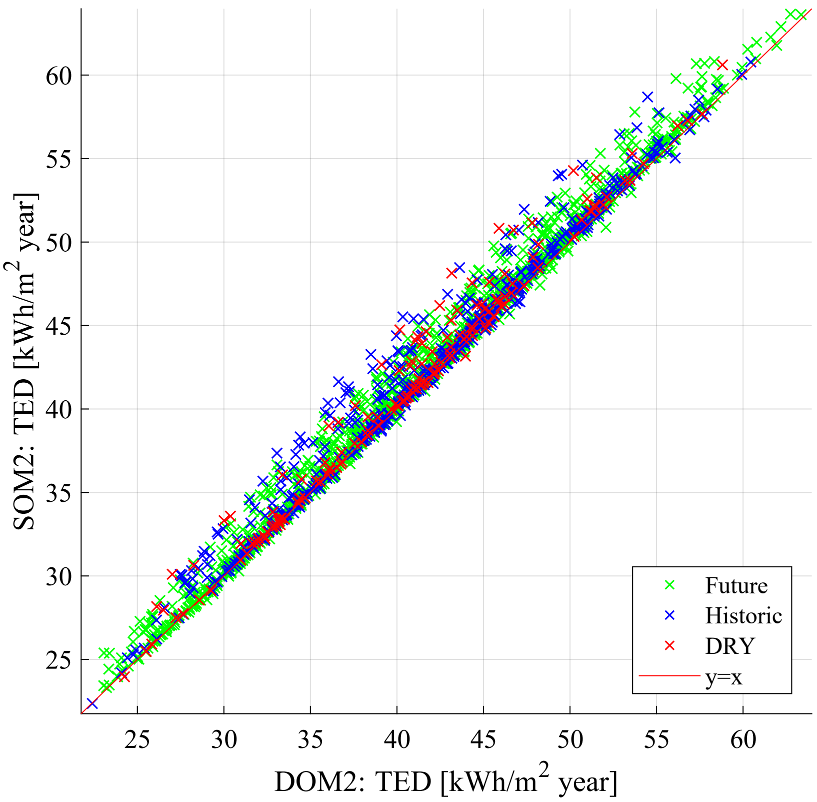


Figure G.14. Scatter plot presenting the TED for DOM2 and SOM2.

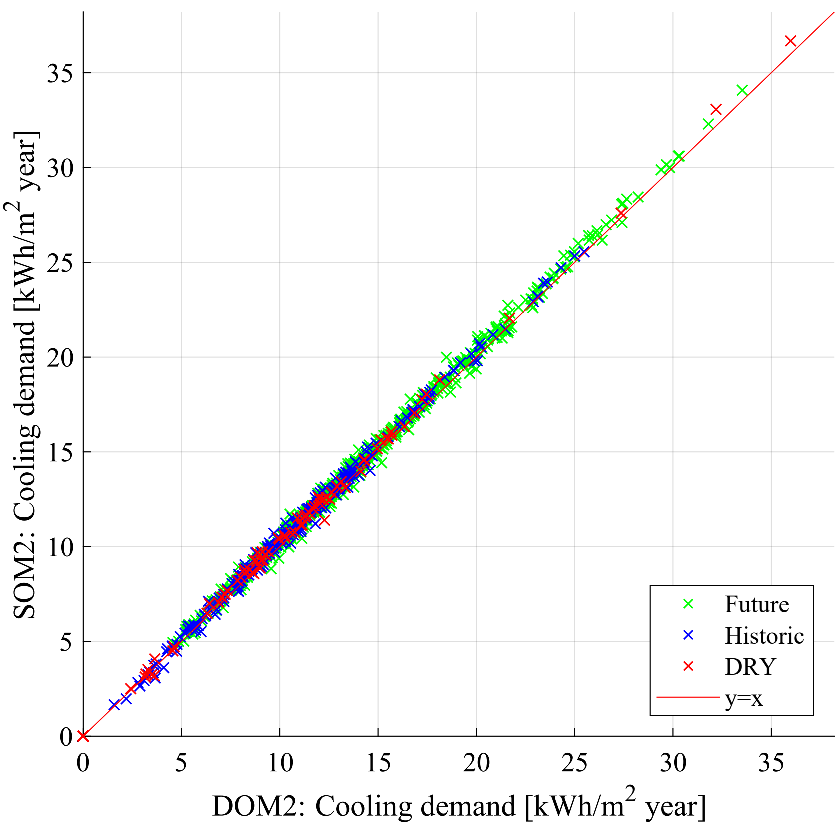


Figure G.15. Scatter plot presenting the cooling demand for DOM2 and SOM2.

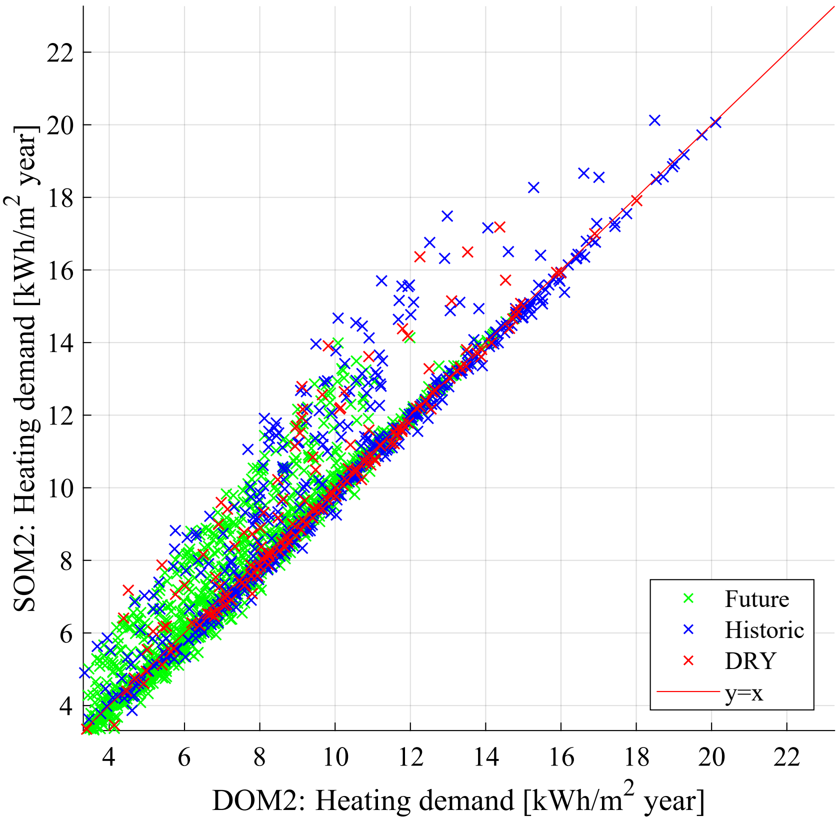


Figure G.16. Scatter plot presenting the heating demand for DOM2 and SOM2.

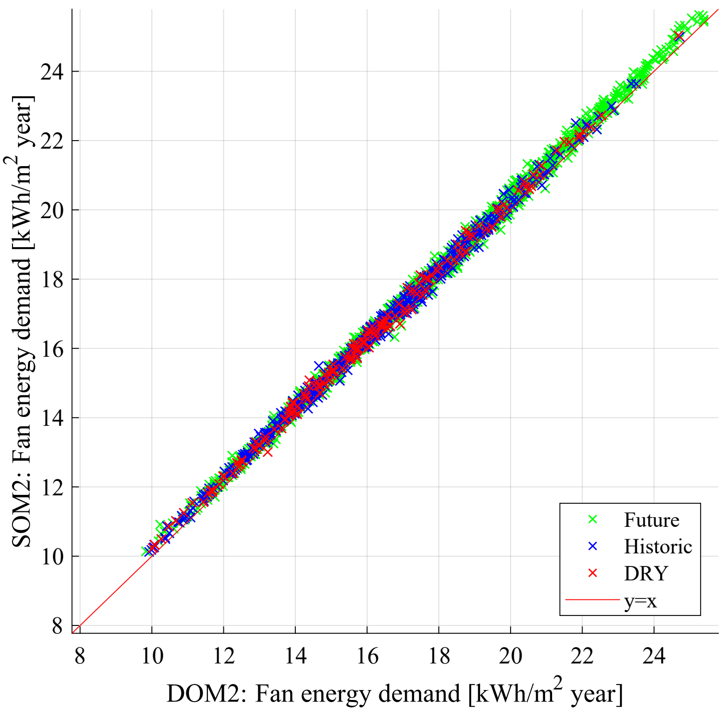


Figure G.17. Scatter plot presenting the yearly fan energy demand for DOM2 and SOM2.

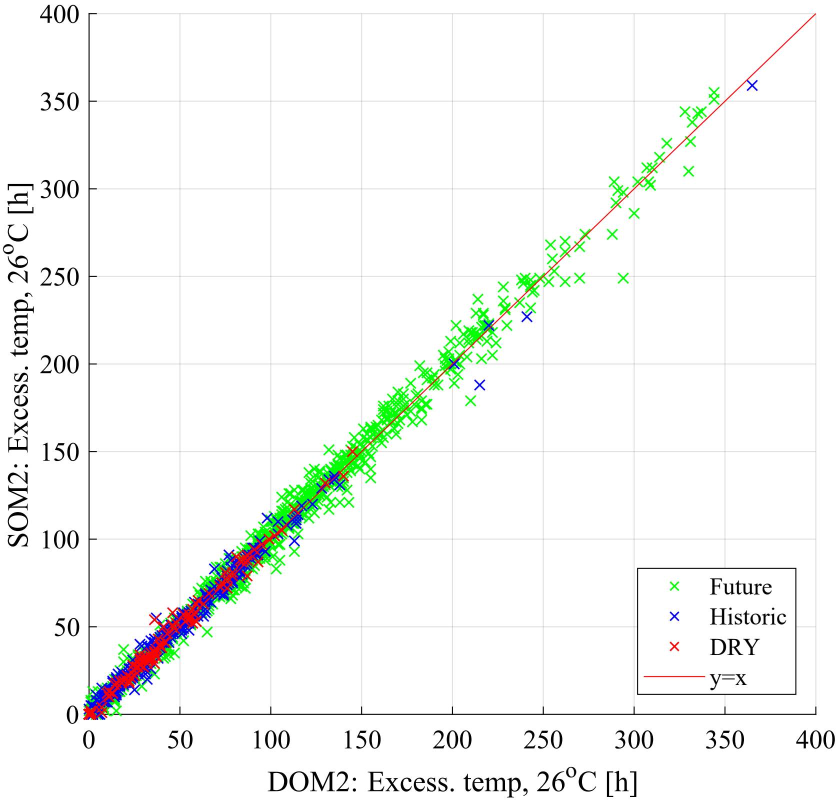


Figure G.18. Scatter plot presenting the exceeding temperatures above 26 °C for DOM2 and SOM2.

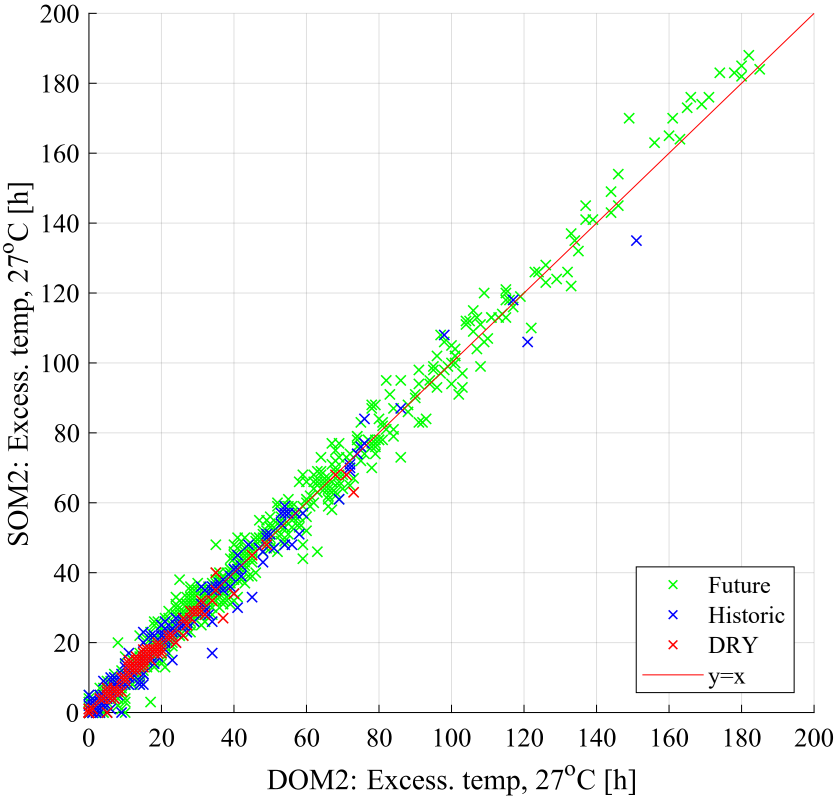


Figure G.19. Scatter plot presenting the exceeding temperatures above 27 °C for DOM2 and SOM2.

The results for DOM1 and SOM1 shows that with most of the design solutions, the two occupancy models induce similar results. The differences in results are even smaller when considering DOM2 and SOM2, indicating that with more occupants present, the difference in the two occupancy profile models decreases.

The future weather files are in general causing higher cooling and fan energy demand, lower heating demand and more hours of excessive temperatures.

G.2.2 Dimensional values

The scatter plots of the dimensional values presented in this section is for an acceptable deviation of 3 %. If interested, see appendix H for scatter plots with 1 % and 5 % acceptable deviation.

G.2.2.1 Comparison of DOM1 and SOM1

Scatter plots presenting the dimensional values for DOM1 and SOM1 are presented in figure G.20, G.21, G.22, G.23 and G.24.

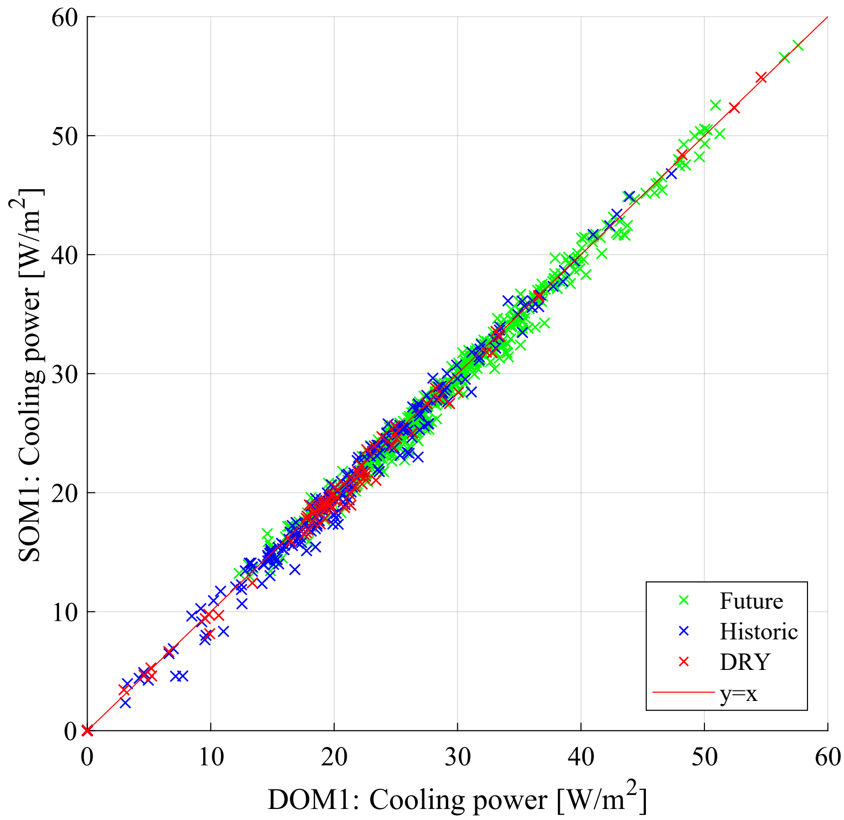


Figure G.20. Scatter plot presenting the dimensional cooling power for DOM1 and SOM1 with an acceptable deviation of 3 %.

