The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

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Copyright statement

Abstract

Over the last 15 years, the estimation of energy consumption in buildings has become a critical process during various stages of building's lifecycle due to growing global scientific and political pressure to respond to climate change. It has been widely acknowledged in the literature that there is a distinct performance gap between predicted and actual energy consumption of buildings which has attracted scholars across the world to investigate the sufficiency of software inputs and presumptions regarding how the buildings are actually used. Several studies have confirmed that occupant's presence, in addition to, their interactions with building systems (such as: opening door and window, changing the thermostat set-point and using appliances), known as passive and active energy consumption behaviours, play significant roles in building's energy consumption. However, the incorporation of occupants' behaviours into the building energy performance analysis has been mostly overlooked.

Most of the existing studies on the impacts of occupants on building energy consumption have focused on residential and office buildings. Therefore, there is a lack of knowledge about the impacts of occupants' behaviours on energy consumption in public buildings such as: galleries, exhibitions, recreational facilities and institutional buildings. In such building occupants have limited access to building systems, and their energy consumption behaviours are limited to their presence and the production of metabolic heat (passive behaviour), in addition to, few activities such as: opening the entrance door.

This research develops a conceptual framework to improve the accuracy of energy consumption assessment in multi-functional spaces at different stages of building's lifecycle by integrating the impacts of occupants' behaviours into building energy predictions to reduce the gap between actual and predicted energy consumption. In this quantitative research, a model simulation method is applied on multiple cases at different stages of the building lifecycle including design, construction and post-occupancy. The first two cases are multi-functional spaces of public buildings at the design and construction stages, which were studied to address the missing information and potential gaps in energy modelling and simulation. The study was then taken forward using case studies at the post-occupancy stage to integrate the realistic observed data into the building energy simulation tool. For each of the cases, energy simulation was run twice: first, using default values of the software, and

second, using the collected data. The data collection included hourly observation of 38 zones in both cases at the post-occupancy stage for the duration of two weeks, in addition to, using available governmental and real-time statistics.

The analysis of energy simulation results using default software values and collected data highlighted that lack of sufficient information regarding building working hours, space layout and function, occupancy density and schedules, the entrance door opening time and HVAC set-points may result significant performance gaps in energy consumption prediction of multi-functional spaces in institutional buildings and galleries.

This study provides conceptual frameworks for the prospect energy modellers and researchers to obtain more accurate energy consumption predictions for multi-functional spaces of public buildings.

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List of Abbreviations

2D	Two Dimensional
3D	Three Dimensional
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BEM	Building Energy Modelling
BIM	Building Information Modelling
BREEAM	Building Research Establishment Environmental Assessment Method
CO_2	Carbon Dioxide
DOE	(U.S.) Department of Energy
DXF	Drawing Exchange Format
EPW	Energy Plus weather data
gbXML	Green Building XML schema
GPS	Global Positioning System
HVAC	Heating, Ventilation and Air-Conditioning
IBPSA	International Building Performance Simulation Association
i-Point	Information Point
IoE	Internet of Everything
LEED	Leadership in Energy and Environmental Design
NREL	(U.S.) National Renewable Energy Laboratory

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Introduction Chapter

"Don't worry about saving the earth. The earth will be fine. However, humans will probably become extinct and no longer habitat the earth. Which is probably a good thing."

— Blake Newman

Chapter 1: Introduction

1.1. Research Background

Global attention towards energy consumption is growing substantially to answer to “climate change” which is considered to be the greatest environmental threat of modern times. EU Statistics by EUROSTAT (2015) show that, building sector including households and services respectively account for 26.8% and 13.8% of the total energy consumption in 2015. Therefore, reductions in energy consumption of buildings will make a dramatic drop in the total energy consumption.

It has been broadly acknowledged that the occupant’s behaviour plays essential role in the energy consumption of buildings, however, it has been constantly overlooked in building energy predictions (Calì, Osterhage, Streblow, & Müller, 2016; Fabi, Andersen, Corgnati, & Olesen, 2013; HUB, 2015; Maier, Krzaczek, & Tejchman, 2009; Martinaitis, Zavadskas, Motuziene, & Vilutiene, 2015; Schakib-Ekbatan, Çakici, Schweiker, & Wagner, 2015; Yang, Santamouris, & Lee, 2015). Occupants interact with building systems to acquire thermal, visual and acoustic comfort, as well as, improving the indoor air quality. HVAC systems, electrical devices and lighting which are responsible to provide thermal and visual comfort for the occupants, are the greatest sources of energy consumption in buildings (Harish & Kumar, 2016). O’Brien and Gunay (2015) mentioned oversimplification of occupant behaviour as the main cause of inaccuracy in energy consumption predictions in buildings.

The impact of occupants on energy consumption in buildings has been studied extensively and the research area is going forward rapidly, however, those studies have not considerably materialised the reduction of the gap between predicted and actual energy consumption in buildings and there is a need for further studies in order to better understand occupants’ behaviours. Occupants’ energy consumption behaviours refer to the occupants’ activities that affect the energy consumption of buildings including: using appliances, opening windows and doors, using hot water, using HVAC system (e.g. adjusting thermostat set-points), using lighting and adjusting blinds. Occupants have impacts on the energy consumption of the buildings, not only by their active energy use, but also, by their presence and production of metabolic heat (known as passive energy behaviour) which increases the internal heat gain of the building. The taxonomic classification of occupants' energy consumption behaviours is shown in figure 1.

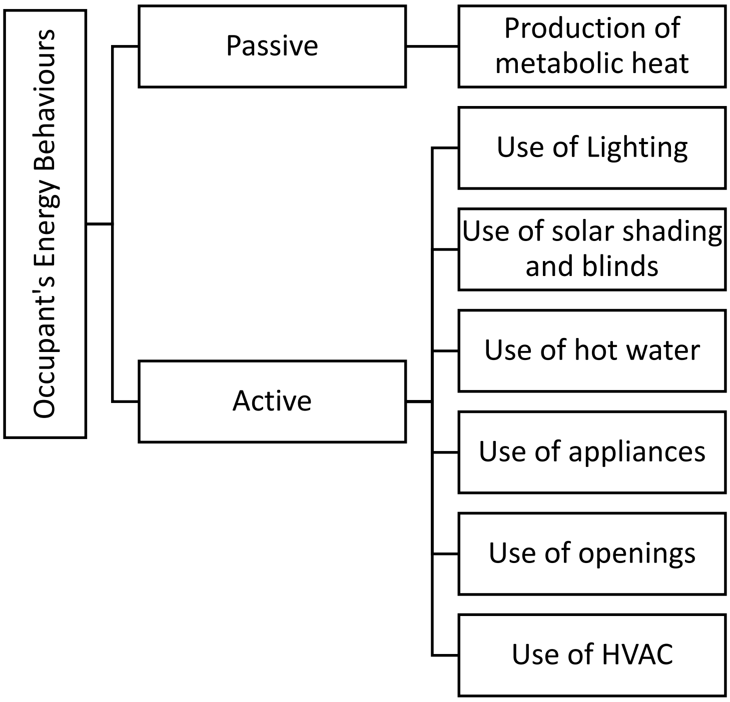


Figure 1. Occupant's active and passive energy behaviours

Occupants' energy behaviour is too complex to be predicted as it is dependent on multiple factors. A comprehensive state-of-art review of more than 120 publications undertaken on the influence of occupants' behaviour on building energy consumption reveals that the climatic (environmental, physical), personal (physiological and psychological), social, economic and legal parameters together with building type and design features are the key factors studied by various researchers around the world. Figure 2 displays the frequency of each of the aforementioned factors being discussed among the reviewed studies. Also, various sub-factors have been reflected by a number of recent studies (Table 1).

Insufficiency of knowledge about influential factors on energy consumption in buildings are considered as the most important obstacles to improve energy performance of buildings (Fabi, Andersen, Corgnati, Olesen, & Filippi, 2011).

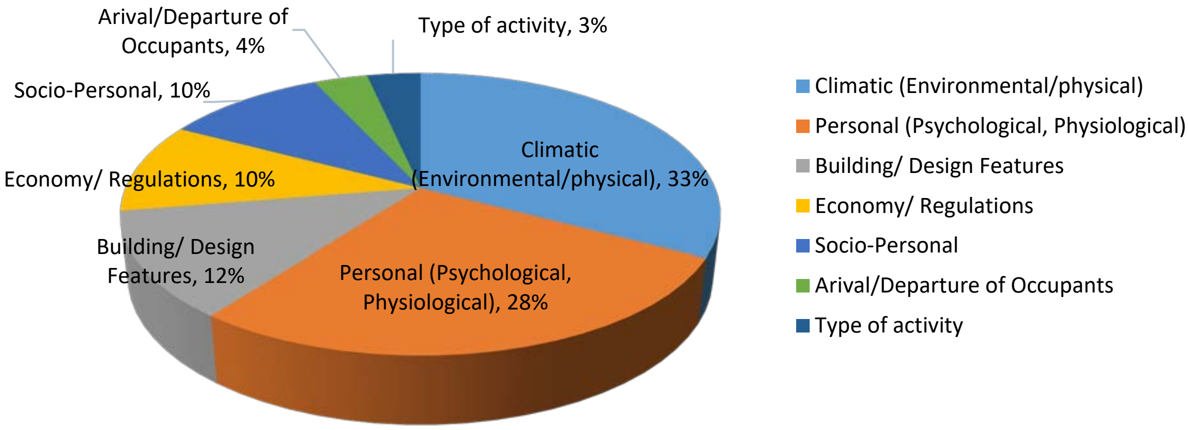


Figure 2. Frequency of influential parameters on occupants' energy behaviours, reviewing more than 100 relevant publications

Main factors	Sub factors	Authors, year
Climatic	Ventilation	Salcido, Raheem, and Issa (2016)
	Indoor/ outdoor temperature	Zhe Wang, Zhao, Lin, Zhu, and Ouyang (2015) Schakib-Ekbatan et al. (2015)
	Humidity	Hom B. Rijal, Humphreys, and Nicol (2015)
	Sunlight	O'Brien and Gunay (2015)
Socio-personal	Psychological	von Grabe (2016)
	Age and gender	Indraganti, Ooka, and Rijal (2015)
	Education and knowledge	Day and Gunderson (2015)
	Information	Jain, Taylor, and Culligan (2013)
	Lifestyle	De Meester, Marique, De Herde, and Reiter (2013) Peng et al. (2012)
Building Features	Design features	Karjalainen (2016) Heydarian, Carneiro, Gerber, and Becerik-Gerber (2015)
	Space function	Goldstein, Tessier, and Khan (2011)
	Old/new buildings	M. Ouf, Issa, and Merkel (2016) Agha-Hossein, El-Jouzi, Elmualim, Ellis, and Williams (2013)
	Environmental Design	O'Brien and Gunay (2015)
	House- family size	De Meester et al. (2013)
	Building type	Zhaoxia Wang and Ding (2015)
	Building orientation	Zhang and Barrett (2012)
Economic	Income	Romero, Bojórquez, Corral, and Gallegos (2013)

Main factors	Sub factors	Authors, year
		Langevin, Gurian, and Wen (2013)
	Socio-economic	Jun Chen, Wang, and Steemers (2013)
Regulation	Governmental regulations	Guerra Santin (2010)

Table 1. Factors affecting occupants' energy behaviours

Most of the existing studies on the impacts of occupants on energy consumption in buildings have investigated residential and office buildings. There is insufficient information about human-behaviour-related factors in other building types such as galleries, exhibitions, museums, institutional buildings and in particular, multi-functional spaces where various activities take place. In multi-functional spaces of the aforementioned building types, occupants are more dynamic and the prediction of their behaviours is more complicated.

The function of the space specifies the activity, therefore, it is one of the most fundamental inputs of energy simulation tools. In energy assessment tools, building type and space function are the basis for estimation of the working hours, comfort temperature, HVAC set-points and hot water and electricity consumption. Energy modellers usually use the labels on architectural/construction plans to specify the function of each building zone. However, it is complicated to determine the space function for large multi-functional spaces of public buildings where various functions take place within one physical zone. In general, design features of the space such as: interior layout and furniture are amongst the most influential parameters on the types and duration of activities in large multi-functional spaces.

Also, software presumptions regarding multi-functional spaces are over-simplified. For example, there are massive daily and monthly variations in the number of occupants/visitors. While, energy simulation tools use fixed occupancy schedule presumptions based on the space function. This research investigates the impacts of occupants' behaviours on energy consumption in multi-functional spaces by incorporating inputs about how the spaces are actually used into energy simulation tool.

1.2. Research Aim and Objectives

1.2.1. Research Aim

This research aims to develop a conceptual framework to reduce the gap between actual and predicted energy consumption in multi-functional spaces at different stages of building's lifecycle by integrating the impacts of occupants' behaviours into building energy predictions. The proposed conceptual framework will provide guidelines for energy modellers to improve the accuracy of energy predictions in multi-functional spaces.

In order to accomplish this aim, the following objectives are formulated:

1.2.2. Research Objectives

1. To review existing literature on the impacts of occupants' behaviours on energy consumption in buildings and identify the gaps in the subject area through a comprehensive quantitative analysis and qualitative review.
2. To analyse energy consumption of multi-functional cases at different stages of building's lifecycle by comparing default software presumptions regarding human-behaviour-related factors with the realistic collected data and investigate the potential gaps in energy assessment.
3. To analyse the collected data and the results of the energy simulations in objective 3, formulate research findings and the conceptual framework.
4. Refinement and validation of the framework through incorporating experts' comments, conclusion and future work.

1.3. Research Methodology

The research methodology of this study consists of 4 main stages to address the research objectives (see: 1.2.2. Research Objectives):

- Formulation of research problem, research focus and research design
- Establishment of research method, case study design and data collection
- Analysis of data and formation of the initial findings
- Development, validation and refinement of the conceptual framework

In this research, in order to investigate occupants' energy consumption behaviours in multi-functional spaces and quantify their impacts on the energy consumption, multiple cases at various stages of building's lifecycle (including design, construction and operation) have been studied. Hence, the case study design includes two stages:

- Stage 1 of the case study design is applied on cases at the design and construction stages that the actual occupants' behaviours data is unavailable. It includes three steps: preparation of information (such as building architectural and construction plans, material and systems), energy modelling and simulation and analysis of the gaps and insufficiency of information regarding occupants' behaviours in prediction of energy consumption in multi-functional spaces at the design and construction stages (See: 3.2.4.1. Case Study Design). Stage 1 of the case study is explained comprehensively in chapter 4. The gaps that have been pointed out through stage 1, were further studied in stage 2.
- Stage 2 of the case study design is an extended form of stage 1 which incorporates realistic observed occupants' behaviour data with the energy simulation tool. Stage 2 is applied on cases at the post-occupancy and operation stage and comprised of five steps: preparation of information, energy modelling and simulation using software default human-behaviour-related assumptions, data collection and analysis, detailed energy modelling and simulation using the collected data, evaluation and quantitative analysis of both simulation outcomes (using software default presumptions and data collection inputs) (See: 3.2.4.1. Case Study Design). Stage 2 of the case study is presented in chapter 5.

The analysis of the findings (including analysis of the collected data and the simulation outcomes) created the initial conceptual framework. The initial framework has been validated through experts' comments and the final framework is formed after refinement to provide guidelines for energy modellers to perform more accurate energy consumption assessments in multi-functional spaces by integrating occupant-behaviour-related factors into the energy simulation process.

1.4. Contribution to Knowledge, Uniqueness and Novelty

Various studies have been undertaken on the impact of occupants on energy consumption in buildings with the aim to decrease the performance gap between the calculated and actual energy consumption in buildings. Reducing the performance gap will provide the opportunity for energy modellers, researchers and designers to achieve more accurate energy consumption predictions in buildings. It is also a necessity to improve energy codes and standards to be used by policy makers.

Contributions of this research are both theoretical and practical. Figure3 illustrates the most important theoretical and practical contributions of this study. The theoretical contribution is accomplished by addressing some of the existing gaps in the literature. In this research, the impact of occupants' behaviours on energy consumption in buildings is studied and quantified, which is a disregarded area causing inaccuracies in building energy prediction. The cases investigated in this study are multi-functional spaces of public buildings (such as galleries, exhibitions and institutional buildings) that have not been studied sufficiently in the literature. In addition to the theoretical contribution to knowledge, the findings of this study contribute in improving the occupancy and occupant-behaviour-related sections of energy simulation tools, which has great practical benefits for energy modellers, researchers and energy simulation software developers.

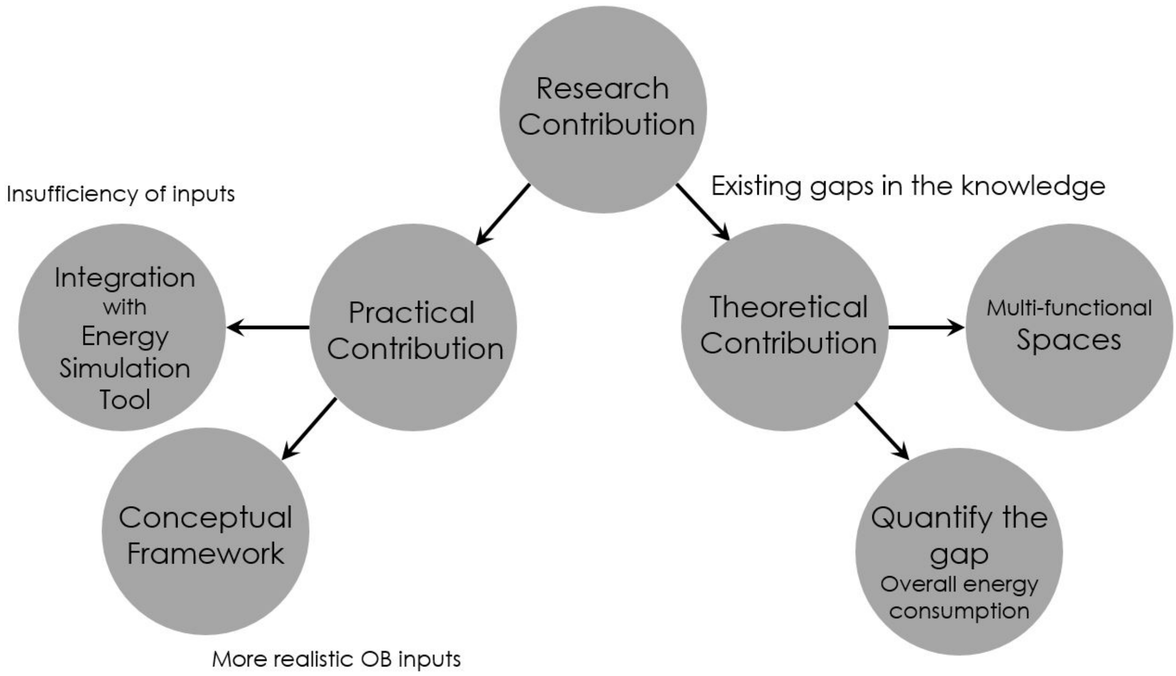


Figure 3. Research practical and theoretical contribution

1.5. Definitions, Technical Terms and Tools

The study is mainly quantitative and does not include very complicated concepts, however, a number of key terms used in this research have wide definitions. Therefore, in order to clarify them, their definitions are described in table 2.

Terms	Definition Description
Energy Behaviour	Occupants' activities that influence energy consumption of a building passively or/and actively.
Active Energy Behaviour	Occupant's planned and intentional activities that influence energy consumption of a building such as: opening windows and use of hot water, electricity and appliances.
Passive Energy Behaviour	Occupant's presence or their unintentional activities which influence energy consumption of a building. Mainly refers to the production of metabolic heat.
Space Design	Decision upon the space appearance, arrangement and functioning. In this research in refers to space design features that influence the energy consumption of a building such as: space layout and furniture.
Occupancy	The state of being present in/ or to occupy a space.
Realistic Energy Consumption	The prediction of energy consumption of buildings using energy simulation tools with realistic inputs taken from primary data collection.
Public Building	"Far from the scale of the private space and its intimate narratives" (Adjaye, Allison, & Eshun, 2006), where, occupants are autonomous and have no responsibility towards energy bills.

Table 2. Definition of the key terms

In addition to the key terms, various technical terms and tools are used as part of this research study which are described in table 3.

Technical terms and tools	Description
Autodesk Revit	Revit is a leading building information modelling software which provides various tools for architects, structural engineers, MEP engineers and construction professionals developed by Autodesk (Autodesk, 2018).
EnergyPlus	EnergyPlus is a building energy simulation tool funded by U.S. department of energy (DOE) and managed by the National Renewable Energy Laboratory (NREL). EnergyPlus is used by engineers, researchers and designers to predict heating, cooling, ventilation, lighting, electricity energy consumption and water consumption in buildings (EnergyPlus, 2018) (See: 2.3. Building Energy Prediction Methods and Tools).
DesignBuilder	An advanced building energy simulation tool linked to EnergyPlus energy simulation engine and commonly used by engineers, architects and energy assessors (See: 4.3. Energy Simulation Tool, DesignBuilder).
gbXML	Green Building XML is a file format which is developed to store and share building properties between building information models and engineering analysis tools to increase the interoperability between design and building energy simulation (gbXML, 2018).
DXF	DXF (Drawing eXchange Format) is a graphical image file format developed by Autodesk which enables interoperability between various Autodesk tools (such as AutoCAD and Revit Architecture) and other programs such as energy modelling and simulation tools (e.g. DesignBuilder).

Table 3. Description of technical terms and tools

1.6. Publications

Most of the findings of this study at different stages of the research development (including literature review, research method, case study design, data collection and the theoretical and conceptual frameworks) have been published in prominent peer-reviewed journals and conference proceedings. The great number of reviews this study received by experts in the research subject domain has highly benefitted its progress.

- A broad review of literature on the influence of occupants in energy consumption of buildings is performed through this research which formed a review paper. The paper (Delzendeh, Wu, Lee, & Zhou, 2017) is published in renewable and sustainable energy reviews journal which is one of the most remarkable journals in the subject area.
- Two conference proceedings are the other outcomes of this research project so far: "a conceptual framework to simulate building occupancy using crowd modelling techniques for energy analysis" in Cib 2016 conference (Wu & Delzendeh, 2016) and "The influence of space layout design on occupant's energy behaviour" in LC3 2017 conference (Delzendeh & Wu, 2017).
- The preliminary findings of this study including analysis of data collection and the preliminary conceptual framework formed a conference paper with the following title: "The role of space design in prediction of occupancy in multi-functional spaces of public buildings" (Delzendeh, Wu, & Alaaeddine, 2018). The paper went through a double-blind review, received very positive and constructive comments and is published in 2018 Building Performance Analysis conference and SimBuild co-organized by ASHRAE and IBPSA-USA.
- The above conference paper was then expanded to include detailed research method, simulation results and the final conceptual framework which formed another journal paper: "A conceptual framework to predict energy consumption in multi-functional spaces".

In addition, active attendance in various postgraduate research conferences and symposiums with both PowerPoint and poster presentations has promoted the development of this research.

1.7. Thesis Structure

This thesis has been created under the following chapters:

- Chapter 1. Introduction: This chapter includes research background, aim and objectives, research method, contribution to knowledge, uniqueness and novelty, definitions and publications.
- Chapter 2. Literature Review: A comprehensive review on the prediction of energy consumption in buildings (tools and methods), the gap between the actual and

predicted energy consumption in buildings and the impacts of occupants' passive and active behaviours on energy consumption in buildings with specific focus on multi-functional spaces in public buildings are presented in this chapter. Besides, the existing gaps in the literature are pointed out and research focus and scope are explained.

- Chapter 3. Methodology: This chapter contains a review of methods used to study the impacts of occupants' behaviours on building energy consumption, followed by, detailed description of research method employed in this study including research philosophy, research approach, methodological choice, research strategy and case study design, time horizon and data collection techniques.
- Chapter 4. Case Study, Stage 1: The chapter includes the selection of multi-functional cases of this study and the energy simulation tool used to integrate the collected data into energy assessment process. Case study stage 1, also, contains case study description, energy modelling and simulation process and their outcomes for the cases at the design and construction stages. As a final point, the potential gaps in energy consumption prediction of multi-functional at design and construction stages are highlighted in this chapter.
- Chapter 5. Case Study, Stage 2: This chapter includes case study description, energy modelling and simulation process, the results of simulation using default software human-behaviour-related assumptions, data collection, the data analysis and classification of the collected data and energy simulation using the collected data for the cases at the post-occupancy stage. The chapter concludes with the analysis of both simulation results (using software assumptions and using the collected data) to quantify the gap between energy consumption predictions using realistic and standard assumptions regarding occupants' energy behaviours.
- Chapter 6. Discussions and Framework: This chapter includes further discussions and the development of conceptual framework, validation and refinement of the framework and the final framework to improve the accuracy of energy consumption assessment in multi-functional spaces by incorporating occupants' realistic energy behaviours into energy simulation tools.
- Chapter 7. Conclusion: This chapter contains the conclusion of the study linked with research objectives, in addition to, research limitations, and future work.

1.8. Chapter Conclusion

This chapter contains the introduction to the research by presenting its most essential aspects including research background, research aim and objectives and research method. It, also, includes the contribution to knowledge (both theoretical and practical), uniqueness and novelty of the research. In addition, the key terms and phrases and technical terms and tools which are used in this study, are introduced in this chapter. A number of publications have been the outcomes of this research study and are used for development of this thesis. The list of publications is provided in this chapter. Finally, the thesis organisation is explained to provide information about the content of each chapter. In the next chapter, a comprehensive literature review is performed to point out the existing gaps in the research domain and specify the research focus.

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Literature Review Chapter

Chapter 2: Literature Review

This chapter provides a comprehensive literature review on the state-of-art of the influence of occupants on building energy consumption. As the research area is fast growing, the reviewed content was mostly selected among the most recent research projects and publications, as well as, the most prominent studies. The first part of this chapter is focused on areas directly relevant to the research problem including energy consumption in buildings, building energy assessment tools, the existing performance gap, occupants' energy consumption behaviours, the influential parameters and thermal comfort. It includes a quantitative analysis and qualitative review of the literature, to address the existing gaps in the subject area, followed by an explanation of the specific focus of this study. Some parts of this chapter has been published in leading peer-reviewed journals (Delzendeh et al., 2017) and conference proceedings which has greatly benefitted the development of this research study (See: 1.6. Publications). The second part of this chapter provides more detailed literature review on the research focus. The chapter organisation and literature review development is illustrated in figure 4.

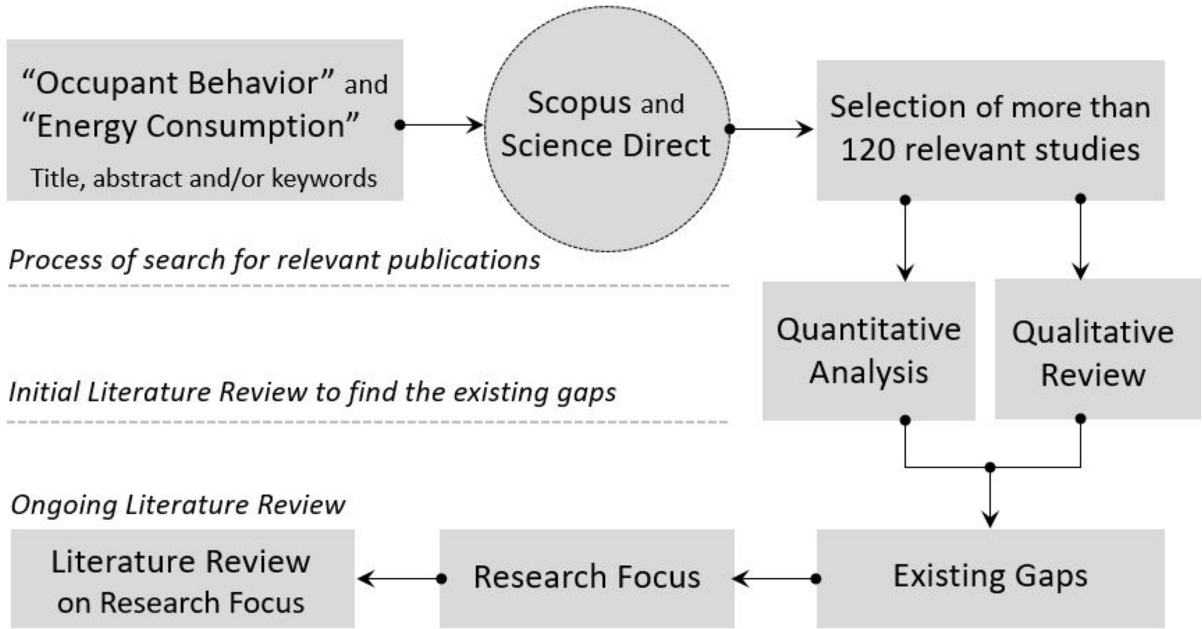


Figure 4. Literature review development

2.1. Energy Consumption in Buildings

Over the years, the need to be more sustainable has significantly increased global focus towards energy consumption related analysis. Climate change is foreseen to be the greatest environmental threat and challenge of modern times. International agreements such as the Paris agreement (Salawitch, Canty, Hope, Tribett, & Bennett, 2017); the Kyoto Protocol (Vasser & Vasser, 2009); European agreements such as the European Emissions Trading Scheme and European Directive on the Energy Performance of Buildings (EPBD); and UK national measures such as the United Kingdom's Climate Change Programme (UKCCP) (Carbontrust, 2005) and the Climate Change Levy (CCL) (GOV.UK, 2001; Pearce, 2006); all demonstrate its prominence. Thus, government, businesses and wider society all have a pivotal role to address human impact (hence, occupant behaviour) on the environment. In this regard, predicting energy demand is becoming more important throughout building's lifecycle, from early design stages to post occupancy. According to Janda (2011), the growth in knowledge and public concern with regards to climate change has ensured increased attention towards energy consumption in relation to buildings. Statistics have affirmed that buildings are colossal consumers of energy. In addition, there are strong economical drivers towards reducing energy consumption in buildings. Energy cost accounts for almost 50% of the total building post-occupancy cost in average (Sekki et al., 2016).

As published in the "International Energy Outlook" by the U.S. Energy Information Administration (eia, 2016), 20% of the total energy consumed worldwide is within the building sector (including residential and commercial). Another study (Wilkes & Goodright, 2015) demonstrated that from 1970 to 2014, the domestic sector alone used between 24% to 27% of the total energy consumption in Europe. Likewise, a separate study undertaken by the European Environment Agency (EEA) (EEA, 2015) presented similar results in their analysis. In 2015, EU statistics (EUROSTAT, 2015) reported that buildings (including services and households) consumed around 40% of the total energy use in 2015. In China and India, the building sector accounts for 37% (Ji, Lomas, & Cook, 2009) and 35% (Manu, Shukla, Rawal, Thomas, & de Dear, 2016) of the total energy consumption, respectively. Also, 59% of the total energy consumption in Finland is consumed in building sector (Sekki, Andelin, Airaksinen, & Saari, 2016). Furthermore, statistics show that building sector accounts for around 30% of global yearly greenhouse gas emissions (Sekki et al., 2016).

Such that is the acute need to drive down energy consumption, in 2002, the Energy Performance Building Directive (EPBD) announced new regulatory conditions for all EU countries to decrease the energy needed for heating, cooling, ventilation and lighting in buildings. Therefore, estimated energy efficiency level of buildings has to be considered in the design of buildings, and subsequently in construction documentations (Fabi et al., 2013) as part of the planning process.

Energy consumption of buildings is related to various factors including: the thermo-physical properties of the building elements, the construction technical details (energy-efficient building elements may not perform efficiently if poorly-constructed), climatic location characteristics, the quality (and maintenance) of the installed HVAC system, and occupants' behaviour and activities towards energy utilization (S. Chen et al., 2015; Jessen Page, Robinson, & Scartezzini, 2007). Throughout building's lifecycle, from early design to post-occupancy and operation stages, energy simulation is used to predict energy consumption of buildings based on available information. However, several studies (Calì et al., 2016; Fabi et al., 2013; HUB, 2015; Maier et al., 2009; Martinaitis, Zavadskas, Motuziene, et al., 2015; Schakib-Ekbatan et al., 2015; Yang et al., 2015) showed that there was a considerable discrepancy between the predicted and actual energy consumption of buildings. The studies demonstrated that the actual energy consumption of buildings is considerably greater than the estimated calculation. For example, Bordass, Cohen, Standeven, and Leaman (2001) stated that the actual energy consumption in Probe's air-conditioned offices were twice higher than predicted. A study by Demanuele, Tweddell, and Davies (2010) on 15 school across the UK demonstrated that the actual electricity consumption was approximately 60% - 70% higher than predicted.

Thus, this performance gap is due to the difference between the building design and the as-built building in terms of the technical workmanship and installations, choice of equipment and material during the construction stage, and the energy behaviour of occupants, which has been disregarded in the energy simulation process (Calì et al., 2016; Fabi et al., 2013; Tian et al., 2018) (Figure 5).

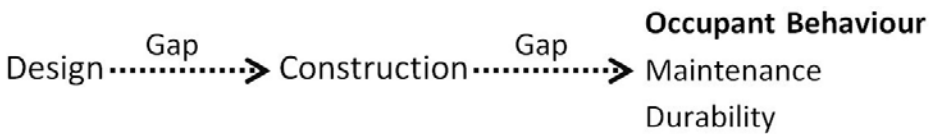


Figure 5. The gap between the predicted and actual use of buildings

Various studies have focused on different aspects of the uncertainty analysis in building energy prediction such as building performance, building stock analysis (Dascalaki, Droutsa, Gaglia, Kontoyiannidis, & Balaras, 2010) and life cycle analysis (Tian et al., 2018). In a comprehensive review study by Tian et al. (2018) four types of uncertainties in prediction of energy consumption were classified: weather data, building envelope, HVAC system and occupant behaviour. The aforementioned uncertainties are believed to cause inaccuracies in building energy assessment.

To predict energy consumption of buildings during design, construction, operation and maintenance stages, energy simulation tools are used. At different stages of building's lifecycle, the available information to use as inputs for energy modelling and simulation vary (Figure 6). The lack of detailed information regarding building material, working hours, space functions, occupancy and occupants' behaviours can result inaccurate energy consumption prediction. Energy prediction at early design stage is usually used for comparison between different scenarios of building volume, shape, orientation, etc. However, lack of building material, services, technical details and space function data at the early design stages may cause expectable and unavoidable inaccuracies in the energy prediction. Likewise, at the design and construction stages, the main missing pieces of information are the building working hours and human behaviour. Moreover, buildings keep evolving even after the post-occupancy stage. For example, the ongoing transformations of the internal layout, space function and furniture. During operation and maintenance stages of a building, energy simulation is used to quantify and select energy saving strategies after refurbishment and energy retrofitting.

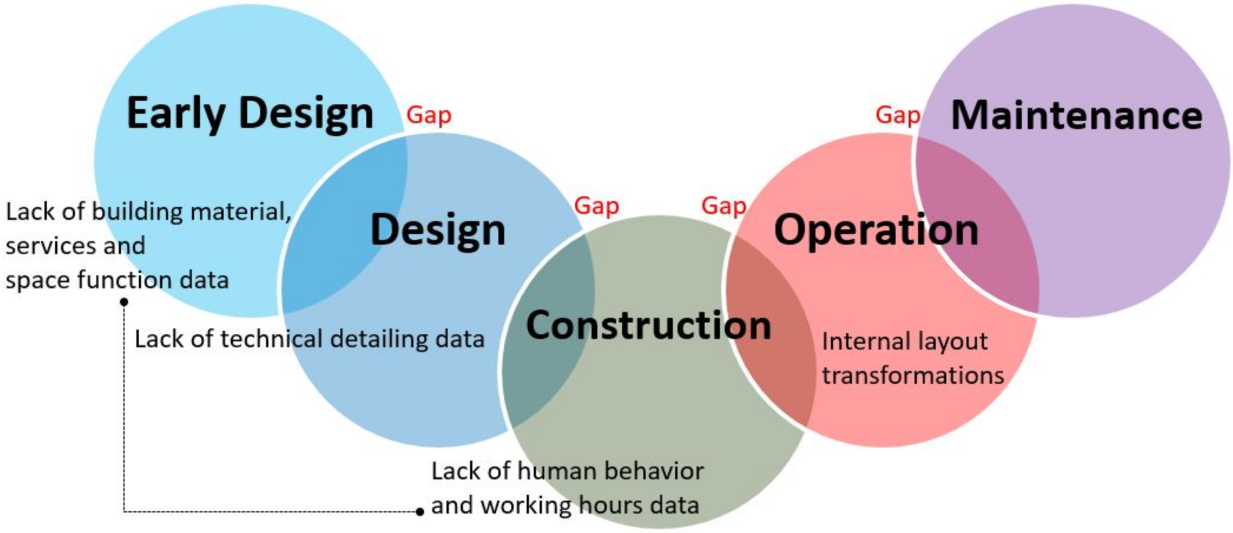


Figure 6. The missing information in building energy prediction at different building's lifecycle

Post-occupancy energy-use evaluation has been analysed in numerous research projects. For example, the ROWNER project (HUB, 2015) considered three stages: design and construction, post-occupancy evaluation and overheating. The project analysis (HUB, 2015) demonstrated a significant difference between the total energy consumption between two flats within the same building block due to differing occupant behaviours, including: different presence at home, different occupancy levels, and variations in the occupants' thermal preferences. In another research by Gill, Tierney, Pegg, and Allan (2010), the comprehensive post-occupancy studies on sustainable UK EcoHomes remarked that occupants' behaviours resulted 51%, 37%, and 11% variations in heating, electricity, and water consumption, respectively. Similarly, major differences in energy consumption of similar building blocks were reported in another study (Kalman, 2012): Martinaitis, Zavadskas, Motuziene, et al. (2015) referred to five different studies to highlight that buildings did not perform as predicted, even when the energy simulation was very accurate. They concluded that human behaviour and occupant preferences as important contributors of the gap between the predicted and actual building energy performance. Furthermore, Schakib-Ekbatan et al. (2015) identified occupants' behaviour as the most overlooked parameter that "might not be considered as part of the energy design" within the chain of design, construction, operation and maintenance. As such, a range of studies have ensued focusing on the influence of occupants' behaviour on building energy consumption with the focus to interpolate behavioural aspects into building energy simulation tools to improve their accuracy (Hong, D'Oca, Turner, & Taylor-Lange, 2015).