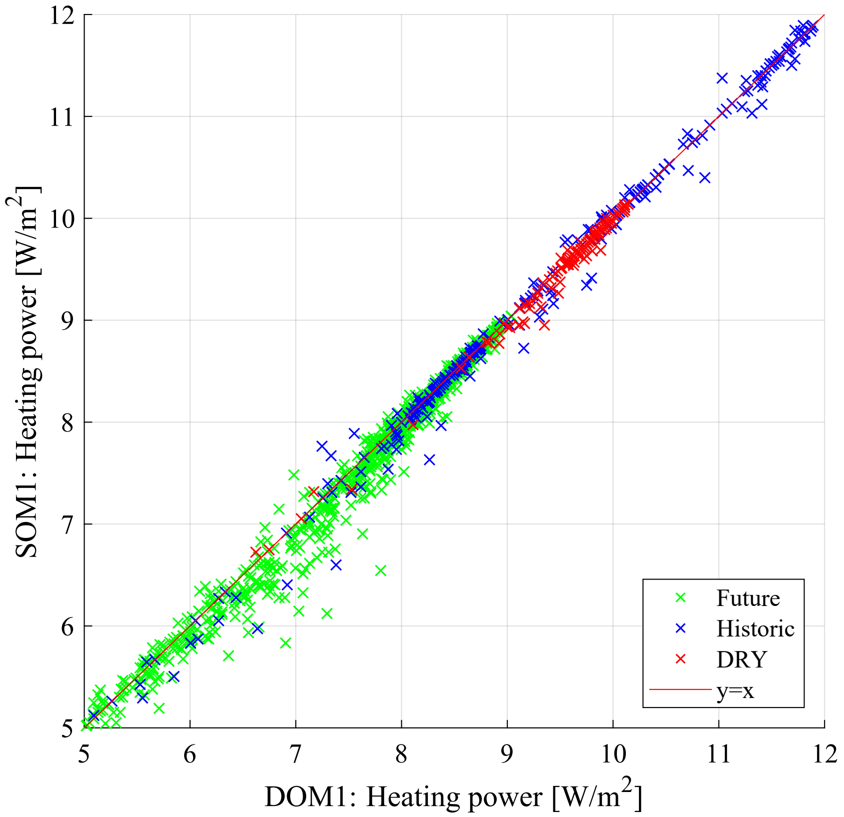


Figure G.21. Scatter plot presenting the dimensional heating power for DOM1 and SOM1 with an acceptable deviation of 3 %.

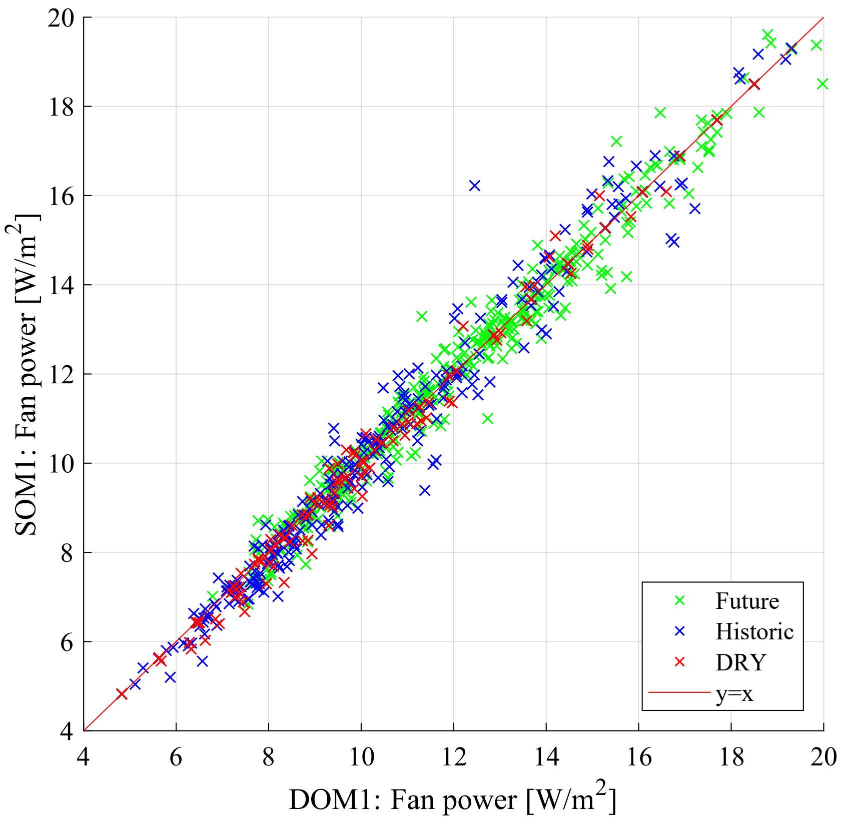


Figure G.22. Scatter plot presenting the dimensional fan power for DOM1 and SOM1 with an acceptable deviation of 3 %.

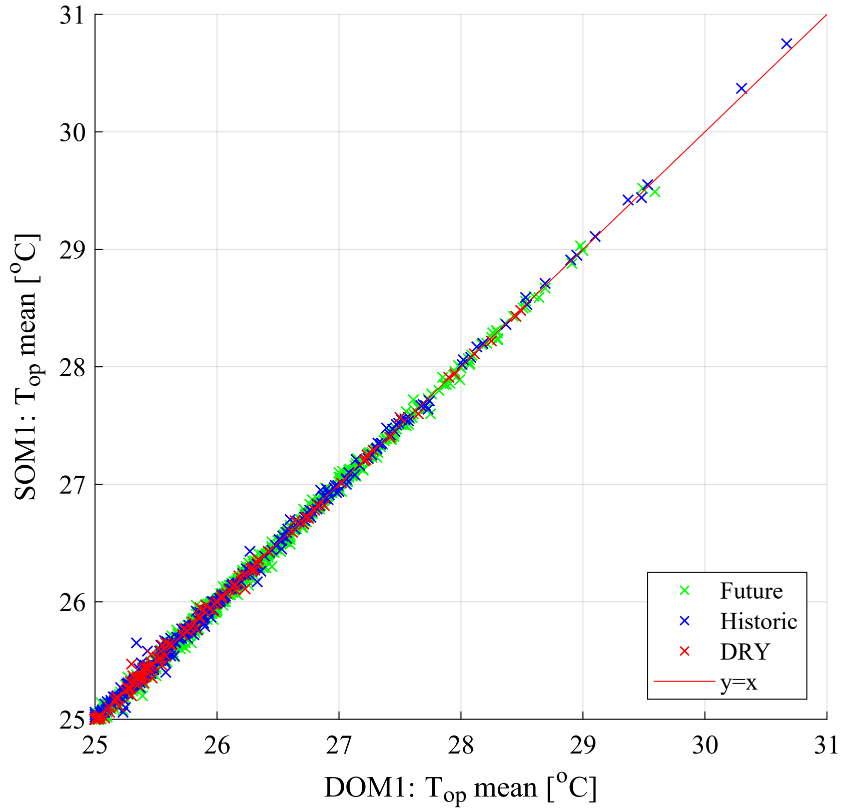


Figure G.23. Scatter plot presenting the mean operative temperatures for DOM1 and SOM1 with an acceptable deviation of 3 %.

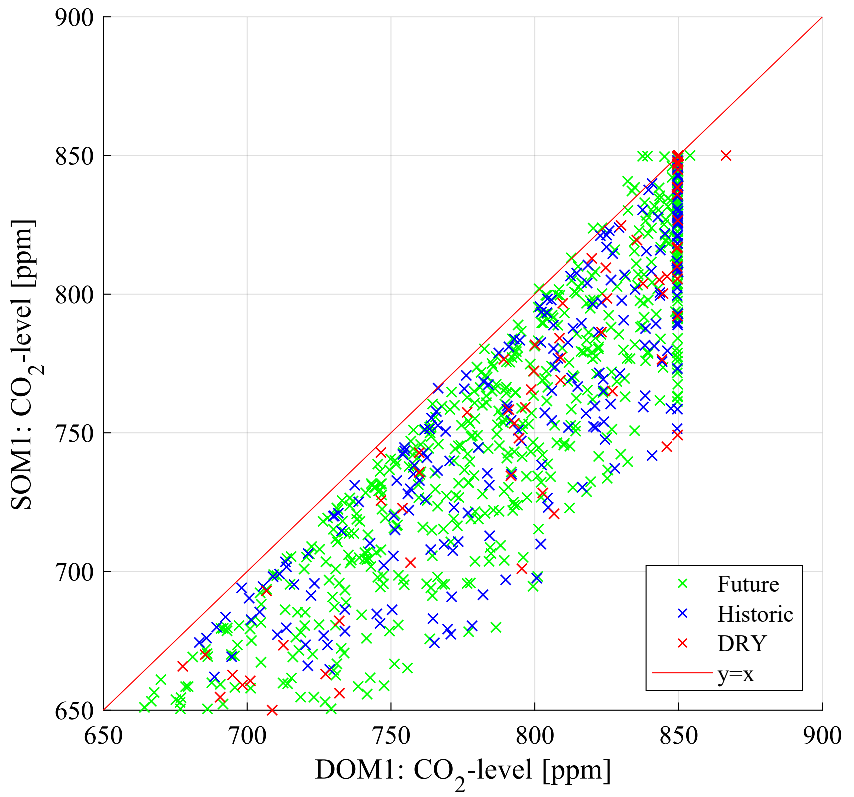


Figure G.24. Scatter plot presenting the CO_2-levels for DOM1 and SOM1 with an acceptable deviation of 3 %.

G.2.2.2 Comparison of DOM2 and SOM2

Scatter plots presenting the dimensional values for DOM2 and SOM2 are presented in figure G.25, G.26, G.27, G.28 and G.29.

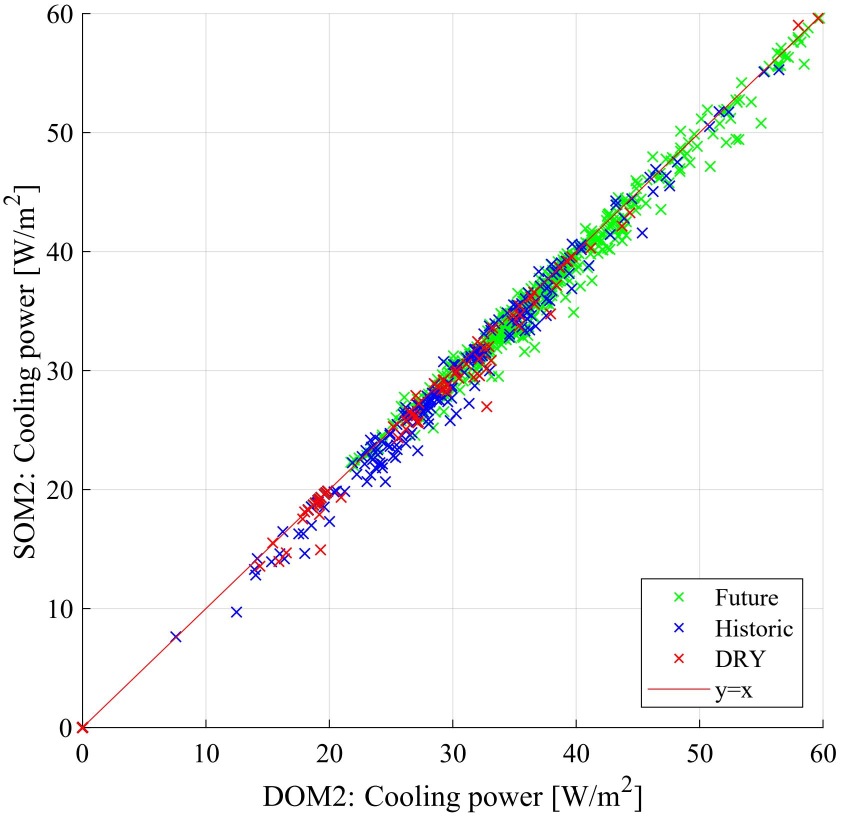


Figure G.25. Scatter plot presenting the dimensional cooling power for DOM2 and SOM2 with an acceptable deviation of 3 %.

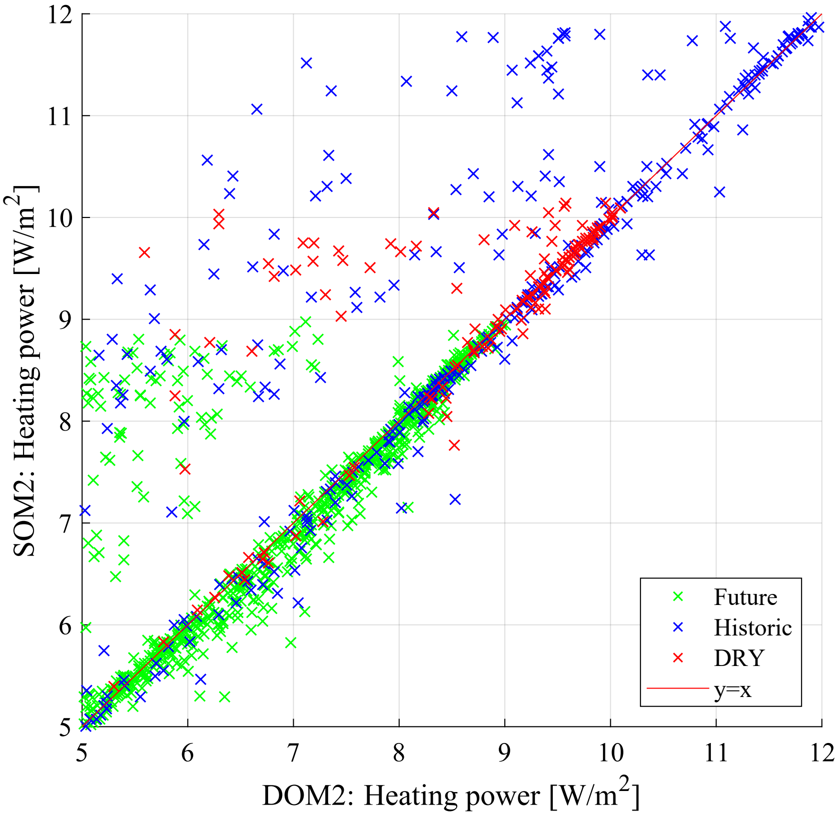


Figure G.26. Scatter plot presenting the dimensional heating power for DOM2 and SOM2 with an acceptable deviation of 3 %.

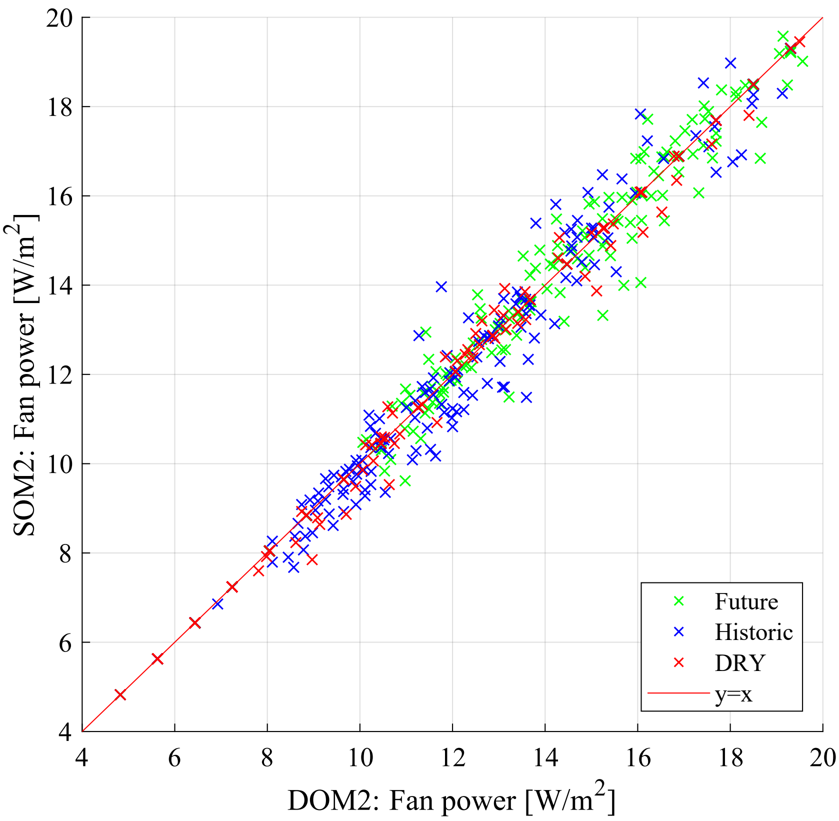


Figure G.27. Scatter plot presenting the dimensional fan power for DOM2 and SOM2 with an acceptable deviation of 3 %.