However, despite vigorous research being undertaken in this area, the findings are fragmented and, therefore, there is a real need for international collaboration in the sharing of collected data and discovered findings (Yan & Hong, 2016). Also, it is widely believed that designing an energy efficient building requires a multi-disciplinary team of designers, mechanical engineers and energy modellers (Shi, Tian, Chen, Si, & Jin, 2016). Without this multi-disciplinary approach, achieving energy optimisation in buildings will remain incomplete.

In the following section, a quantitative analysis and qualitative review of the existing literature in the state of art of the influence of occupants' behaviours on energy consumption in buildings is performed.

2.2. Review of the Existing Literature: Quantitative Analysis and Qualitative Review

This section aims to undertake a comprehensive review of the existing studies to provide a summary of the extant literature and identify research gaps. The selection criteria was primarily based on the direct relevance to the subject, in addition to, a number of studies which focused on related subjects due to their substantial importance.

Literature review usually follows a process of 'search' for relevant publications, utilising citation indexes against pre-determined criteria for eligibility and relevance to form an inclusion set relating to the research area. To reduce bias in this process, an objective and transparent approach for research synthesis was adopted, including both quantitative analysis and qualitative reviews. Therefore, Science Direct and Scopus databases, two of the leading citation index organisations, were used. For this study, the terms "building energy" and "occupant" were used to select any papers where it was found in the title, abstract and/ or keywords. In order to limit this wide scope (more than a thousand papers were identified by Science Direct and Scopus) and to focus closely on the influence of occupant behaviour on building energy consumption, a further search was made through the existing database using more relevant keywords. As a result, both "occupant behaviour" and "energy consumption" have been repeatedly used in the title, abstract and as keywords of various research papers that were considered as the closest key words for the topic of this research review paper. Following such, a search identified more than 120 research papers for the first stage of literature review in this study which were used to classify research gaps and select research focus and scope of this study. Most of the selected papers were directly related to the impacts of occupants’ behaviours on building energy consumption and were published in recent years, to reflect this fast developing research area.

According to the reviewed papers, the most frequent key words used by scholars in this subject area are ‘occupant behaviour’, ‘energy consumption or energy use’, ‘energy simulation or modelling’ and ‘energy efficiency or performance’, followed by ‘comfort’ and ‘behaviour'. Thus, this identifies the notable relevance of comfort-related studies, especially thermal comfort, in occupant behaviour.

The studies identified were subsequently categorised in terms of the methodology used, building type (i.e. residential, offices, etc.), occupants’ types of interaction with buildings and the influential parameter(s) on occupants’ energy behaviours (see: table 4).

Author(s), year	Methodology	Building type	Occupants interactions	Influential parameter
Gandhi and Brager (2016) (Gandhi & Brager, 2016)	2 Years Field Study, Data Analysis Using Rstudio	Commercial, Offices	Plug Load (desktops, laptops, monitors, and task lights)	Personal (Influence of Game)
Jang and Kang (2016) (Jang & Kang, 2016b)	Case Study, Survey, Gaussian Process Classification	Residential (High-Rise)	Heating and Electricity consumption	-
Rafsanjani and Ahn (2016) (Rafsanjani & Ahn, 2016)	Non-Intrusive Occupant Load Monitoring (NIOLM)	Commercial	Occupants' energy behaviours	Arrival-Departure
Karatas, Stoiko, and Menassa (2016) (Karatas, Stoiko, & Menassa, 2016)	Pre and Post-occupancy Measurements, Clustering	Residential, Commercial	Occupants' energy behaviours	Personal (Behavioural Studies)
Karjalainen (2016) (Karjalainen, 2016)	Case Study, Survey	Offices	Occupants' energy behaviours	Design Features
Ahn and Park (2016) (K.-U. Ahn & C.-S. Park, 2016)	Experiment, Real-time Monitoring	Laboratory	Occupants' Presence and energy behaviours	-
von Grabe (2016) (von Grabe, 2016)	Decision Theory, Qualitative Data	-	Occupants' energy behaviours	Personal (psychological)
Salcido, Raheem, and Issa (2016) (Salcido et al., 2016)	Review	Offices	Use of mixed-mode ventilation	Climatic
Ryu and Moon (2016) (Ryu & Moon, 2016)	Experiment, Decision Tree and Hidden Markov Model	Building Integrated Control Test-bed	Electricity Consumption	Climatic

Pisello, Castaldo, Piselli, Fabiani, and Cotana (2016) (Pisello, Castaldo, Piselli, Fabiani, & Cotana, 2016)	Case Study, Monitoring using sensors	Educational	Electricity Consumption and windows/doors opening	Personal/ Climatic
Pellegrino, Simonetti, and Chiesa (2016) (Pellegrino, Simonetti, & Chiesa, 2016)	Case Study, Field Measurement	Residential	Use of air conditioning	Climatic
Ouf, Issa, and Merkel (2016) (M. Ouf et al., 2016)	Case Study	Educational (School)	Electricity Consumption	Old/ New Building - Type of Activity
Khosrowpour, Gulbinas, and Taylor (2016) (Khosrowpour, Gulbinas, & Taylor, 2016)	Sensor-based Monitoring, Classification and Predictions	Commercial	Use of appliances	Personal
Kazmi, D'Oca, Delmastro, Lodeweyckx, and Corgnati (2016) (Kazmi, D'Oca, Delmastro, Lodeweyckx, & Corgnati, 2016)	Case Study, Monitoring, Sensitivity Analysis	Residential	Use of hot water	-
Calì, Osterhage, Streblow, and Müller (2016) (Calì et al., 2016)	Field Study, Monitoring	Residential	Occupants' energy behaviours	-
Langevin, Wen, and Gurian (2016) (Langevin, Wen, & Gurian, 2016)	Agent-based Behavior Model, Case Study Simulation	Offices, Building Controls Virtual Test Bed	Occupants' energy behaviours	-
Yu, Li, Li, Han, and Zhang (2015) (Z. Yu, Li, Li, Han, & Zhang, 2015)	Existing 2-year Survey Data, Data mining-based Methodology	Residential	Use of appliances	-
Hong et al. (2015) (Hong et al., 2015)	Ontology	-	-	Personal (Behavioural Studies)
Wang, Zhao, Lin, Zhu, and Ouyang (2015) (Zhe Wang et al., 2015)	Field Measurement, Questionnaire Survey, Sensitivity Analysis	Residential	Heating	Climatic
Tetlow, van Dronkelaar, Beaman, Elmualim, and Couling (2015) (Tetlow, van Dronkelaar, Beaman, Elmualim, & Couling, 2015)	Questionnaire	Offices	Electricity Consumption	Socio-Personal (psychological: TPB)
HUB (2015) (HUB, 2015)	Case Study, Occupant Questionnaire, Post Occupancy Measurements	Residential	Gas, Electricity and Water consumption	Socio-Personal
Indraganti, Ooka, and Rijal (2015) (Indraganti et al., 2015)	Thermal Comfort Survey, Logistic Regression	Offices	Occupants' satisfaction	Personal(Age, Gender)

Feng, Yan, and Hong (2015) (Feng, Yan, & Hong, 2015)	Agent-based Model, One-year Field Study	Offices	Occupants' energy behaviours	Climatic, Behaviour Theories
Schakib-Ekbatan et al. (2015) (Schakib-Ekbatan et al., 2015)	Case study, Monitoring Data, Logistic Regression Analyses	Offices	Windows opening	Climatic (Indoor/outdoor temperature)
Langevin, Gurian, and Wen (2015) (Langevin, Gurian, & Wen, 2015)	Longitudinal Case Study, Survey, Measurements, Human Tracking	Offices	Occupants' energy behaviours	Personal
Hom B. Rijal, Humphreys, and Nicol (2015) (Hom B. Rijal et al., 2015)	Survey, Measurements	Residential	-	Climatic (Humidity)
Mohamed, Al-Habaibeh, Abdo, and Elabar (2015) (Mohamed, Al-Habaibeh, Abdo, & Elabar, 2015)	Survey, Questionnaire	Residential	Occupants' energy behaviours	Socio-Personal
Gulbinas, Khosrowpour, and Taylor (2015) (Gulbinas, Khosrowpour, & Taylor, 2015)	Experimental data analysis	Commercial	Occupants' energy behaviours	Personal
Wang and Ding (2015) (Zhaoxia Wang & Ding, 2015)	Multiple-Case Study, Polynomial and Markov Chain–Monte Carlo Methods	Offices (Business, Administration, Scientific Research)	Use of appliances (Computers)	Type of activity
Heydarian, Carneiro, Gerber, and Becerik-Gerber (2015) (Heydarian et al., 2015)	Experiment	Virtual Environments	Lighting choice	Design Features
S. Chen et al. (2015) (S. Chen et al., 2015)	Multiple-Case Study, Statistical Survey	Residential	Occupants' energy behaviours	Classification of Influential Parameters
Feng et al. (2015) (Feng et al., 2015)	Review, Simulation	-	Occupancy	-
Zhao, Lasternas, Lam, Yun, and Loftness (2014) (Jie Zhao, Lasternas, Lam, Yun, & Loftness, 2014)	Experiment, Data Mining	Offices	Use of appliances	Climatic
Masoudifar, Hammad, and Rezaee (2014-2015) (Masoudifar, Hammad, & Rezaee, 2014-2015)	Monitoring, Real Time Location Systems, Wireless Energy Meters	Offices	Occupancy	-
Johnson, Starke, Abdelaziz, Jackson, and Tolbert (2014) (Johnson, Starke, Abdelaziz, Jackson, & Tolbert, 2014)	Time Use Survey, Markov Chain Statistical Model	Residential	Occupants' interactions	-

D'Oca, Fabi, Corgnati, and Andersen (2014) (D'Oca, Fabi, Corgnati, & Andersen, 2014)	Dynamic Simulation Tool IDA Ice	Residential	Thermostat, Window opening	-
Gunay, O'Brien, Beausoleil-Morrison, and Huchuk (2014) (Gunay, O'Brien, Beausoleil-Morrison, & Huchuk, 2014)	Kalman Filter Algorithm	Offices	Lighting/ Window blinds	-
Jiayu Chen and Ahn (2014) (Jiayu Chen & Ahn, 2014)	Experiment, wireless Network for Monitoring	Educational, Commercial	Occupants' energy behaviours	-
Li, Li, Fan, and Jia (2014) (Li, Li, Fan, & Jia, 2014)	Field Observation, Data Analysis Using SPSS Statistical Software	Offices	Window opening	Climatic
Simona D'Oca and Hong (2014) (Simona D'Oca & Hong, 2014)	Combined Statistical Analysis (with two data-mining techniques: cluster analysis and association rules mining)	Offices	Window opening	-
Yun, Choi, and Kim (2014) (Yun, Choi, & Kim, 2014)	Case Study, Field Monitoring	Offices	HVAC system (Air handling unit)	-
Hom B. Rijal (2014) (Hom B. Rijal, 2014)	Thermal Comfort Survey, Occupant Behavior Survey	Residential	Window opening / use of fans	Climatic
Burgas, Melendez, and Colomer (2014) (Burgas, Melendez, & Colomer, 2014)	Case Study, Monitoring, Data mining	Educational	Electricity Consumption	Climatic
Romero, Bojórquez, Corral, and Gallegos (2013) (Romero et al., 2013)	Field Study, Survey	Residential (Low-income)	Electricity Consumption (Air conditioning)	Climatic/ Economic/ Building quality
Langevin, Gurian, and Wen (2013) (Langevin et al., 2013)	Interview	Residential (Low-income)	Occupants' energy behaviours	Personal/ Economic
Blight and Coley (2013) (Blight & Coley, 2013)	Sensitivity Analysis, Multiple Regression Techniques	Passive Residentials	Heating	-
Kavousian, Rajagopal, and Fischer (2013) (Kavousian, Rajagopal, & Fischer, 2013)	Smart Meter Data Analysis	Residential	Electricity	Climatic
Jun Chen, Wang, and Steemers (2013) (Jun Chen et al., 2013)	Survery Study	Residential	Occupants' energy behaviours	Socio-Economic (age and income)
Agha-Hossein, El-Jouzi, Elmualim, Ellis, and Williams (2013) (Agha-Hossein et al., 2013)	Pre and Post-occupancy Surveys	Offices	Occupants' satisfaction	Old/ New Building (Refurbishment)

Fabi et al. (2013) (Fabi et al., 2013)	Case study, Medium/Long-term Monitoring	Residential	Window opening	-
Andersen, Iversen, Madsen, and Rode (2014) (Andersen, Iversen, Madsen, & Rode, 2014)	Case Study, Markov Chain	Offices	Presence	-
Martinez-Gil, Freudenthaler, and Natschlaeger (2013) (Martinez-Gil, Freudenthaler, & Natschlaeger, 2013)	Experiment	Residential, Offices	Electricity consumption	-
Aldossary, Rezgui, and Kwan (2014) (Aldossary, Rezgui, & Kwan, 2014)	Multiple-Case Study, Interviews	Residential	Occupants' energy behaviours	Climatic
Jain, Taylor, and Culligan (2013) (Jain et al., 2013)	Empirical Study	Residential	Occupants' energy behaviours	Personal (Information)
De Meester, Marique, De Herde, and Reiter (2013) (De Meester et al., 2013)	Case Study	Residential	Heating	Personal (lifestyle), House/ Family size
Andrews, Chandra Putra, and Brennan (2013) (Andrews, Chandra Putra, & Brennan, 2013)	Year-round Survey	Commercial	Occupants' energy behaviours	-
Fabi, Andersen, Corgnati, and Olesen (2012) (Fabi et al., 2013)	Review	-	Window opening	Influential Parameters
Park and Kim (2012) (Park & Kim, 2012)	Field Study, Airflow Measurements, Energy Data Collection, Questionnaire	Residential	Use of fans	Climatic/ Economic
Peng et al. (2012) (Peng et al., 2012)	On-site Observations, Quantitative Data Measurements	Residential	Occupants' energy behaviours	Socio-Personal (lifestyle)
Dall’O’, Galante, and Torri (2011) (Dall’O’, Galante, & Torri, 2011)	Monitoring, On-site Survey, Regression Analysis	Residential	-	-
Yu Zhun Jerry, Haghighat, Fung, Morofsky, and Yoshino (2011) (Yu Zhun Jerry, Haghighat, Fung, Morofsky, & Yoshino, 2011)	Case Study, Data mining	Residential	Occupants' energy behaviours	-
Hom B. Rijal, Tuohy, Humphreys, Nicol, and Samuel (2011) (Hom B. Rijal, Tuohy, Humphreys, Nicol, & Samuel, 2011)	Field survey, Observation	-	Use of windows and fans	-

Schweiker and Shukuya (2011) (Schweiker & Shukuya, 2011)	Field Measurement, Internet-based Survey	-	Heating and Cooling	Personal (Information)
Goldstein, Tessier, and Khan (2011) (Goldstein et al., 2011)	Case Study	Offices	Occupancy	Space Layout Design/ Type of Activity
Guerra Santin (2010) (Guerra Santin, 2010)	Governmental Database, Regression Analysis	Residential	Occupants' energy behaviours	Regulations
Larsen et al. (2010) (Larsen et al., 2010)	Review, Mixed Method	Residential	Occupants' energy behaviours	-
Indraganti and Rao (2010) (Indraganti & Rao, 2010)	Field study	Residential	Occupants' satisfaction	Climatic/ Socio-personal
Steemers and Yun (2009) (Steemers & Yun, 2009)	Existing "Residential Energy Consumption" Survey (RECS)	Residential	Occupants' energy behaviours	Socio-Economic/ Climatic
Juodis, Jaraminiene, and Dudkiewicz (2009) (Juodis, Jaraminiene, & Dudkiewicz, 2009)	Variability Analysis of Existing Data	Residential	Heating	-
Page, Robinson, Morel, and Scartezzini (2008) (J. Page, Robinson, Morel, & Scartezzini, 2008)	Stochastic Model, Markov Chain	Offices	Presence	-
Yun and Steemers (2008) (Yun & Steemers, 2008)	Case Study, Monitoring Data	Offices	Window opening	Arrival- Time Dependant
Hom.B. Rijal et al. (2008) (Hom.B. Rijal et al., 2008)	Adaptive Algorithm, One-year Field Survey	Offices	Windows, doors and fans	Climatic
Page et al. (2007) (Jessen Page et al., 2007)	Stochastic Model/ Markov Chain	Offices, Educational	Occupant presence and energy behaviours	-
Reinhart (2004) (Reinhart, 2004)	Case Study, Field Data, Use of Sensors	Offices	Electricity lighting/ Blinds	-
Al-Mumin, Khattab, and Sridhar (2003) (Al-Mumin, Khattab, & Sridhar, 2003)	Case Study, Survey	Residential	Use of appliances (Electricity)	Personal (lifestyle)

Table 4. Categorisation of the reviewed papers by year of publication, methodology, building types, occupants' interactions with buildings and influential parameters

Analysis of table 4 is concluded as follows:

- Residential buildings and offices respectively account for 44% and 31% of the reviewed studies in this topic area. Less than 20% of these studies used commercial and educational/institutional buildings as their case studies, and cultural and recreational buildings and health centres have not been sufficiently researched and reported, and thus, require further investigation. The number and percentage of each building types used as case studies in the reviewed papers is illustrated in a pie chart (Figure 7).

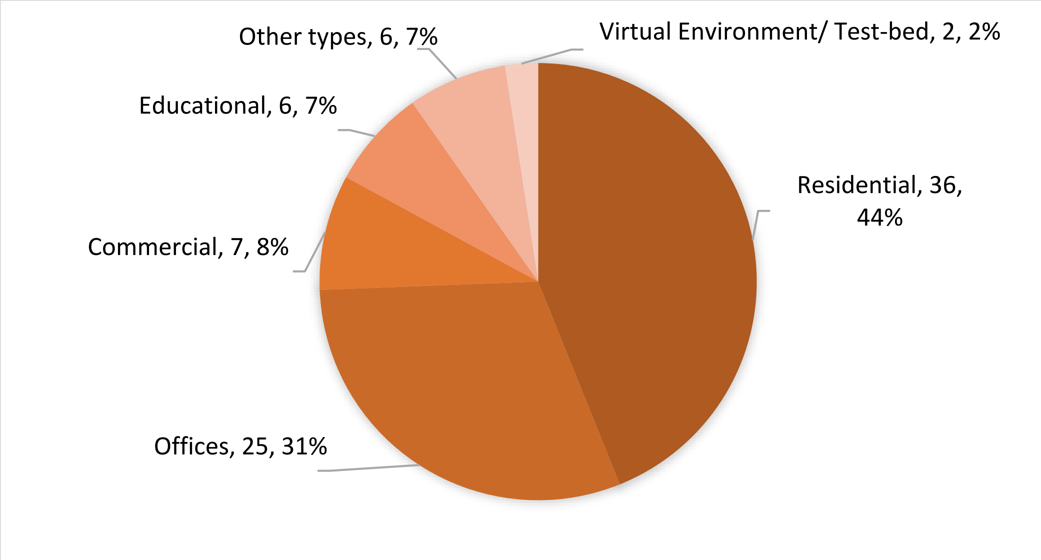


Figure 7. Different building types used as cases

- The majority of studies focused on one or more particular types of occupant's interaction, such as the use of electricity and plug loads (31%), window opening behaviour (18%) and use of fans/ air conditioning (15%) (Figure 8). Although the use of hot water (4%) is limited in the literature, it starts to appear in the more recent publications.

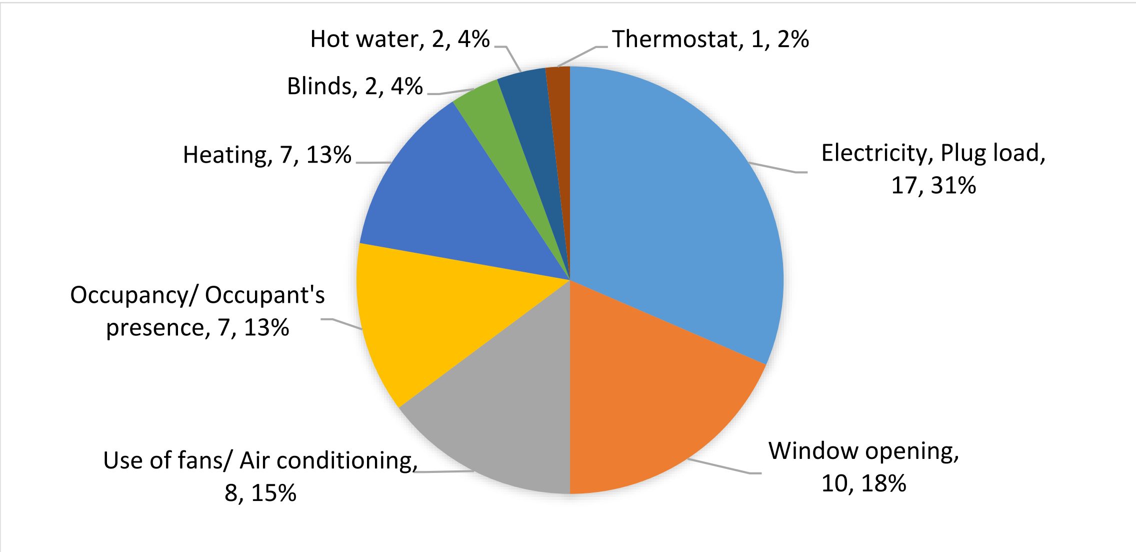


Figure 8. Different types of occupants' interactions

- Many studies focused on one or more influential parameters of the occupant's choices of behaviours and satisfaction. Among those parameters, climatic (environmental, physical) and personal (psychological and physiological) parameters have attracted more attention than other parameters, and accounted 33% and 28% respectively of the totally review papers. Other parameters, such as building features (old/ new conditions and design quality), economy and regulations, socio-personal, occupant's arrival and departure, and type of activity, were investigated in different studies (Figure 9).

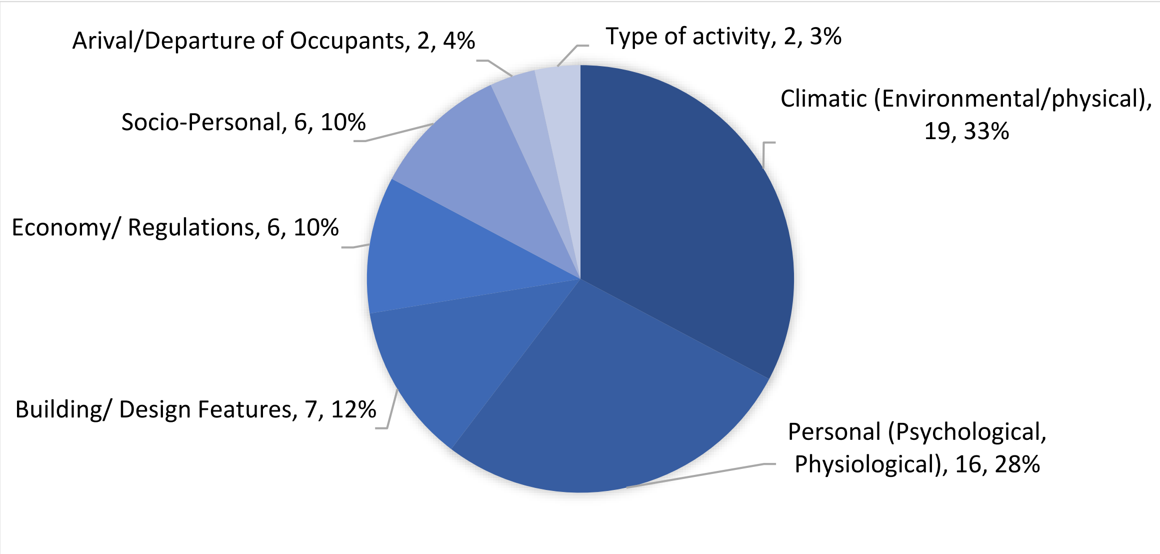


Figure 9. Influential parameters on occupants' energy behaviours

In the following sections, in order to study the gap between predicted and actual energy consumption due to occupants' behaviours, a review of building energy prediction methods and tools and occupants' energy consumption behaviours and the link between these topics are discussed.

2.2.1. Energy Performance Gap

Several studies have pointed out the gap between the actual and predicted energy consumption in buildings and its causes. The energy performance gap refers to the difference between the actual measured energy consumption and the result of calculation-based building energy performance assessment (de Wilde, 2014). In a comprehensive study about building energy performance gap, Zou, Xu, Sanjayan, and Wang (2018b) reviewed and analysed 227 publications and categorised the causes of the building energy performance gap in three main groups: First, the gap between design and operation and lack of sufficient presumptions for the building energy assessment. Second, the gap between building construction and its final design such as: poor construction techniques and workmanship. Third, the gap caused by building operation which is mainly caused by occupants' behaviours. The causes of the gap are usually divided into two major groups: user errors in energy modelling and simulation, and insufficient and inaccurate energy-performance-related assumptions and inputs in energy performance assessment (Allard et al., 2018).

In a study by Strachan, Svehla, Heusler, and Kersken (2016), measured information regarding energy performance of two identical buildings were given to 21 energy modelling teams who used various energy simulation software. The study aimed to create a dataset for validation of various energy simulation tools in predicting energy consumption of full-scale multi-zone buildings. Its findings demonstrated acceptable agreement between the predicted and measured energy consumption which confirmed the reliability of most of the energy simulation tools. However, the study pointed out various user input errors which resulted considerable inaccuracies in energy predictions using energy simulation software. One of the main important user input errors were zoning and the way the energy modellers interpret each zone in energy simulation process. Other errors included the calculation of thermal bridges and solar transmissions. Also, some studies have mentioned use of abstract and simplified models of the buildings as a cause of discrepancy between the predicted and actual energy consumption in buildings (Marshall et al., 2017). Most of the 3D models of the buildings are not simple enough or suitable to be used in energy simulation tools. Also, there is no comprehensive guideline for energy modellers about creating a simplified energy model.

As mentioned earlier, user error in energy simulation and modelling is not the only cause of the gap between predicted and actual energy consumption in buildings. The reliability of the mathematical calculations behind energy simulation tools have been confirmed broadly, however, insufficient and inaccurate energy-performance-related assumptions and inputs used in energy performance assessment are other causes of the aforementioned gap. Unrealistic inputs regarding weather data, building operation and occupant behaviour are believed to be amongst the most significant causes of the performance gap (Pollard, 2011; Zou et al., 2018b).

Various studies have confirmed inaccurate weather data as one of the causes of inaccuracies in energy predictions (Erba, Causone, & Armani, 2017; Kočí, Kočí, Maděra, & Černý, 2019; Lindberg, Binamu, & Teikari, 2004; Liu, Stouffs, Tablada, Wong, & Zhang, 2017; Lundström, 2017). Hourly weather data (such as: solar radiation, relative humidity and dry bulb air temperature) is a critical input for energy consumption prediction of buildings at various stages and scales (Liu et al., 2017). Hence, the accuracy of weather data is essential to achieve reliable energy performance predictions. The global warming issue has caused faster weather variations year by year which has been the focus of many studies in building energy performance research domain.

Studies confirm that six stakeholder groups cause the energy performance gap in buildings: designers, contractors, suppliers, energy modellers and energy managers, in addition to, building owners and occupants (Zou et al., 2018b). Here are some examples how each of these groups cause energy performance gap in buildings: A designer's lack of attention to building users and design of complex building systems and non-flexible spaces, a contractor's lack of performance testing during construction, a supplier's low quality materials, the energy modeller's errors and lack of experience, the owner's and occupant's lack of knowledge and communication (Zou, Wagle, & Alam, 2019). Among all the causes of the energy performance gap in buildings, there is no doubt that occupants have significant impact on the operation and consequently energy consumption in buildings.

2.2.2. Occupant behaviour

Occupant behaviour refers to the interaction with building systems in order to control the indoor environment for health, and to obtain thermal, visual and acoustic comfort inside buildings. Mankind's "desire for control" (Endler, 1993) over environmental factors is not limited to the outside environment, but also, within their living spaces. According to Bluyssen (Bluyssen, 2009), improvement in air quality (by bringing fresh air and eliminating air pollution and odour), acoustical conditions (by avoiding unwanted noise and vibrations), visual or lighting quality (by controlling luminance ratios, reflections and glare) and aesthetic status, in addition to, improving thermal comfort inside the living environment, are the building inhabitants' prerequisites for being able to adjust building systems and components.

Therefore, occupants can influence the indoor environment through their presence and activities in the building.

Cabanac (1971) coined the term “alliesthesia,” composed of two words “allios” meaning “changed” and "aisthesis" meaning “sensation”. Using this term, the author described that “a given external stimulus can be perceived as either pleasant or unpleasant depending upon signals coming from inside the body”. People naturally try to avoid unpleasant conditions and look for pleasant ones. “If a change occurs, such as to produce discomfort, people react in ways to restore their comfort” (Nicol & Humphreys, 2002). However, due to physical, physiological and psychological differences between people, and many other external drivers such as economic and regulatory issues, people do not “receive, perceive, and respond” the same way (Bluyssen, 2009).

The term “thermal comfort” was introduced during the late 19th century. The principal definition of thermal comfort was described by the American Society of Heating and Air-Conditioning Engineers (ASHRAE, 2004) as: “that condition of [the] mind which expresses satisfaction with the thermal environment and is assessed by subjective evaluation”. Despite the subjective nature of thermal comfort, two quantitative formulas, first developed by Fanger (Fanger, 1972), are used for its measurement: predicted mean vote (PMV) and predicted percentage dissatisfied (PPD). PMV models integrate the impacts of temperature (air temperature and mean radiant temperature), humidity, air velocity, the metabolic heat rate and clothing thermal properties to predict the thermal comfort level (Ekici, 2016). Since their emergence, thermal comfort and specifically PMV and PPD models have been studied widely and modified by several researchers for use in different types of buildings worldwide. Thermal comfort factors discussed in PMV models (such as: indoor temperature, humidity, clothing type, etc.) are considered in building energy assessment tools, however, there is the individual aspect in thermal comfort related to personal experiences and expectations which is not reflected in the estimation of energy consumption in buildings.

The total energy consumption of buildings is not only influenced by the metabolic heat produced by occupants passively, which is considered within the occupancy section of energy simulation software, but also by their active energy use. Occupants interact with control systems and building elements to reach their own personal desired level of comfort in different ways: use of building openings (e.g. opening and closing windows), use of lighting and controlling solar shading (e.g. adjusting blinds), use of HVAC systems (e.g. turning air-conditioning on or off and adjusting thermostat temperature), use of hot water and electrical appliances (Figure 10).

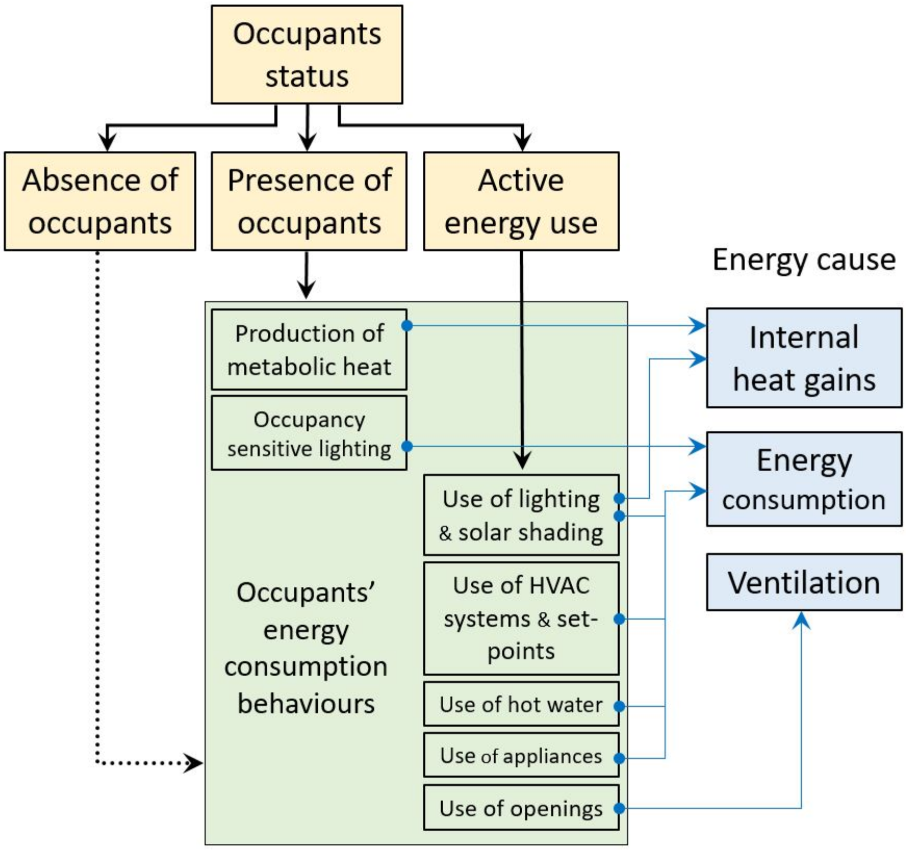


Figure 10. Occupants' types of activities affecting building energy consumption. Adapted from (J. Page et al., 2008)

The occupant's choice of the type of controls to reach his/ her comfort is based on its efficiency, ease and its potential unwanted consequences (Hom B. Rijal et al., 2011). Hong et al. (2015) identified actions (such as adjusting the level of clothing, opening a window and turning down the thermostat temperature) and inactions (such as moving to a different location and tolerating some discomfort) as differing strategies of occupants 'behave' (behaviour) towards the same thermal discomfort. These approaches, however, impact on the amount of energy use, and thus, it is important to understand the relationship between the building and its users' living style and their energy use behaviour (S. Chen et al., 2015; Hong et al., 2015; Schakib-Ekbatan et al., 2015). HVAC systems, electrical devices and lighting that enable users [occupants] to manage their own thermal and visual comfort, are the key sources of energy consumption in buildings (Harish & Kumar, 2016) and variations in using these systems can cause significant variations in the total energy consumption in buildings, and hence, accounts for the gap between actual use and predicted energy consumption.

Several scholars have categorized occupants and their energy attitudes to different groups. D'Oca et al. (2014) divided occupants into active, medium and passive users of energy. The active user changes the heating set point to get warmer/ cooler; conversely, the passive user choses to do nothing and tolerates some level of discomfort. In another categorization, Hong et al. (2015) ranged people's actions more descriptively from "energy frugal" to "energy profligate" via "energy indifferent". Operating another method, S. Chen et al. (2015) classified behavioural factors within residential buildings into three levels according to their complexity: simple, intermediate and complex. Further, he suggested three research methods to study each category: statistical analysis, case studies and detailed diagnostics/ simulation, respectively. Thus, occupants profiling based on their energy behaviours could lead to more accurate assumptions in the energy analysis of buildings. However, a large-scale comprehensive study with significant quantitative data is needed to produce reliable energy profiles, which is presently not available.

Additionally, some scholars have focused on a single activity of occupants affecting building energy consumption. For example, the window opening behaviour of occupants has been widely studied within various building types in differing climates (Simona D'Oca & Hong, 2014; D'Oca et al., 2014; Fabi, Andersen, Corgnati, & Olesen, 2012; Fabi et al., 2013; Li et al., 2014; Pisello et al., 2016; Hom B. Rijal, Honjo, Kobayashi, & Nakaya, 2013; Hom B. Rijal et al., 2011; Schakib-Ekbatan et al., 2015; Yun & Steemers, 2008). Most of the studies on window opening behaviour have focused on the effect on ventilation (Polinder et al., 2013) and studied the time, frequency and duration of opening windows. However, the calculation of the influence of an open window on building energy consumption requires complex air movement considerations that are not effectively accomplished in any of the existing studies.

Moreover, a number of studies have focused on other types of occupants' energy behaviours such as: the use of appliances and electrical consumption (Al-Mumin et al., 2003; Andrews et al., 2013; Burgas et al., 2014; Gandhi & Brager, 2016; Kavousian et al., 2013; Khosrowpour et al., 2016; Martinez-Gil et al., 2013; Ouyang & Hokao, 2009; Jessen Page et al., 2007; Pisello et al., 2016; Ryu & Moon, 2016; Zhaoxia Wang & Ding, 2015; Z. Yu et al., 2015; Jie Zhao et al., 2014), use of lighting (Gunay et al., 2014; Heydarian et al., 2015; M. Ouf et al., 2016; Reinhart, 2004), use of fans (Park & Kim, 2012; Hom B. Rijal et al., 2011) and air conditioning (Pellegrino et al., 2016; Yun et al., 2014), adjusting blinds (Gunay et al., 2014; Reinhart, 2004) and changing thermostat set-points (D'Oca et al., 2014). The use of hot water also has been considered, albeit in fewer studies (S. Chen et al., 2015; HUB, 2015; Kazmi et al., 2016; Trust, 2008). A recent study (Harish & Kumar, 2016) showed that water heating accounts for 7% and 18% of the total energy consumption in residential and commercial buildings in the USA, respectively, which is considered as the 4th and 2nd most sources of energy consumption in these building types. Therefore, depending on the building type, it would appear that the use of hot water might have critical influence on the total energy consumption of a building; however, this requires further investigation to be conclusive.