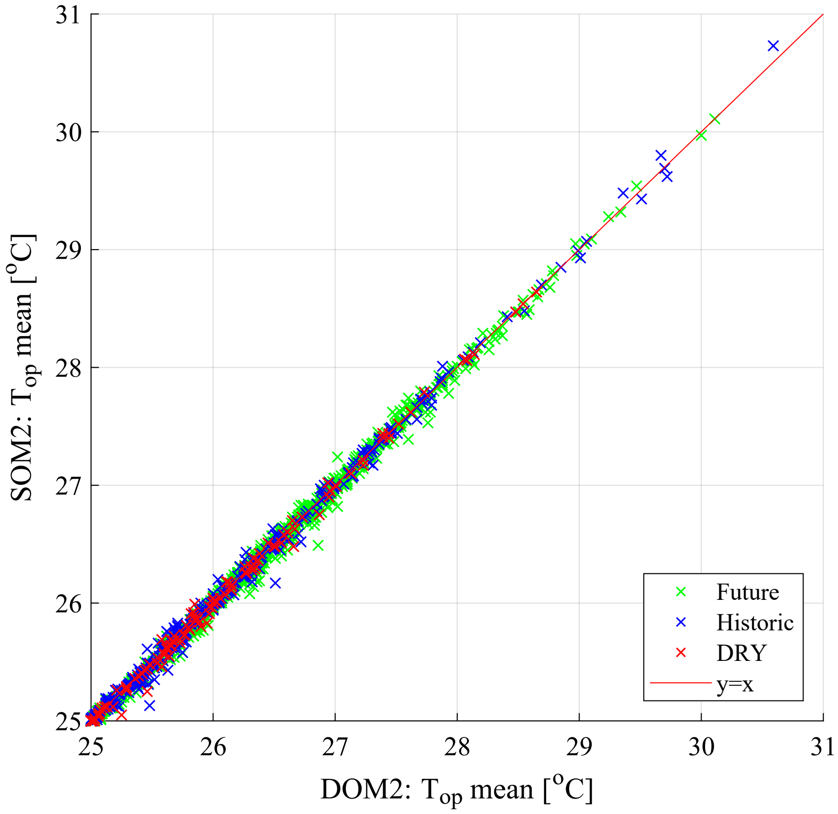


Figure G.28. Scatter plot presenting the mean operative temperatures for DOM2 and SOM2 with an acceptable deviation of 3 %.

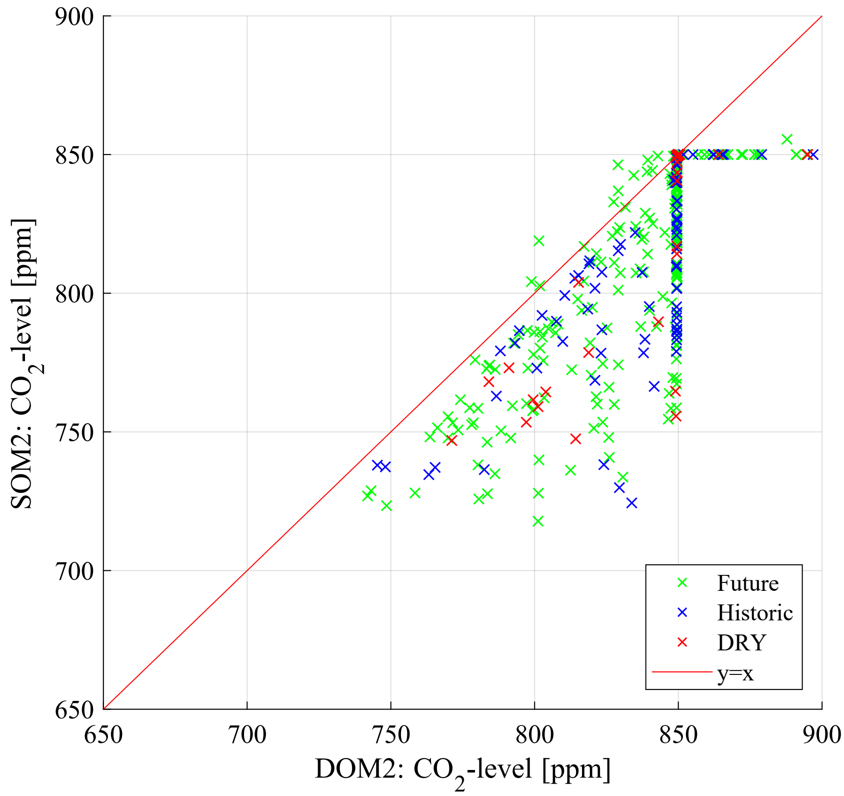


Figure G.29. Scatter plot presenting the CO_2-levels for DOM2 and SOM2 with an acceptable deviation of 3 %.

AD [%]	Model comparison	Cooling [W/m^2]		Heating [W/m^2]		Fan power [W/m^2]		TopMean [°C]		CO_2 [ppm]	
1	DOM1 & SOM2	5.7	14%	0.7	9%	0.1	1%	0.3	1%	14.3	2%
3	DOM1 & SOM2	6.5	20%	0.9	14%	1.1	8%	0.2	1%	20.3	2%
5	DOM1 & SOM2	7.0	25%	0.9	16%	1.5	13%	0.2	1%	24.8	3%
1	DOM1 & SOM1	0.8	3%	0.1	1%	0.0	0%	0.0	0%	22.3	3%
3	DOM1 & SOM1	0.6	3%	0.1	1%	0.1	1%	0.0	0%	16.2	2%
5	DOM1 & SOM1	0.5	6%	0.1	1%	0.1	1%	0.0	0%	12.2	2%
1	DOM2 & SOM2	1.0	3%	0.8	9%	0.0	0%	0.0	0%	7.3	1%
3	DOM2 & SOM2	0.7	2%	0.6	8%	0.1	1%	0.0	0%	5.3	1%
5	DOM2 & SOM2	0.5	2%	0.5	7%	0.1	1%	0.0	0%	4.2	1%

Table G.1. Mean absolute deviation (MAD) of occupancy model comparisons for the dimensional values. In gray the mean absolute percentage error (MAPE) is shown for DOM as the predicted value. AD is the acceptable deviation.

The results for DOM1 and SOM1 shows that the main part of the solutions induce similar results with the two occupancy profile models. The differences in results are even smaller when considering DOM2 and SOM2, indicating that with more occupants present, the difference in the two occupancy models decreases. This is supported by the MAD values presented in table G.1.

The future weather files are in general causing higher required cooling power, heating power and fan power.

The results in figure G.24 shows that the DOM2 has higher CO_2-levels than SOM2. Some building designs reaches the set-point of 850 ppm for DOM2 before SOM2. Furthermore some are exceeding the set-point for DOM2 only. This is due to the peak occupancy loads caused by the dynamic occupancy model.

Evident from figure G.21, when using DRY as the weather file, a much smaller range of heating power is necessary to keep the 3 % acceptable deviation of work hours. When combining DRY and the historic weather files, it can be concluded that the DRY represents a mean of the historic weather files but not the actual uncertainty caused by the weather files. This might be due to the fact that the coldest and warmest historic weather file are included in the historic weather files.

G.3 Sensitivity analysis

The sensitivity analysis performed on results from BSim are based on TOM. Recall that the dummy represents an input with no influence on the output, thus inputs with a lower or equal sensitivity is noninfluential.

The sensitivity analysis gives an understanding of which parameters are causing the uncertainty in the results. This can be compared to which parameters causes the uncertainty of the given output within the scatter plots.

G.3.1 Building performance

G.3.1.1 Total energy demand

The sensitivity analysis shown in figure G.30 is filtered for the models that contains cooling systems. Recall that 50 % of the models are without cooling.

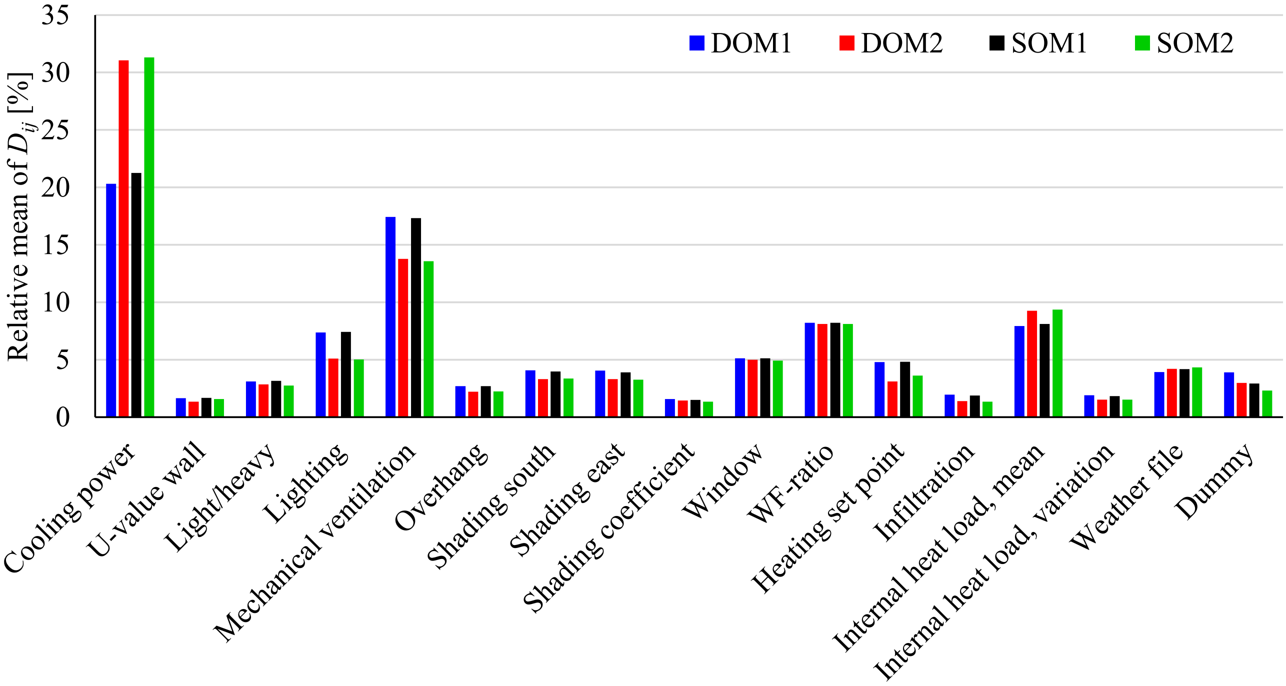


Figure G.30. Sensitivity analysis for the TED. The method used is TOM.

From figure G.30 it can be concluded that the cooling power is the most influential parameter on the TED. The mechanical ventilation is the second most influential, followed by window-to-facade ratio and the mean of the internal heat load. It is noticeable that the rankings are almost not changing when varying occupancy model, though are sensitivity measure for cooling power and mechanical ventilation changing. This variance is because of the factor of 1.3 between the mean IHL of models DOM1 and SOM1 compared to DOM2 and SOM2.
As shown in the figure the mean of the internal heat load has a higher influence on the TED than the changing weather files. This means that when including the variability of users, the variance of the TED is increased. This might reflect the real uncertainty of energy consumption better and therefore help decrease the performance gap.

G.3.1.2 Total energy demand and excessive temperatures

Including the excessive temperatures in the sensitivity yields a difference in the ranking. In figure G.31 this is show.

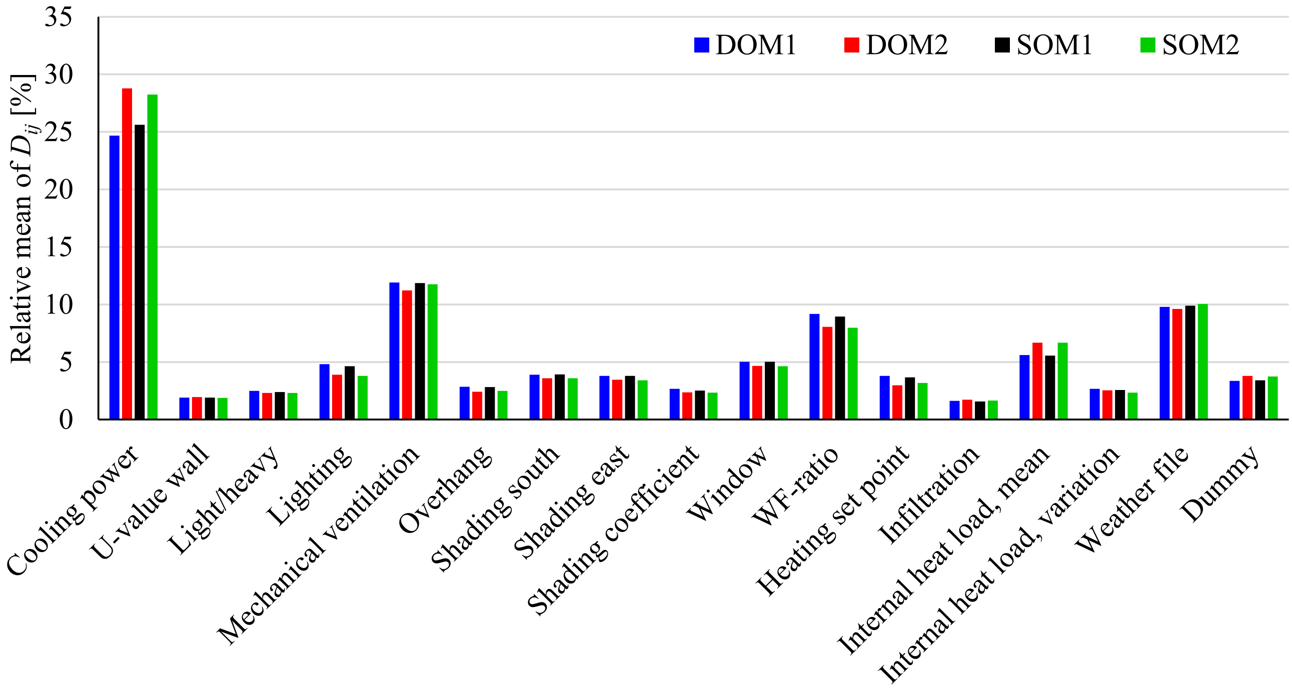


Figure G.31. Sensitivity analysis for the TED and exceeding temperatures using TOM.

Here it is shown that the cooling power has a significant high influence on the three evaluated parameters. The effect from the internal heat load, window-facade ratio and mechanical ventilation are reduced, but their ranking is still within top 4 inputs. The results shows that including the variability of weather will impart the overall performance of the building. It is therefore recommended to use multiple weather files in an factorial experiment to conclude which building designs grant a high robustness towards weather.

G.3.1.3 Cooling

The results from the sensitivity analysis presented in figure G.32 shows that the occupancy models have influence on the ranking and the magnitude of the sensitive inputs. For DOM2 and SOM2 the most sensitive parameter is the mean of the internal heat load. For the models with reduced internal heat load, DOM1 and SOM1, the window-facade ratio have an increased sensitivity and the cooling power is reduced. This means that when decreasing the internal heat load by modelling breaks, the size of the cooling system has a smaller influence on the cooling demand. One way of interpreting the results is that the variability of users leads to uncertainty of the cooling demand.

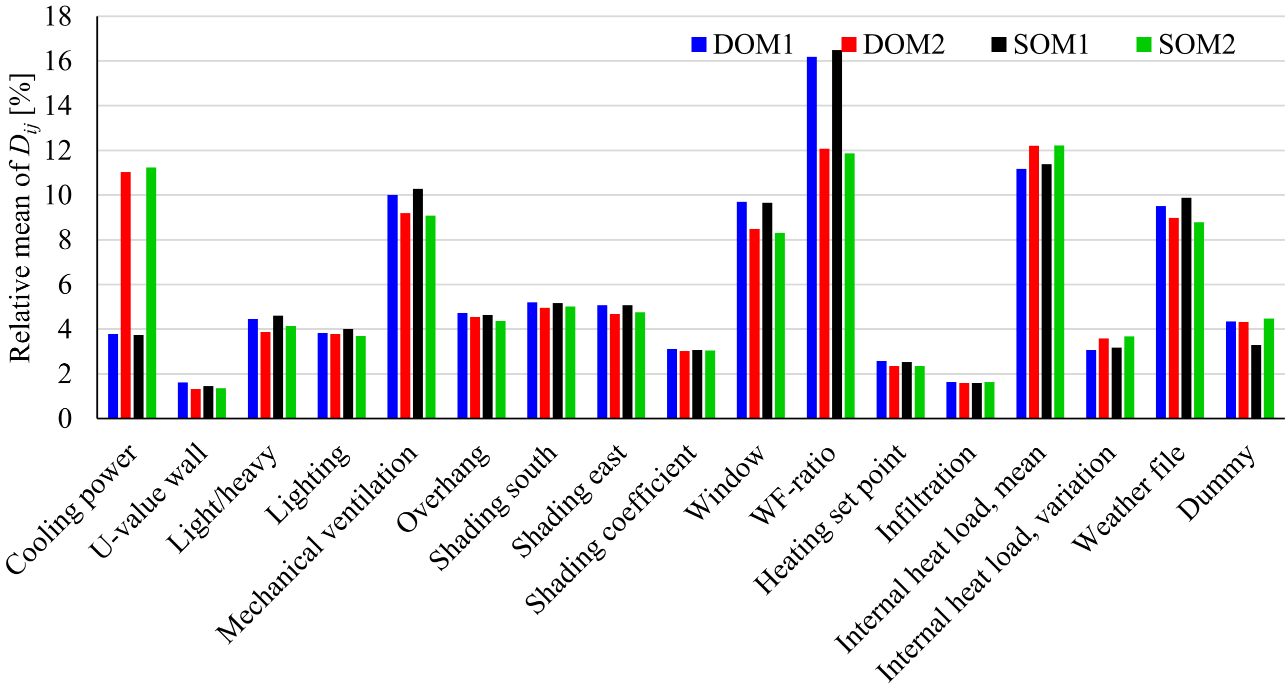


Figure G.32. Sensitivity analysis based of yearly cooling demand using TOM.