Of critical consideration, the majority of existing studies focus on a single energy behaviour, however, in reality, energy behaviours are often inter-linked. The inter-relationship between different energy behaviours of occupants has been highlighted by some scholars in the literature. Bourgeois, Reinhart, and A. Macdonald (2005) criticised that although the findings of some studies showed that using automated control in lighting decreased the lighting consumption, in some cases it did not reduce the total energy consumption. In this regard, they (Bourgeois et al., 2005) suggested the link between the use of natural lighting and energy consumption through cooling or heating and thus developed the “lighting:cooling:heating ratio”. In another study, Yan et al. (2015) discussed how occupants’ use of window blinds affects the use of daylight. Studies on the inter-relationship between various energy behaviours of occupants are useful but currently limited and further analysis is much needed.

In addition to active energy use, the metabolic heat produced by occupants themselves impact on the building’s energy passively by directly increasing the internal heat gain. Occupant’s presence and movement within building spaces have been investigated and modelled by a number of scholars (Andersen et al., 2014; Martinaitis, Zavadskas, Motuziene, et al., 2015; Masoudifar et al., 2014-2015; J. Page et al., 2008; Jessen Page et al., 2007) using various indoor localisation techniques, such as crowd modelling tools and other statistical analysis methods (Andersen et al., 2014; Martinaitis, Zavadskas, Motuziene, et al., 2015; Masoudifar et al., 2014-2015; J. Page et al., 2008; Jessen Page et al., 2007). J. Page et al. (2008) reported occupant’s presence “as an inhomogeneous Markov chain” which was disrupted with absence periods. Later, a model of the presence profile in office buildings with single or more occupants using observation together with inhomogeneous Markov chains was proposed by Andersen et al. (2014). The findings of these studies can improve the accuracy of occupancy profiles in building energy predictions, and are beneficial to be extended and used in studies on occupants’ active energy behaviours. As an example, Masoudifar et al.

(2014-2015) applied two wireless sensors, one for occupancy location monitoring and the other for monitoring their energy behaviours; in conclusion, they demonstrated a link between occupant's presence and active energy behaviours. Moreover, several studies have demonstrated that the consequences of occupants' behaviours significantly increase the total energy consumption of buildings during non-working and unoccupied hours (Yang et al., 2015). A study on the energy consumption of six commercial buildings in South Africa (with hot and dry climates) reported that 56% of the total energy consumption was consumed during non-working hours which was believed to occur simply because of occupants failed to turn off the HVAC system and lights before vacating buildings (Masoso & Grobler, 2010).

Human behaviour is a complex phenomenon; therefore, most human behaviour studies adopted probabilistic methods. Fabi et al. (2013) underlined that the gap between simulated and actual energy consumption of buildings was the result of deterministic methods and unrealistic schedules used in simulation tools. In a fixed environmental condition, a person may behave completely differently on different occasions, which confirms the importance of using comprehensive data. This emphasizes the importance to use more realistic and comprehensive methods in this subject area.

2.2.3. Parameters influencing occupants' energy behaviour

As discussed earlier, comfort (specifically thermal comfort) is a state of mind that varies from person to person due to personal (physiological, psychological) and social parameters, which directly affect occupant's energy use. In addition, climatic parameters, economical parameters, regulations and policies, architecture and interior design of the space and building types directly influence energy behaviour of occupants (Figure 11). Fabi et al. (2012) reported the influential parameters on window opening behaviour of occupants, and classified these parameters into five groups: physical environmental factors, contextual factors, psychological factors, physiological factors and social factors.

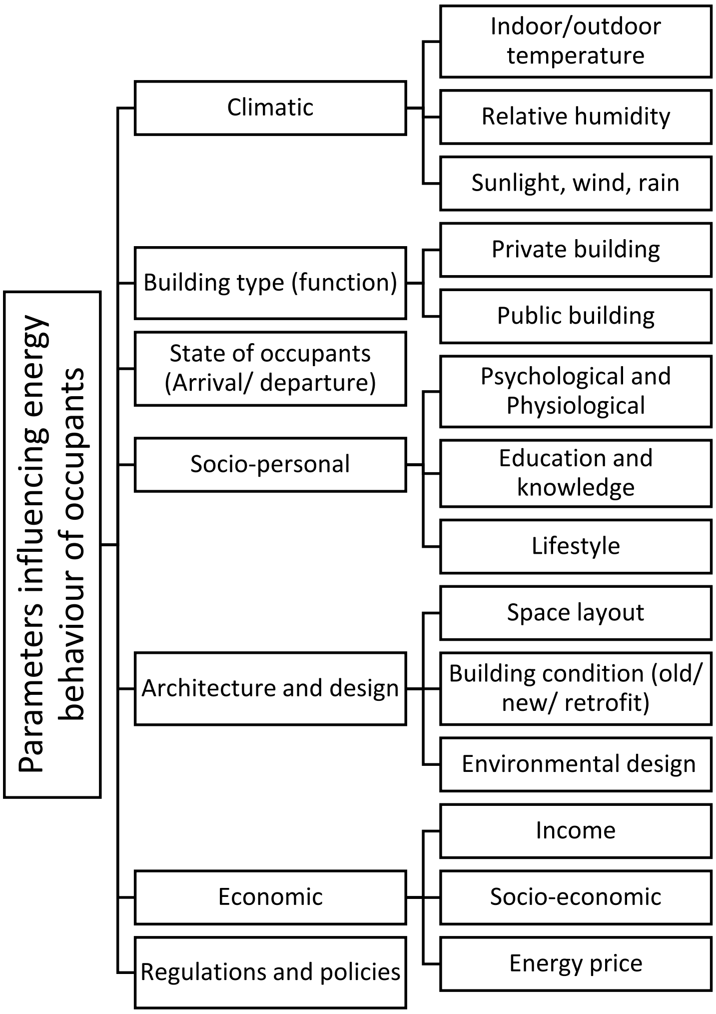


Figure 11. Factors and sub-factors influencing energy behaviour of occupants.

2.2.3.1. Climate

Climatic (environmental, physical) parameters such as outdoor temperature, relative humidity, solar radiation, wind and rain are important parameters influencing occupants' interactions with building systems to acquire thermal comfort. A research study (Hom B. Rijal et al., 2011) used a clear description of the climatic parameters by providing an example of an office block consisting of different cellular offices: it considered each cellular office had a window and was occupied by one person; the outside weather was cold and all the windows were closed. The research concluded that if the room temperature increased gradually, more and more occupants would feel too warm and would open their windows. The outcome of this research was presented as a curve to show the probability of having open windows, which can be extended to other activities using different scenarios. The influence of climatic parameters on occupants' energy behaviour has been widely studied for different types of climatic conditions (Aldossary et al., 2014; Jun Chen et al., 2013; Kavousian et al., 2013; Langevin, Wen, & Gurian, 2015; Li et al., 2014; Hom B. Rijal, 2014; Hom B. Rijal et al., 2013; Hom B. Rijal et al., 2015; Hom.B. Rijal et al., 2008; Schakib-Ekbatan et al., 2015; Zhe Wang et al., 2015; Jie Zhao et al., 2014). These parameters are time/ date dependent, therefore, in many studies stochastic models are used to estimate the probability of potential outcomes. Monitoring occupants' real interactions or (and) occupant behaviour surveys, in addition to, year-round thermal measurements are introduced and used in these climate related studies (Hom B. Rijal et al., 2013).

2.2.3.2. Building Type

The building type determines the type of activity, clothing type, production of metabolic heat, together with the occupants' specific needs and expectations and their possible degree of interactions with building systems. Various research studies have focused on particular **building types (or type of activities)**, focussing heavily on **residential buildings** (Al-Mumin et al., 2003; Aldossary et al., 2014; Blight & Coley, 2013; Calì et al., 2016; Jun Chen et al., 2013; S. Chen et al., 2015; Simona D'Oca, 2012; Dall'O' et al., 2011; De Meester et al., 2013; Fabi et al., 2013; Guerra Santin, 2010; Indraganti & Rao, 2010; Jain et al., 2013; Jang & Kang, 2016b; Juodis et al., 2009; Karatas et al., 2016; Kavousian et al., 2013; Kazmi et al., 2016; Langevin et al., 2013; Larsen et al., 2010; Martinaitis, Zavadskas, Motuziene, et al., 2015; Mohamed et al., 2015; Nicol & Humphreys, 2002; Park & Kim, 2012; Pellegrino et al., 2016; Peng et al., 2012; Hom B. Rijal, 2014; Hom B. Rijal et al., 2013; Hom B. Rijal et al., 2015; Romero et al., 2013; Steemers & Yun, 2009; Zhe Wang et al., 2015; Z. Yu et al., 2015; Yu Zhun Jerry et al., 2011) and **offices** (Agha-Hossein et al., 2013; K.-U. Ahn & C.-S. Park, 2016; Simona D'Oca & Hong, 2014; Gandhi & Brager, 2016; Goldstein et al., 2011; Indraganti et al., 2015; Karjalainen, 2016; Langevin, Gurian, et al., 2015; Langevin, Wen, et al., 2015; Langevin et al., 2016; Li et al., 2014; Masoudifar et al., 2014-2015; J. Page et al., 2008; Salcido et al., 2016; Schakib-Ekbatan et al., 2015; Tetlow et al., 2015; Zhaoxia Wang & Ding, 2015; Yun et al., 2014; Jie Zhao et al., 2014). The level of attention paid to residential buildings and offices is due to their critical impact on the total energy consumption in the building sector. Still, statistics confirm the great role of non-residential buildings on the total energy consumption and CO^2 emission. For example, non-residential buildings account for around 19% of the total CO^2 emissions in UK (Gul & Patidar, 2015). Some studies have investigated commercial (Jiayu Chen & Ahn, 2014; Gandhi & Brager, 2016; Gulbinas et al., 2015; Karatas et al., 2016; Khosrowpour et al., 2016; Rafsanjani & Ahn, 2016) and educational buildings (Burgas et al., 2014; Jiayu Chen & Ahn, 2014; M. Ouf et al., 2016; Pisello et al., 2016) with limited findings. There have been sparse studies undertaken on other public building types such as exhibitions and health centres.

Furthermore, the vast majority of research on occupants' energy behaviour focuses on single buildings and there are only a few studies that investigate the urban scale impacts (Dall'O' et al., 2011; Park & Kim, 2012). It is suggested that future research could extend to the urban design scale (Andrews et al., 2013) as the understanding of the impact of occupants' energy behaviours on energy consumption on a larger scale improves the credibility of energy consumption policies made using more realistic data. The existing methodologies used to study the subject area in single buildings can be adjusted and used as the basis of further similar studies on the urban scale.

2.2.3.3. Social and Personal Parameters

Social and personal (psychological and physiological) parameters play a substantial role in occupants' comfort and energy attitude and has been broadly studied. Martinaitis, Zavadskas, Motuziene, et al. (2015) identified social and personal factors affecting energy behaviour of households such as: users' awareness of energy issues, gender, age, employment, family size and socio-cultural belonging. Also, Janda (2011) highlighted the effect of education and awareness-raising on people's energy attitude. Some studies have discussed one social or individual parameter; for example, the differences between male and female thermal preferences have been stated by some scholars (Chow, Fong, Givoni, Lin, & Chan, 2010; Indraganti et al., 2015; Indraganti & Rao, 2010; Lan, Lian, Liu, & Liu, 2008). However, the most dependable and comprehensive studies with regards to social and personal factors in this subject area, combined two parameters using human behavioural theories by Tetlow et al. (2015) and Ajzen (1991) to study occupants' electricity consumption in office buildings. Also, Hong et al. (2015) applied an ontology called DNA's framework, using a behavioural-cognitive theory, to suggest four key components governing occupants' energy behaviour: drivers, needs, actions and systems. Various behavioural theories, for example, the theory of planned behaviour (Ajzen, 1991), cognitive complex theory (Kieras & Meyer, 1997) and cognition as a network of task (Freed, 1998), considered the changeable human cognition process by connecting human and environment. Unfortunately, there is little evidence to suggest that the findings have been incorporated into building energy assessment tools. The authors believe that a multi-disciplinary approach is needed to bring together social scientists, energy modellers and construction engineers to tackle this complex problem. In addition, more detailed quantitative studies governing the sociology aspects of occupants' behaviours are suggested as necessary by some scholars (Yan & Hong, 2016), which is essential to improve the accuracy of energy consumption predictions in buildings.

2.2.3.4. Regulations and Economical Parameters

Energy regulations and **economical parameters** such as energy price and employment have been discussed in various studies. In addition, the influence of these parameters on occupants' energy consumption behaviour in buildings has been raised by some scholars (Calì et al., 2016; Guerra Santin, 2010; HUB, 2015; Langevin et al., 2013; Martinaitis, Zavadskas, Motuziene, et al., 2015; Park & Kim, 2012; Hom B. Rijal et al., 2011; Romero et al., 2013; Zhe Wang et al., 2015). Studies show that when occupants are directly responsible for pay energy bills they act more energy frugal (Zhe Wang et al., 2015). Hom B. Rijal et al. (2011) investigated the relationship between energy price and occupants' thermal tolerance, which affects the total energy consumption of buildings. According to the findings of the study by Park and Kim (2012), more than half of the respondents to their questionnaire indicated energy costs as the main reason for avoiding the use of mechanical fans and accepting some level of discomfort. However, Romero et al. (2013) showed that in harsh climatic conditions (e.g. very hot weather), low-income occupants consumed more electricity for cooling in comparison to other households due to the inadequate thermal insulation of the buildings. Similarly, Jun Chen et al. (2013) stated that occupants' economic situation could determine the quality and size of their housing, which would consequently affect energy consumption. In another study, Langevin et al. (2013) conducted semi-structured interviews of occupants in low-income public housing, which revealed notable differences of energy behaviours between rental paying occupants and government subsidised occupants.

2.2.3.5. State of Occupants: Arrival and Departure

A number of studies have revealed that occupants tended to adjust building systems and appliances more at arrival than at departure of a building. Therefore, **state of occupants** (arrival, presence in the space and departure) have been considered and modelled in a number of research projects (J. Page et al., 2008; Jessen Page et al., 2007; Rafsanjani & Ahn, 2016; Yun & Steemers, 2008) and the connection between occupants' movements and their behaviours have been investigated. In order to simulate the occupant's presence, J. Page et al. (2008) proposed an algorithm by supposing present/absent status of occupants in each zone as a miscellaneous Markov Chain. Some studies used different indoor tracking methods to capture occupants' movements and presences such as: sensor-based systems (e.g. passive infrared (PIR) motion sensors) (Azghandi, Nikolaidis, & Stroulia, 2015), vision-based methods (Milan, Schindler, & Roth, 2013; C.-R. Yu, Wu, Lu, & Fu, 2006), ultrasound (Knauth, Jost, & Klapproth, 2009) and WLAN location fingerprinting (Fet, Handte, Wagner, & Marrón, 2013; Shih, Chen, Chen, Wu, & Jin, 2012). Furthermore, integration of these methods in studies related to occupant's energy behaviour can provide new insight towards the subject area.

2.2.3.6. Design Features

The impact of **architecture and space design features** on occupant's behaviour has been broadly studied (Augustin, 2009; Caan, 2011). With regards to energy consumption, the term "sustainable interior design" describes the integration of sustainability principles in the interior design of space as part of building construction (Moxon, 2012). The practice is mainly focused on use of green material and energy efficient systems (E. Lee, Allen, & Kim, 2013). The interior design of space can influence occupant behaviour in differing ways, including: visual quality of building openings (windows and doors), the architecture circulation and colours, material and compositions of interior spaces which may change occupants' thermal perception. A number of studies have demonstrated the impacts of colours, textures and material sensation on occupants' perception of the indoor temperature and thermal comfort (Ulusoy & Nilgün, 2017; Ulusoy & Olguntürk, 2016). However, the effects of interior design of space on occupants' energy consumption behaviours have not been studied extensively. The differences between occupants' behaviours in old and new (or refurbished) buildings have been reported in several studies (Agha-Hossein et al., 2013; M. Ouf et al., 2016). Moreover, Goldstein et al. (2011) stated that space layout could influence occupant's presence, as it could link to the type of activity that occurs at the location within a space. Therefore, the probability of occupant's presence in certain locations based on different functions of the space could be simulated. Also, there is a proven link between lighting design and the occupant's lighting consumption. Gandhi and Brager (2016) investigated the influence of occupants on plug load (electricity and lighting) energy consumption in office buildings and proposed an energy efficient strategy by decreasing the general ambient lighting and using task lights instead. Based on a rational statement, Karjalainen (2016) suggested that using fixed and robust design strategies can decrease the effects of occupant behaviour on energy consumption in buildings, however, some studies highlighted that built environments with fixed thermal properties consume more energy and do not provide more thermal comfort for the occupants (Zhu, Ouyang, Cao, Zhou, & Yu, 2016).

The term "design for sustainable behaviour," which is mainly used in product design, refers to the role of designer in directing sustainable user behaviour during the design stage (Lilley, 2009; Wilson, Lilley, & Bhamra, 2013). It is posited that if appropriate strategies are applied to the design of a product, the designer can positively influence the sustainable use of the product (Lilley, 2009). Also, a number of studies have confirmed the successful role of games, such as Cool Choices ("Cool Choices," 2016), as a motivation for occupants to practice more sustainable behaviours (Gandhi & Brager, 2016). In order to change occupant's energy behaviour, two main approaches have been suggested: disincentive and motivation approaches (e.g. laws and regulations) and by increasing individual's knowledge and awareness (Crocker & Lehmann, 2013). Day and Gunderson (2015) pointed out that it is essential to educate occupants and improve their knowledge and understanding of building systems, especially in high-performance buildings. Karatas et al. (2016) embraced a framework to measure the results of occupant's behavioural change in energy consumption using a "motivation-opportunity-ability" method. As a result, the study demonstrated effective behavioural change approaches to attain falls in energy consumption in buildings.

2.3. Building Energy Prediction: Methods and Tools

Energy simulation of a building is a mathematical analysis of physical properties of the building elements considering thermal and lighting aspects (Fabi et al., 2013). Jang and Kang (2016b) explained "building form, thermal properties and energy controls" as different inputs of building energy modelling. There are over 400 building energy modeling and simulation tools available ranging from very detailed to very simple (Shi et al., 2016).

Energy simulation engines such as EnergyPlus, TRNSYS and ESP-r follow almost similar procedures to calculate energy consumption in a building:

1- Specifying the location of the building and accessing its climate data

2- Using the 3D model of the building with its existing orientation and specifying its different energy zones

3- Providing information regarding the thermo-physical properties of building elements

4- Determining the type of HVAC system

5- Assessing building working hours, occupancy patterns and any special equipment's used in every zone

6- Selecting the demanded simulation period and running the simulation.

The final outputs of energy assessment tools are heating/ cooling/ ventilation design data, lighting data, CO_2 emission, the total energy consumption and cost, in addition to, various building energy standard certificates. Different standards are used to certify green building and energy efficient design such as BREEAM in the UK (Barlow, 2011), LEED in USA (Cottrell, 2012) and Green Building Label in China (Shi et al., 2016; Ye, Cheng, Wang, Lin, & Ren, 2013). Most of the prominent energy simulation tools such as DesignBuilder and IES VE provide measurements based on LEED and BREEAM standards which can be used by designer and energy modellers as building energy consumption certificates.

Energy prediction of a building is often used for two main purposes: energy efficiency comparison and energy consumption calculations. Energy efficiency comparison is often used in design stages or for building refurbishment to quantify energy saving strategies. It provides a more reliable data by modification of quantifiable parameters, while, energy consumption calculations are less dependable due to the influence of various stochastic parameters.

Harish and Kumar (2016) reviewed the most significant existing modelling and simulation methodologies used in building energy schemes. They used the term “building energy systems” (BES) for any devices, tools or processes which consume energy in buildings. In general, models and simulations are mathematical or non-mathematical; mathematical models are divided into two categories: theoretical and empirical (Harish & Kumar, 2016). According to this categorisation, energy simulation tools use mathematical equations driven from physics and particularly thermo-physics. Reeves, Olbina, and Issa (2015) used case studies to evaluate “interoperability, usability and available inputs and outputs” of 12 building energy modelling tools and developed a guideline for their application in different phases of the building lifecycle. They highlighted the importance of the compatibility of building energy modelling (BEM) with building information modelling (BIM) tools for energy analysis of buildings, to improve the usability in difference phases from early design stages to operation and maintenance. In another study, S. Wang, Yan, and Xiao (2012) suggested a framework to classify energy prediction methods based on various criteria such as: calculation range and complexity of evaluation. Also, they categorized energy assessment methods into three groups: calculation-based, measurement-based and hybrid methods, based on the energy data attainment methods (Figure 12). In another classification, by performing a comprehensive literature review on design energy optimization from architect’s viewpoint, Shi et al. (2016) categorized various terms that has been used to define building energy simulation and modeling tools Since 1990: computational optimization, simulation-based optimization, building performance optimization and performance driven design.

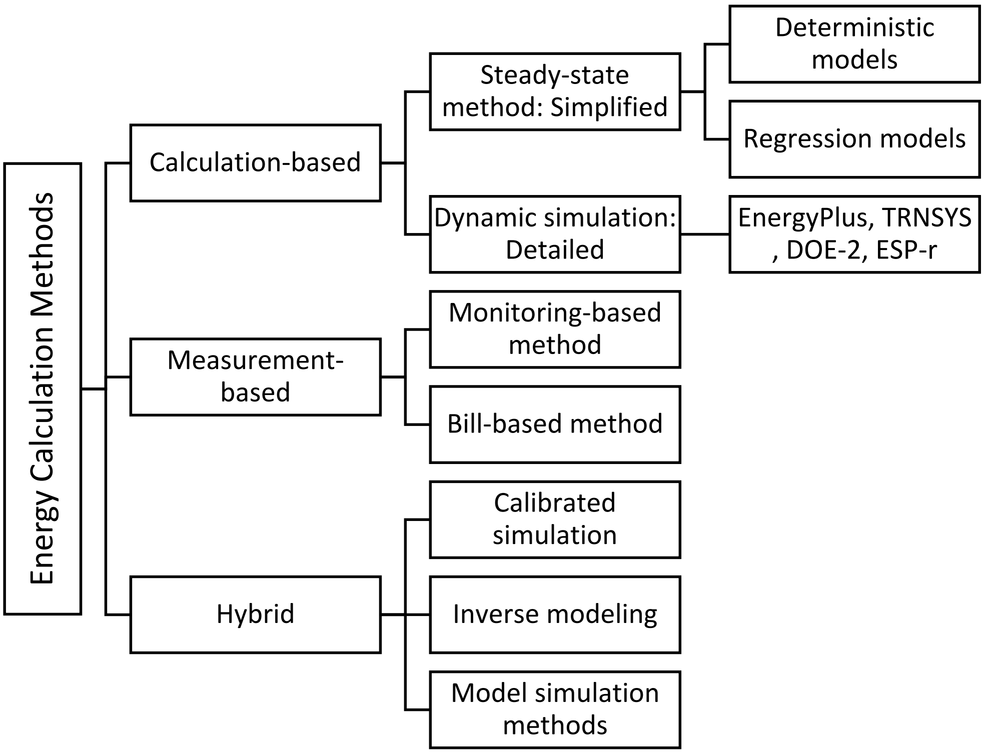


Figure 12. Energy calculation methods adopted from (S. Wang et al., 2012)

From computing point of view, use of “imperative programming languages” in current energy simulation software was criticized by some scholars (Wetter, Bonvini, & Nouidui, 2016). They suggested using computer algebra instead which is a lot faster and more accurate. They declared problems such as difficulty for programmers to develop the current programs, to add new parameters and solve new problems. Also, they pointed out the non-user-friendly nature of energy simulation software that makes it difficult for operators to recognize their possible interactions with their assumptions and parameters (Wetter et al., 2016).

Dynamic energy simulation tools such as: EnergyPlus, TRNSYS, DOE-2 and ESP-r, are considered as very strong and reliable tools for building energy consumption predictions (S. Wang et al., 2012). In addition, several studies confirm that the most powerful building energy simulation engines provide the most detailed inputs, which increases the accuracy of their calculations. In this regard, EnergyPlus, TRNSYS and DOE-2 are repeatedly mentioned by researchers as the most reliable building energy assessment tools.

Among the existing energy simulation engines, EnergyPlus is considered as one of the most novel tools made in 1996 by a US federal agency called the National Renewable Energy Laboratory (NREL), which was the result of combination and development of two other existing tools: DOE-2 and BLAST (Crawley et al., 2001; Shabunko, Lim, & Mathew, 2018). Many simulation-based studies on building energy performance have used EnergyPlus as their energy simulation tool because of its capability to calculate detailed and dynamic inputs with high reliability: Martin, Afshari, Armstrong, and Norford (2015) used EnergyPlus to measure urban temperature and specific humidity. Rempel et al. (2013) integrated collected solar data into EnergyPlus to achieve a climate-responsive design. Many studies on energy retrofit (S. H. Lee et al., 2015) and energy saving (Boyano, Hernandez, & Wolf, 2013) strategies used EnergyPlus to compare various design and detailing alternatives. Like other pioneer energy simulation engines, EnergyPlus lacks user-friendly interface. Therefore, other mediator modelling software such as DesignBuilder are used which provide better graphical interfaces (S. Wang et al., 2012).

In addition to performing calculations, energy modelling and simulation tools provide various adjustable presumptions about building lighting, electricity and HVAC requirements. The reliability of the final output of energy prediction tools, is strongly related to the accuracy of the initial energy model (which is sometimes a simplified version of a complex volume), together with, to set correct data to all the available parameters of the software. The consensus from researchers is that behavioural parameters should be fully incorporated into energy simulation tools in order to provide more accurate energy predictions.

2.4. Human-behaviour-related inputs in energy prediction tools

Several studies underline the influence of occupants' behaviours on energy consumption in buildings. However, neither within both energy efficiency certification methods nor in energy simulation software, are occupants' energy behaviours fully evaluated or considered (Martinaitis, Zavadskas, Motuziene, et al., 2015). Occupants' energy behaviours are either passive or active. Occupant's presence (which mainly refers to the natural production of metabolic heat) or their unintentional activities which influence energy consumption of a building are called passive energy behaviours. Also, active energy behaviour refers to occupant's planned and intentional activities that influence the energy consumption of a building such as: opening windows and use of hot water, electricity and appliances. The critical importance of occupancy information in indoor environmental quality, energy consumption and building energy simulation is highlighted by some scholars (Yang et al., 2015). Several attempts have been made towards understanding the impacts of occupants' behaviours on the energy consumption in buildings. But, there is a lack of integration of the findings of these studies into building energy simulation tools.

Existing building energy assessment tools provide various user-interface for energy modellers and designers to incorporate occupants' behaviours. For example, in DesignBuilder, a leading energy simulation tool, occupant's energy behaviour is considered in the "activity" section of the software (Figure 13). This section includes occupancy (to modify the density of people within each zone), activity factor, gender adjustments, clothing and use of computer and other equipment.

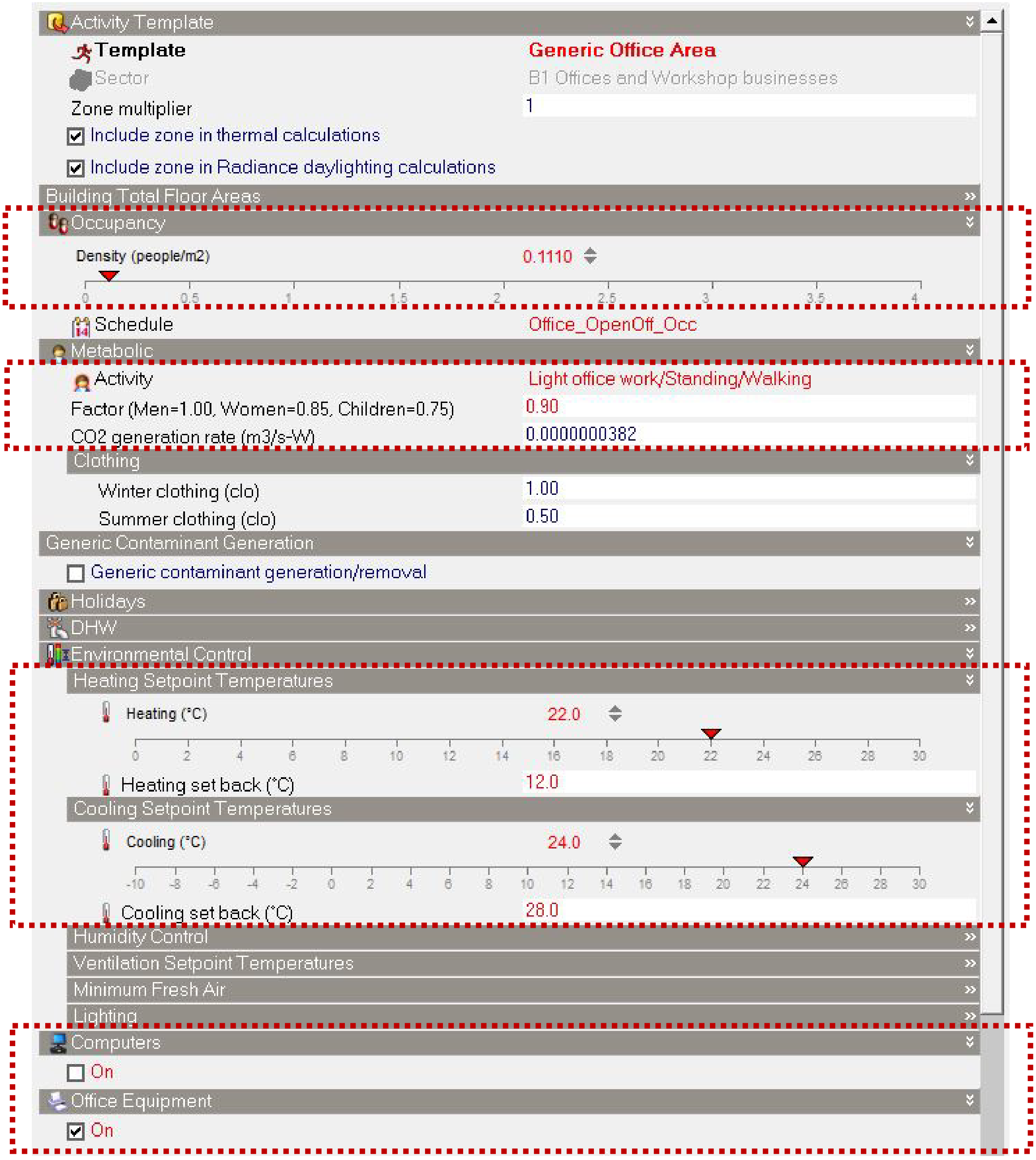


Figure 13. Occupancy in DesignBuilder software

Another widely used tool, EcoDesigner, has less occupancy inputs including: occupant's presence schedule and type of activity that determines the human heat gain (Figure 14).

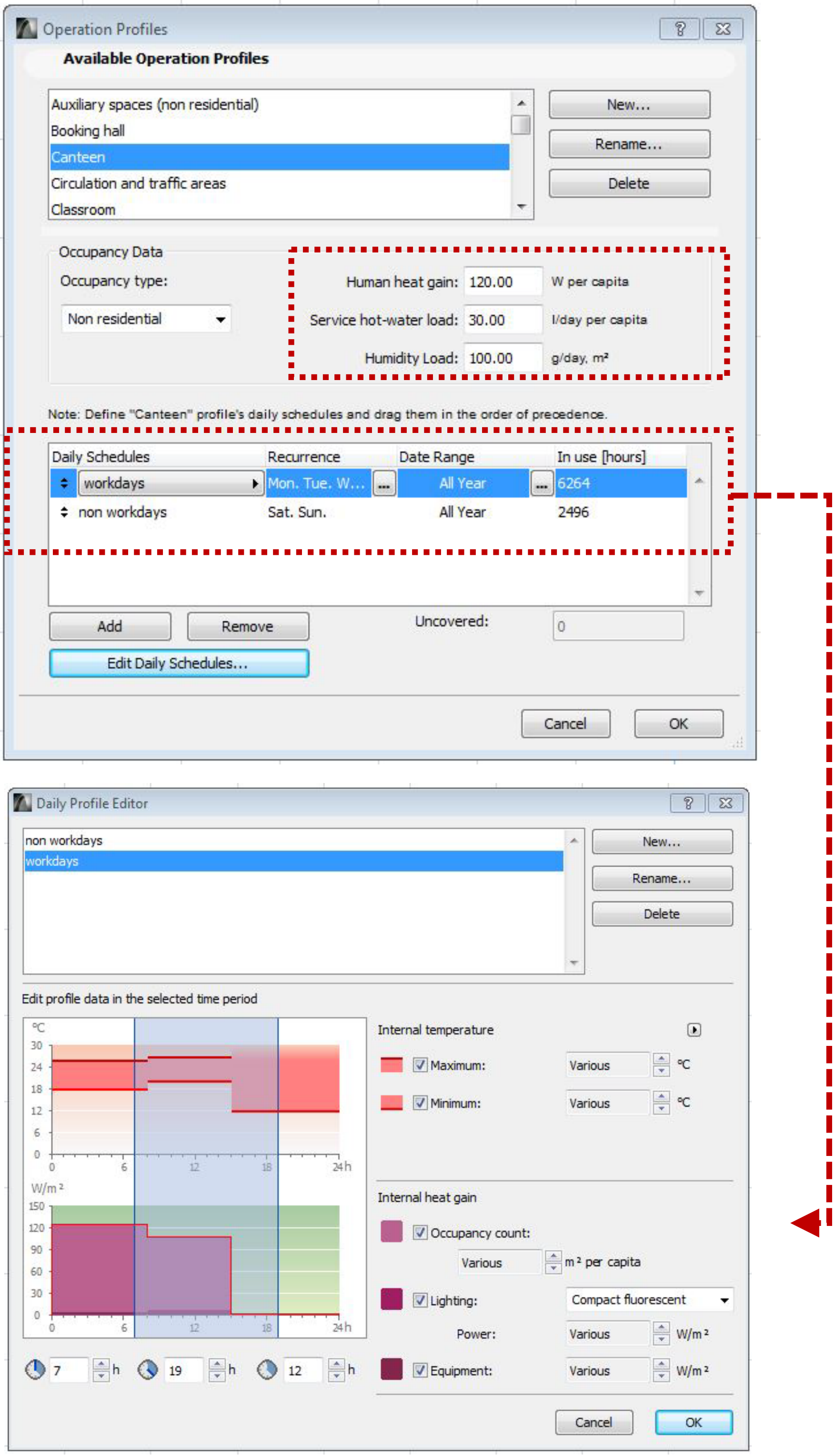


Figure 14. Occupancy in EcoDesigner software

OpenStudio energy assessment tool combines EnergyPlus engine for energy modelling and Radiance for advanced daylight analysis. This software provides a user-friendly interface considering various inputs related to occupants energy behaviours including: density, type of activity, use of lighting and appliances (Figure 15).

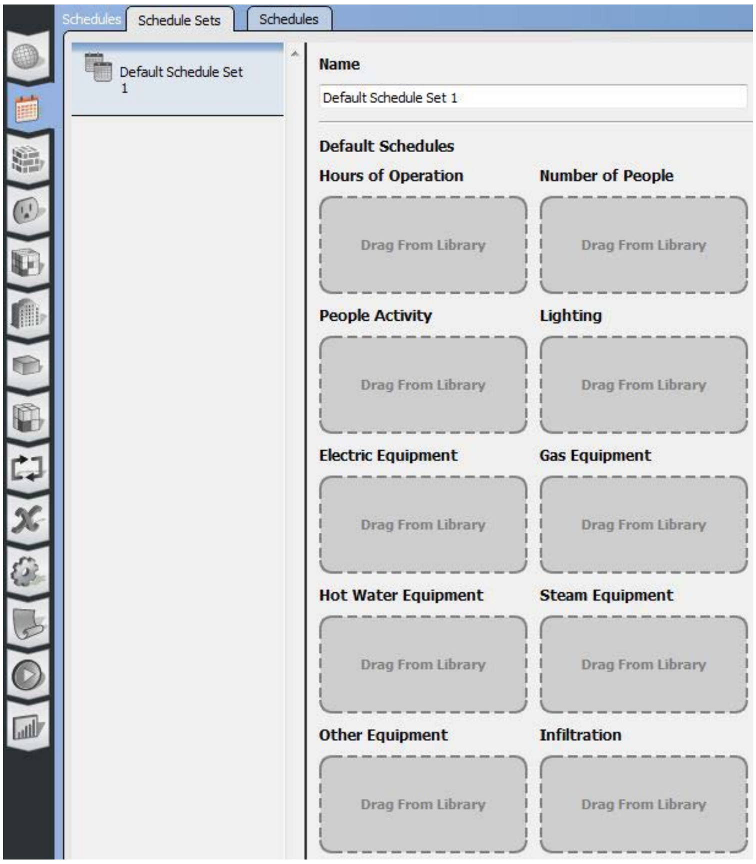


Figure 15. Occupancy in OpenStudio

In many construction projects, BIM tools such as: Autodesk Revit Architecture, are used to create incorporated models of all design disciplines (architecture, structure and mechanical). Therefore, the combined BIM model is sometimes used for energy prediction, with or without modifications. However, Autodesk Revit Architecture's energy section mainly focuses on the physical and thermo-physical properties on the building elements and its location, and it does not integrate much data regarding occupancy and occupants' behaviours (Figure 16). In Autodesk Revit Architecture, DOE-2 energy engine does the calculations, which is considered as a strong energy simulation engine. However, the adjustable inputs provided in the energy simulation process are very limited and not sufficiently detailed.