G.3.1.4 Heating

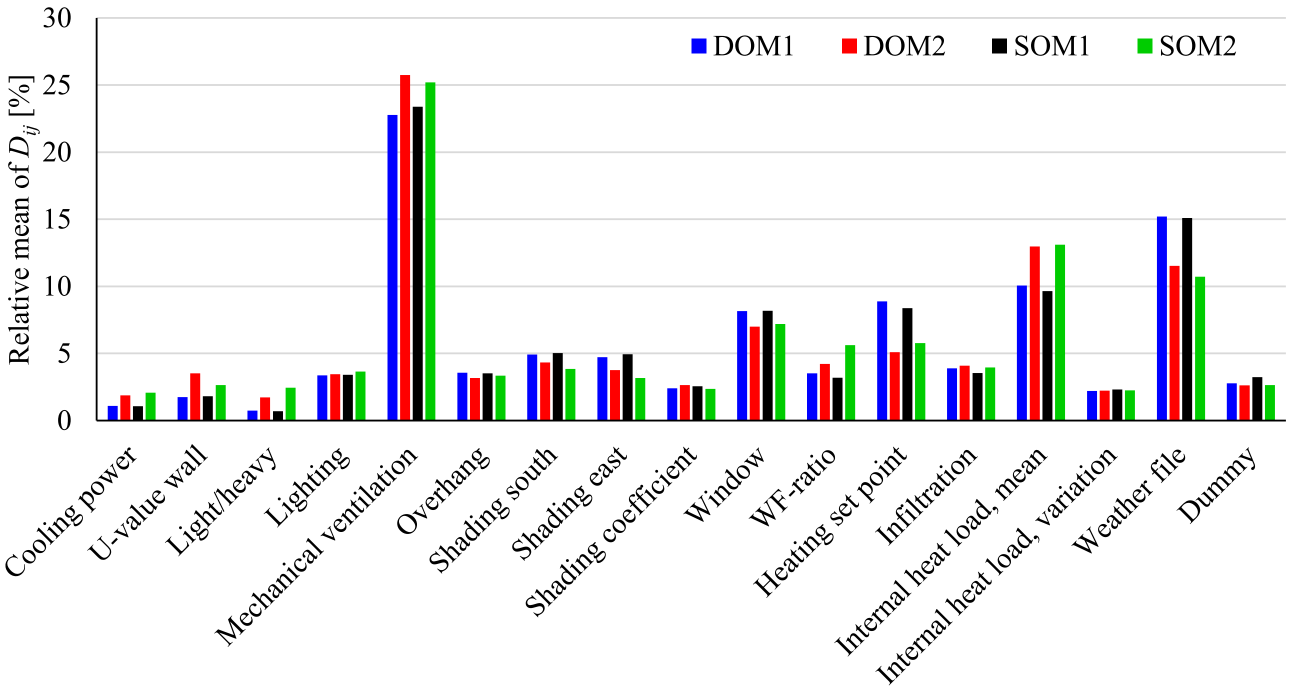


Figure G.33. Sensitivity analysis of yearly heating demand using TOM.

From figure G.33 it can be concluded that the heating demand is most sensitive to the mechanical ventilation. Therefore the heat loss from ventilation must be greater than for transmission and infiltration. The amount of heating required is also affected by the weather and mean of IHL. Note that they are switching ranks for the two occupancy models with and without modelled breaks.

G.3.2 Dimensional values

G.3.2.1 Cooling

In figure G.34 the result from the sensitivity analysis is shown. The sensitivity analysis is performed for the models with enabled cooling system only.

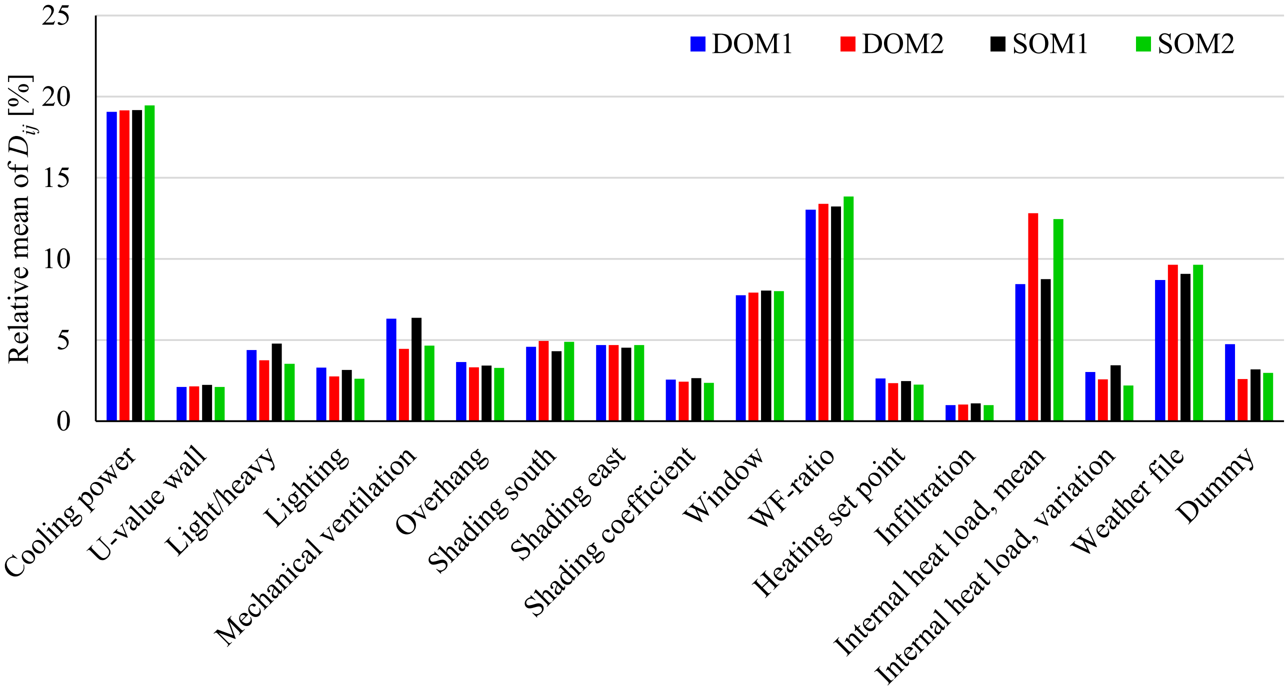


Figure G.34. Sensitivity analysis on the dimensional values for the cooling system at an acceptable deviation of 3 %.

The result shows that the weather file and mean of the internal heat load has a significant influence on the dimensional cooling power with ranks 3 and 4. The variability of occupancy and weather might result in under performing cooling systems. It is recommended to determine the robustness of the building design, to avoid this problem. This can be done by using a factorial experiment with user mean and weather files as factors.

DOM2 and SOM2 shows increased sensitivity for the mean of the internal heat load, which is due to the difference in the occupancy models. The variation of the internal heat load has little to no influence on the cooling power. Therefore it is not necessary to model this variation.

G.3.2.2 Heating

Results for the dimensional heating are shown in figure G.35.

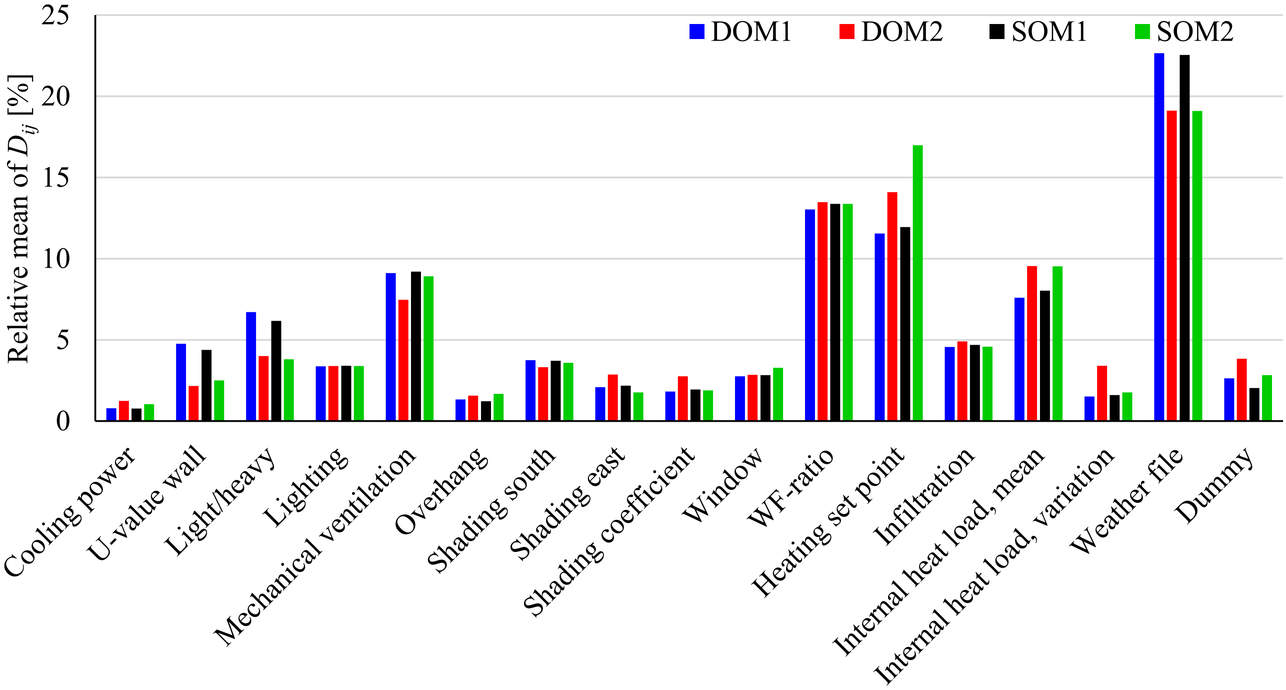


Figure G.35. Sensitivity analysis on the dimensional values for the heating system at an acceptable deviation of 3 %.

For the dimensional heating power, the most sensitive parameters are weather files and heating set-point. This complies with the comparison from the scatter plots, where the filtering of weather file categories showed a clear division for the dimensional heating values. The scatter plot is shown in figure G.35.

G.3.2.3 Thermal comfort

The most influential parameter is the cooling power. Since the mean of IHL was ranked 3 for the cooling power, the mean of IHL has an even higher influence on the operative temperature than showed from the results. The window-facade ratio has reduced sensitivity for DOM2 and SOM2 compared to DOM1 and SOM1. The window type is also affecting the operative temperature, which is due to the g-value. Overall the weather and the solar heat gain to the room has a higher influence on the operative temperature than the internal heat load.

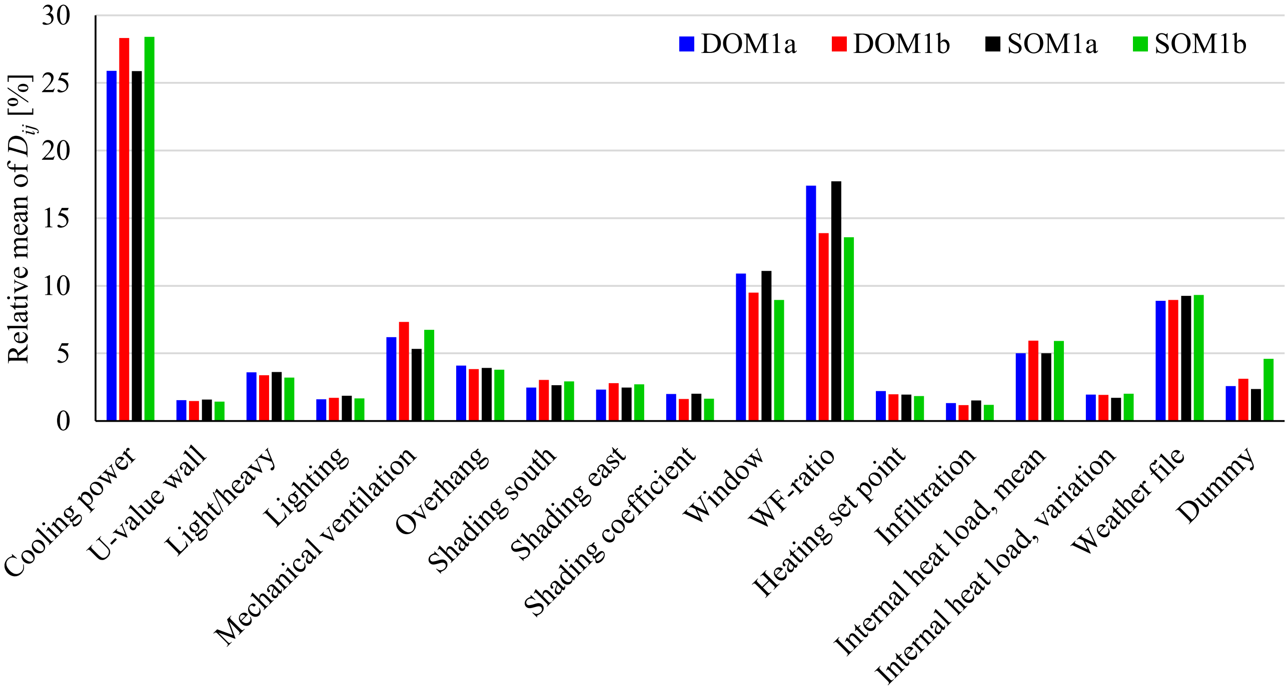


Figure G.36. Sensitivity analysis on the operative temperature that is exceeded 3 % of the work time.

The day to day variance of IHL is noninfluential and should not be considered when evaluating on the building performance or system dimensioning.

Supplementary Scatter Plots H

In this appendix, scatter plots of the results for the dimensional values for an acceptable deviation of 3 % and 5 % from the BSim simulations are presented. The plots are presented without any additional comments.

H.1 1 % acceptable deviation

H.1.1 Comparison of DOM1 and SOM2

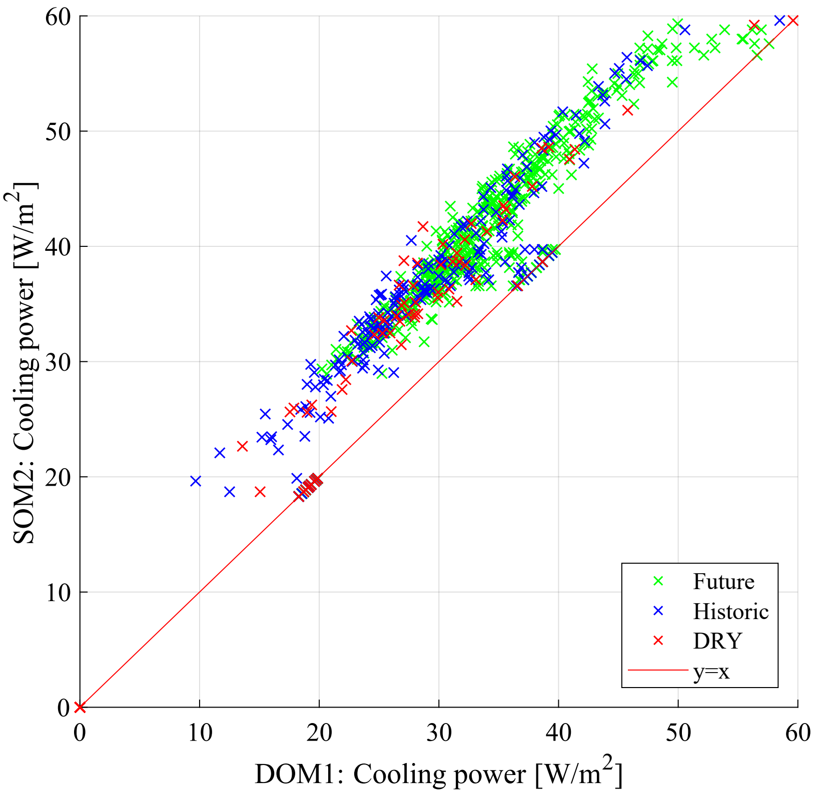


Figure H.1. Scatter plot presenting the dimensional cooling power for DOM1 and SOM2 with an acceptable deviation of 1 %.

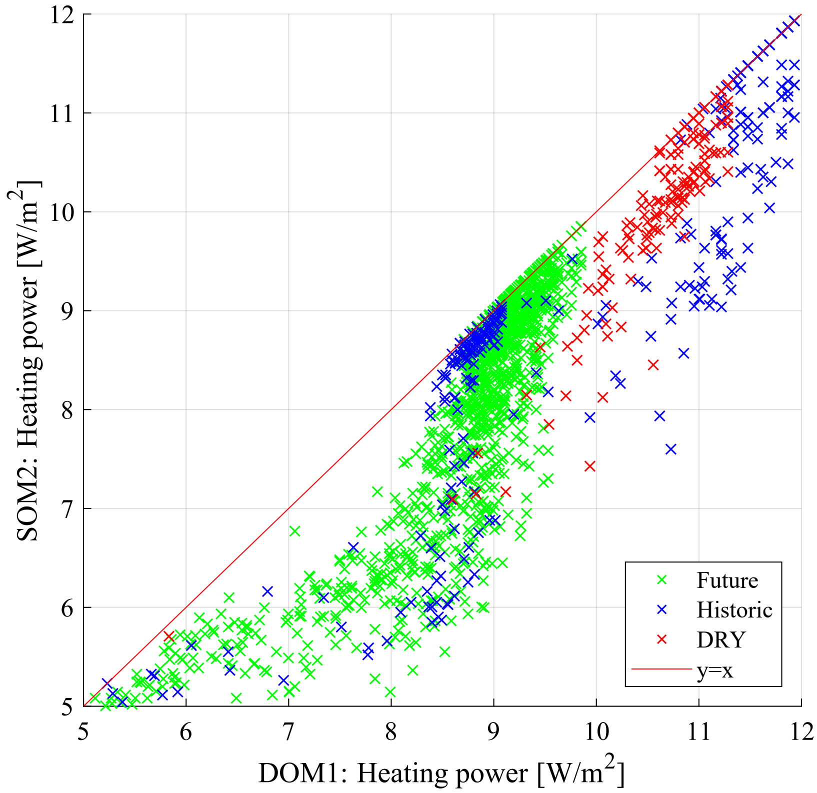


Figure H.2. Scatter plot presenting the dimensional heating power for DOM1 and SOM2 with an acceptable deviation of 1 %.

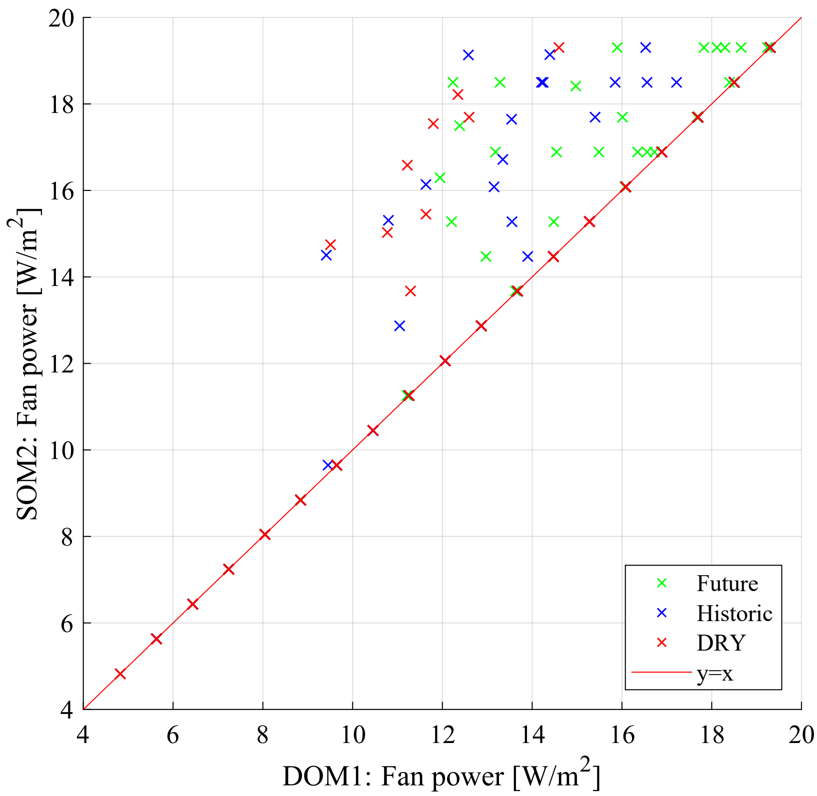


Figure H.3. Scatter plot presenting the dimensional fan power for DOM1 and SOM2 with an acceptable deviation of 1 %.

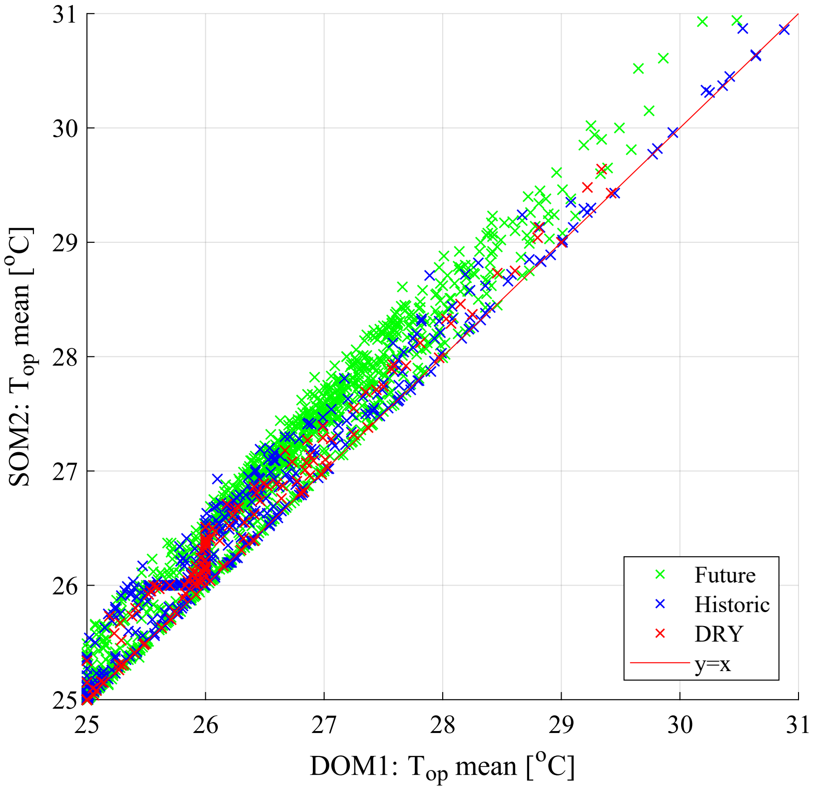


Figure H.4. Scatter plot presenting the mean operative temperatures for DOM1 and SOM2 with an acceptable deviation of 1 %.

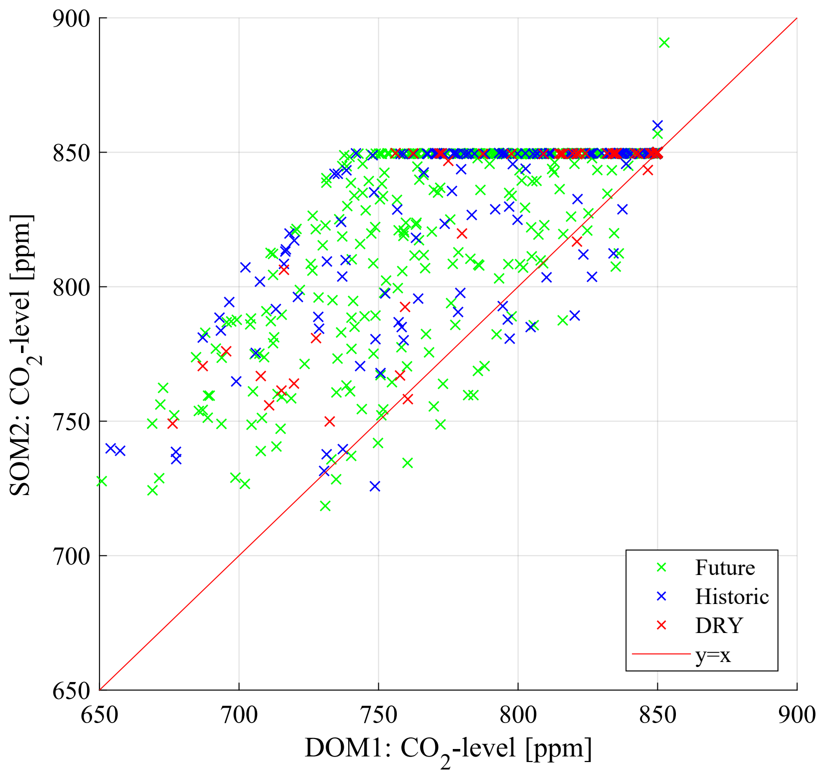


Figure H.5. Scatter plot presenting the CO_2-levels for DOM1 and SOM2 with an acceptable deviation of 1 %.

H.1.2 Comparison of DOM1 and SOM1

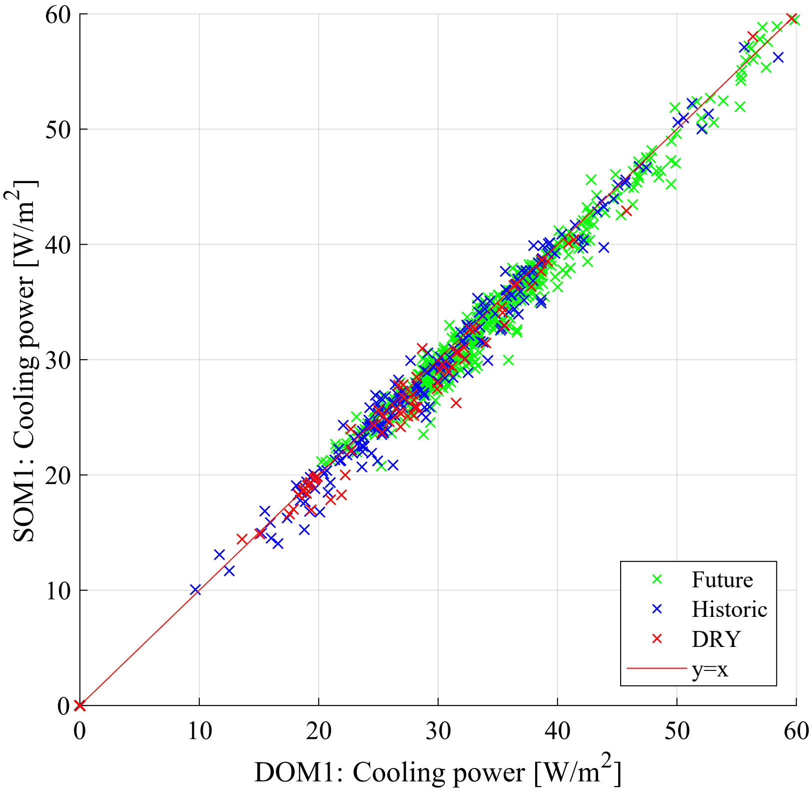


Figure H.6. Scatter plot presenting the dimensional cooling power for DOM1 and SOM1 with an acceptable deviation of 1 %.

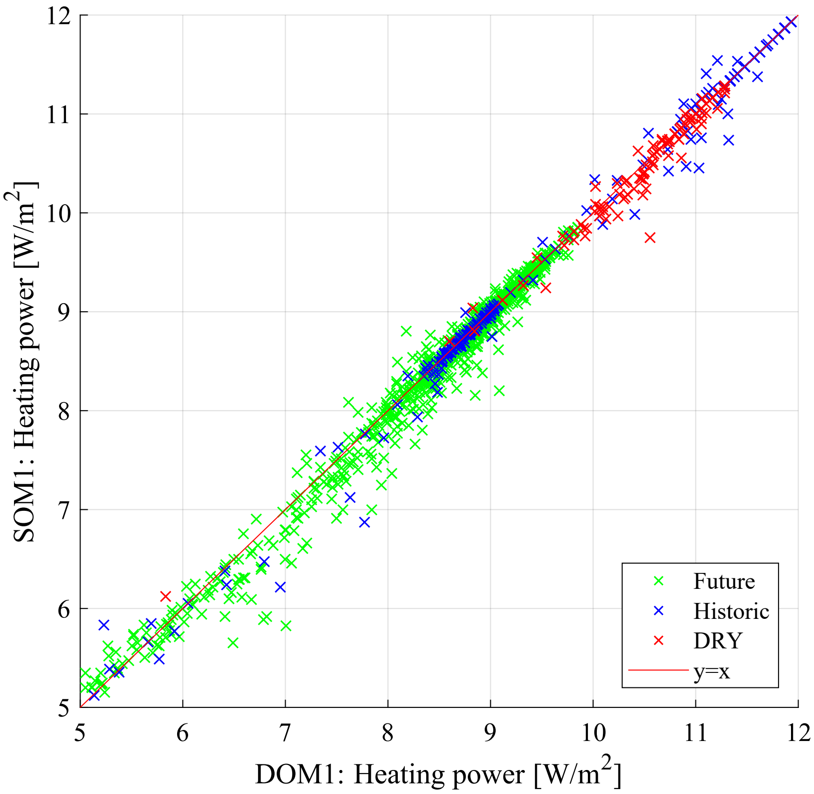


Figure H.7. Scatter plot presenting the dimensional heating power for DOM1 and SOM1 with an acceptable deviation of 1 %.

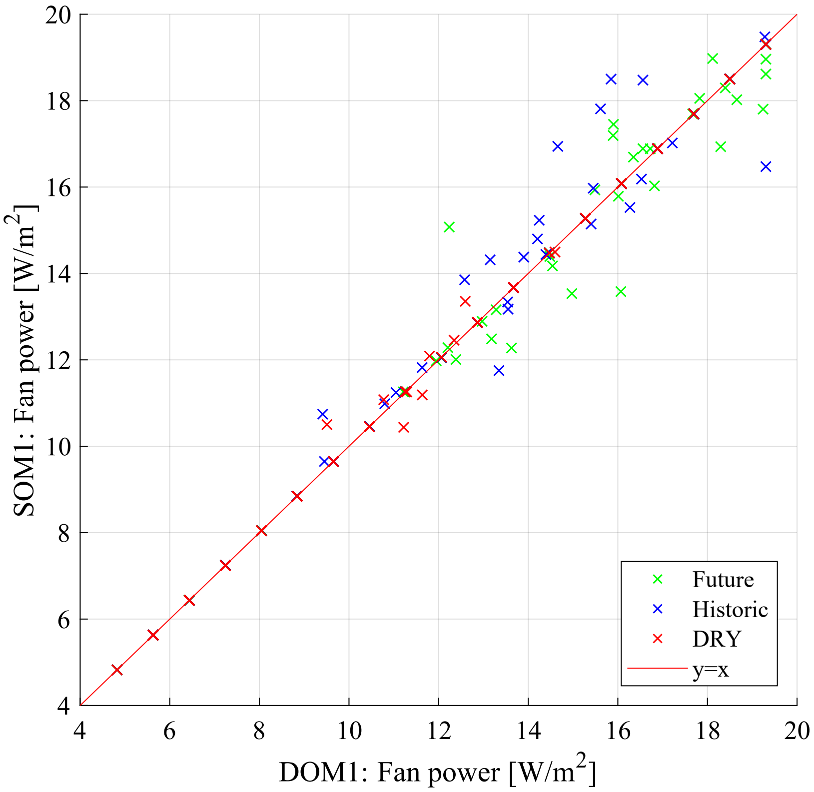


Figure H.8. Scatter plot presenting the dimensional fan power for DOM1 and SOM1 with an acceptable deviation of 1 %.