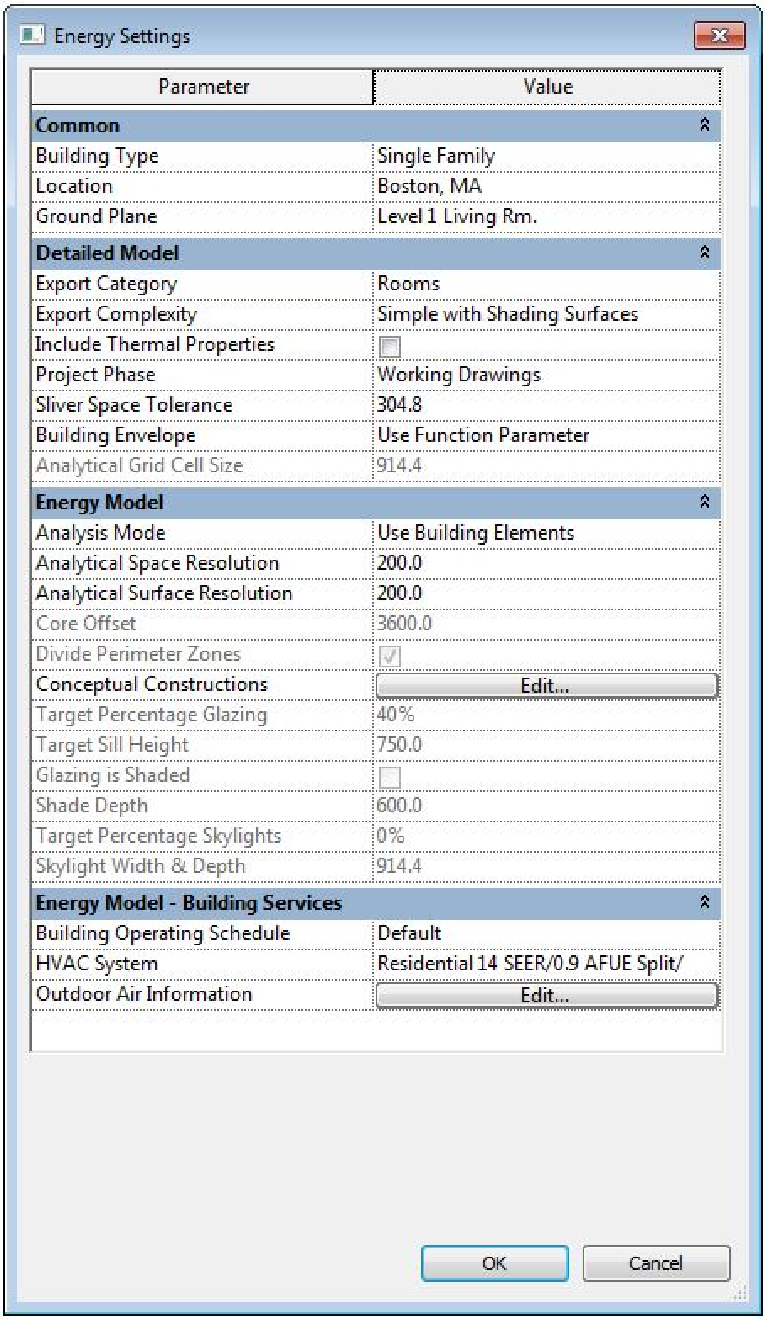


Figure 16. Energy setting in Revit Architecture 2016

In the following section, the evaluation and incorporation of occupants' passive and active energy behaviours in DesignBuilder, EcoDesigner, OpenStudio and Revit Architecture energy prediction tools is investigated.

2.4.1. Passive energy behaviour: Occupancy

Occupancy is commonly defined as the state of being present in or to occupy a space (Christensen, Melfi, Nordman, Rosenblum, & Viera, 2014) and is usually calculated using density (people/m^2) and zone area (m^2) in energy prediction tools. It is also referred to as "the number and time-based" schedule of building occupants (W. Wang, Chen, & Hong, 2018). The production of sensible and latent heat and generation of CO^2 are the most direct impacts of occupant's presence on building indoor conditions. Therefore, occupancy data is a necessity in prediction of energy consumption in buildings. Most of the leading energy simulation tools including: EnergyPlus, TRNSYS and ESP-r, deliberate occupancy profiles as important inputs of building energy assessment (Yang, Santamouris, & Lee, 2016). However, input data regarding occupancy in energy simulation software is limited to occupants' presence in fixed and scheduled patterns that does not reflect reality (Fabi et al., 2013; Martinaitis, Zavadskas, Motuziene, et al., 2015). There are various models to predict occupancy in buildings; however, its complex nature has caused great inaccuracies in all the existing models. In a research study by Mahdavi and Tahmasebi (2015), long-term monitored data was used to investigate the accuracy of two probabilistic occupancy models by Reinhart (2004) and J. Page et al. (2008). This study concluded that occupancy predictions of both probabilistic models were quite inaccurate and they proposed a non-probabilistic model that provided more realistic short-term occupancy data. In their model, two sets of occupancy data: "aggregated presence probability and best-fitting threshold" were used to generate a Boolean occupancy profile (Mahdavi & Tahmasebi, 2015). Experts firmly believe that reaching to accurate occupancy density and pattern predictions is extremely difficult and even impossible (Tian et al., 2018). Therefore, the majority of energy modelling and simulation specialists rely on default occupancy schedules of energy simulation software for energy analysis.

In a comprehensive research study (Melfi, Rosenblum, Nordman, & Christensen, 2011) about building occupancy, its different extents is explained in a simple model (Figure 17). The model suggests that when studying occupancy in a building three sets of information that should be taken into account: space-based, time-based and presence-based. The space-based or "spatial resolution" is concerned with the space range and its boundaries, which is studied in different scales: building, floor, room, zone, etc. The time-based or "temporal resolution" is about different occupancy time span: monthly, weekly, daily, hourly, etc. The presence-based dimension of occupancy (occupancy resolution) investigates the following parameters:

1. Presence: Weather the occupant is present or not, true/false.
2. Count: the number of people in a particular space.

3. Location: Occupant's precise position and exact location in the space.
4. Distribution: Spatial distribution of occupants and visitors in each zone.
5. Track: Movement of occupants, linking occupants' locations with their near-future position in the space.
6. Identity: Who is in the room, space or zone?
7. Activity: Linking occupants' presences with their activities.

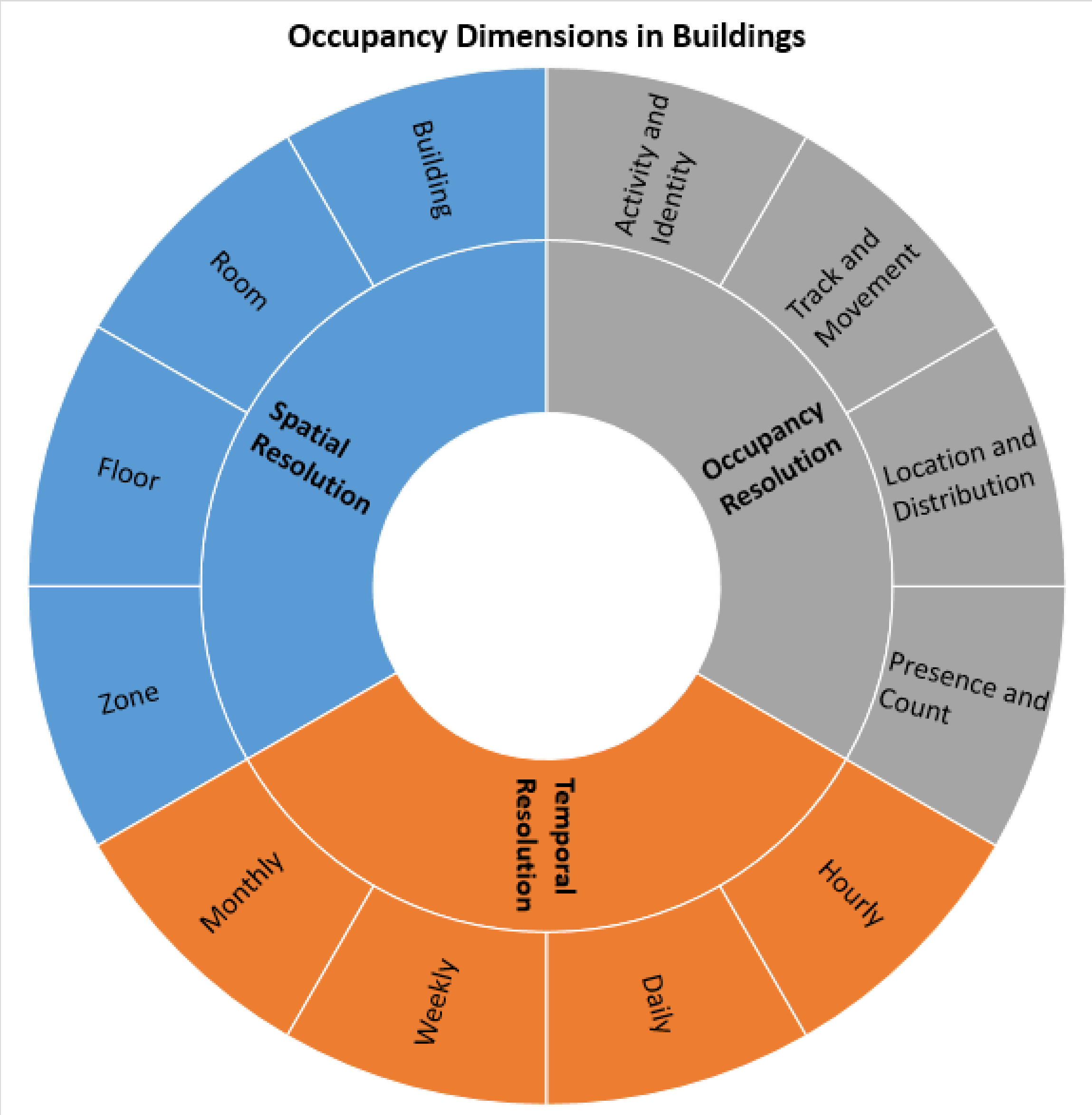


Figure 17:

Figure 17. Occupancy dimensions in buildings, adopted from (W. Wang et al., 2018)

Various methods have been used for indoor localisation of occupants. Similar techniques have been applied to predict occupancy density and pattern in buildings. Indoor localisation methods can be classified in three main groups: Information-based methods, sensor-based methods and connection networks (Figure 18). Information-based methods such as use of questionnaire, interviews and surveys, need collaboration of occupants, which has its own pros and cons. While, the two others are more involuntary. Connection networks including: WLAN, cellular networks, Bluetooth, GPS, etc. rely on the fast growing existence of mobile phones and tablets everywhere. (Shih et al., 2012) categorises Wireless Local Area Networks (WLANs) to model-based and fingerprint-based systems. Model-based systems are not accurate and reliable for indoor spaces due to their unpredictable natures, however fingerprint based systems have been used for indoor localization (Fet et al., 2013; Shih et al., 2012). (Fet et al., 2013) mentions use of dead-reckoning defined as the procedure of predicting occupant's location using its previous defined locations together with fingerprinting method to achieve more accurate outcomes. Also, (Azghandi et al., 2015; Shih et al., 2012) mentions that the accuracy of Indoor localization of occupants should be at least up to 1-2 meters, therefore, GPS-based methods are not useful due to insufficient coverage for indoor environments. Sensor-based methods are considered as the most nonintrusive tools for monitoring occupants' movements (Vlasenko, Nikolaidis, & Stroulia, 2015). In order to define a single occupant's pathway, Vlasenko et al. (2015) located wireless passive infrared (PIR) sensors in the ceiling downward to get the freest vision of the space. Using this system, the occupant does not have to carry specific tools or badges which is considered as an advantage. However, this method is not useful for tracking several occupants. Azghandi et al. (2015) applied a method using the combination of "anonymous (PIR) and identity (RFID) sensors" to track the location of multiple occupants.

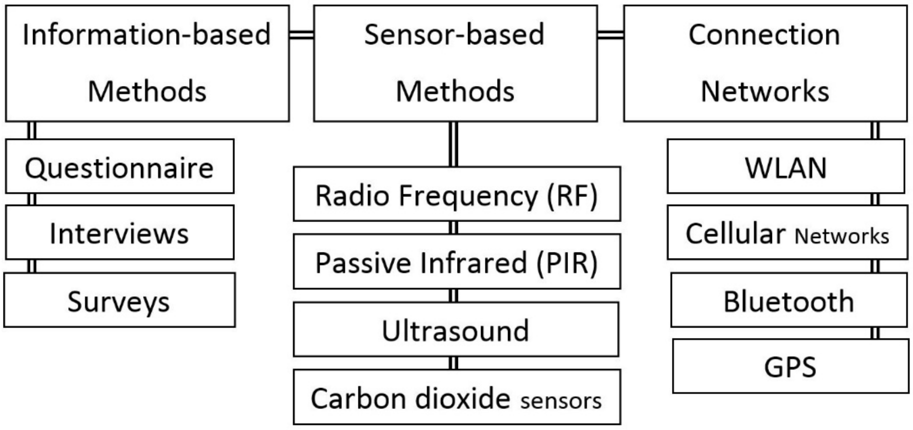


Figure 18. Methods of Indoor localisation

The efficiency and reliability of localisation techniques are related to various parameters such as the accuracy of the technology, process and algorithm being used, together with the placement of sensors and tools (Vlasenko et al., 2015). Vlasenko et al. (2015) suggests that improvement of the location of sensors will result more accurate localization outcome. For this, the architectural drawing of the space should be studied and mobility patterns should be extracted, to clarify the most optimized placement of the sensors. Azghandi et al. (2015) mentions the suitability of vision-based methods used by some scholars (Milan et al., 2013; C.-R. Yu et al., 2006) for indoor multiple occupant tracking. This study (Azghandi et al., 2015) also states the disadvantages of these methods including: privacy concerns, the possibility of blockage by other objects and the higher on-site computational needs. The tracking system should be chosen based on the type of space, the numbers of people and the predictability of possible routes. For example, a kind of badge can be given to all the visitors of a gallery is not feasible in a public square or metro station.

The predicted occupancy patterns of private building types seem to be more accurate in comparison to public buildings. For example, in residential buildings, there are low variations in the number of occupants. Martinaitis, Zavadskas, Motuziene, et al. (2015) confirmed the reliability of default occupancy for the energy efficiency assessment of households consisting of four occupants with high accuracy, concluding that there is a direct relationship between the importance of occupancy information in energy simulation and the “complexity” factor of the energy performance assessment. Office buildings are not private, but the number of occupants is predictable and occupants are not anonymous. However, in multi-functional spaces of public buildings such as: galleries, exhibitions, leisure centres and educational buildings, there are high variations in the number of occupants, therefore, density predictions are complicated. Statistical data regarding monthly visits of museums and galleries in the UK (Delaney, 2017), shows more than 30% difference in the number of visitors in the months of January and August in 2016. However, the current energy prediction tools do not fully incorporate the aforementioned monthly occupancy variations.

2.4.2. Active energy behaviours

Most of the existing building energy assessment tools have various inputs to incorporate occupants' active behaviours such as use of lighting, appliances and hot water into their calculations. These inputs are modifiable; however, most of the energy modellers rely on the default software values. They usually do not change most of the software presumptions, as they have no access to any more accurate data and in sometimes they are not aware of the gap that can be caused by over-simplification of occupants' behaviours in building energy assessment. In the following sections (See: 2.4.2.1 to 2.4.2.6) the integration of various occupants' active behaviours into building simulation tools is explained.

2.4.2.1. Use of appliances

The impacts of computers, equipment and appliances that consume energy and/ or produce internal heat are calculated in predictions of energy consumption in buildings. Although, not many energy simulation tools provide clear and detailed inputs for occupants' use of appliances, in DesignBuilder, by selecting the suitable type of building and space the energy modeller will enable software presumptions regarding use of appliances. In DesignBuilder, use of computer and various equipment can be modified by adjusting the maximum heat gain (W/m^2) which follows the zone's schedule and operation profile, meaning in peak hours the maximum heat gain is calculated, and in other times of the day less amount of heat gain is estimated (Figure 19).

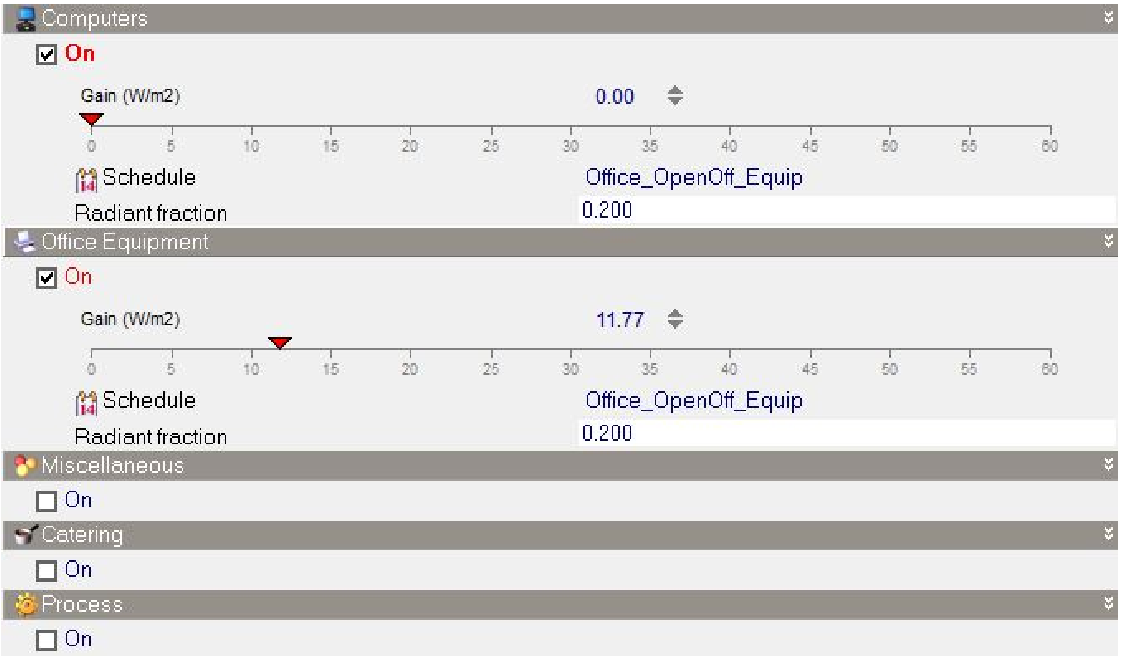


Figure 19. Equipment and appliances

2.4.2.2. Use of openings

In the most prominent building energy simulation tools, doors and windows are considered to be openable and their opening properties are adjustable and calculated based on the openable area, opening time duration and inside-outside air pressure difference. However, in less detailed building simulation tools, this feature of building openings is either completely neglected, or not adjustable.

In DesignBuilder, in order to include the effects of air exchange through open doors and windows, natural ventilation section should be turned on, otherwise, their effects will not appear in the calculations. The overall openable percentage of the glazing area of windows and the type and position of the opening can both be specified. In addition, door-opening inputs in DesignBuilder include the openable area of the door and the duration of door opening time in percentages (Figure 20).

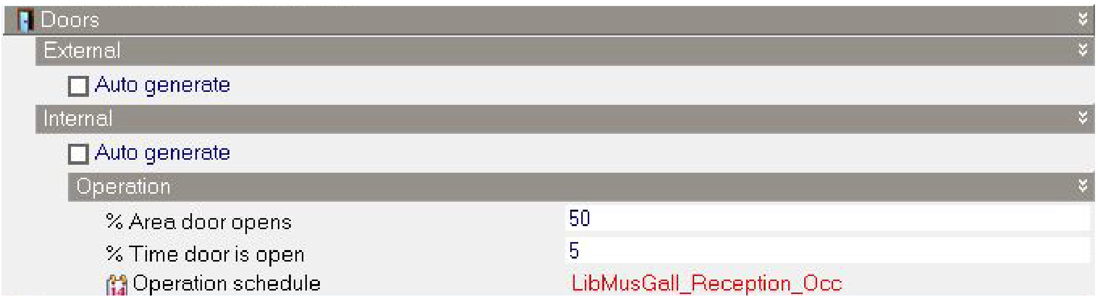


Figure 20. Door opening in DesignBuilder

Because of the complicated and vibrant nature of the inside/outside air pressure difference and opening time pattern, calculation of the effects of open doors and windows are a lot more complicated than other types on occupants' active energy consumption behaviours (such as use of appliances and lighting). Also, software default inputs regarding opening time need to be modified which is often overlooked. For instance, by changing the type of building from residential to supermarket, the default value remains the same causing inaccuracies in energy predictions.

2.4.2.3. Use of lighting

Lighting assumptions play an important role in the energy predictions of a building. Electricity consumption and internal heat gain by lighting system of each space are calculated in building energy assessment. Energy simulation software have default target illuminance and/or lighting density for each building zone based on the type of activity which is usually connected to operation profile of the space to consider the working hours. However, in public multi-functional spaces, the lighting requirements vary based on the type of activities, the physical layout and the space design. For example, in museums and galleries various lighting designs are used, ranging from full bright to partially bright in order to emphasize on one particular artefact.

In EcoDesigner, for each space, different choices of lighting can be made including incandescent, LED light, Fluorescent lighting tube, compact Florescent. For each type of lighting, there is a default power W/m^2 presumption (Figure 21).

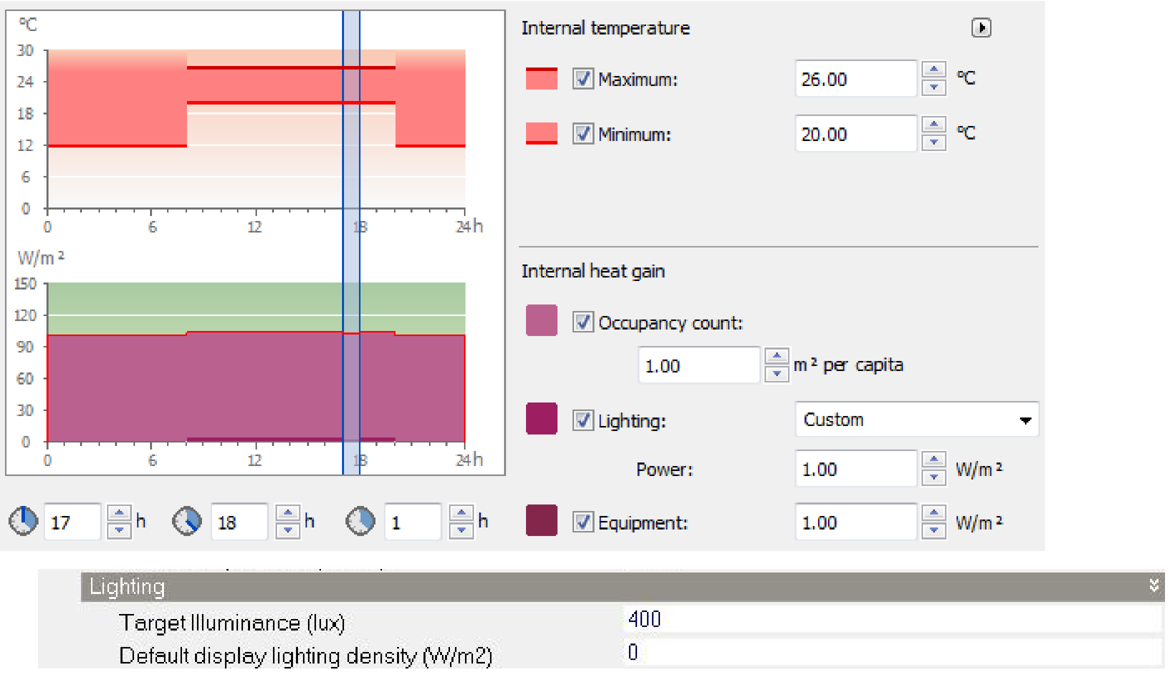


Figure 21. Lighting in EcoDesigner

2.4.2.4. Use of solar shadings and blinds

In building simulation tools, solar shading elements can be modelled like other building components. In addition, in some energy simulation tools such as DesignBuilder, solar shadings and blinds are considered as modifiable properties of windows and can be added without being modelled. DesignBuilder has one of the most advanced interfaces regarding solar shading and blinds in which the type of window shading and its position can be specified (Figure 22).

Figure 22. Windows, solar shading and blinds in DesignBuilder

2.4.2.5. Use of HVAC systems and set-points

The type of HVAC system and the internal minimum and maximum temperature set-points can be specified in the energy prediction tools. In EcoDesigner, for example, there is a full section called "building systems" where all heating, cooling and ventilation properties can be adjusted. In Autodesk Revit Architecture, the type of HVAC system can be selected from an available list, however, the detailed properties of each system are not accessible or modifiable.

2.4.2.6. Use of hot water

The incorporation of hot water consumption into building energy simulation tools greatly vary and it is often referred to as an overlooked area in building energy assessment (Harish & Kumar, 2016). In EcoDesigner, use of hot water is considered through "service hot water load (l/day per capita)" which has default values based on the space function. In DesignBuilder, too, each zone is associated with a default DWH (domestic hot water) consumption rate (l/m^2 per day) which is adjustable. OpenStudio software, has more advanced setting for use of hot water, where for each space water use connections, water use equipment and water heater set-point temperature can be specified (Figure 23).

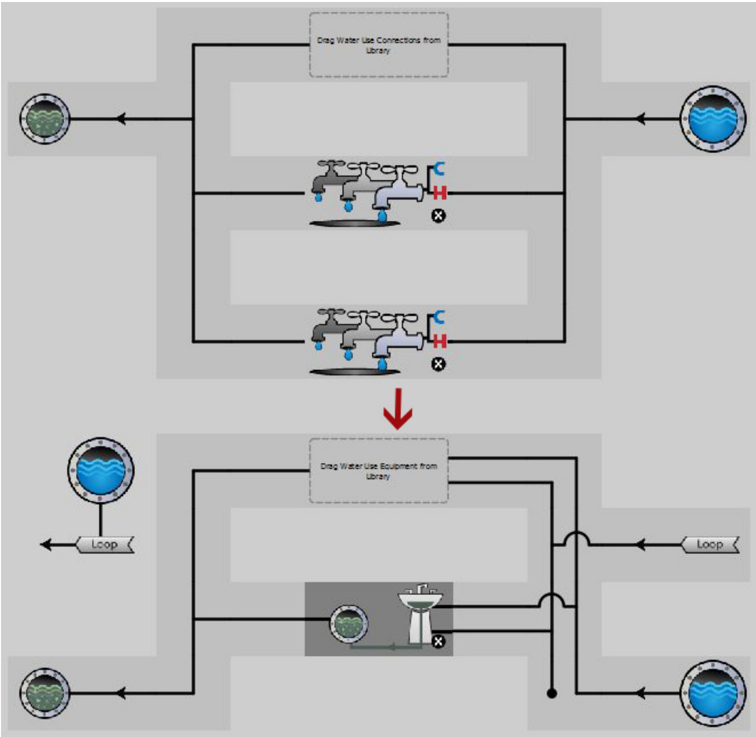


Figure 23. Use of hot water in OpenStudio

2.4.3. *Summary: incorporation of occupants' behaviours into energy prediction tools*

In general, each energy prediction tool provides an interface where the energy modeller can insert the relevant occupancy and human-behaviour-related inputs. The accuracy of the energy prediction is significantly related to the precision of the inputs in the first place. The investigation of the incorporation of occupants' behaviours in four different energy prediction tools (DesignBuilder, EcoDesigner, OpenStudio and Revit Architecture) suggests that most of the energy calculation tools provide the initial inputs regarding occupants' behaviours. However, the main issue is that the initial assumptions and the default values. Among all the aforementioned tools, DesignBuilder has the most detailed inputs regarding occupancy and occupants' behaviours. In addition, its user-friendly interface is an advantage for the energy modellers, not only to pay more attention to human-behaviour-related factors, but also, to have an idea about how their impacts are calculated.

2.4.4. Existing Gaps in the Literature

The impact of occupants' behaviour on buildings is a fast growing research topic. Numerous studies have investigated the impact of occupants on the energy consumption in buildings with the need to reduce the performance gap between the predicted and actual energy consumption of buildings. Occupants' active and passive energy behaviours (including: window opening, use of solar shading and blinds, adjusting HVAC set-points, use of hot water, etc.) are not fully considered in current energy analysis tools. Thus, there is an inherent demand for energy modellers, researchers and designers to improve the calculation of energy consumption of buildings by considering energy behaviour of occupants. The main challenge is the complexity and dynamic nature of occupant's energy behaviour, which are influenced by various internal and external, individual and contextual factors. Therefore, occupants' motivations and reasons, and the various factors influencing their decisions to interact with building systems together, with the impacts of their actions on the total energy consumption of buildings, have to be studied in a multi-disciplinary approach to incorporate the factors from a sociology, psychology, economics, engineering and design perspectives. A summary of the key findings of the literature review suggest following research gaps:

- Approximately 75% of the reviewed research, which directly studied the impact of occupant behaviour on building energy consumption, have focused on residential and offices buildings (44% and 31% respectively); fewer number of studies have analysed commercial and educational buildings, while, some building types such as exhibitions, recreational, institutional and healthcare facilities have been given sparse attention and require further analysis.
- The review of the literature also revealed that the majority of the research concentrates on single buildings, and urban scale impact has not been investigated adequately, forming a highly recommended area for future research. Likewise, at the micro level, the impact of interior design in terms of space layout, fixtures and fittings on occupants' action scenarios, thermal perceptions, and consequently on their

energy behaviour has been overlooked and requires further investigation. Particularly, there has been very limited studies on large multi-functional spaces where various functions are formed by space layout design and furniture.

- In terms of the parameters influencing occupants' energy behaviours, personal (physiological and psychological) parameters have been taken into account in many studies (approximately 30% of the reviewed papers). The most recent behavioural methodologies suggest the consideration of not only the individual and personal characteristics of occupants, but also the particular features of their social context. However, only 10% of the reviewed papers have focused on both social and personal (socio-personal) factors. Therefore, the authors believe multi-disciplinary approaches are needed to combine socio-personal parameters through psychological cognitive behavioural methods (e.g. theory of planned behaviour (Ajzen, 1991), cognitive complex theory (Kieras & Meyer, 1997) and cognition as a network of task (Freed, 1998), which could provide new insights to the domain.
- According to the reviewed publications, the different types of occupants' interactions with building systems, such as use of electricity, use of fans (or air conditioning) and use of building openings (windows and doors), have been investigated. However, some areas, such as the use of hot water has a significant impact on energy consumption in some building types (e.g. residential), have received scant attention in comparison but are considered to have a likely impact on energy use. Furthermore, future investigations about the inter-relationship between different energy behaviours of occupants are needed, which will generate more realistic assumptions in building energy predictions.
- A considerable number of studies contain detailed methodologies including case studies and experiments, using different types of qualitative and quantitative data gathered by pre and post-occupancy surveys, occupant monitoring (using sensors or observation), field measurements and questionnaires, followed by data analysis (Markov Chain, Monte Carlo and logistic regression) and simulations. The findings of these studies have provided a clearer insight towards understanding the impacts of occupants' behaviours on the energy consumption in buildings. However, the findings, at present, have yet to offer significant improvements in predicting occupants' energy

behaviour in buildings. Particularly, the translation and integration of the findings of these studies into building energy simulation tools to reduce the gap between predicted and actual energy consumption in buildings remain a significant research challenge in this area.

2.5. Research Focus

Research gaps have been pointed out through a comprehensive literature review and the research scope has been specified to address some of the existing gaps in the research area. Therefore, this research is shaped to contribute in three main existing gaps: studying multi-functional spaces in buildings such as galleries and institutional buildings, incorporation of space design in building energy assessment as an influential parameter to specify space function and integration of the research findings with energy simulation tools (practical contribution) (Figure 24). In the following sections, the research focus will be discussed in details.

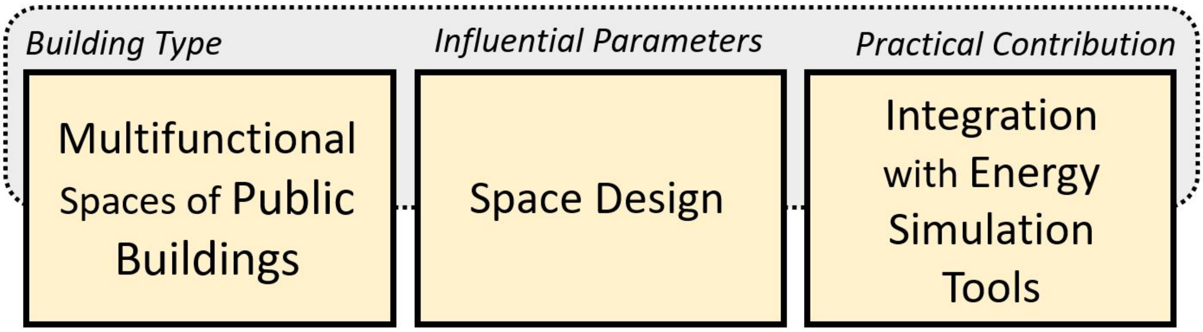


Figure 24. Existing gaps studied in this research and research focus

2.5.1. Energy prediction in multi-functional spaces of public buildings

According to the quantitative analysis of the current literature, three out of every four studies in this research area have focused on residential buildings or offices and there is a gap in the knowledge regarding other building types such as galleries, exhibitions and educational buildings. There are fundamental differences between the impacts of occupants' behaviours on energy consumption in residential and office buildings and more public buildings. Residential buildings are private and there are low variations in the number of occupants. Office buildings are not private, but the number of occupants is predictable and their identity is recognisable. In this research public buildings with high variations in density are studied which is a gap in the literature. Table 5 shows the main differences between the characteristics of the mentioned public buildings and residential buildings or offices.

High density public building	Residential and office buildings
Wide variations in the number of occupants	Low variations in the number of occupants
Occupants have no responsibility towards energy bills	Occupants are directly or indirectly responsible for energy bills
Autonomous occupants	Non-autonomous occupants
Limited access to building systems	Wide variations in occupants' access to building systems
Number of visitors are more than permanent occupants	Number of permanent occupants are more than visitors

Table 5. Public building characteristics

To predict the energy consumption of a building, depending on the inputs provided by the energy simulation tool, the energy modellers add all the available building data and modify the presumption of the software. In case of unavailability of some data, the energy modeller relies on software default data, which highlights the essential role of software default assumptions. Function of each space is one of the primary inputs of energy assessment tools, however, the selection of space function can be sometimes challenging. The word "function" has various meanings in different subjects. In design and architecture, it refers to the practical use or purpose (OxfordDictionaries, 2018). Similarly, the well-known architect, Louis Sullivan, defined the function of a building as its purpose and reason (Sullivan, 1947). Function and purpose of the building has been the subject of various architecture theories such as the famous theory of Vitruvian, the Roman architect. In his theory, he mentioned utility, firmness and beauty (utilitas, firmitas and venustas) as the three key values every architecture should encompass. There is not a common agreement on the exact implication of "utilitas", but it is usually interpreted as purpose, commodity and convenience.

With regard to the energy consumption, not only the function of the building, but also, various disciplines and activities that take place in different spaces and zones of the building influence the building energy consumption (Khoshbakht, Gou, & Dupre, 2018). In energy assessment tools, building type and space function are the basis for estimation of the working hours, comfort temperature, HVAC set points, occupancy density and schedule and hot water and electricity consumption (Figure 25).

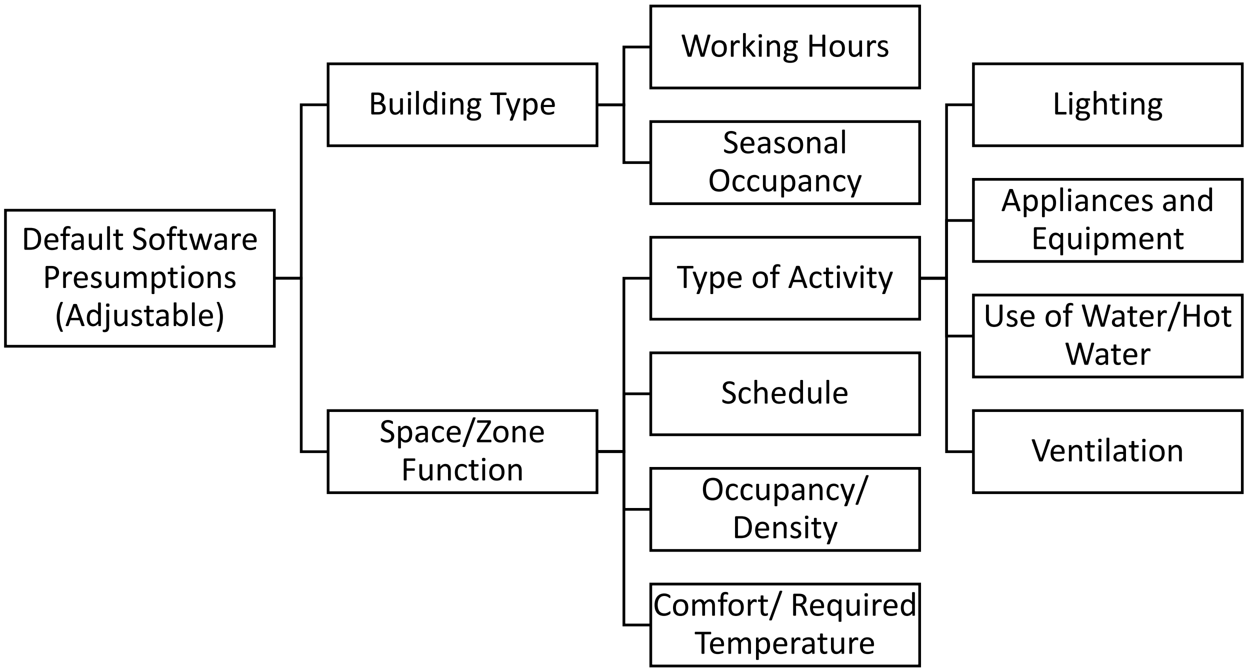


Figure 25. Parameters related to building type and space function in building energy prediction process

Energy modellers usually use the labels on architectural/construction plans to specify the function of each building zone. However, it is complicated to determine the space function for large multi-functional spaces. In Oxford and Cambridge dictionaries, the word multi-functional is defined as having or fulfilling several functions and uses (CambridgeDictionary, 2018; OxfordDictionaries, 2018). With regard to space design, the term multi-functional can be described as the incorporation of different functions in time and space (CRCResearch, 2018). However, some scholars challenged the existing definitions and stated that multi-functionality is an obscure term and challenging to implement into design and planning (Hansen, Olafsson, van der Jagt, Rall, & Pauleit, 2017). Large multi-functional spaces provide or have the capacity to offer multiple functions and services (Hansen et al., 2017), therefore, energy consumption prediction of such spaces is very complicated.