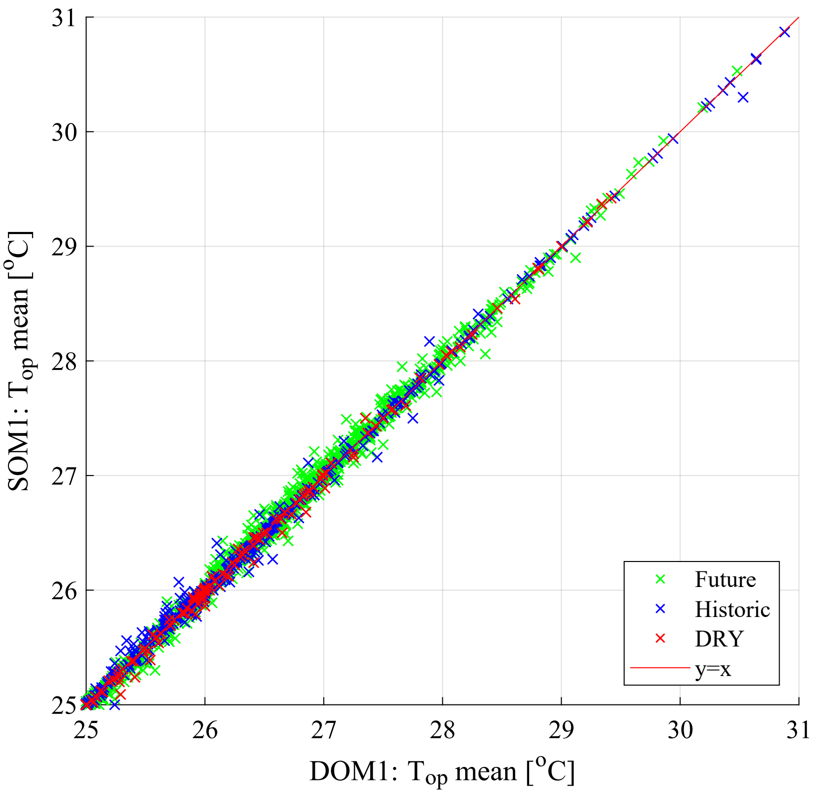


Figure H.9. Scatter plot presenting the mean operative temperatures for DOM1 and SOM1 with an acceptable deviation of 1 %.

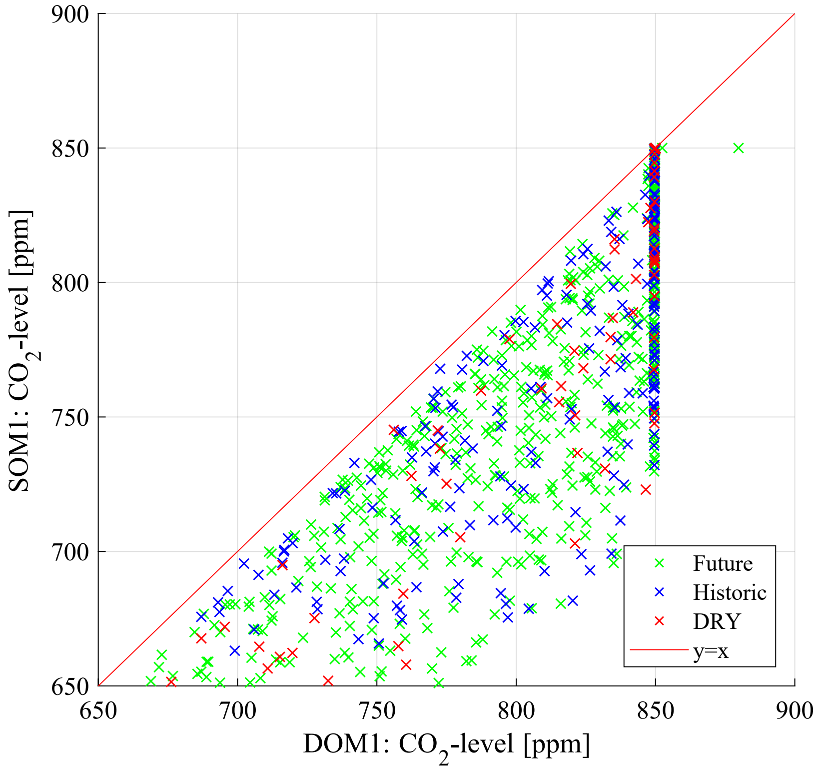


Figure H.10. Scatter plot presenting the CO_2-levels for DOM1 and SOM1 with an acceptable deviation of 1 %.

H.1.3 Comparison of DOM2 and SOM2

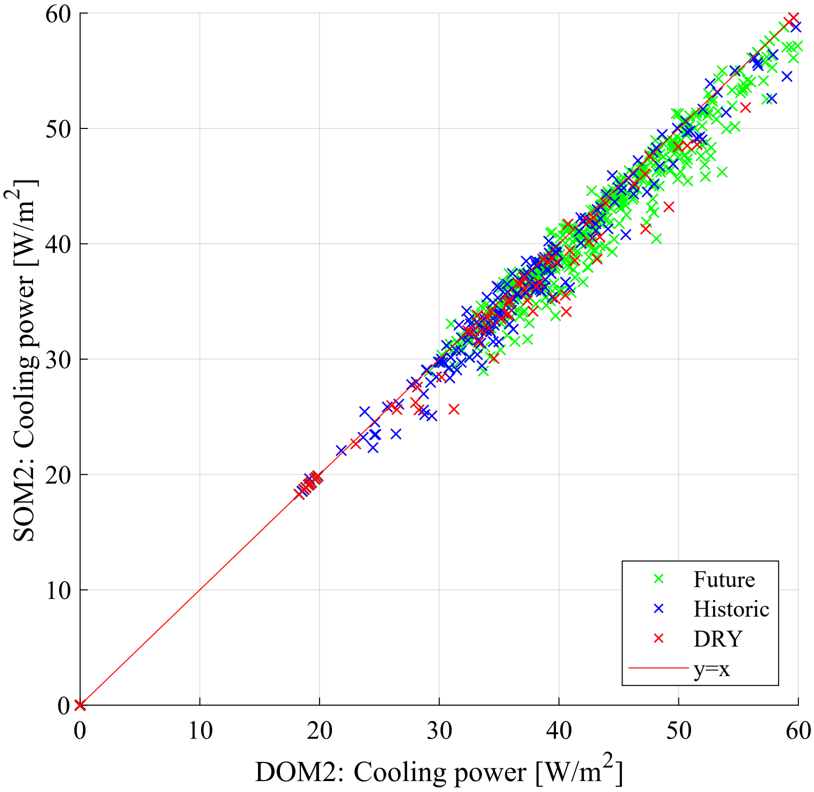


Figure H.11. Scatter plot presenting the dimensional cooling power for DOM2 and SOM2 with an acceptable deviation of 1 %.

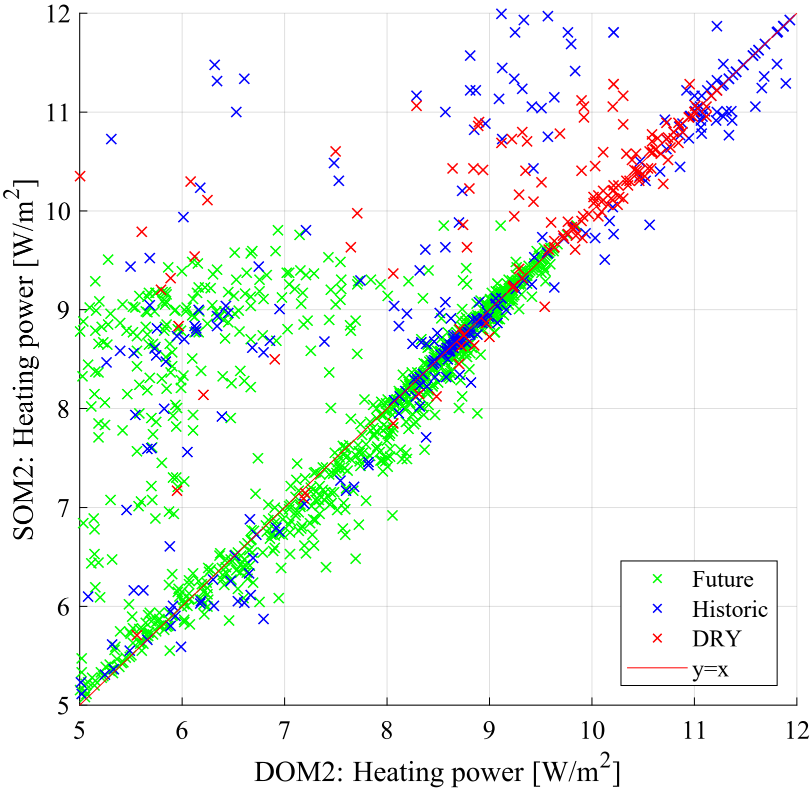


Figure H.12. Scatter plot presenting the dimensional heating power for DOM2 and SOM2 with an acceptable deviation of 1 %.

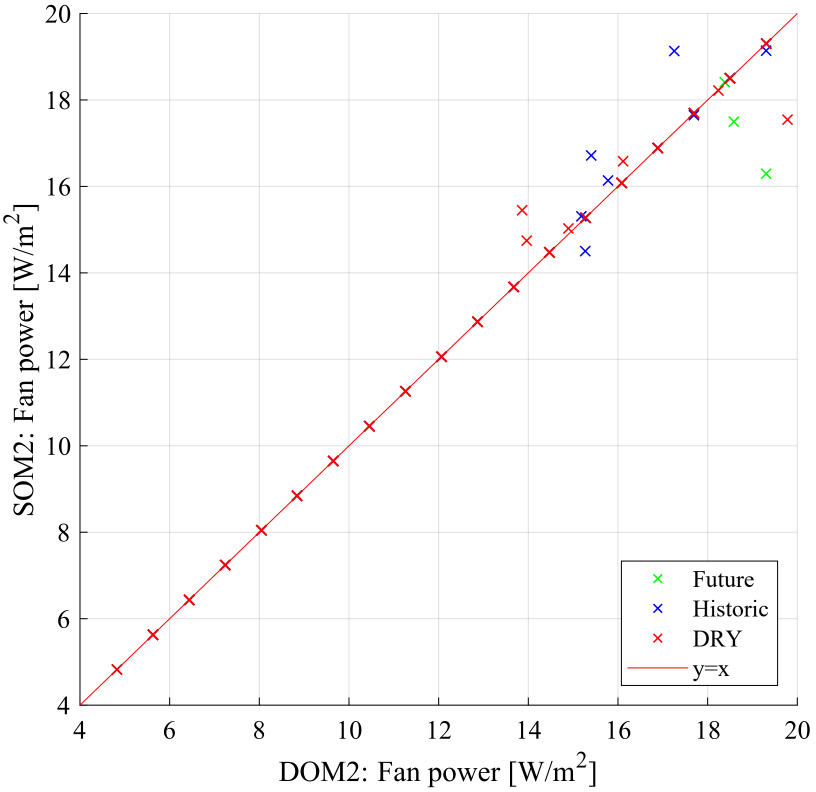


Figure H.13. Scatter plot presenting the dimensional fan power for DOM2 and SOM2 with an acceptable deviation of 1 %.

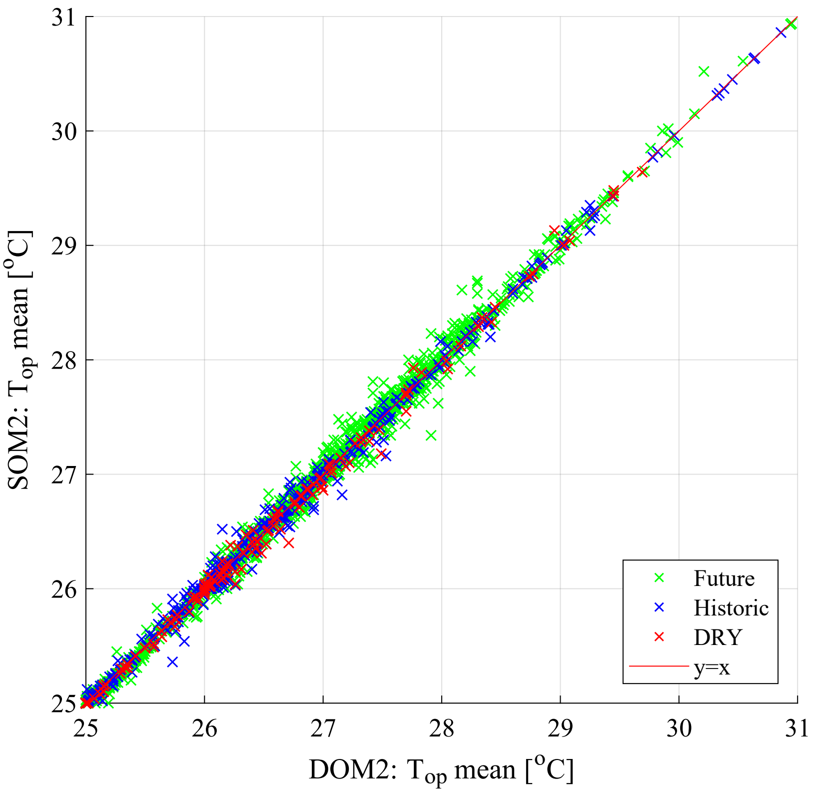


Figure H.14. Scatter plot presenting the mean operative temperatures for DOM2 and SOM2 with an acceptable deviation of 1 %.

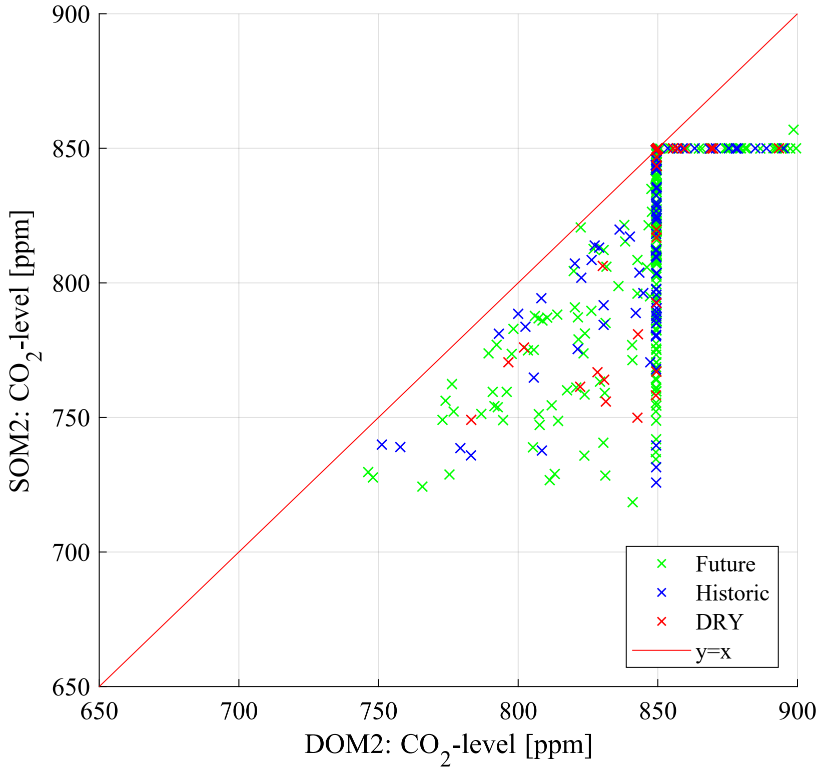


Figure H.15. Scatter plot presenting the CO_2-levels for DOM2 and SOM2 with an acceptable deviation of 1 %.