In energy prediction of new multi-functional public buildings, the occupancy data is usually not available and in energy predictions of existing buildings, the incorporation of the actual occupancy data of the spaces into the simulation tool is often overlooked. In some probabilistic occupancy prediction models of office buildings, inputs such as: first arrival, last departure, intermediate departure and duration of in-between absence (e.g. lunch breaks) are used (Mahdavi & Tahmasebi, 2015) which are not particularly useful in public buildings with non-regular occupants. As mentioned above, building energy simulation tools have presumptions regarding the occupancy and density (number of people per square meter) of each space based on its main function. Most of the leading energy simulation tools use ASHRAE 90.1 User's Manual standard (ASHRAE, 2016), COMNET appendix B (COMNET, 2016a), and COMNET appendix C (COMNET, 2016b) as their main sources of occupancy density and schedule presumptions in energy modelling. However, when it comes to multi-functional spaces, there isn't a specific main function or purpose, instead, a number of activities take place: sitting, standing, walking, etc. Therefore, to assign more accurate occupancy rate to multi-functional spaces, the space should be divided to different zones based on similar activities. Space furniture is a key element to take into consideration while defining the type of activity in multi-functional spaces. Thus, there is a need to provide data and specifications on the actual space furniture and interior elements, as this interior setup and layout in a multi-functional space contributes in defining function, purpose and activity zones, consequently, leading to more accurate occupancy rate for these zones. The role of space design is further explained in the next section (See: 2.5.2. Space Design and Energy Consumption).

In public buildings such as galleries, exhibitions and institutional buildings, most of the occupants are autonomous with various semi-regular and non-regular visits to the building. Therefore, occupants of such buildings are also referred to as "visitors". One of the limitations in predicting occupancy schedules in multi-functional spaces of public buildings is the various types of activities that take place within the space which consequently attract different number of visitors at different times. Several factors affect the number of visitors, which makes it difficult to have an accurate occupancy density assumption. In such buildings, occupants have limited access to building systems such as: HVAC set-points, windows, shading devices, etc. Therefore, their impacts on the energy consumption of the buildings are limited to few interactions with building elements (e.g. opening the entrance door) and passive energy consumption behaviours (e.g. presence and occupancy sensitive lighting). It can therefore be hypothesized that in public buildings with high number of visitors, passive energy consumption has noticeable impacts on the energy consumption of the buildings, however, there is a need for more quantitative analysis in this regard.

2.5.2. Space Design and Energy Consumption

The impacts of design features of the space on occupant's behaviour have been studied broadly (Augustin, 2009; Caan, 2011). There is a famous quote by Winston Churchill, which says: "We shape our buildings; thereafter they shape us." Space design is defined as decision upon the space appearance, arrangement and functioning. Space design has various impacts on behaviours of occupants and their interactions with building systems; therefore, it affects the energy consumption of buildings. With regard to energy consumption issue, the term "sustainable interior design" refers to being committed to sustainability principles in interior design of the space as part of building construction (Moxon, 2012). It mainly focuses on use of green material and energy efficient systems for interior design of the spaces (E. Lee et al., 2013); however, occupant's actual energy behaviour is still an existing gap in the subject. The term "design for sustainable behaviour" which is mainly used in product design, refers to the role of designer in directing behaviour of users to more sustainable performs (Lilley, 2009; Wilson et al., 2013). It is believed that if proper strategies are implied to a design product before it is used, designer can influence sustainable use of the product positively (Lilley, 2009). Space design impact occupant's energy behaviours through its psychological and physical aspects (Figure 26).

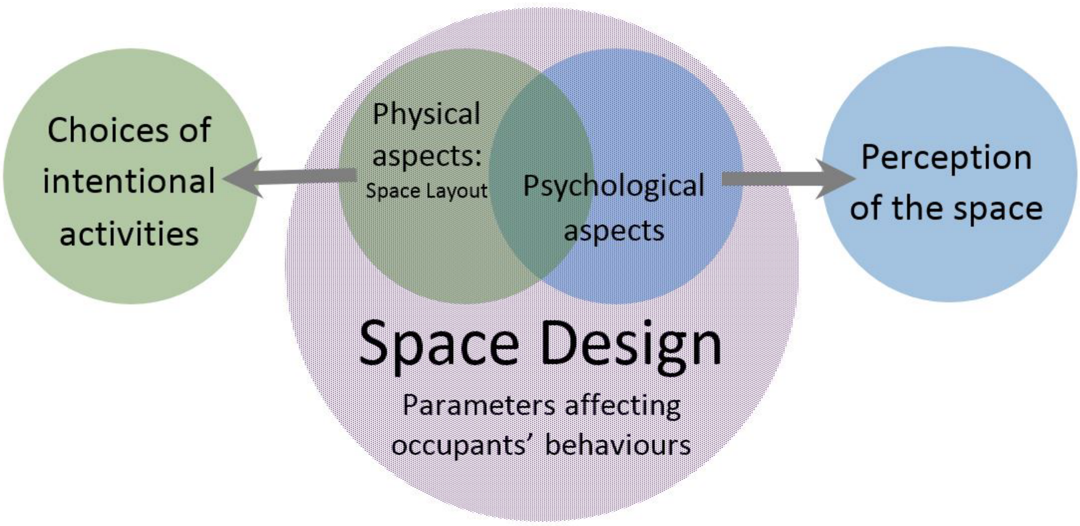


Figure 26. Space design aspects affecting occupants' energy behaviours

The occupant's perception of the space is influenced by its design characteristics such as: colours, materials, light, form and shape (Arnheim, 2004) which are considered as the psychological features. Augustin (2009) states that the design of a space impacts the mental and psychological state of occupants and shapes their attitudes. Some studies have demonstrated the impacts of colours, textures and material sensation on occupants' perception of the indoor temperature and thermal comfort (Ulusoy & Nilgün, 2017; Ulusoy & Olguntürk, 2016). Conventional psychology declared that any behaviour has two involved phenomena: the person and the environment, as behaviour is believed to be a response to the "physical word" (Oseland, 2009). Also, some scholars mentioned the role of "cultural meanings" attached to plan design (Nasar, Stamps, & Hanyu, 2005). Besides, it has been widely confirmed that there is a strong link between space design features and occupant's satisfaction and efficiency (S. Lee, Alzoubi, & Kim, 2017). People try to elude unpleasant conditions and search for pleasant ones (Cabanac, 1971), as well as, looking for comfort. The pleasure and comfort within living environments are deeply related to people's perceptions of the space, which affect their behaviours.

Also, the physical aspects of the space such as: space layout, have impacts on the occupant's energy behaviour by moderating and manipulating their actions and affecting their choices of intentional activities (Figure 27). Space layout (or physical arrangement) is the special order and embellishment of objects and furniture within the space. However, the current models of occupant behaviour lack considerations regarding the impacts of building design features and interior layout on occupants' behaviours (Gilani, O'Brien, Gunay, & Carrizo, 2016). This highlights the need to develop models to predict occupancy for non-residential and office buildings by incorporating space design features.

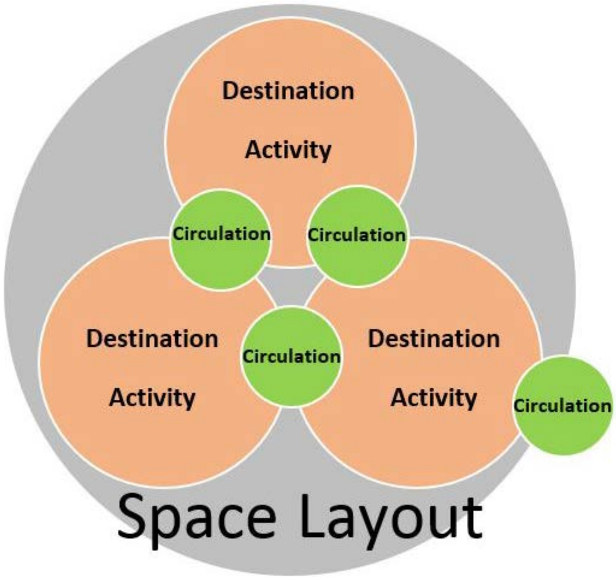


Figure 27. Space layout and occupant's behaviour

Among parameters influencing occupants' behaviours, the impacts of space design, layout, fixtures and fittings on occupants' choices of activities, thermal perceptions, and consequently on their energy behaviour has been overlooked (Figure 28). Also, the existing studies in this domain have targeted single or multiple buildings, while, this research gives attention to multifunctional spaces at the micro level.

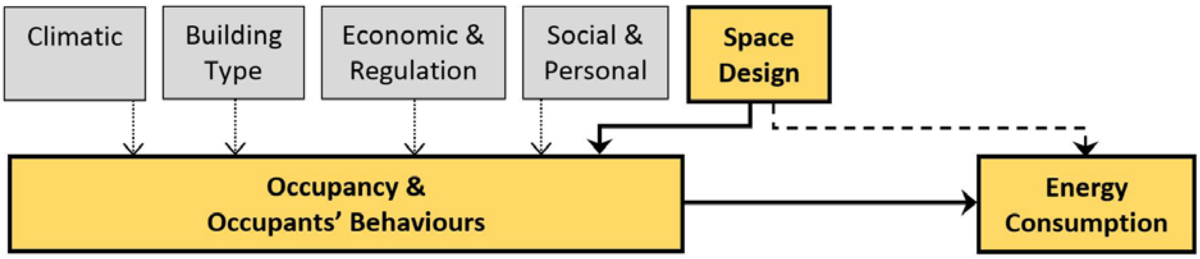


Figure 28. Parameters influencing occupants' energy behaviours and the research focus

The link between space layout design and occupants' presences and their distributions in different spaces was pointed out by Goldstein et al. (2011). Space design specifies what type of activity takes place in the space and provides site-specific occupancy information (Goldstein et al., 2011). Studies confirm that not only building interior design, but also, its external design affects the building occupancy. In public buildings, the building form, external appearance and its connotative meanings influence people's decision whether they want to visit and spend time in the building or not (Nasar et al., 2005). Specific design features of a space convey messages to occupants and influence their decisions, for example the characteristics of windows (such as: size, transparency, presence of grills, etc.) encourage the non-visual or visual properties of the space and moderate the relation of building's inside and outside (Nasar et al., 2005).If the exterior of building fails to communicate its purpose, the percentage of visits over intended users will drop (Nasar et al., 2005). If the outside of the building is untidy, uninviting or uninspiring, it will give the impression to potential visitors that the spaces inside do not have the proper quality and the service is poor. Confirming the direct link between different aspects of space design with building energy efficiency, some scholars (Shi et al., 2016) have studied design energy optimization from architect's viewpoint to link building energy efficiency with design process. Gilani et al. (2016), too, studied the impacts of presumptions related to occupants' behaviours in building energy prediction tools with the aim to promote better design solutions. They stated that the existing experimental occupant behaviour models have not been able to improve energy codes to be used in design stages (Gilani et al., 2016) which yet needs to be studied and highlighted.

Occupants' behaviours and the occupancy patterns in a building are crucial inputs for building energy consumption assessment, which are predicted based on the building/ space function. Several studies highlighted the impacts of building design features, architecture, interior design and space layout on occupancy and occupants' energy consumption behaviours. In addition to occupancy density, other design related parameters such as lighting and appliances are incorporated into energy simulation tools as space function-related inputs (Figure 29).

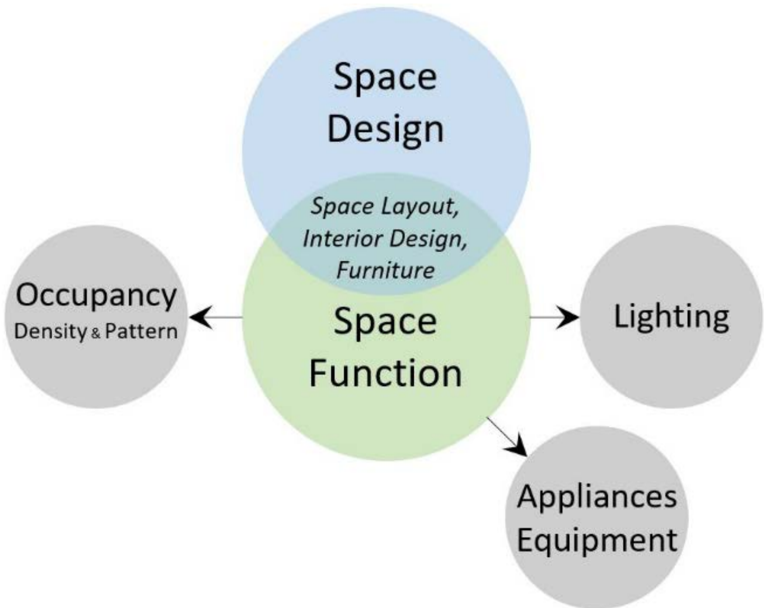


Figure 29. Space design inputs in energy simulation

In general, space design contains all decision upon the space appearance, arrangement and functioning. The interior arrangement of the space specifies circulations and types of activities and has various impacts on occupants' energy behaviours. Besides, there is a discrepancy between the actual and predicted space function, which creates inaccuracies in energy predictions of buildings. Therefore, this research aims to study the gap between predicted and actual energy consumption in multi-functional spaces of public building buildings by incorporating the impacts of space design on occupancy, occupants' behaviours and energy consumption (Figure 30).

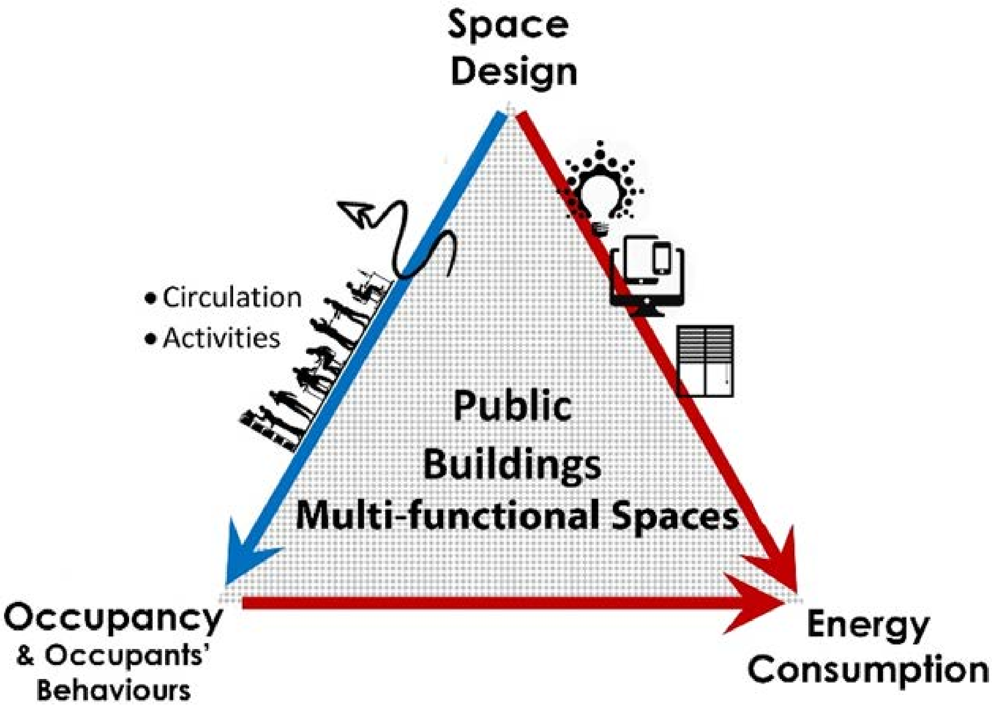


Figure 30. Incorporation of the impacts of space design on occupancy, occupants' behaviours and energy consumption in multi-functional spaces

2.5.3. Integration with energy simulation tools

In order to understand the impact of different influential parameters on occupants' energy consumption behaviours, a great number of studies in this research domain have focused on one single behaviour of occupants such as window opening or electricity consumption. In these studies, the researchers investigate occupants' intentions and their drivers towards one specific energy consumption behaviour. However, other studies have shown inconsistencies

between the findings of single-behaviour studies and the actual overall energy consumption which includes all occupants' behaviours and their interactions with the building systems.
Which means, the findings of studies on occupants' electricity consumption behaviour, for instance, do not replicate the impacts of occupants on total energy consumption in the building. For this, in this research, the overall and combination of all occupants' behaviours has been studied. In addition, targeting single zones of multi-functional spaces in public buildings as cases, where occupants' types of interactions with building systems are limited, has made it possible to study occupants' overall behaviours in this research.
Also, most of the existing studies on this subject area have applied qualitative methods, consequently, the findings of these studies could not be incorporated into building energy simulation tools. Therefore, another significance which shaped the research design and method of this study was the challenge to integrate the findings into energy prediction tools. There is no doubt that by integrating realistic measured data into building energy simulation tools more accurate outputs can be achieved (Coakley, Raftery, & Keane, 2014).

2.6. Chapter Conclusion

This chapter reviews the existing studies on the influence of occupants' behaviours on energy consumption in buildings. It provides a comprehensive quantitative and qualitative study on occupants' active and passive energy consumption behaviours and parameters influencing occupants' energy behaviours. Then, it discusses the existing methods and tools for building energy prediction and the incorporation of occupants' behaviours into current energy assessment tools. After addressing the existing gaps through a broad review of the existing studies in the research domain, the research focus to address three existing gaps in the literature are explained: the impacts of occupants' behaviours on building energy consumption in multi-functional spaces with focus on galleries, exhibitions and institutional buildings, the role of space design on occupants' behaviour and energy consumption and the integration of the findings into a building energy simulation tool with the aim to point out the causes of uncertainty and measure them. In the next chapter, the research methodology of this study is explained.

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Research Method Chapter

Chapter 3: Research Method

In this chapter a qualitative and quantitative review of the methods and techniques used in current studies on "occupants' behaviours and energy consumption" is presented. Following the analysis of research methods in existing studies, different layers of the research methodology of this study are discussed. For this, "research onion" model by Saunders and Lewis (2012) is used which includes: research philosophy, research approach, methodological choice, research strategy and case study design, time horizon and data collection. At the end of this chapter, the research design of this study is explained and illustrated. The research design includes 4 main stages: formation of research problem, establishment of research method (including case study design and data collection), data analysis and formation of initial findings and development of the conceptual framework (including initial framework, validation and refinement).

3.1. Research Method in Existing Studies

The existing studies on the impacts of occupants on energy consumption in buildings research domain, have adopted agent based or/and stochastic approaches to improve the deterministic energy models used in the existing energy simulation tools (K.-U. Ahn & C. S. Park, 2016). Stochastic methods consider parameters and probabilities derived from the collected data of a certain case and have been implemented by various scholars (Jang & Kang, 2016a; Jessen Page et al., 2007). Agent based approaches focus on occupants' intentions and perceptions (K.-U. Ahn & C. S. Park, 2016). There has been also a third approach using a combination of both agent based and stochastic methods, such as: Multiple Modules (MuMo) model proposed by Liao and Barooah (2010) to simulate multiple occupants' movements between multiple zones. In another classification, Jing Zhao, Xin, and Tong (2012) mentioned model simulation methods and statistical analysis as the two prominent methods used to determine the energy performance in buildings. Statistical methods are used to analyse big data and generate general information regarding energy consumption. The reliability of such studies directly depends on how big the data is. Recently, machine learning techniques are becoming more and more prominent to integrate the results of previous studies using statistical analysis (Alaaeddine & Wu, 2017). Model simulation methods are usually applied to incorporate realistic collected data into mathematical calculation of building energy consumption to quantify the impacts.

The existing studies on this research area have applied various research methodological choices including: quantitative, qualitative and both. A review study (Zou, Xu, Sanjayan, & Wang, 2018a) on research methods used in the past decade showed that more than 80% of the current studies on occupants' energy consumption behaviours are quantitative, and scholars tend to take positivist philosophical position. some scholars in the research domain believe that due to the complex nature of occupants' energy consumption behaviours, mixed methods which combine different aspects of human behaviour including social and natural sciences lead to more reliable results (Zou et al., 2018a). However, as energy simulation is a purely numerical process, applying quantitative methodological choice seems to be a logical decision especially if the research aim to improve the accuracy of building energy prediction tools. To quantify the performance gap in building energy analysis, two general approaches are applied on mathematical models which are classified as forward and inverse uncertainty analysis (Tian et al., 2018). Forward uncertainty investigates the gap in the final outcome of the system caused by unreliable inputs, while, inverse uncertainty deals with unidentified input discrepancies once the actual building energy consumption data is collected (Tian et al., 2018).

According to the comprehensive literature review of more than 120 studies in this research area which was performed to design this research, 71% of the reviewed studies, used case study as their research strategy with different data collection techniques: survey, monitoring and observation, field measurements, interviews and questionnaire. In addition to case studies, experiments, reviews, various models and simulations were used in 13%, 10% and 6% of other relevant reviewed studies, respectively (Figure 31). According to the reviewed publications, the most common research strategies and data collection techniques used in studies on the impact of occupants' behaviours on energy consumption in buildings are case studies with surveys and/or monitoring.

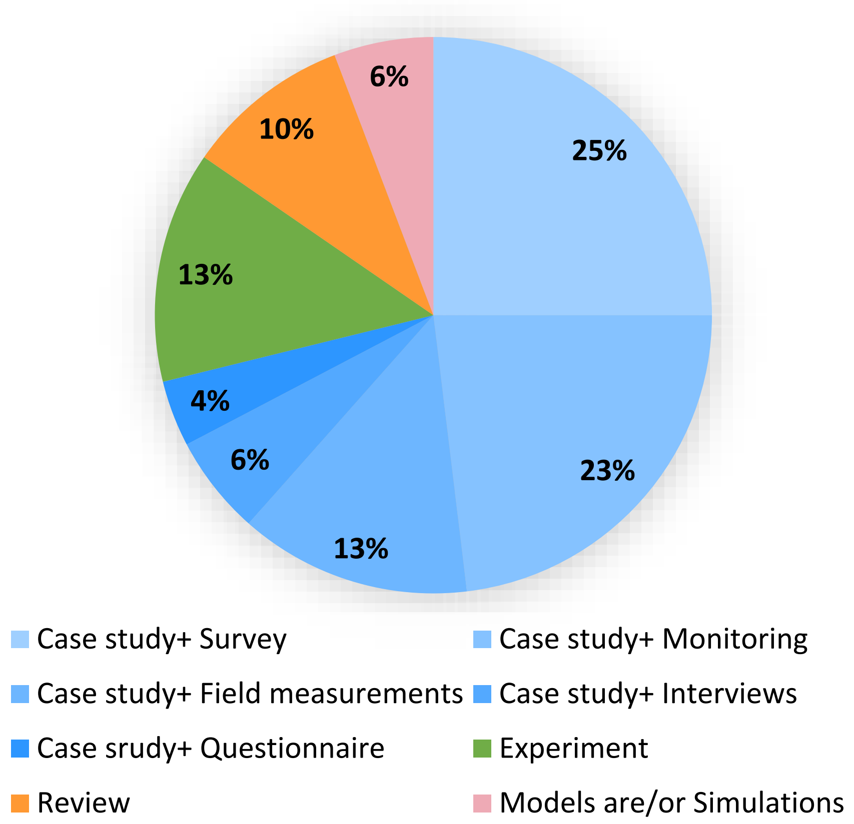


Figure 31. Research strategies used among 120 reviewed papers in "occupant behaviour and energy consumption" research domain

Investigating the existing research approaches used in this research domain and considerations regarding the specific research design of this study have shaped its research method. Therefore, in order to achieve the aim of the study which is the integration of the findings with building energy simulation tools, model simulation method using case studies and monitoring are adopted which is explained further in research method section.

3.2. Layers of Research Methodology

Research is a series of strategic and planned investigations with the aim to expand the existing knowledge and to establish new facts (Ahmed, Opoku, & Aziz, 2016). Research methodology is guideline of the research, which presents the rational process and procedure to reach the research aim and objectives. Therefore, it contains several layers which should be considered one after another. Saunders and Lewis (2012) used an illustrated model called "the research onion" to present several layers of the research methodology including: research philosophy, approach, methodological choice, strategy, time horizon and techniques and procedures. The research onion model keeps evolving to incorporate new methods. Not all its classifications are accepted by all scholars, however, its sequence and structure is believed to provide a comprehensive way of explaining a research method. Therefore, research onion model is used to explain methodological layers of this research which are discussed in this chapter (Figure 32).

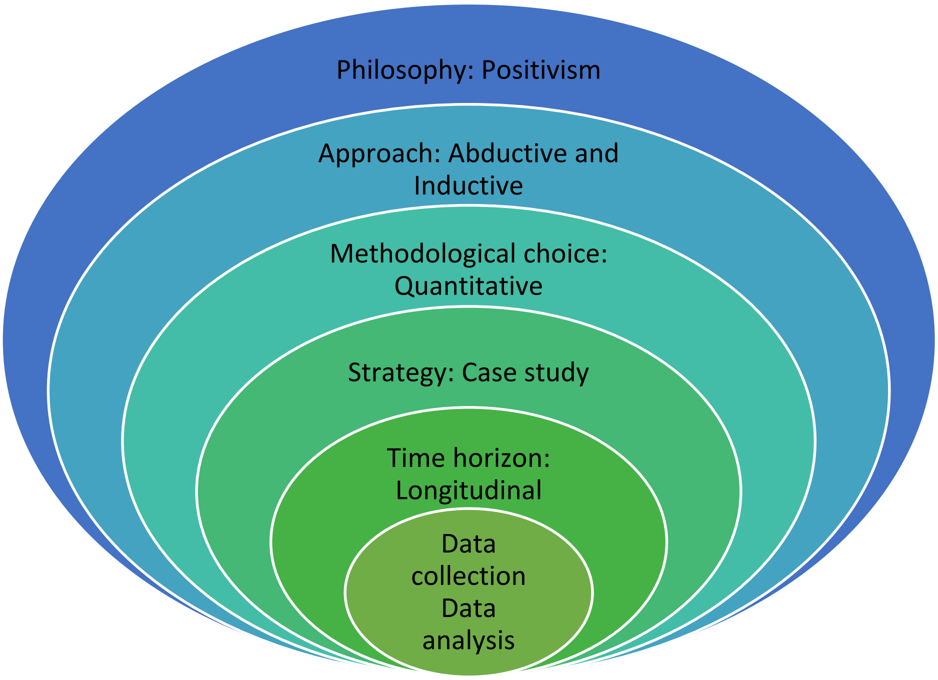


Figure 32. The research onion adopted from (Saunders & Lewis, 2012; Saunders, Lewis, & Thornhill, 2012)

Following the aim and objectives of this study, the methodology of this research includes reviewing the existing literature, defining the gap in the subject area, formulating research design, case study design, data collection, data analysis, final findings and development, validation and refinement of the framework.

3.2.1. Research Philosophy

Research philosophy is the conceptual foundation of the researcher's viewpoint about the nature of the knowledge and its relation to the outside world (Duignan, 2016). Research philosophy is a general term linked with the creation and expansion of knowledge and defines the nature of acceptable knowledge in the research (Saunders et al., 2012). Burrel and Morgan (1979) pointed out that different types of assumptions such as: epistemological assumptions (related to human knowledge), ontological assumptions (related to realities) and axiological assumptions (related to values), appear in every research which influence how the research problem in understood by the researcher (Saunders, Lewis, & Thornhill, 2016a). Ontology explains the nature of reality, answering to the question about "what exists", epistemology refers to assumptions about knowledge and the acceptable sources of knowledge and axiology is related to values and morals considered in the research (Saunders et al., 2016a). The ontology, epistemology and axiology of this research are realism, positivism and value-free (Table 6).

Objectivism	Assumption type	Subjectivism
	🡐 **Ontology** 🡒	
Real **External**	What is the nature of reality? What is the world like?	Nominal Socially constructed
	🡐 **Epistemology** 🡒	
Natural sciences **Facts** **Numbers**	Source of knowledge? Acceptable knowledge? Good-quality data?	Arts and humanities Opinions Narratives
	🡐 **Axiology** 🡒	
Value-free **Detachment**	Reflection of personal values when doing research? The values of research participants?	Value-bound Integral and reflective

Table 6. Ontology, epistemology and axiology, adopted from (Saunders et al., 2016a)

Saunders et al. (2016a) mentioned 5 main types of research philosophies: positivism, realism, interpretivism, postmodernism and pragmatism. Positivism philosophy is when the researcher conducts observable data to develop a law-like general statement. In positivism philosophy, the accuracy and reliability of the knowledge is guaranteed through use of unbiased facts and existing theories (Saunders et al., 2016a). Besides, the position of the researcher is external and outside the collected data.

Therefore, this research has positivism philosophy because of its dependence on general laws, observable and measurable reality of the research problem, its value-free nature and the objective position of the researcher (Table 7).

Positivism			
Ontology	Epistemology	Axiology	Typical methods
One true reality	Observable and measurable facts	Value-free research Objective position	Usually deductive, planned, quantitative

Table 7. Adopted from (Saunders et al., 2016a)

3.2.2. Research Approach

Research approach represents reasoning and logical process of the research. The two widely recognised forms of research approaches are deductive and inductive. There is, however, a third research approach remarked by some scholars, which is usually referred to as abductive or probabilistic (Ormerod, 2010). Depending on the nature of a study, it may have one single research approach or a combination of multiple approaches at different stages.

Dudovskiy (2018) explained the three mentioned research approaches with a simple graph (Figure 33). Deductive reasoning which is mostly used in quantitative studies is the use of a general rule or theory to reach to a specific conclusion (Kovács & Spens, 2005) and is considered as a strong and reliable research reasoning. Inductive and deductive reasoning, on the other hand, drive logical conclusions and theories from observation.

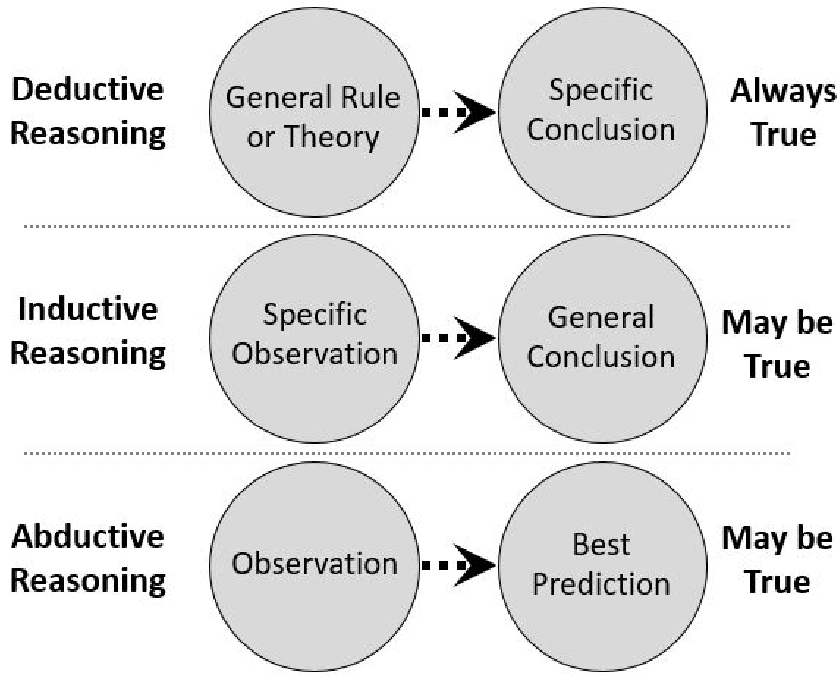


Figure 33. Deductive, inductive and Abductive research approaches adopted from Dudovskiy (2018)

Human behaviour is a complex phenomenon and the more reliable studies in this topic, use probabilistic data. Fabi et al. (2013) underline that the gap between simulated and actual energy consumption of buildings is the result of deterministic methods. Most of the existing studies in this research use inductive and abductive reasoning to reach general findings, despite their quantitative nature. That is because, the data collection usually shows unpredicted patterns which are the main findings of the studies. The core of this study, however, is using observation of cases and other available sources of real-time and governmental data to find out the existing gaps and missing information in a stablished procedure (building energy simulation). In this research, not all findings are not meant to be generalised, however, both prediction and general conclusion are among its various outcomes, which are known as abductive and inductive reasoning, respectively.

3.2.3. Methodological Choice

Methodological choice is another layer of Saunders et al. (2012)'s research onion model that shows the selection between qualitative, quantitative and mono, mixed and multi methods. The methodological choice depends on the nature of research question, range of control over the phenomena, and its relevance to current happenings (Yin, 2014). It also reveals the data collection methods of the research. However, the most significant difference between quantitative and qualitative methodological choices is the analysis of the data (Gelo, Braakmann, & Benetka, 2008). In general, quantitative methods deal with measurements, numbers and statistical analysis, while, qualitative methods study thoughts, opinions and meanings.

This research applies quantitative method in which the collected quantitative data will create parameters that will later be interpreted into energy simulation tool with the aim to improve the accuracy of energy predictions in multi-functional spaces (Figure 34). While this study incorporates occupants' behaviours into building energy simulation process, it focuses on frequency and duration of behaviours and their numerical impacts on the total energy consumption of the building, not the thoughts and opinions. The energy simulation tool, too, follows a quantitative and mathematical process.

Figure 34. Research methodological choice

In this research, the actual human-behaviour-related factors are compared with the default software inputs which are often referred to as the predicted data. The studied parameters include: building and zones working hours, HVAC set-points, space function, occupancy density and patterns and occupants' energy consumption behaviours and the impacts on the energy consumption on the cases (Table 8). Working hours are essential inputs for prediction of energy consumption in buildings. The longer the duration is, the more the energy consumption is expected to be. Occupancy schedule shows the number of people occupying each zone in the multi-functional spaces which is a necessary data in building energy assessment. All the mentioned parameters are quantitative and numerical.

No.	Predicted information: **Simulation**	Realistic information: **Observation**
1	Working hours	Working hours of the building and various zones within the multi-functional space.
2	HVAC set-points	Who sets the HVAC set-points? What are the temperature set-points for each zone?
4	Space function	Detailed zoning of all spaces using space layout design and furniture.
5	Density, schedule (default)	Number of people in each zone and schedule patterns: daily and hourly occupancy density and pattern.
6	Occupant behaviours	What are occupant energy consumption behaviours? What are the impacts on building energy consumption?

Table 8. Observed parameters

3.2.4 Research Strategy

Research strategies are the recognised and clear procedures of action to achieve the aim and objectives (Yin, 2014). Saunders et al. (2012) introduced eight common research strategies: experiment, survey, archival research (history), case study, ethnography, action research, grounded theory, and narrative inquiry. One of the most important steps before choosing the research strategy is to carefully define the research questions (Yin, 2014).

This research aims to answer the following main questions:

1- What and how much are the impacts of human-behaviour-related factors on energy consumption in multi-functional spaces?

2- How can occupants' energy behaviours be integrated into energy simulation tools to reduce the gap between predicted and actual energy consumption in multi-functional spaces?

Among all the aforementioned research strategies, three of them answer “how” questions: history, experiment and case study (Yin, 2014). “What” questions are considered as “how” questions when they are defined as “how much”. To differentiate between these methods, two questions are asked which then suggest us what the most common research strategy is (Table 9). The two question are: does the study deal with contemporary events? If no, it is a history or archival research, if yes, does it require control over existing parameters and conditions? If yes, it is an experiment, otherwise, case study can be the research strategy.

Research question: how? , why?		
Method	Requires control	Contemporary events?
History	No	No
Experiment	Yes	Yes
Case Study	**No**	**Yes**

Table 9. Different methods for how and why questions, adopted from (Yin, 2014)

Current events are the target of case studies when there is no control on the behaviours (Yin, 2014). In experiments, the researcher manipulates the existing situation and usually the number of variables are limited to one or two, that’s why most of the experiments take place in laboratories. Yin (2014) explained that a case study lets the researcher to investigate a “case” in order to obtain a real and comprehensive prospect, as an example, “studying small group behaviour”. In case study, two types of data collection techniques are often used: observation and interview. In this research multiple buildings are used as cases and observation is the main data collection technique.