H.2 5 % acceptable deviation

H.2.1 Comparison of DOM1 and SOM2

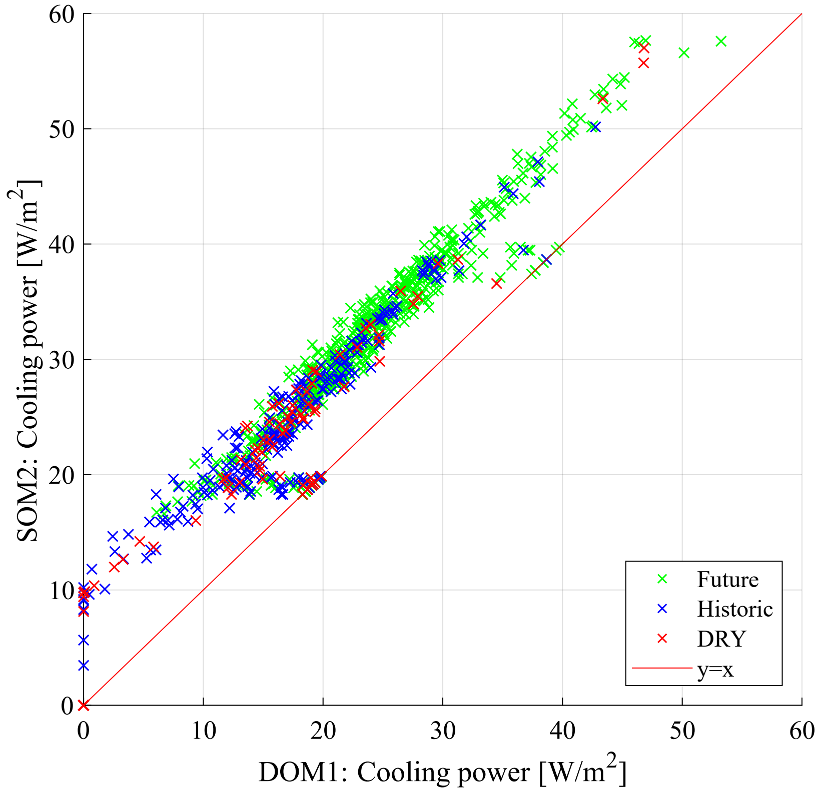


Figure H.16. Scatter plot presenting the dimensional cooling power for DOM1 and SOM2 with an acceptable deviation of 5 %.

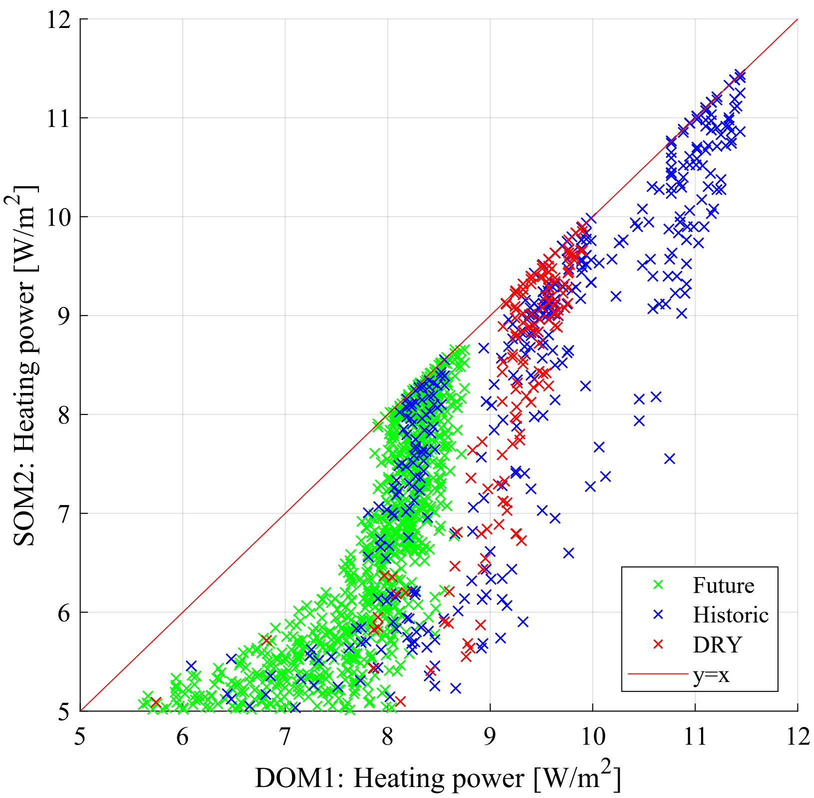


Figure H.17. Scatter plot presenting the dimensional heating power for DOM1 and SOM2 with an acceptable deviation of 5 %.

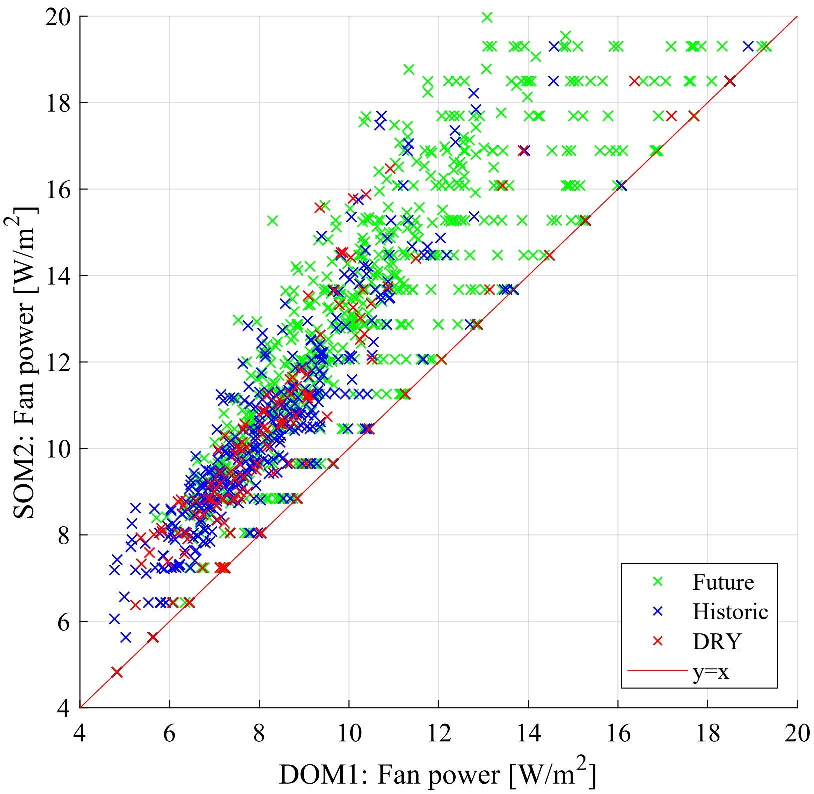


Figure H.18. Scatter plot presenting the dimensional fan power for DOM1 and SOM2 with an acceptable deviation of 5 %.

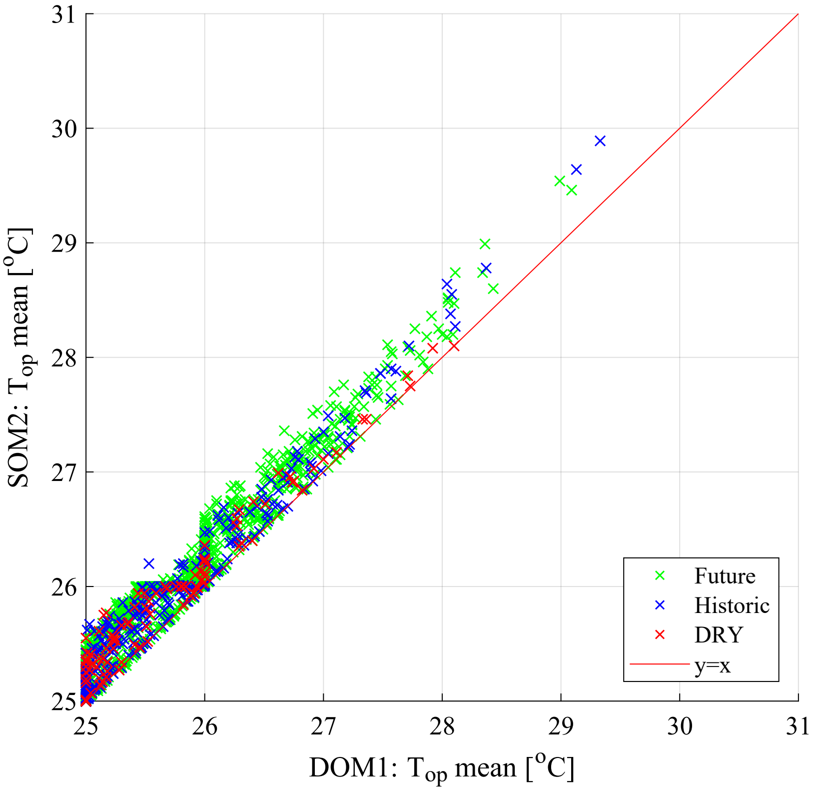


Figure H.19. Scatter plot presenting the mean operative temperatures for DOM1 and SOM2 with an acceptable deviation of 5 %.

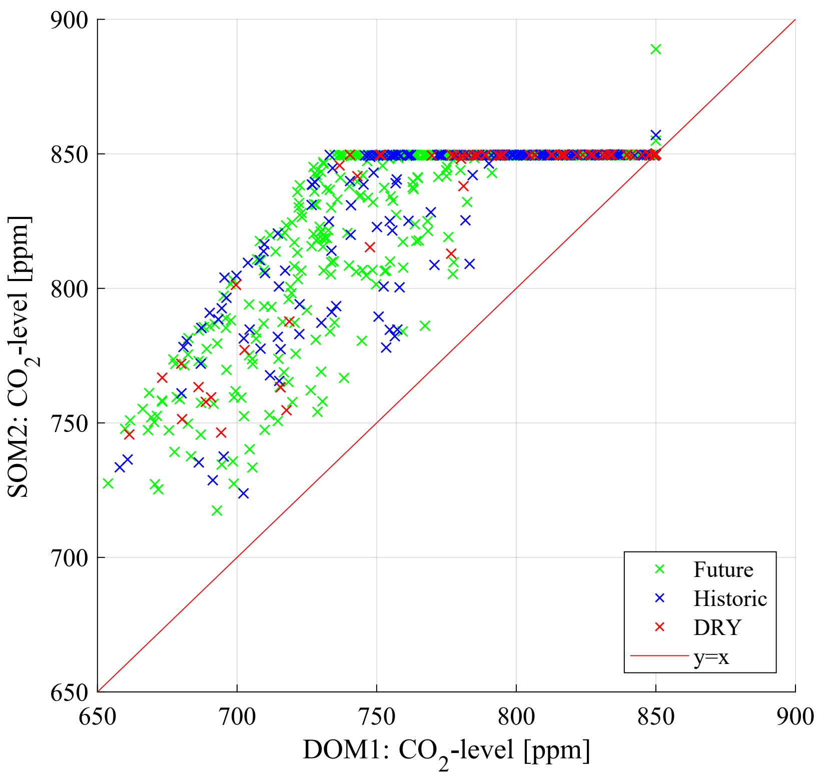


Figure H.20. Scatter plot presenting the CO_2-levels for DOM1 and SOM2 with an acceptable deviation of 5 %.

H.2.2 Comparison of DOM1 and SOM1

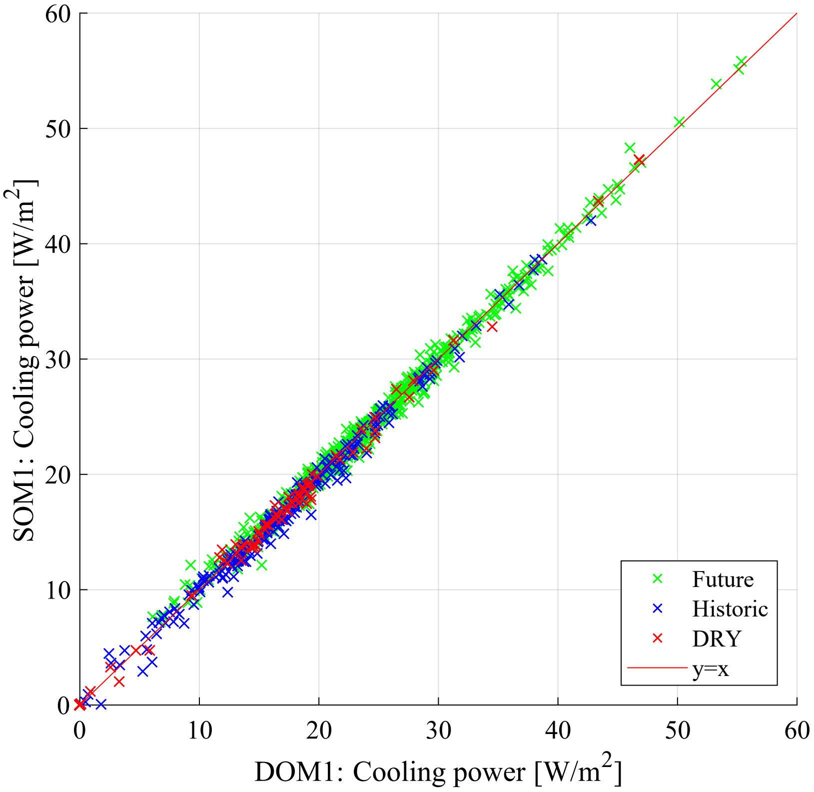


Figure H.21. Scatter plot presenting the dimensional cooling power for DOM1 and SOM1 with an acceptable deviation of 5 %.

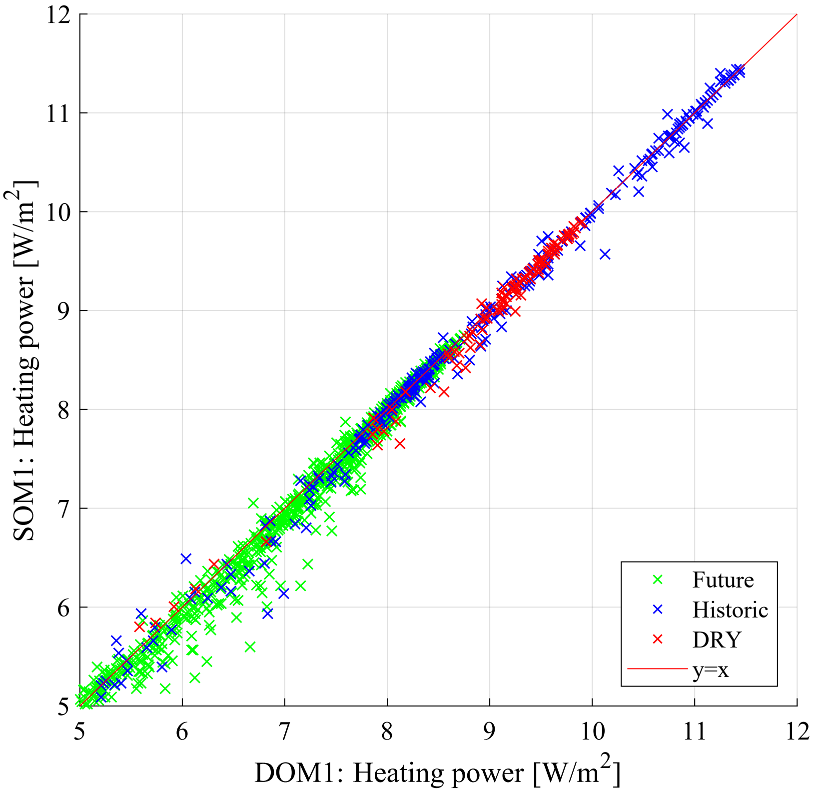


Figure H.22. Scatter plot presenting the dimensional heating power for DOM1 and SOM1 with an acceptable deviation of 5 %.

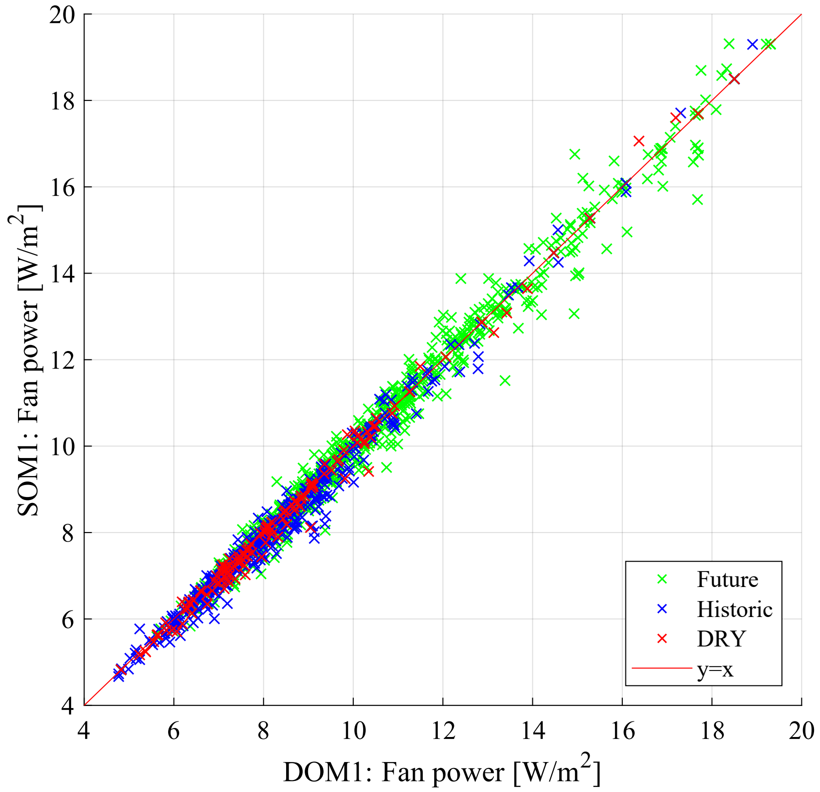


Figure H.23. Scatter plot presenting the dimensional fan power for DOM1 and SOM1 with an acceptable deviation of 5 %.