3.2.4.1. Case Study Design

Case study design of this research is constructed in two stages to investigate the impacts of occupants’ energy consumption behaviours on energy consumption in multi-functional spaces. Stage 1 is applied on buildings at the design and construction stages. It includes 3 steps: preparation of information (for example: architectural/construction plan, building materials and systems), energy modelling and simulation of the cases using energy simulation software (DesignBuilder) default value, and analysis of gaps and insufficiency of information to address human-behaviour-related factors in prediction of energy consumption in multi-functional spaces using the energy simulation tool. Stage 2 is an extended version of the stage 1 to incorporate primary collected data. It consists of 5 steps including: preparation of information, energy modelling and simulation of the cases using software default value, data collection, energy modelling and simulation of the cases using the collected data and analysis and comparison of the collected data and simulation results (using software default presumptions and data collection inputs) (Figure 35).

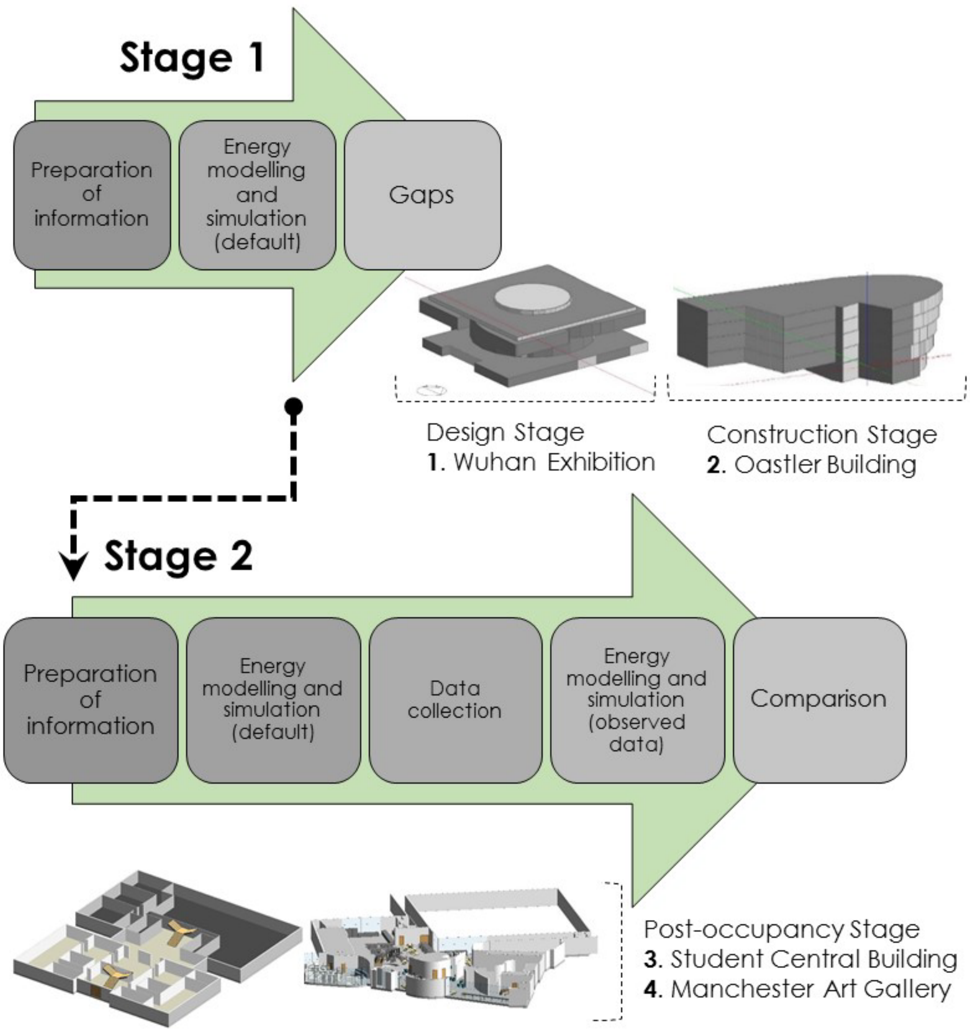


Figure 35. Case study stages

The first case study was a gallery building at design stage (Wuhan gallery) which was used to support and create the structure of this research and point out the types of missing information at the design stage. The 2nd case which was an institutional building at the construction stage, highlighted the occupancy and occupant behaviour related gaps and insufficiency of the information (see: Case study Stage 1 Chapter). The first and second cases (stage 1) suggested the required data to be collected and used in stage 2. The final output of the stage 2 includes the quantified potential gap in energy consumption prediction of the cases caused by overlooking the impacts of occupants' behaviours.

3.2.5. Time Horizon

Time horizon of data collection in research is often categorised into two: cross sectional and longitudinal. In Cross sectional studies, data are collected at a particular period, whereas, in longitudinal research, the data in gathered at various snap shots in a period of time (Sekaran & Bougie, 2010). This study intends to collect data at more than a single point in time, therefore, it is considered as longitudinal. As mentioned before, occupancy in public zones has a dynamic nature. Based on the objectives of this research, various occupancy patterns and distribution of occupants in the space will be inspected. Longitudinal time horizon provides a proper platform to study transitions, transformations and developments over influential parameters being considered (Saunders, Lewis, & Thornhill, 2016b).

For the first two case studies of this research, collecting primary occupancy and human-behaviour-related data was not possible, as the buildings were at the design and construction stages. Therefore, data collection for the cases at the operation stage was planned and modified after a short pilot study. As occupancy is one of the major parameters investigated in this research, a general consideration of monthly, daily and hourly occupancy patterns in the buildings were required to outline the data collection duration and method.

The first post-occupancy case study of this research (student central building, University of Huddersfield) is a multi-functional space within an institutional building which follows two main occupancy patterns: crowded or high-season (during academic-semester) and quiet or low-season (during school holidays). Therefore, the data was collected during two weeks: one week in July (low-season) when students are not usually present and one week in November (high-season). For this case, a pilot study was performed in late May to refine data collection details. Data was collected once every hour between 10:00 AM to 8:00 PM for 3 weekdays which revealed the critical hours (such as peak hour). Further specific data were then collected for 2 more weekdays creating more than 40 hours of data for each zone (See: 5.1.3. Data Collection).

The second post-occupancy case study of this research is a multi-functional space inside Manchester art gallery. The occupancy patterns in galleries are influenced by several factors and range from “high-season” to “low-season” with monthly variations. As an example, bank holidays, school holidays and weekends are considered as high-season, when galleries have the most visitors. According to UK governmental data (Delaney, 2017), August, July and October have the most monthly visits of museums and galleries in UK respectively, and the least visits happen in January.

A pilot study was performed on Manchester art gallery in September and the data collection technique was adjusted to be suitable for various zones within the multi-functional space. The final data was collected in October for duration of one week including weekdays and weekends. The availability of detailed google real-time data facilitated data collection for this case (See: 5.2.3. Data Collection).

There are some exceptional days or hours when the spaces are more crowded like the registration, graduation and open days and during special events for institutional buildings and group visits and events for gallery and exhibition buildings. Those exceptions were noted and excluded from the final analysis for both cases.

As part of the data collection, door opening time percentage was also measured at the end of each hourly data collection. The term “door opening time” refers to the duration of time that the door is open over the whole period of time, which is studied in percentages in energy simulation process. In order to obtain the realistic door opening time percentage of the main entrance doors in both cases, they were under observation for the duration of 5 minutes every hour. For instance, if the entrance door was open for 4 minutes out of the 5-minute period of the observation, the door opening time percentage would be 80%. As during weekdays, the occupancy density and pattern is approximately similar, it is hypothesized that the door opening time percentage follows the same pattern from Monday to Friday.

3.2.6. Data Collection

In terms of research techniques and procedures, Yin (2014) explained six sources of data collection for case study strategy including: document review, archival records, interviews, direct observations, participant observations, and physical artefacts. It is widely accepted that observing behaviour is a reliable and direct method of collecting data from this dynamic phenomena (Zeisel, 2006). Also, Saunders et al. (2016b) stated that observation is clearly one of the best ways to study any research related to occupant behaviour. Therefore, this study proposes to collect primary data through observation and real monitoring of occupants, which has been used as a method of data collection in similar previous studies (Andrews et al., 2013; S. Chen et al., 2015; D'Oca et al., 2014; Hong et al., 2015; Schakib-Ekbatan et al., 2015). Using observation to capture occupancy of spaces, instead of sensors, provides a deeper understanding of unexpected factors and improves the accuracy of the collected data. Besides, it is believed that using monitored data of occupancy profile in a building is mainly useful to estimate the "near-future" performance of the building and there is a need for a comprehensive theory to create a model of occupancy to be used for further occupancy predictions in other buildings at other times (Mahdavi & Tahmasebi, 2015). There are several classifications of observation types based on the nature of the observant, the position of observer in relation to the observant. In this research the researcher's identity is hidden and researcher does not play any role except for observation (Figure 36).

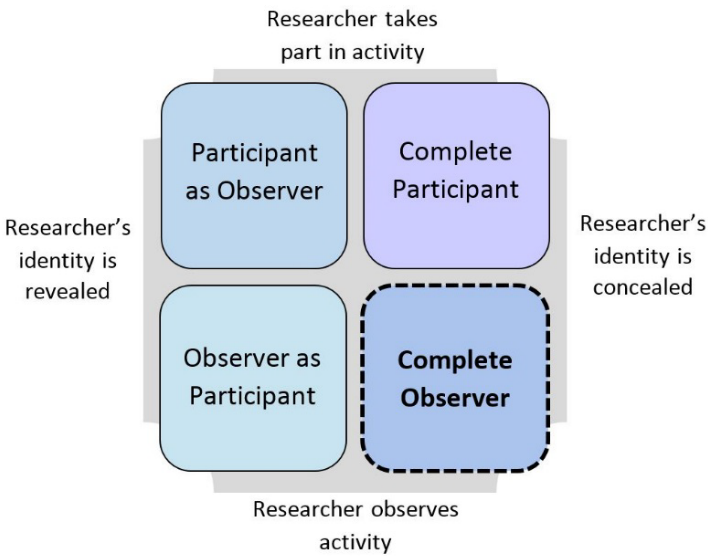


Figure 36. Different types of observation with regard to researcher's position, adopted from (Saunders et al., 2016b)

Saunders et al. (2016b) categorized forms of observation in two parts: participant observation and structured observation (Table 10). In structured observation, the observed phenomena and the procedure of the observation are clearly defined by the researcher in advance, while, in participant or unstructured observation, every aspect related to the phenomena is observed. This research is quantitative and concerned with the occurrence and frequency of certain behaviours rather than the meanings and drivers behind them, therefore, structured observation is used in this study.

Participant Observation	**Structured Observation**
Qualitative	**Quantitative**
Concerned with meanings and drivers of actions	**Concerned with frequency of actions**
Roots in Sociology or Anthropology	Roots in Computer technology

Table 10. Forms of observation (Saunders et al., 2016b)

The initial method of observation included following the same route to count the number of occupants in each zone once every hour. The proposed method of instant observation is suitable for zones where occupants stay longer at one point such as: sitting, eating and reception areas. However, when it comes to zones such as corridors and exhibition areas, where occupants frequently move from one zone to another, the instant number of people does not lead us to an accurate set of data due to sudden density changes. For such spaces, either a very large number of data is needed, or the duration of observation should be extended to more than an instant moment. Therefore, the observation method was altered, and each space was observed for the duration of 5 minutes every hour, counting the occupancy once every minute for 5 times and the average of 5 numbers were considered as the actual occupancy.

In addition to observation, archival records such as: building plans and any available data regarding building systems and the energy performance of building are used at the modelling stage. In addition, available real-time data (such as google popular times) and governmental data were used in this study.

3.3. Research Design

In order to address the research objectives (see: 1.2.2. research objectives), the research method of this study consists of 4 main steps: formulation of research problem, research method design and data collection, data analysis and preliminary findings, and development, validation and refinement of the final framework. Figure 37 illustrates the research methodological design stages of this research project.

- The first step is the formulation of **research problem** which includes a comprehensive literature review to define the existing gaps in the knowledge (objective 1), following by, the establishment of research focus and research method (objective 2).
- The second step is the detailed **research method** which includes selection of case studies, data collection and the application of model simulation method on cases to compare software presumptions with the realistic collected data (objective 3). The case study design includes the investigation of multiple cases using model simulation method in two stages: stage 1 for cases at the design and construction stages, and stage 2 which is applied on cases at the operation and post-occupancy stages. Figure 37 demonstrates research method and case study design of this research, in addition to, the relationship between the two stages of the case study. Stages 1 and 2 of the case study design are explained in chapters 4 and 5, respectively.

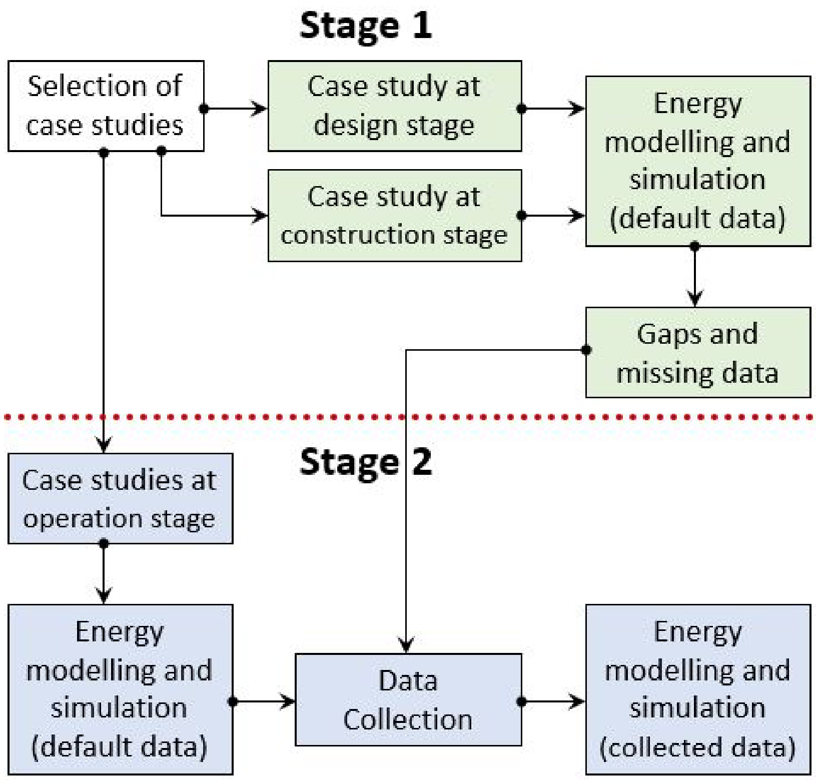


Figure 37. Graphical representation of research method and case study design

- The next step contains **data analysis** and formation of the initial findings (objective 4). Data analysis includes quantitative analysis of the collected data (such as hourly occupancy and door opening time data) and comparison of energy simulation results using software standard (default) presumptions regarding occupants' behaviours and the realistic occupant-behaviour-related inputs generated by analysis of the collected data.

- The final step includes development, validation and refinement of the **conceptual framework** and formulation of the final framework (objective 5). Following data analysis, the initial framework is formed and validated by experts' comments. The final framework is then formulated that is presented in chapter 6.

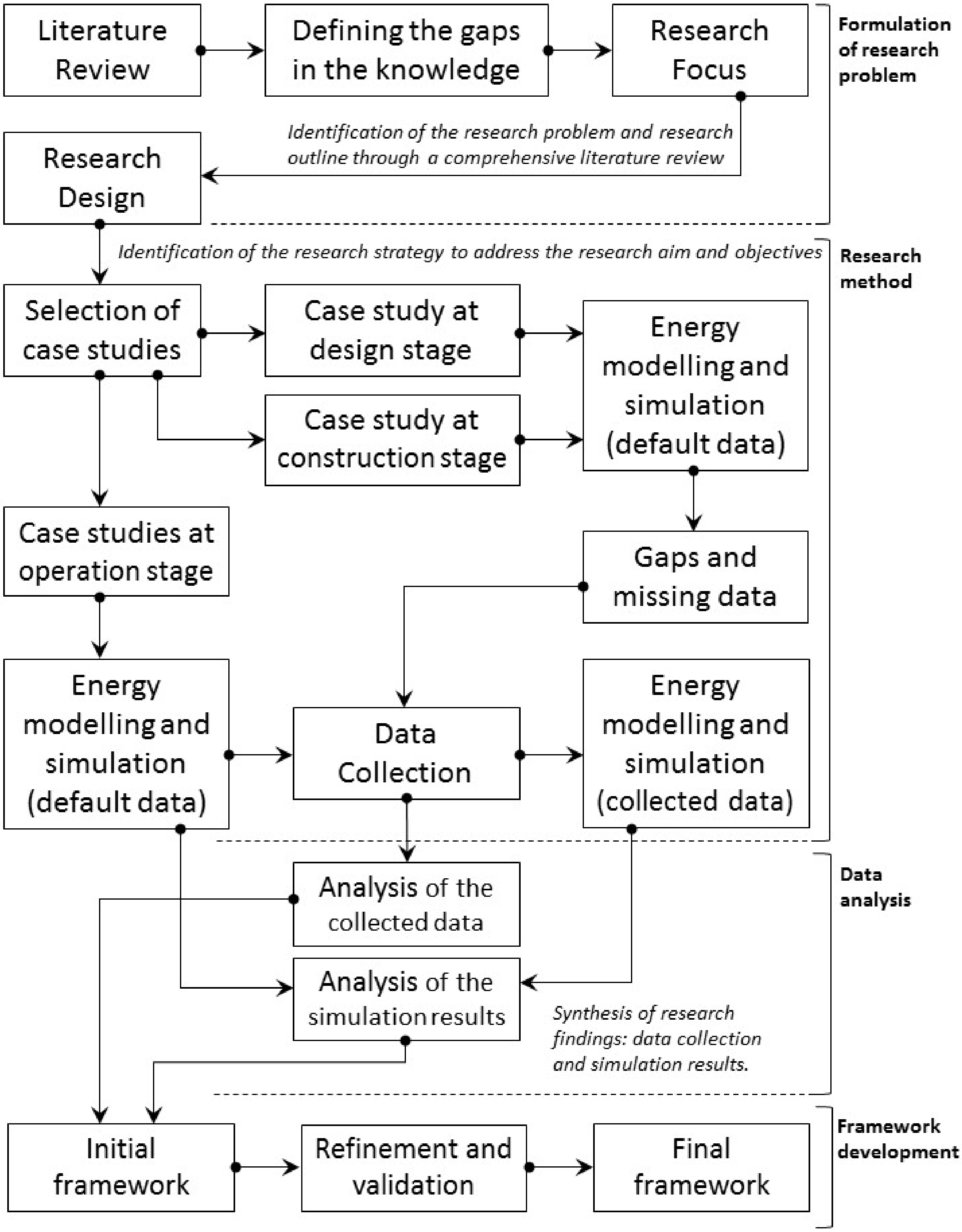


Figure 38. Graphical representation of research methodological design

3.4. Chapter Conclusion

Research method chapter provides a comprehensive description of the research method applied in this study. It includes a review of the methods used in similar studies and explanation of different layers of research method based on Saunders and Lewis (2012) “research onion model”. This quantitative study has a positivism philosophy with mixed reasoning approaches (both abductive and inductive). Furthermore, in this research multiple case studies are investigated and observation is the main data collection technique. The case study design is constructed in two stages: stage 1 for cases at the design and construction stages of the building’s lifecycle and stage 2 is applied on cases at the operation stage. A detailed description of the case study design, data collection method and time horizon is provided in this chapter. In the following chapters, case study stage 1 and 2 are discussed comprehensively.

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Case Study (Stage 1) Chapter

Chapter 4: Case Study Stage 1

As explained in research method chapter, case study design of this study follows two stages: stage 1 is applied on the cases at the design and construction stages and stage 2 is applied on cases at the post-occupancy and operation stages (see: 3.2.4.1. Case Study Design). In this study, a model simulation method is applied on multiple cases of multi-functional spaces to integrate the realistic primary data into a prominent energy simulation tool (DesignBuilder). In this chapter, first, selection of cases, characteristics of the model simulation method, selection of the energy simulation tool (DesignBuilder) and the process of energy modelling and simulation using DesignBuilder is explained which is also applied on stage 2 case studies. Then, this chapter provides a full description of stage 1 case studies. It includes the following sections for both stage 1 cases: case study description, energy modelling and simulation, and analysis and findings. In the first case study (Wuhan exhibition) which was at the design stage, default software data and secondary data were used for energy analysis. The second case study of this research was a multi-functional space in an institutional building at the construction stage (Oastler building, University of Huddersfield). The analysis of both cases pointed out the unavailability and insufficiency of information in building energy simulation during design and construction stages.

4.1. Selection of cases

The type of cases considered for this research are large multi-functional indoor spaces, specifically, entrance, lobby and gathering spaces of buildings with vibrant and dynamic flow of visitors and occupants such as institutional buildings and galleries. In such spaces, there are different circulation patterns and high variations in the number of occupants: hourly, daily, monthly, etc. Another necessity in selection of the cases was the availability of construction and design plans, in addition to, other required inputs for the energy simulation such as weather data. Besides, the accessibility of the cases at the post-occupancy stage essential for hourly observation and data collection. The final selection of the cases, after considering the aforementioned factors, was based on convenience sampling technique. The study is focused on multi-functional spaces, however, in selectin of the cases the building type was also taken into account: two of the cases are located in galleries and exhibition buildings and the other two are as part of institutional buildings. Figure 39 summarises and illustrates the selection criteria of the cases in this study.

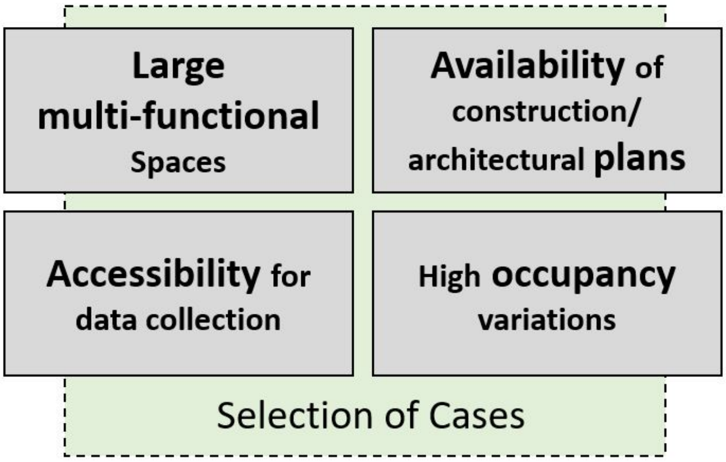


Figure 39. Case study selection criteria

4.2. Model simulation method

Among various methods and techniques used to investigate the impacts of occupants' behaviours on building energy consumption, model simulation method and statistical analysis as the two methods widely applied in various studies: model simulation methods, which are the expanded version of model-based methods, use the integration of actual observed data and the mathematical calculation of building energy consumption and statistical analysis methods use great number of data and generate findings regarding energy consumption by analysing them (Jing Zhao et al., 2012). The application of each method depends on the nature of studied parameters, the availability of data and the purpose of the study. Most of the studies on this subject area applied statistical analysis on big data to reach more reliable general conclusions. Model simulation method, too, has been used in different studies to integrate actual energy consumption parameters into building energy consumption calculations and energy simulation tools (Carriere, Schoenau, & Besant, 1999; Federspiel, Zhang, & Arens, 2002; W.-S. Lee, 2008). The aim of using model simulation methods, however, is not to reach to a general conclusion. It is mainly applied to reach accurate calculations on single or multiple parameters and to quantify and classify the impacts. In a research by Carriere et al. (1999) a model simulation method using DOE-2 energy simulation tool was applied to study energy saving alternatives of large-scale buildings. Also, Federspiel et al.

(2002) implemented a model-based benchmarking to study the minimum energy requirements in laboratory buildings.

Energy modellers, architects and designers use various energy simulation tools which enable them to run intricate building energy consumption calculations. The availability of such programs has been extremely advantageous for industrial and research purposes. Therefore, implementation of such tools in research which allows the integration of theoretical knowledge into the existing energy simulation tools will benefit both researchers and software developers. One of the gaps in the subject area is that the translation of the findings and outcomes of many studies have not yet been incorporated into energy simulations tools to improve their accuracy which is still a challenge in the research domain (see: 2.4.4. Existing gaps in the Literature).

Building energy analysis is a mathematical calculation and the process of building energy assessment is almost similar using different simulation engines such as: EnergyPlus, TRNSYS, ESP-r and DOE-2. The 3D model of the building is the basis of the simulation and various inputs such as: building location and orientation, space functions, building materials, HVAC system and set-points, working hours and occupancy schedule, in addition to, the simulation period are set before running the energy simulation. However, some energy simulation tools provide more detailed inputs and the rest keep the simulation process simpler with less detailed inputs. The simulation engines with more detailed inputs are more accurate in theory, however, their non-user-friendly interfaces makes it difficult for the energy modellers to apply the right assumptions and parameters. Selection of simulation tool, collecting data and integration of the data with the simulation tool are the key components of every model simulation method.

4.3. Energy simulation tool: DesignBuilder

In this research, EnergyPlus engine and DesignBuilder interface are used as the energy simulation and modelling tools. DesignBuilder energy simulation graphical interface uses EnergyPlus engine and provides detailed inputs for building energy assessment while offering a user-friendly interface. Particularly, its inputs regarding occupants' energy behaviours are thorough and easily adjustable and understood by energy modellers (Rahman, Rasul, & Khan, 2010). For occupancy related inputs, DesignBuilder uses ASHRAE standards (American Society of Heating et al., 2009) which is commonly believed to be the most accurate source. DesignBuilder was used in various studies on occupants' behaviours and occupancy profiles (Becchio, Bello, Corgnati, & Ingaramo, 2016; Carpino, Mora, Arcuri, & De Simone, 2017; Martinaitis, Zavadskas, Motuzienė, & Vilutienė, 2015). A study on energy management in an office building (Fathalian & Kargarsharifabad, 2018) resolutely confirmed the high accuracy of energy analysis by DesignBuilder by comparing the monthly gas and electricity bills. The study reported less than 1.6% gap between the actual and predicted energy demand. The gap is too little and may be a fortunate coincident to an extent, however, it indicates the reliability of Designbuilder as an accurate energy simulation tool.

Many simulation-based studies have taken advantage of DesignBuilder for modelling and simulation of building energy assessment (Cárdenas et al., 2016; Fathalian & Kargarsharifabad, 2018; Rahman et al., 2010; Streckienė & Polonis, 2014). DesignBuilder has also been used in various studies for specific calculations. For example, (Boafo, Ahn, Kim, & Kim, 2015) applied DesignBuilder tool to calculate thermal bridge for energy retrofit. Also, in another study, DesignBuilder was used to estimate natural ventilation through a chimney using CFD (Computational fluid dynamics) (de la Torre & Yousif, 2014). Slavković (2017) ran detailed simulations on a double skin façade using DesignBuilder.

Another benefit of using DesignBuilder in studies which are concentrated on some parts of the building (such as one floor or a single zone) is that the software offers a clear arrangement of spaces divided by building block, floors, zones and surfaces (Rahman et al., 2010). In this research which is focused on multi-functional spaces and multiple zones, DesignBuilder lets the inclusive calculations for the studied spaces. In conclusion, DesignBuilder energy assessment tool was selected for modelling and simulation phase of this research because of its accuracy, detailed occupancy and occupant-behaviour-related inputs, user-friendly interface and the availability of the software.

4.3.1. Energy modelling and simulation process

In order to run energy simulation for a building or a part of it, a series of actions should be made by the energy modeller. The same process applies for most of the energy simulation tools with very minor differences in the type of inputs and the level of details (See: 2.3. Building energy Prediction: Methods and Tools).

For energy modelling and simulation of the case studies of this research using DesignBuilder software the following steps were taken (Figure 37):

1- Selection of building location, weather data using the closest weather station to the building location and building type.
2- Creating 3d model of the building using architectural/construction plans and sections or exporting the available 3d model of the building from another software (for example Revit Architecture).
3- Assigning any available information regarding building material, thermo-physical properties of building elements, HVAC system and special equipment used in different spaces or using software presumptions.
4- Zoning and determining functions for all the spaces using activity section in DesignBuilder. Working hours, occupancy and human-behaviour-related presumptions of the software are attached to and associated with building type and the function of each space/zone.
5- Selecting the energy simulation period, running the energy simulation and analysing the simulation reports and outcomes.

For the purpose of this study, zoning and determining functions, together with, occupancy and occupant-behaviour-related parameters were the main focused areas during the simulation process and data collection (Figure 40).

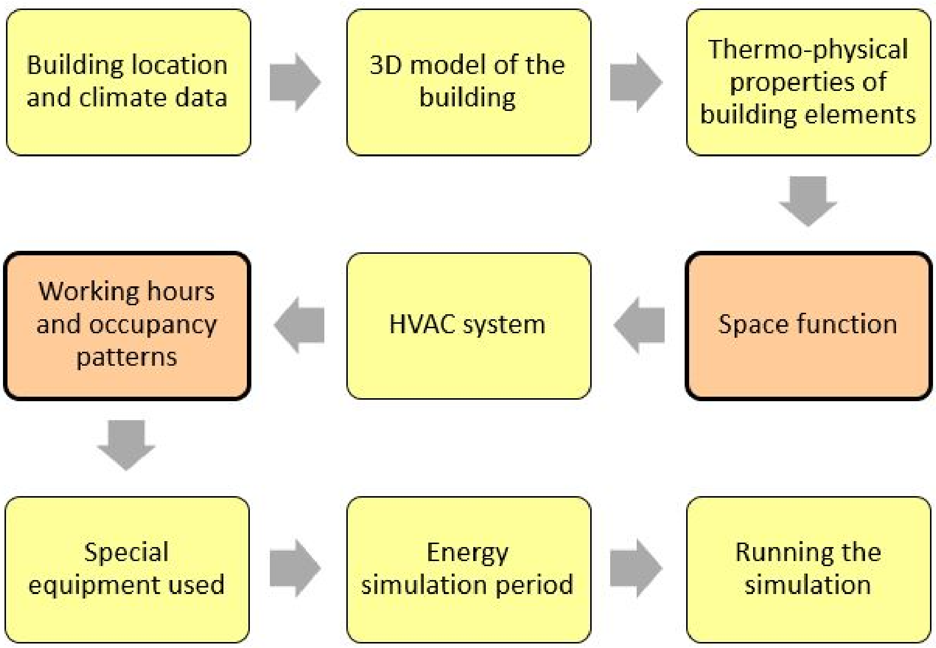


Figure 40. Energy modelling and simulation using DesignBuilder

4.4. Design Stage Case Study: Wuhan Gallery

4.4.1. Case Study Description

Wuhan art gallery and exhibition is a 4-floor building which is currently under construction and is located in Wuhan, China. This building was studied in this research at its final design stage. The project is large scale and has a relatively complex geometry. The building interior, contains a massive void in its centre where the vertical circulations including lifts and escalators are located. There is a glass dome at the top of the void which brings great amount of day-light into the space. The building has different types of spaces including: display and public areas, small scale workshops, office areas and circulation areas (corridors and staircases). The ground floor includes the main entrance, the atrium space, some administrative, office, service and circulation areas (Figure 41). The atrium encloses the main vertical connections of the building and is responsible to circulate building users to their main destinations at different floors. The first floor contains multi-functional spaces which can be used for small workshops, exhibitions or seminar rooms (Figure 42). The second floor includes the main exhibition areas and galleries: four galleries that are connected and can be used separately when necessary (Figure 43). The third floor contains offices only.

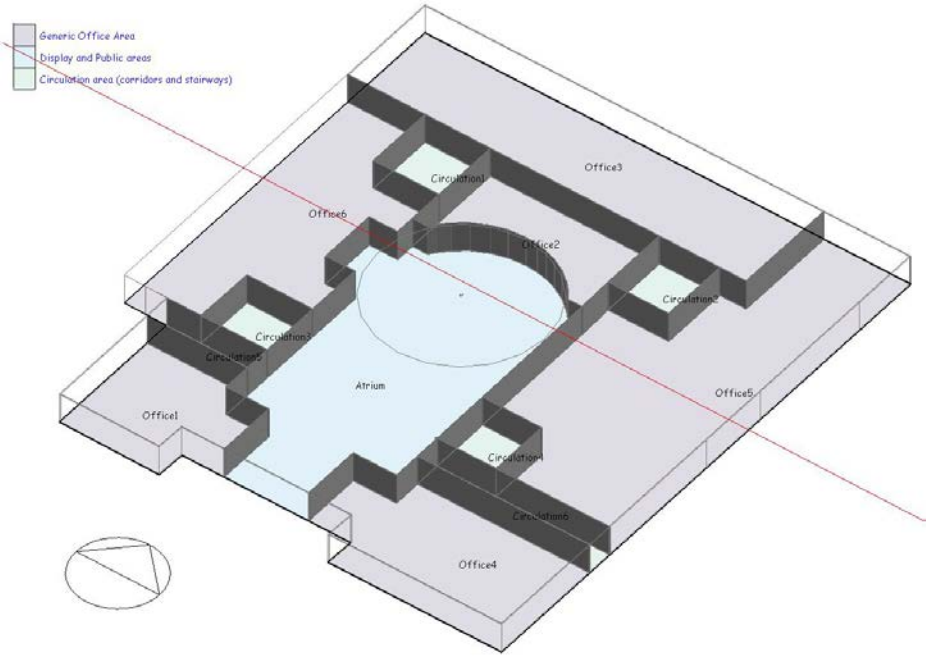


Figure 41. Ground floor zoning

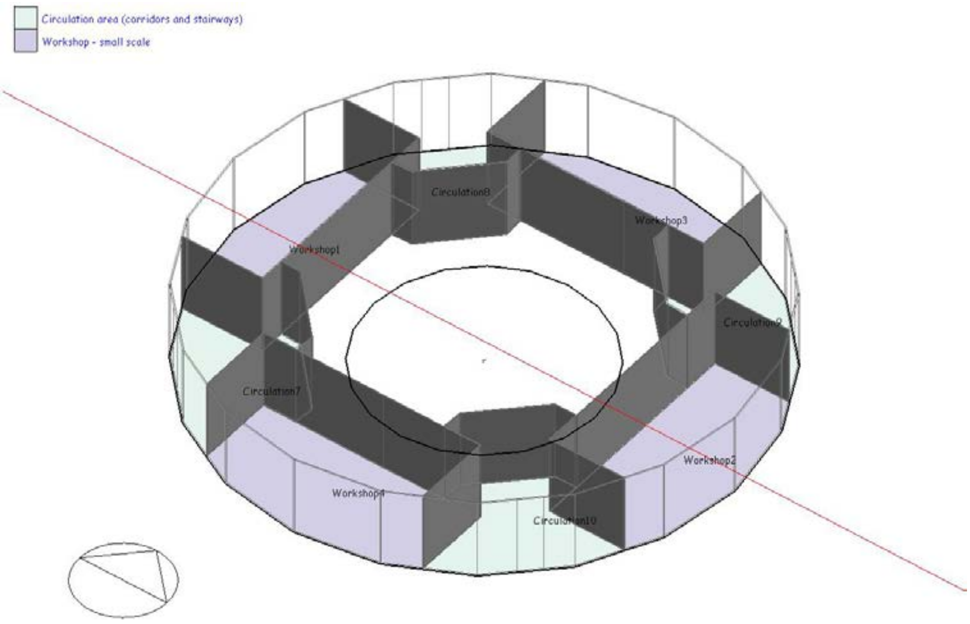


Figure 42. First floor zoning

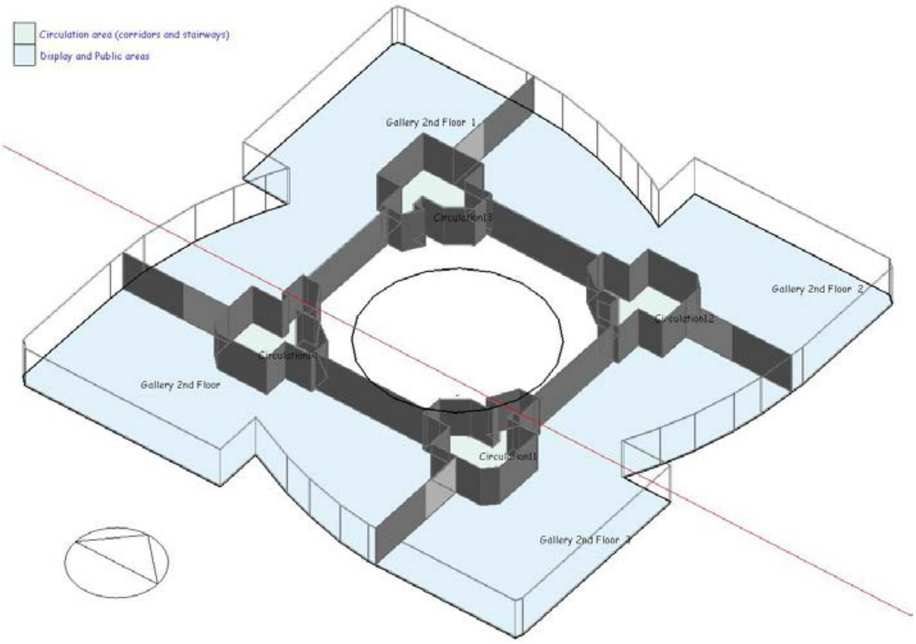


Figure 43. Second floor zoning

4.4.2. Energy Modelling and Simulation

Wuhan exhibition is a huge multi-functional building containing various office, education centres, seminar and lecture theatres, galleries and exhibitions with the total area of 60391.08 m^2. The building is more than 50 m high. Energy modelling of the building was challenging due to its complicated geometry. Therefore, the building volume was first simplified and re-modelled using DesignBuilder modelling tool. The glass dome of the building was reformed to an equivalent glass cube in Design Builder software (Figures 44 and 45).