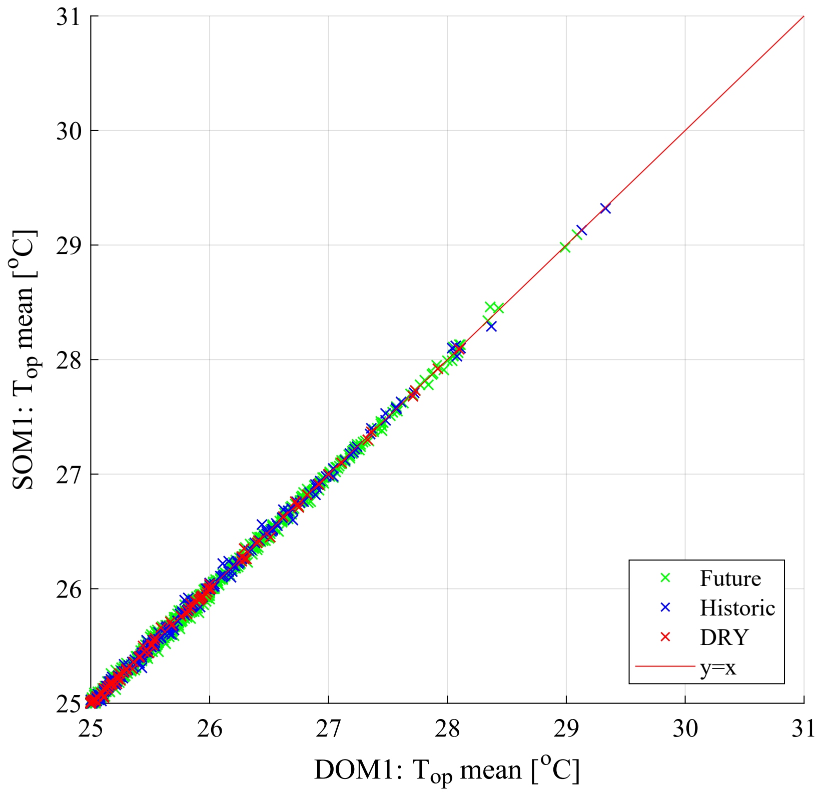


Figure H.24. Scatter plot presenting the mean operative temperatures for DOM1 and SOM1 with an acceptable deviation of 5 %.

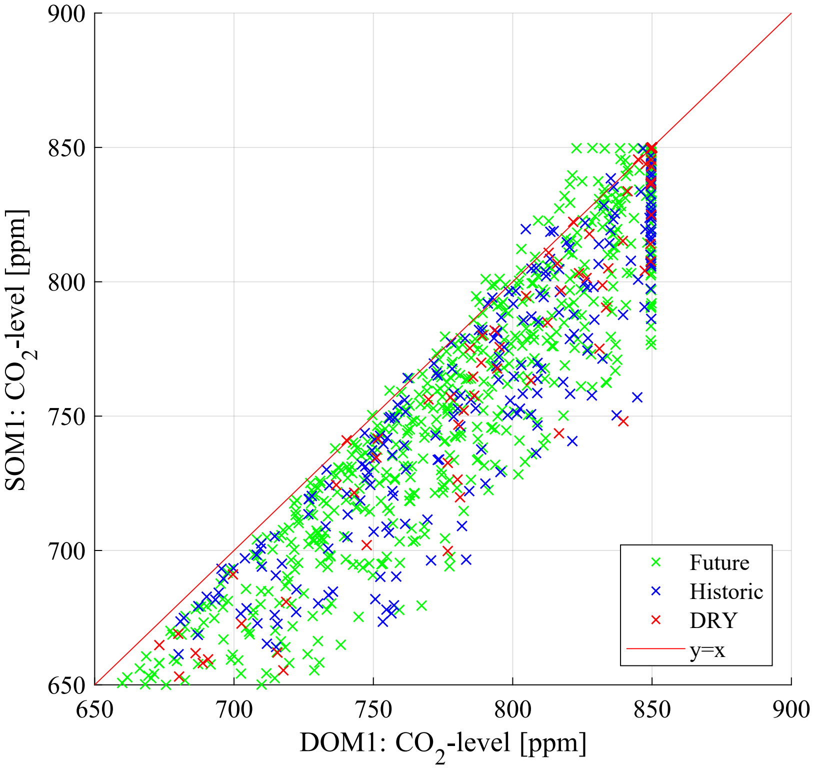


Figure H.25. Scatter plot presenting the CO_2-levels for DOM1 and SOM1 with an acceptable deviation of 5 %.

H.2.3 Comparison of DOM2 and SOM2

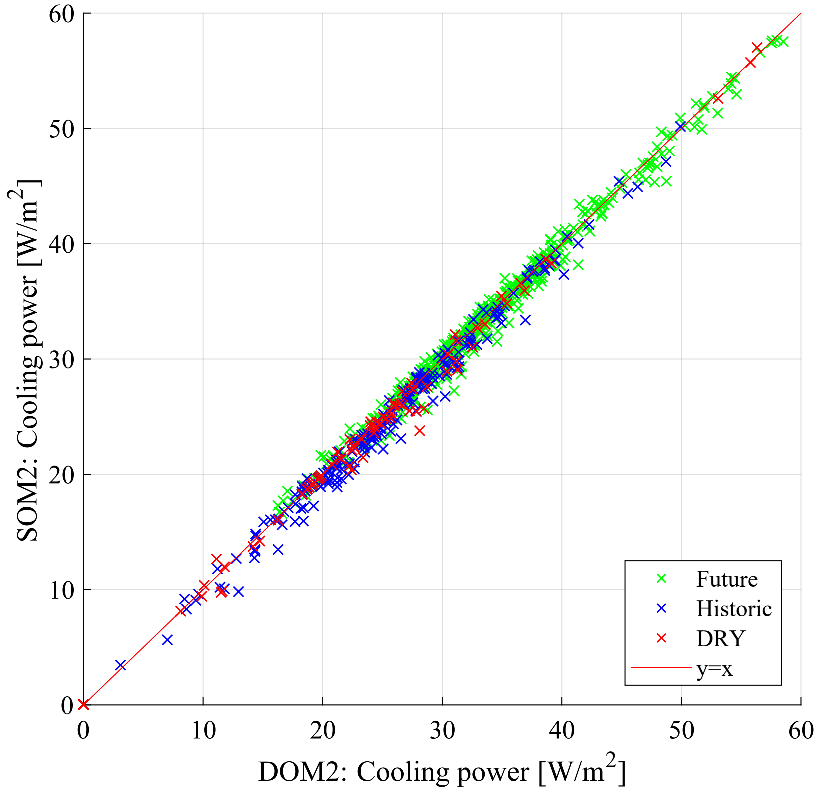


Figure H.26. Scatter plot presenting the dimensional cooling power for DOM2 and SOM2 with an acceptable deviation of 5 %.

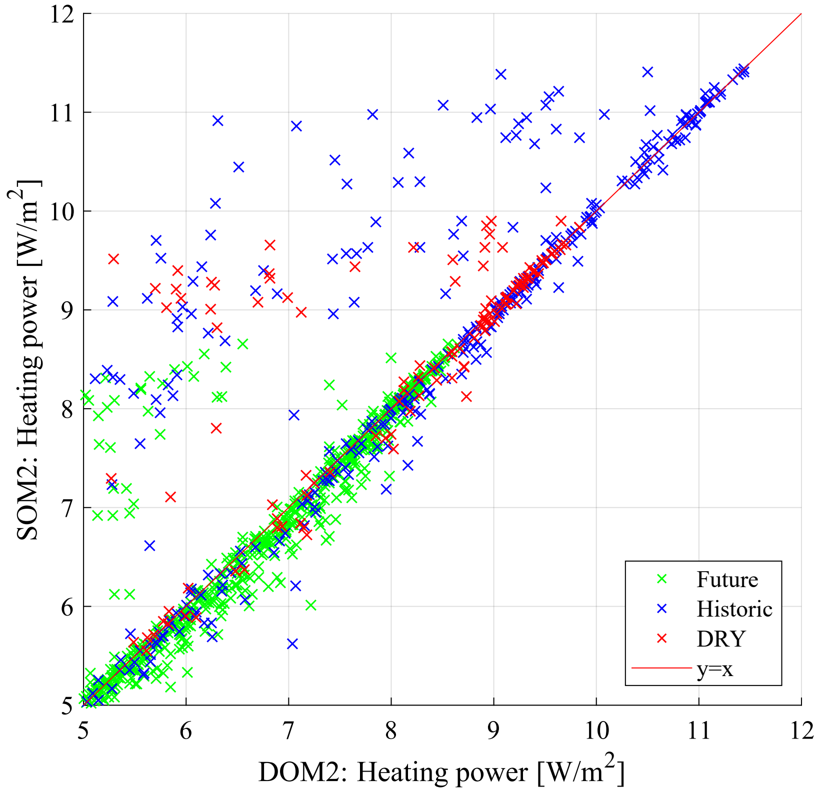


Figure H.27. Scatter plot presenting the dimensional heating power for DOM2 and SOM2 with an acceptable deviation of 5 %.

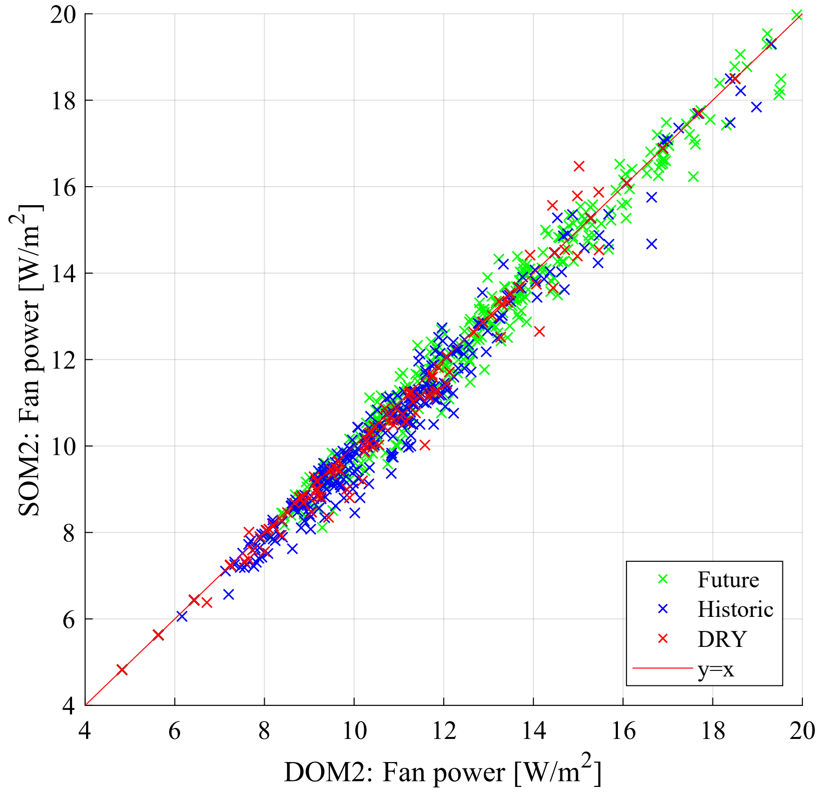


Figure H.28. Scatter plot presenting the dimensional fan power for DOM2 and SOM2 with an acceptable deviation of 5 %.

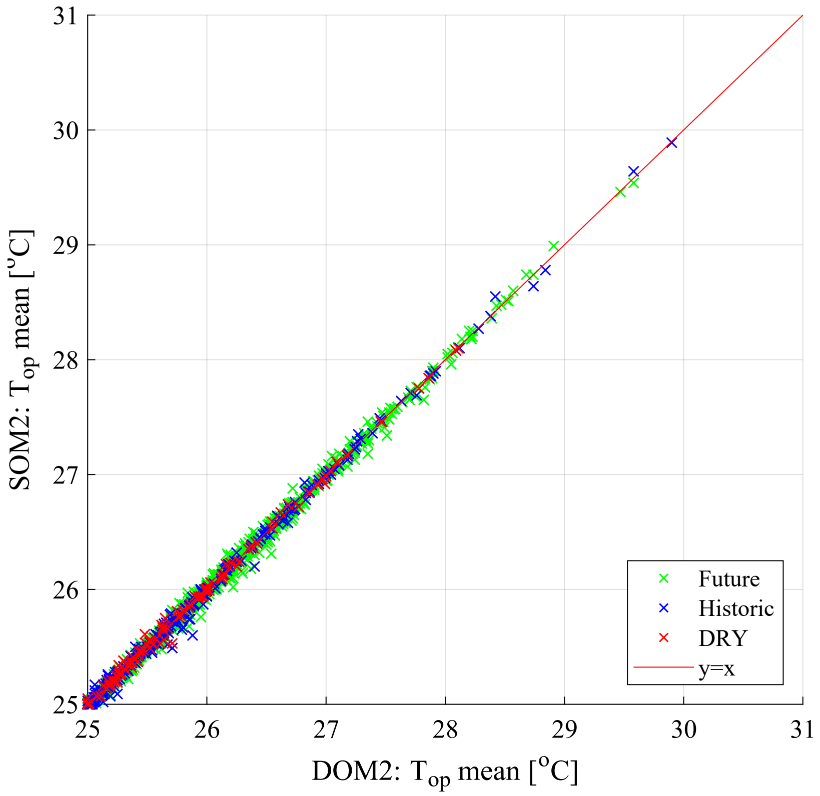


Figure H.29. Scatter plot presenting the mean operative temperatures for DOM2 and SOM2 with an acceptable deviation of 5 %.

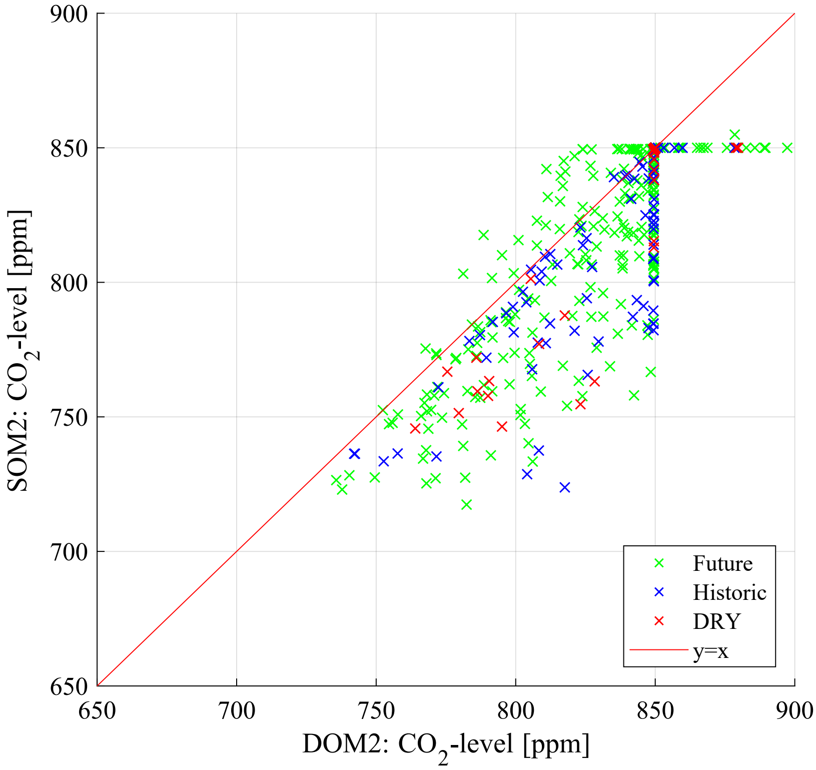


Figure H.30. Scatter plot presenting the CO_2-levels for DOM2 and SOM2 with an acceptable deviation of 5 %.