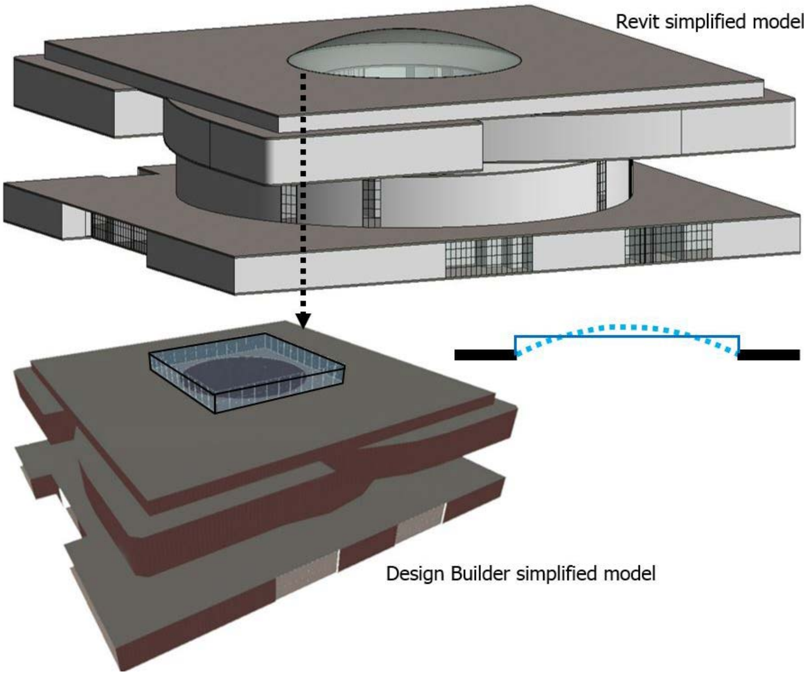


Figure 44. DesinBuilder simplifications

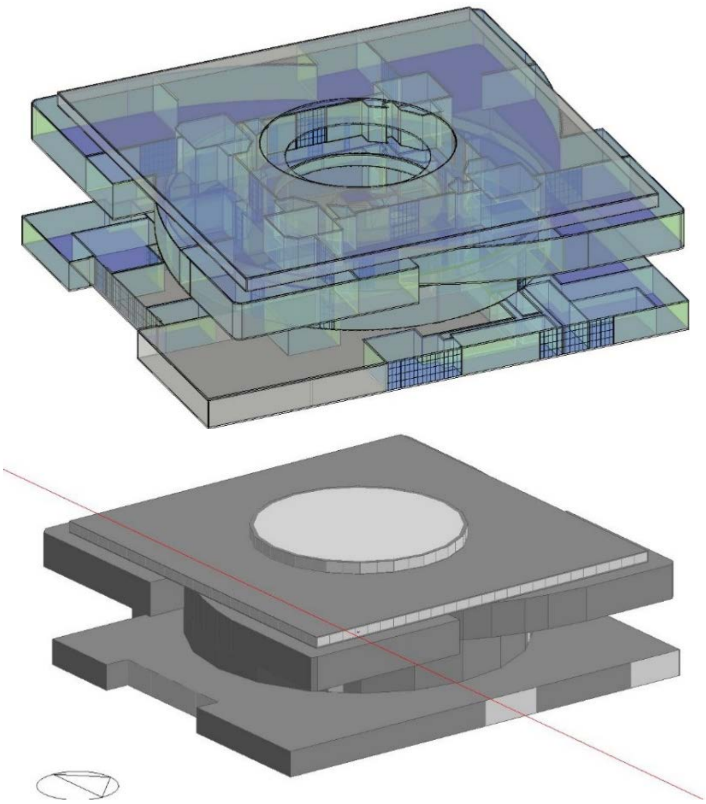


Figure 45. Revit Architecture (top) and DesignBuilder (bottom) Energy models of the building

Some of the default values used for the initial energy modelling and simulation including default heating and cooling set-points, occupancy density, equipment gain and lighting are displayed in table 14. Default energy simulation software value regarding building's HVAC system considers natural gas as the source of energy for heating and electricity for cooling. Also, both mechanical and natural ventilations were "on" for the energy simulation.

Spaces	Environmental control		Occupancy	Equipment and lighting
	Heating set-point	Cooling set point	Density	
Circulation spaces	Heating 20 °C Heating set-back 12 °C	Cooling 23 °C Cooling set-back 28 °C	0.1173 (people/m^2)	Equipment gain: 1.85 W/m^2
Display and public areas	Heating 20 °C Heating set-back 12 °C	Cooling 24 °C cooling set-back 28 °C	0.1497 (people/m^2) Activity: Lighter manual work	Normalised power density: 5 (W/m^2-100 lux)
Reception	Heating 20 °C Heating set-back 12 °C	Cooling 23 °C Cooling set-back 28 °C	0.0947 (people/m^2)	Equipment gain: 6.19 W/m^2
Eating and drinking areas	Heating 23 °C Heating set-back 12 °C	Cooling 25 °C Cooling set-back 28 °C	0.32 (people/m^2)	Target illuminance 150 lux
Toilet	Heating 20 °C Heating set-back 12 °C	Cooling 25 °C cooling set-back 28 °C	0.1238 (people/m^2)	Target illuminance 200 lux

Table 11. DesignBuilder default values used for the energy simulation

Building spaces were classified based on their types of activities to be used in "activity" section of DesignBuilder software. Due to unavailability of detailed interior design and space furniture data, the labels on the plans were used to specify space function. Some spaces were labelled as multi-functional or multi-purpose which made it challenging to choose the right type of space in energy model of the building.

Wuhan weather data (EPW file) was taken from Energy Plus weather data library and used to Design Builder software for the energy simulation. The number of zones were reduced by combining rooms with similar energy properties and profiles in DesignBuilder software. Default density assumption of each zone in building energy simulation software is predicted based on the zone's function and the type of activity, however, the presumptions are adjustable using people/m^2 or m^2/people units.

During the design stage, designers consider the density of each space according to the requirements of the project. For this purpose, designers use design standard and guidelines such as Architects' data book (Buxton, 2018; Neufert, Neufert, & Kister, 2012), study the relation between human body and the design requirements and provide guidelines for designers. For some building types, the number of occupants is more predictable, for instance, in residential buildings. While, it is nearly impossible to know the density of some other building types such as: exhibitions and galleries, because of their miscellaneous and diverse natures (Deloitte, 2010). Lord and Piacente (2014) mentioned "crowd tolerance" as the criterion and standard for density considerations in museum exhibitions and suggested to have between 30-50 ft^2 (2.8- 4.6 $m^{2)}$ of space per person, and for more expensive and special exhibitions up to 100-200 ft^2 (9.3-19 m^2) per person. Also, Engineering ToolBox website developed a table to show the occupancy in different building types to be used for <u>human sensible and latent heat load</u> calculations and suggested between 30-100 ft^2 (2.75-9.2 m^2) per person for exhibitions and museums (EngineeringToolBox, 2003).

DesignBuilder considers 0.14 people per m^2 for display and public areas in galleries, museums and libraries (Figure 46), while 30-100 ft^2 per person is equal to 0.1-0.36 people per m^2 (Figure 47). Based on the differences between density numbers which are shown in the illustrations, there may be huge inaccuracies in energy predictions.

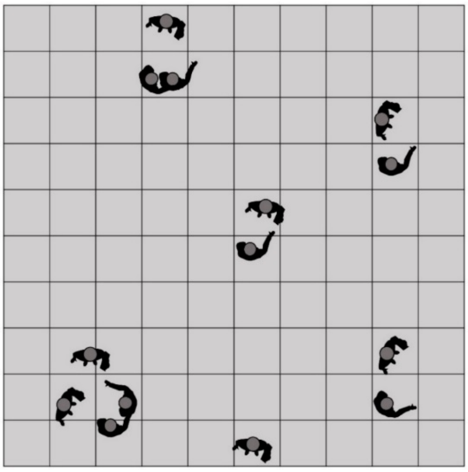


Figure 46. Illustration of density 0.14 people/m^2: default density of DesignBuilder for exhibitions and galleries

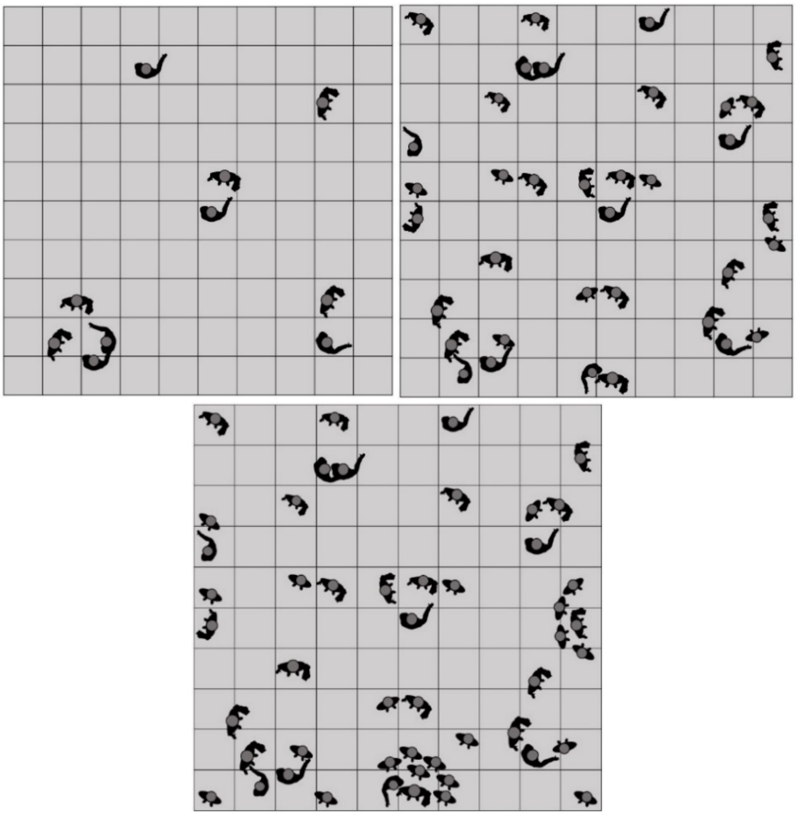


Figure 47. Illustration of minimum and maximum densities in design of exhibitions and galleries: minimum 0.1 people/m^2 (left), maximum 0.36 people/m^2 (right) and 0.5 people/m^2 (down)

In order to quantify the impacts of density variations in energy consumption predictions of exhibition buildings, the yearly energy simulation (1st January to 31st December) was run for the case study with two scenarios: first, using default density values for all the building zones and second, using the maximum density of 0.5 people/m^2 for the gallery zones of the case study while keeping all the other factors with no changes. The density changes in the second simulation were only made to the gallery zones located in the second floor which include nearly 1/10 of the total volume of the building. Table 11 shows the results of the two simulation scenarios.

Scenario No.	Density in gallery zones	Total energy consumption [KWh]	KWh/m^2	Simulation Period
1	0.149 (default)	17998522.77	298.04	Yearly
2	0.5	20380388.71	337.48	Yearly

Table 12. Yearly energy simulation scenarios

The findings of these simulations, confirm **11.68%** increase in the total energy consumption prediction in the case study considering the maximum density in exhibition zones. Running both simulations again **for the period of 1st July- 31st August**, showed **17.18%** variations in the energy predictions of the building (Table 12).

Scenario No.	Density in gallery zones	Total energy consumption [KWh]	KWh/m^2	Simulation Period
1.2	0.149 (default)	5489240.86	90.90	1 July- 31 August
2.2	0.5	6628001.94	109.75	1 July- 31 August

Table 13. Simulation scenarios for the period of 1 July- 31 August

4.4.3. Analysis and Findings (Case Study 1)

It is widely acknowledged that the more accurate energy simulation inputs are the smaller the performance gap between the actual and predicted energy consumption will be. Building energy consumption assessment is performed at different stages of building's lifecycle. At the design stage, many features of the buildings are not finalised. The detailed investigation of the first case study in this research suggested unavailability of sufficient information regarding building material, HVAC systems, building working hours, occupancy and space furniture and appliances (Table 13).

Data availability for energy modelling and simulation of Wuhan exhibition	
Available	**Not available**
• 2D and 3D models of the building • Weather data • Function of spaces	• Detailed building material • HVAC systems • Working hours • Occupancy • Space furniture and appliances

Table 14. Available and not available data for energy prediction of Wuhan exhibition at the design stage

Therefore, during the energy assessment of the case, default software assumption was used for the aforementioned inputs without any modification. Because of the particular focus of this study on occupancy and occupants' behaviours, the simulation was repeated using various architectural standard values for maximum occupancy in gallery and exhibition areas. The analysis of the simulation results showed 11.68% difference between the yearly energy consumption prediction using software default occupancy and other standard occupancy values used by architects to design the gallery spaces (Lord & Piacente, 2014). The simulation revealed 17.18% difference between the two aforementioned scenarios in summer (from 1st July to 31st August) due to warm weather in Wuhan. The measured variations in the energy prediction of the building using different occupancy values confirm the necessity to further study and quantify the actual impacts of occupancy and human-behaviour-related factors in spaces with high unknown occupancy variations.

4.5. Construction Stage Case Study: Oastler Building, University of Huddersfield

4.5.1. Case Study Description

The second case study of this research is the multi-functional lobby space located at the ground floor of the Oastler building which is a newly built building at the University of Huddersfield. For the purpose of this research, the energy consumption of the Oastler building was studied during its construction stage. Additionally, when the construction of the building finished in April 2017, the study further expanded observations and investigations.
The building mainly aims for University's Law School and the School of Music, Humanities and Media. However, its central location and the direct connection with student central building, together with its design features, all together make it a dominant building through University. The building contains classrooms, offices, lecture theatres, service areas and circulation areas. The ground floor has a lobby area with visual and physical connection to the lower floor, lecture theatres and dynamic circulation areas.

4.5.2. Energy Modelling and Simulation

Availability of the building's construction plans and a detailed Autodesk Revit BIM model was an advantage to understand the building's complex internal and external geometry. There is an advanced interoperability between BIM models and DesignBuilders energy simulation tool. BIM models generated using any BIM tool such as Autodesk Revit, ArchiCAD and Microstation can be imported to DesignBuilder via "gbxml" data exchange (DesignBuilder, 2018b). To import an Autodesk Revit model into Designbuilder, three simple steps should be followed: creating a Revit Analytical model, generating Green Building XML (gbxml) model, loading the gbxml model in DesignBuilder (DesignBuilder, 2018a). However, when the BIM model is very detailed, importing it into energy simulation tools usually causes several errors and incompatibilities. Therefore, the first step is to simplify the existing BIM model, which is usually overlooked. As the existing BIM model of the Oastler building was very detailed, heavy and not suitable for energy assessment purposes, in this study, the building was modelled in DesignBuilder (Figure 48).

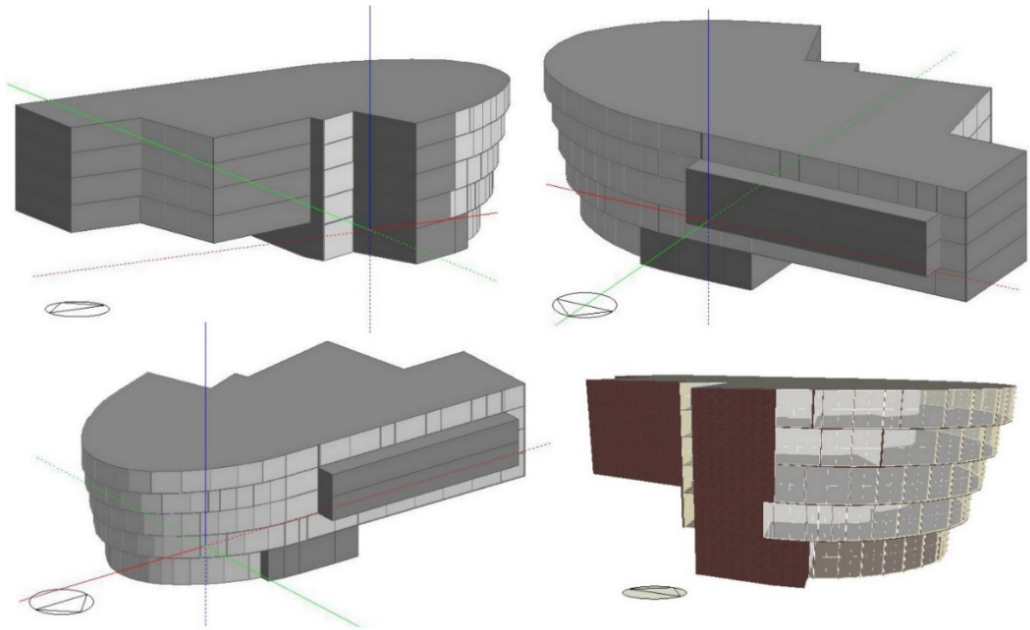


Figure 48. Oastler energy modelling, DesignBuilder

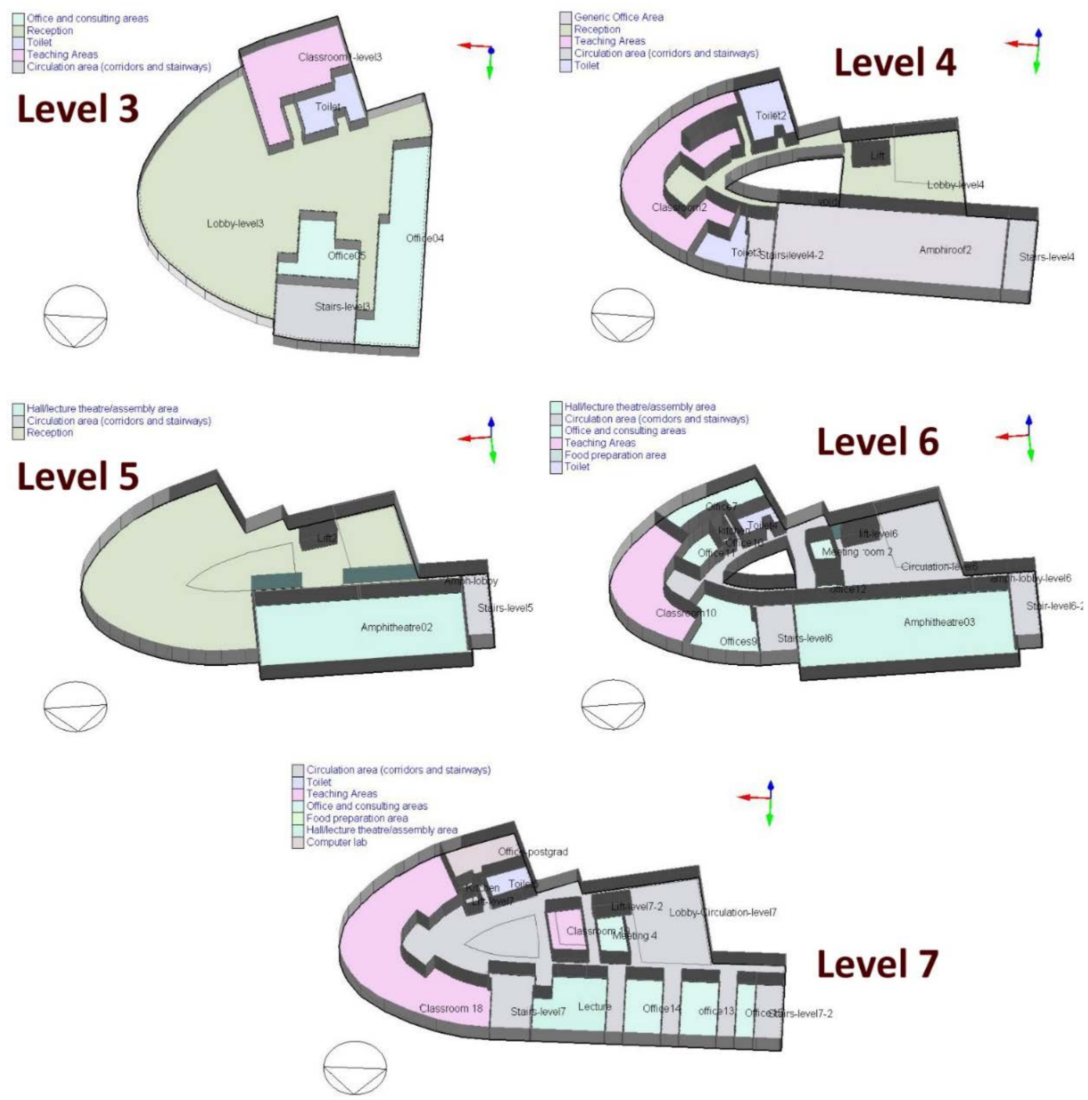


Figure 49. Oastler building simplified space use, extracted from DesignBuilder model

Default heating and cooling set-points, occupancy density, equipment gain and target illuminance values used for various spaces during the initial energy modelling and simulation including are displayed in table 15.

Spaces	Environmental control		Occupancy Density	Equipment and lighting
	Heating set-point	Cooling set point		
Circulation area (corridors and stairways)	Heating 15 °C Heating set-back 12 °C	Cooling 23 °C Cooling set-back 28 °C	0.11 (people/m^2)	Equipment gain: 2.00 W/m^2 Target illuminance 100 lux
Office area	Heating 21 °C Heating set-back 12 °C	Cooling 24 °C cooling set-back 28 °C	0.103 (people/m^2)	Equipment gain: 11.99 W/m^2

				Target illuminance 400 lux
Reception	Heating 20 °C Heating set-back 12 °C	Cooling 23 °C Cooling set-back 28 °C	0.1155 (people/m^2)	Equipment gain: 5.59 W/m^2 Target illuminance 200 lux
Teaching areas	Heating 18 °C Heating set-back 12 °C	Cooling 23 °C Cooling set-back 28 °C	0.5523 (people/m^2)	Equipment gain: 4.70 W/m^2 Target illuminance 280 lux
Toilet	Heating 15 °C Heating set-back 12 °C	Cooling 25 °C cooling set-back 28 °C	0.11 (people/m^2)	Equipment gain: 5 W/m^2 Target illuminance 200 lux
Hall, lecture theatre, assembly area	Heating 20 °C Heating set-back 12 °C	Cooling 23 °C cooling set-back 28 °C	0.2183 (people/m^2)	Equipment gain: 2 W/m^2 Target illuminance 300 lux
Food preparation area	Heating 17 °C Heating set-back 12 °C	Cooling 21 °C cooling set-back 28 °C	0.0943 (people/m^2)	Equipment gain: 40 W/m^2 Target illuminance 500 lux

Table 15. Default DesignBuilder values used for the initial energy simulation

The final energy consumption prediction of the case using DesignBuilder and EnergyPlus tools are shown in tables 16 and 17. Also, figures 51, 52 and 53, display the final simulation, heating design and cooling design outputs of energy simulation by EnergyPlus.

	Electricity (kWh)	**Natural Gas (kWh)**	**District Cooling (kWh)**	**District Heating (kWh)**	**Water (m^3)**
Heating	-	-		361271.20	-
Cooling	-	-	127065.55	-	-
Lighting	217994.47	-	-	-	-
Equipment	127442.07	-	-	-	-
Water Systems	-	-	-	21948.39	343.69
Total End Uses	**345436.54**	**0.00**	**127065.55**	**383219.59**	**343.69**

Table 16. End uses

There are two terms commonly used in energy simulation tools to demonstrate and quantify the energy consumption in buildings: total site energy and total source energy. Total site energy shows the total energy consumption in a building, while, total source energy is site energy plus all the production, transmission and distribution losses. Depending on the type of energy consumed in the building (such as: electricity, gas, fuel, etc.) the site to source energy conversion factor differs (Fumo & Chamra, 2010). Although the total source energy is the realistic total energy consumption which includes all the energy losses, total site energy is the basis for building energy performance assessment and shown in building energy meters and energy bills (Fumo & Chamra, 2010; Scofield, 2009). Table 17 shows both annual total site energy and annual total source energy for Oastler building.

Annual Building Utility Performance Summary (values gathered over 8760 hours) EnergyPlus Version 8.5.0		
	Total Energy (kWh)	Energy Per Total Building Area (kWh/m^2)
Total Site Energy	855721.68	107.85
Total Source Energy	2612836.50	329.29

Table 17. Annual building utility performance summary

The analysis of the predicted energy consumption in Oastler building suggests that heating and electricity consumption are accountable for 45% and 40% of the total energy consumption, respectively (Figure 50).

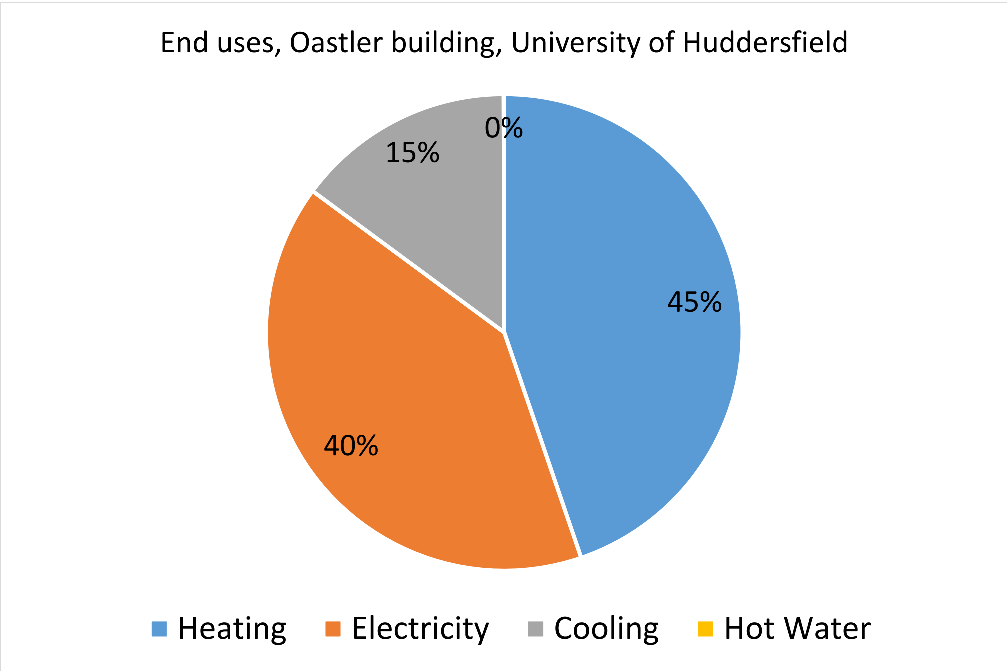


Figure 50. End uses analysis, Oastler building, University of Huddersfield

The final outcomes of energy simulation for Oastler building include the graphical and numerical representation of heat gains and energy consumption for every month with details of the source of energy consumption (such as: lighting, electricity, cooling, heating, etc.) (Figure 47). In addition, details of temperature and total, hourly and sub-hourly heat loss in heating and cooling design are other outcomes of DesignBuilder energy simulation (Figures 48 and 49).

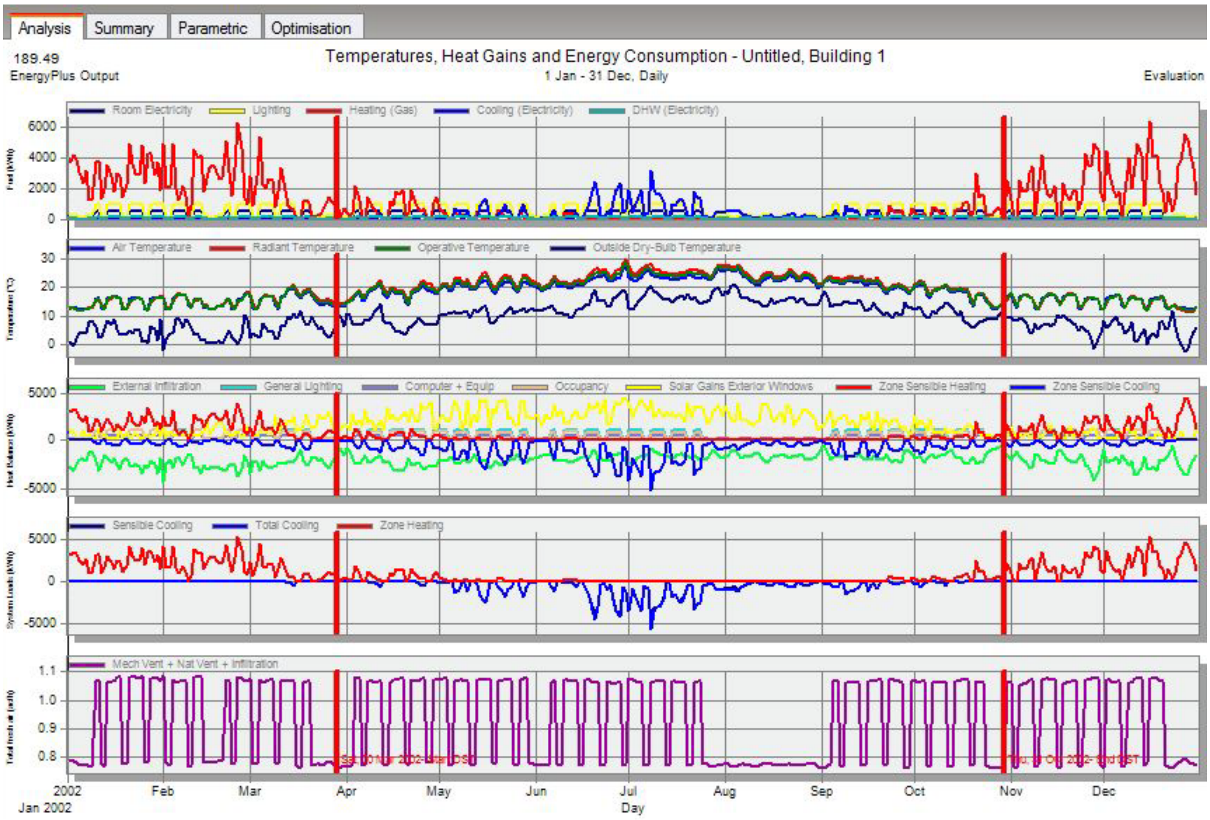
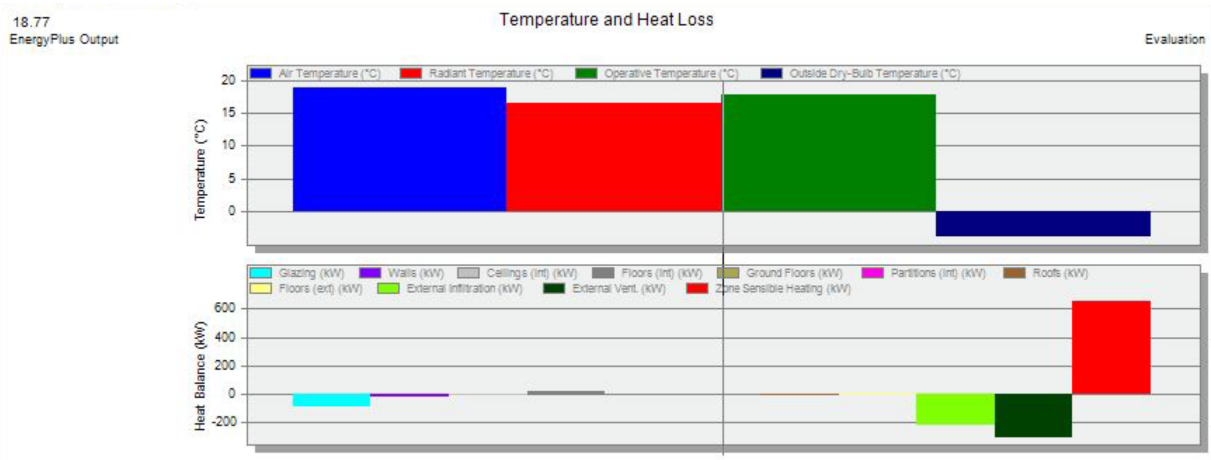


Figure 51. Simulation, DesignBuilder and EnergyPlus output



Air Temperature (°C)	18.77
Radiant Temperature (°C)	16.38
Operative Temperature (°C)	17.57
)utside Dry-Bulb Temperature (°C)	-3.80
Glazing (kW)	-89.80
Walls (kW)	-17.44
Ceilings (int) (kW)	-14.16
Floors (int) (kW)	14.17
Ground Floors (kW)	0.20
Partitions (int) (kW)	0.00
Roofs (kW)	-13.28
Floors (ext) (kW)	-7.51
External Infiltration (kW)	-217.14
External Vent. (kW)	-304.81
Zone Sensible Heating (kW)	649.77

Figure 52. Heating design, EnergyPlus output

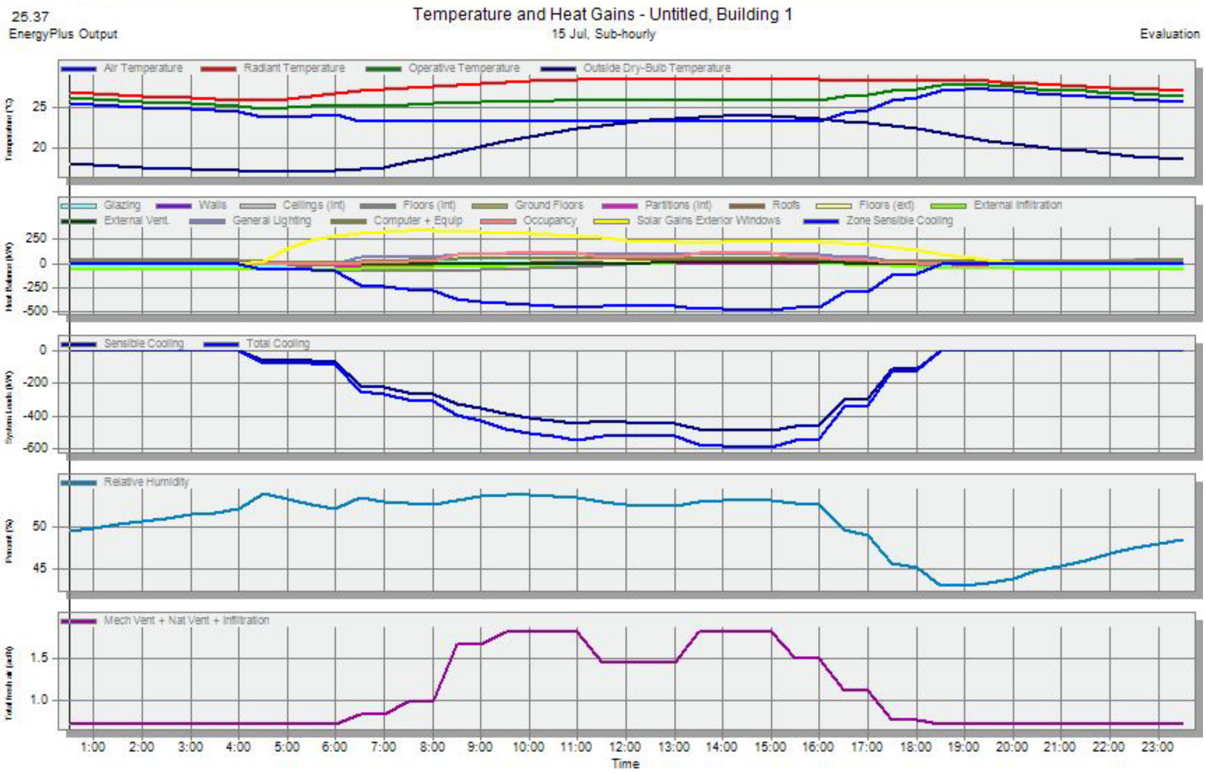


Figure 53. Cooling design, EnergyPlus output

4.5.3. Analysis and Findings (Case Study 2)

Detailed analysis of the energy modelling and simulation of the Oastler building at the construction stage confirmed less insufficiency of information in comparison to the first case study of this research (Wuhan gallery) at the design stage (Table 18).

Availability of detailed building material, HVAC systems and working hours certainly resulted more accurate energy consumption prediction for the building. However, there were no additional data regarding occupancy and occupant-behaviour-related inputs. Also, as the case study included some multi-functional spaces, unavailabity of detailed information about space furniture, made it difficult to predict various functions and activities in the multi-functional space. Space furniture is a guide to divide the multi-functional spaces into different zones in building energy simulation tools. The analysis of the second case study of this research suggests that occupancy and detailed space furniture are among the most significant missing information for prediction of energy consumption in multi-functional spaces of buildings at the construction stage.

Data availability for energy modelling and simulation of Oastler building, University of Huddersfield	
Available	**Not available**
• 2D and 3D models of the building • Weather data • Function of spaces • Detailed building material • HVAC systems • Working hours	• Occupancy • Detailed space furniture

Table 18. Available and not available data for energy prediction of Oastler building at the construction stage

4.6. Chapter Conclusion

This chapter includes the description of the case studies at the design and construction stages (stage 1), in addition to, energy modelling and simulation of each case. The findings of each case, highlighted the gaps and insufficiency of presumptions in simulation tools to incorporate human-behaviour-related factors into the building energy prediction. The investigation of the first case demonstrated that during the design stage, unavailability of detailed data about building material, HVAC systems, space furniture and appliances, in addition to, building working hours and occupancy may lead to considerable inaccuracies in energy assessment of the case. The analysis of the findings of the second case, too, indicated that during the construction stage, space furniture, working hours and occupancy data are amongst the most significant lack of information during energy assessment of the multi-functional spaces. The analysis of the findings of both stage 1 case studies were used to support and create the backbones of stage 2 which is explained in the next chapter.

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Case Study (Stage 2) Chapter

Chapter 5: Case Study Stage 2

As explained in research method chapter (See: 3.2.4.1. Case Study Design), energy assessment of multi-functional spaces during building operation and post-occupancy stages were investigated in case study stage 2 which consists of several steps: selection of the cases and preparation of information, energy modelling and simulation of the selected cases using default data of energy prediction software (DesignBuilder and EnergyPlus), data collection, running energy simulation for each case using the collected data, comparison and analysis of the collected data and simulation results. Two multi-functional spaces at the operation stage were studied in this research: student central building at the University of Huddersfield and Manchester art gallery ,both located in the North England. To quantity the impacts of occupants' energy behaviours on energy consumption of the studied zones, model simulation method was applied on each case (Figure 54). Therefore, the energy simulation was run multiple times to calculate the gap between the energy consumption prediction using software default inputs and the realistic collected data. Therefore, first, default software presumptions were used to determine the predicted energy consumption for each case. Then, series of energy simulations using each observed parameter including: realistic door opening time percentage data, occupancy density and pattern and actual working hours were carried out, with the aim to quantify the impacts of each parameter on energy consumption of the case. Finally, the initial predicted simulation data was compared with the results of the final simulation using all the collected data.

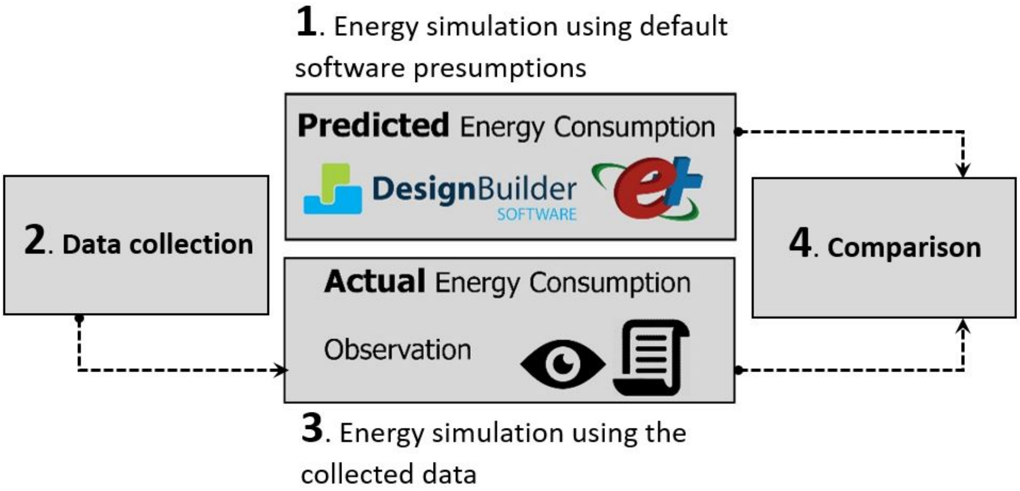


Figure 54. Model simulation method

This chapter contains description of each case, energy modelling and simulation based using software default presumptions, the process and duration of data collection, data analysis and energy modelling and simulation using the collected data.

5.1. Post-Occupancy Stage Case Study: Student Central Building, University of Huddersfield

5.1.1. Case Study Description

The first case study of this research at the post-occupancy stage is the multi-functional lobby space located at the ground floor of the student central building, University of Huddersfield. Student central building opened in 2014 to perform as a connection point for some essential and common parts of the University of Huddersfield including central administrative, management and services. The main university campus accommodates more than 20 separate buildings where nearly 20,000 students pursue their aducation (Figure 55).

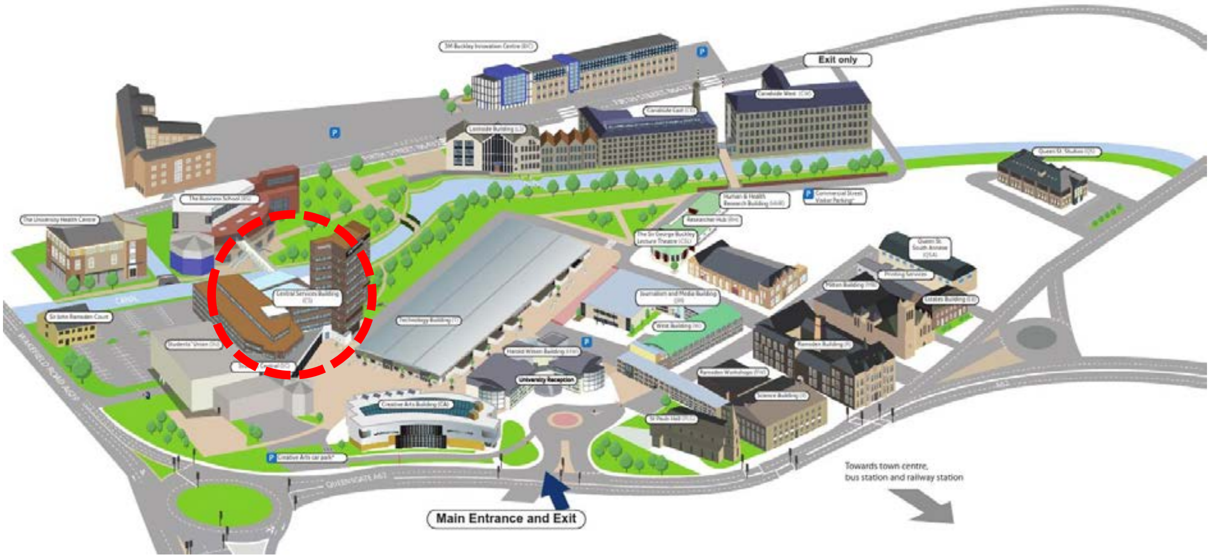


Figure 55. The University of Huddersfield and student central building

The multi-functional space contains different zones including: the main entrance, reception (iPoint), Student Union's shop, food preparation and canteen, eating, sitting and socialising areas, offices, services and circulation zones (Figure 56). The reception space, which is called iPoint, is located in front of the main entrance door and functions as a general information desk for all the students and visitors. Various types of cold and warm food and drinks are prepared and sold in the food shops located in various locations at the multi-functional space. The Students' Union shop is located very close to the main entrance door and sells various snacks and stationery.

Figure 56. Space layout analysis: entrance, circulation and function of spaces

Such central spaces in institutional buildings contain constant flow of people as they accommodate several essential functions. Besides, the space is directly connected to some other substantial spaces including: central library, computer room, gym and fitness studio, the Student's Union, career and employability services, disability and wellbeing services, students' accommodation (Hudlet) and bank. The central library is divided into 6 floors and contains various reading and studying spaces. The library working hours has daily and monthly variations. During school-semester, some parts of the library (including the computer room) are open 24 hours a day. The gym and fitness studio are open during weekdays from 7:00 AM to 10:00 PM and weekends from 9:00 AM to 5:00 PM. Different working hours of various zones in a multi-functional space make occupancy predictions more complicated.

5.1.2. Energy Modelling and Simulation (Default)

The student central building is attached to other buildings and the chosen multi-functional space in this study is directly connected to other parts of the building. Therefore, in order to simplify the model, the multi-functional space is modelled in details and the other buildings are modelled as simple building blocks (Figure 57).

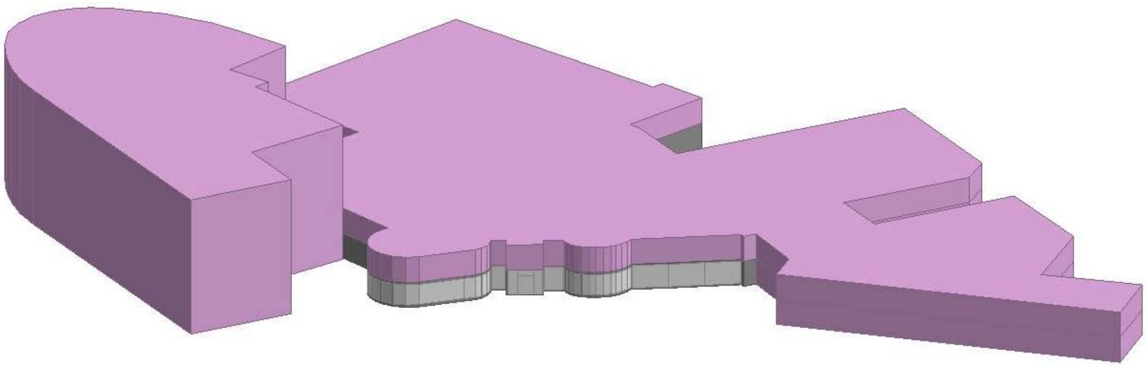


Figure 57. DesignBuilder model of the student central building, University of Huddersfield

The building's original AutoCAD 2D drawings were imported to DXF files and used to create the model in DesignBuilder software. However, the interior spaces were not clearly identified in the original building construction plans (Figure 58). Zoning which means specifiying the function of every zone, is an important step in building energy modelling and simulation. For interior zoning of the multi-functional space of the case in DesignBuilder, except for the shop, offices and food preparation areas which were specified in the original construction plans, other spaces were considered as circulation (Figure 59).

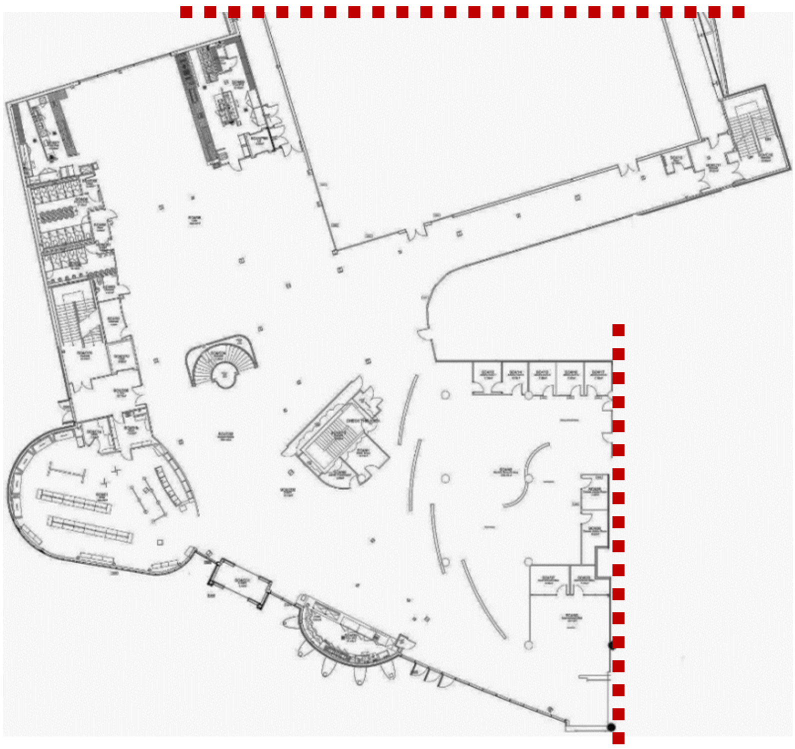


Figure 58. Original construction plans, student central building, University of Huddersfield

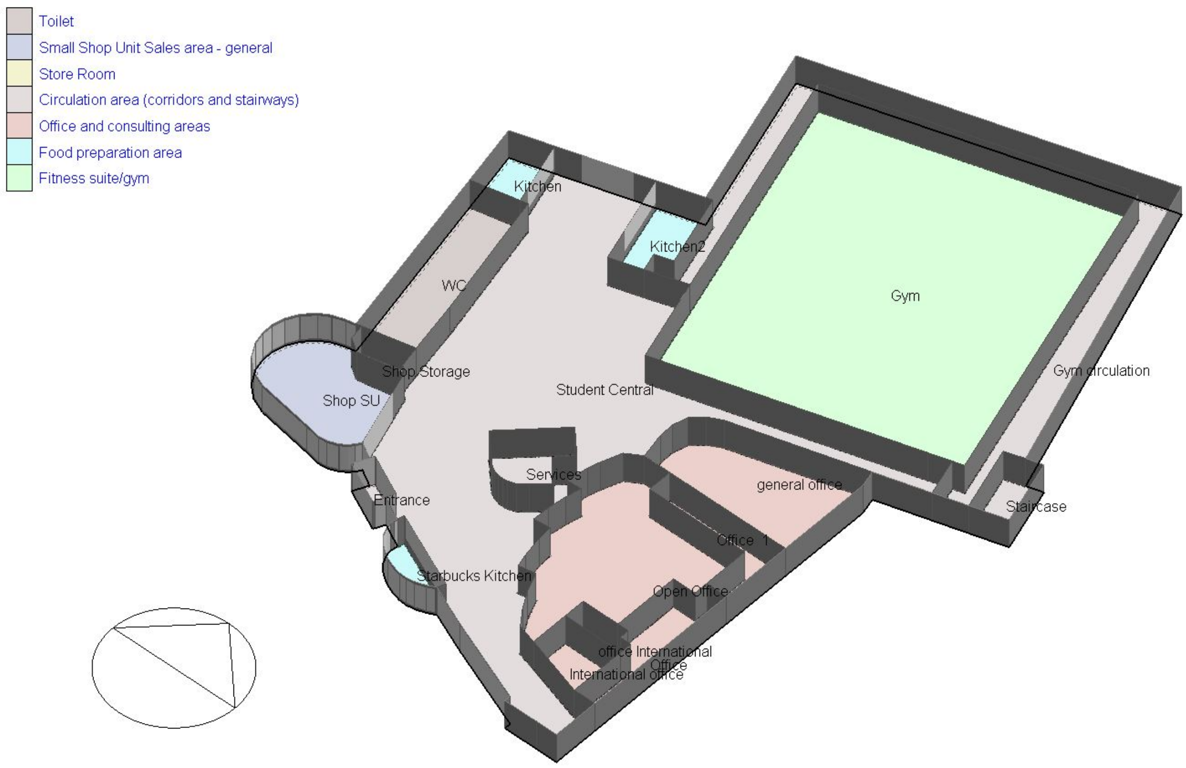


Figure 59. DesignBuilder model and the interior layout of the student central building

5.1.3. Data Collection

A pilot study and preliminary data collection was performed to acquire more information about the case during its post-occupancy stage. The analysis of the pilot study then formed the detailed data collection of the study. In the following subchapters (5.1.3.1. and 5.1.3.2.), pilot study and data collection of the case are explained.

5.1.3.1. Pilot Study

The pilot study included the priliminary observation of the type of spaces and their functions within the multi-functional space, occupants' types of interactions with the spaces and their energy consumption behaviours (both passive and active) followed by collecting data for the duration of 9 hours in one weekday on 31st May 2017. The findings of the preliminary data collection are presented in this section:

- The main functions of the space at the operation stage include: entrance and reception (iPoint), a shop, various sitting areas, food preparation zones and circulation. Also, spaces such as services and offices were directly connected to the multi-functional space of the case.

- The space function and its interior design has evolved after occupancy to place different functions. Figure 60 illustrates the actual diagram of space function and circulation. One of the major changes on the interior layout is the formation of reception area and information point. This space was not fully specified in the initial space layout and the current space takes up more space than planned primarily. It also contains several computers and some electrical heaters.

- Furthermore, different types of furniture used in the big open space, in addition to, the limited availability of electricity sockets, have divided the main sitting areas to different categories: eating areas located near food preparation zones with hard canteen furniture, cosy and quiet studying spaces with electricity sockets, and multi-purpose soft furniture for socialising, gathering, having small group casual meetings etc. The analysis of the collected data confirms that the space furniture has not only shaped the sitting areas and occupants' behaviours, but also, has determined the maximum occupancy of the space during its peak hours.

- Other transformations of the space include adding more food containers in empty spaces of the food preparation area which blocks a part of sunlight coming from the large exterior glazing.

- Also, some of the door on the building exterior are actually fire doors which have restricted use during certain times or by a particular group of occupants, e.g. the glass fire doors in area number 2. The preliminary observation confirmed that space layout and its furniture have a direct influence on the function of each zone.

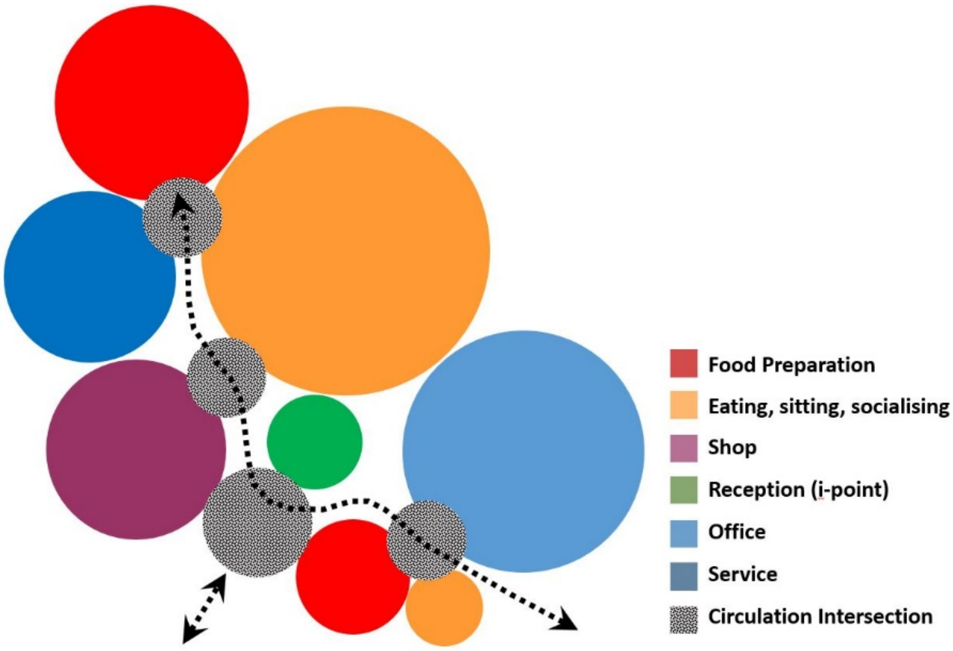


Figure 60. Space function and circulation diagram, student central building, University of Huddersfield, UK

- The student central building is occupied by three groups of people: students, the staff and visitors. The university estates department fully manages building HVAC systems. The pilot study demonstrated that occupants' energy behaviours in the case are limited to their presence, use of entrance door and appliances such as computers and laptops. However, the impacts of using appliances on the total energy consumption of the zone is very minor and neglectable, due to unavailability of electicity sockets in most of the spaces except for zone 11 (Figure 62). Therefore, data collection included hourly observation of the number of people in each space and measurement of the entrance door opening time percentage. The priliminary occupancy data collection results are shown in figure 61.

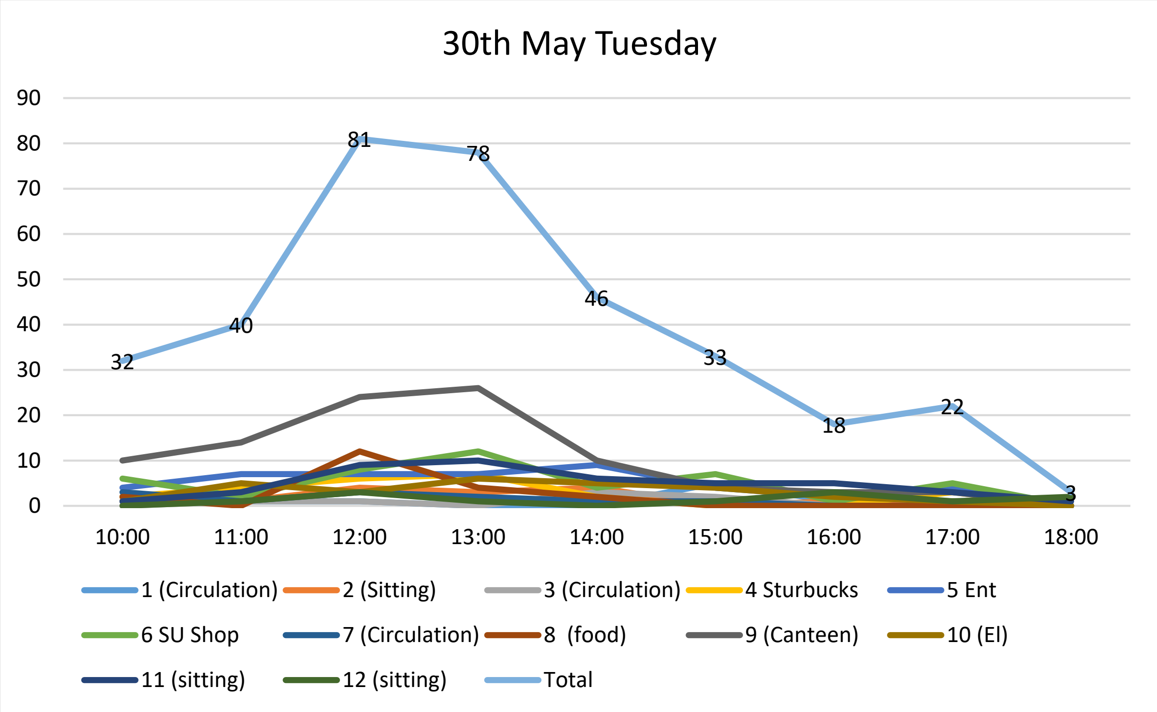


Figure 61. Preliminary occupancy data collection, student central building, University of Huddersfield

5.1.3.2. Zoning

The selected multi-functional space of the student central building is located in an institutional building which has two distinguished occupancy patterns throughout the year: school academic semester and school holiday. The occupancy density in school academic semester months are considerably higher than in non-semester months. Therefore, two sets of weekly data were collected in two months: one week in July which is a non-semester month and one week in November when the building is in full operation with presence of students. Hourly data was collected regarding occupancy and occupants' behaviours from 10:00 AM to 8:00 PM for 3 weekdays which demonstrated the critical hours (such as peak hour). Further specific data were then collected for 2 more weekdays generating more than 40 hours of data for each zone. The observation of post-occupancy uses of space, together with, the actual space layout and furniture, suggested a new diagram of the space utilisation consisting 12 zones. Therefore, the observation process of the case follows the numerical order which is shown in figure 62.

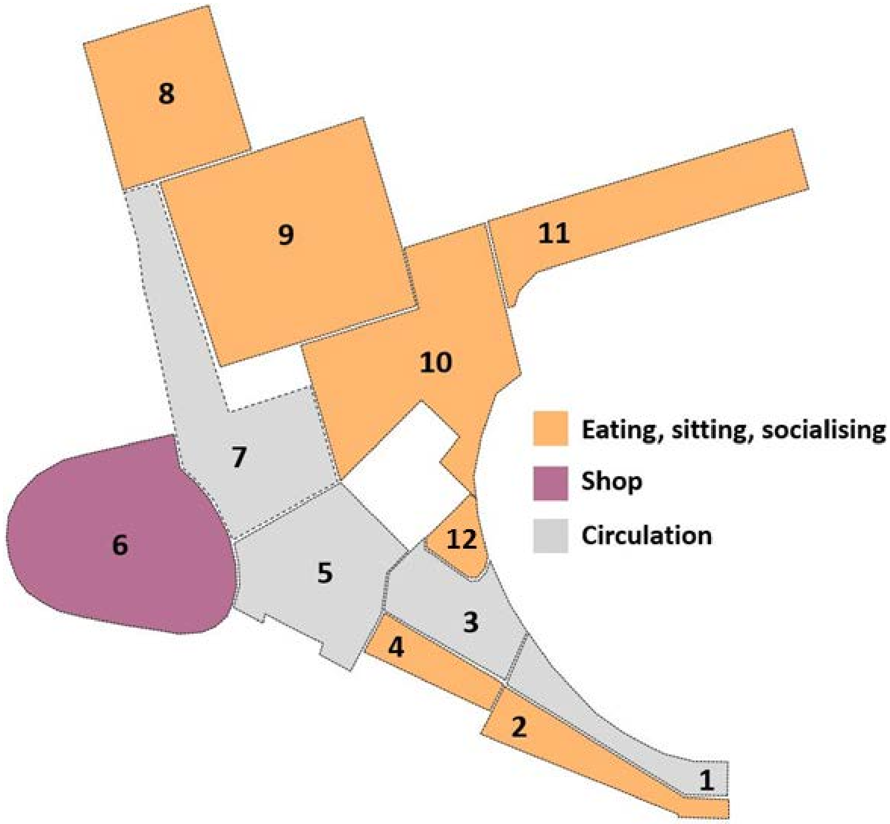


Figure 62. Observation route of the multifunctional space, student central building, Huddersfield, UK

In order to calculate occupancy density for each zone, particularly to estimate maximum occupancy at peak hours which is useful for energy calculations of the case, two sets of data is required: the number of people occupying the spaces and the area (m^2) of each zone. Following the pilot study, data collection was carried out as explained. The comprehensive analysis of the collected data is presented using diagrams in the next section.

5.1.4. Data Analysis

To study the impacts of occupants' active and passive behaviours on the energy consumption of the multi-functional space in student central building at the University of Huddersfield, hourly observation was perfomed. The first collected data was regarding space function and zoning which was comprehensively discussed in the previous section. Working hours, occupancy and door opening were the other parameters investigated in this case study.

5.1.4.1. Working Hours

The building's working hours define its operation period and is a critical parameter in building energy consumption assessment. The longer the working hours are the higher amount of energy is expected to be consumed in the building. In addition, outside temperature and sunlight vary at different times of the day resulting less or more lighting and HVAC requirements in building spaces.

In institutional buildings, prediction of working hours in central multi-functional spaces is a lot more complicated than administrative and teaching spaces. There are not sufficient inputs and assumptions related to multi-functional spaces in public buildings. For instance, the library, gym and postgraduate researchers' offices are among spaces with very dynamic working hours. Therefore, the main entrance and some circulation areas are sometimes in use 24 hours a day. Therefore, specifying accurate working hours for some spaces in university buildings is very challenging. In this study, the HVAC working hours of the building was considered as its operating hours for energy assessment. However, an increase in electricity and lighting consumption is expected in the actual energy consumption of the building due to activities after the business hours.

5.1.4.2. Occupancy: Low season (school holiday)

The data for school holiday month (low-season) was collected for weekdays in a week starting from 3rd July. 29 hourly occupancy data was collected for each of the 12 zones which created the diagrams presented in figures 63, 64 and 65. The data was then complemented by specific hourly data collected for determining peak hours and peak occupancy. Peak hours of the multi-functional space are lunch time between 12:00 PM to 13:00 PM.

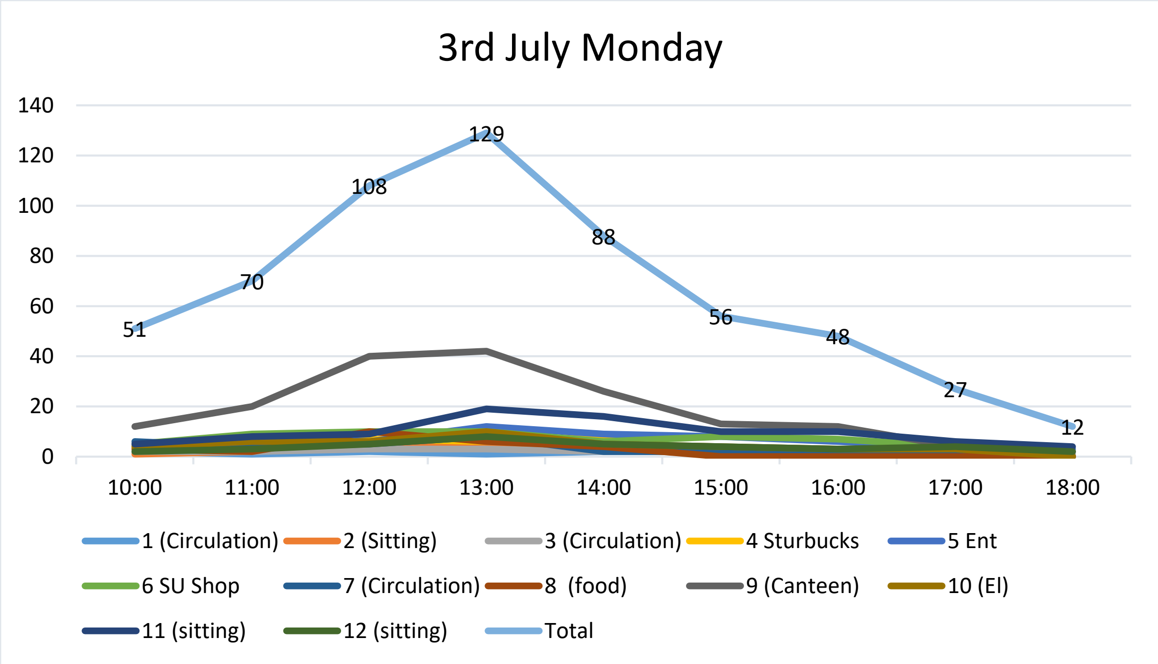


Figure 63. Occupancy data collection, low season, student central building

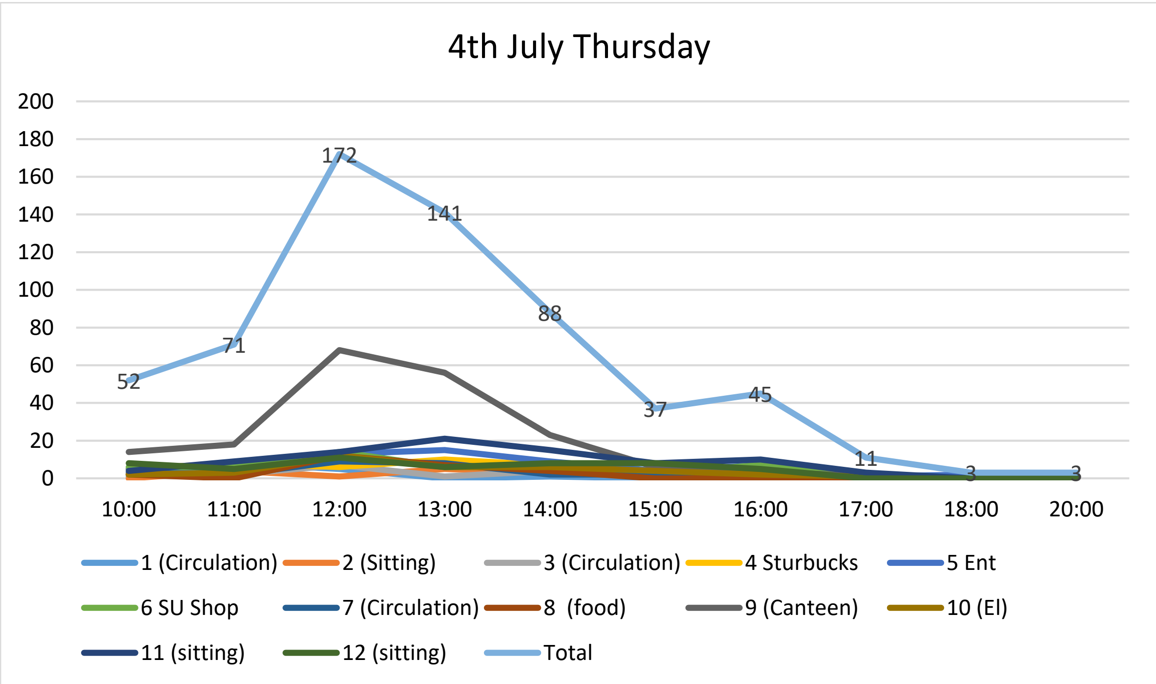


Figure 64. Occupancy data collection, low season, student central building

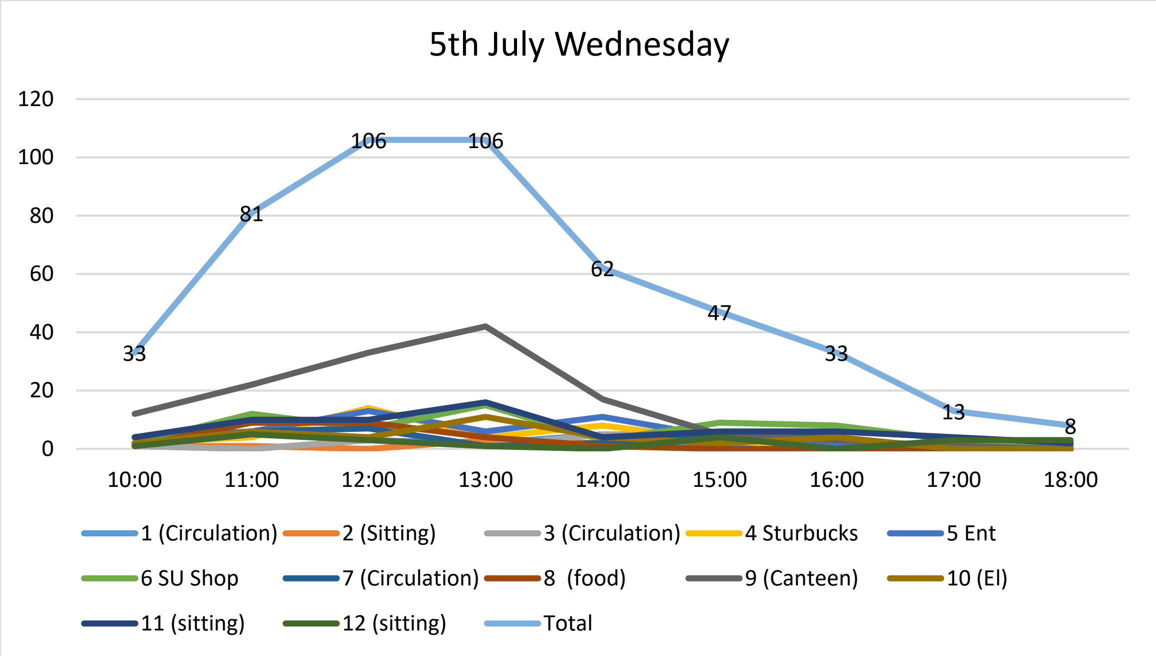


Figure 65. Occupancy data collection, low season, student central building

5.1.4.3. Occupancy: High season (school academic year)

The data for school semester month (high-season) was collected during weekdays in a week starting from 6th November. Similar to the data collection during non-school-semester months, hourly occupancy and door opening data was gathered from 10:00 AM to 6:00 PM for each zone. Figures 66, 67 and 68 present the number of people occupying each zone every hour and the total number of people in the multi-functional space. Further data was collected during peak hours to be used for maximum occupancy calculation in each zone. The peak hours in most of the zones within the multi-functional space are between 12:00 PM to 13:00 PM, which is similar to non-school-semester months.

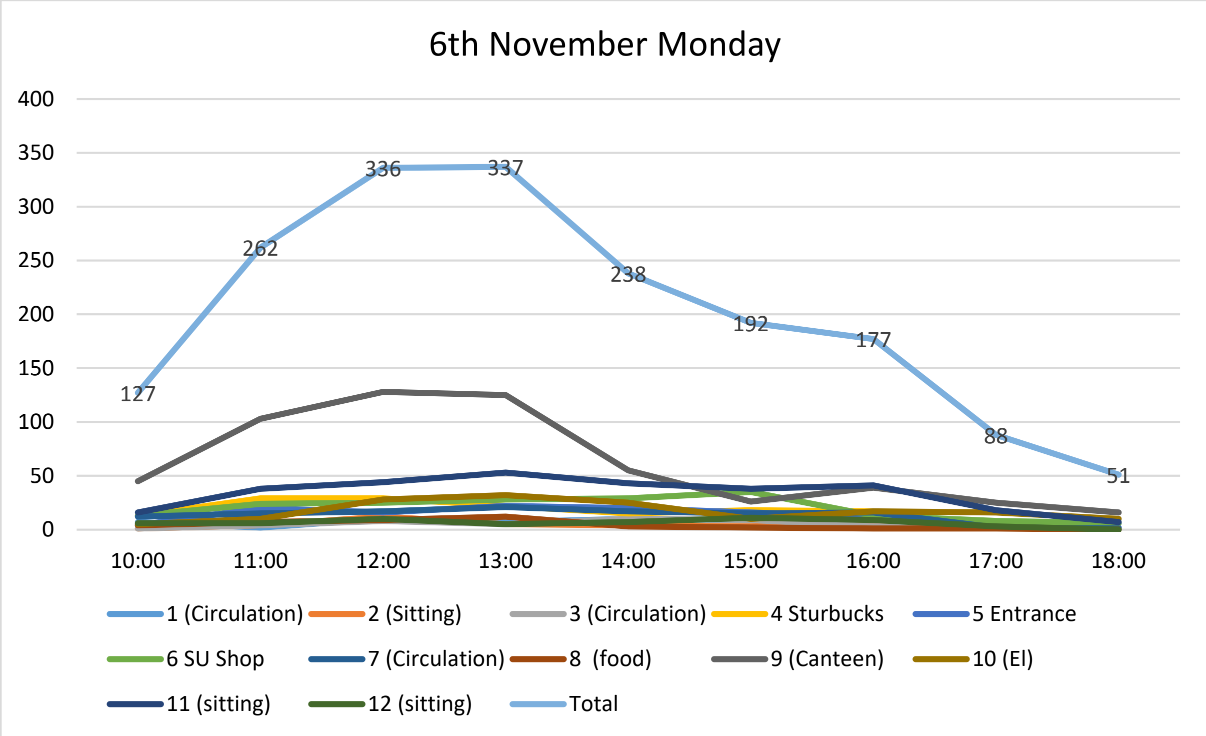


Figure 66. Occupancy data collection, high season, student central building

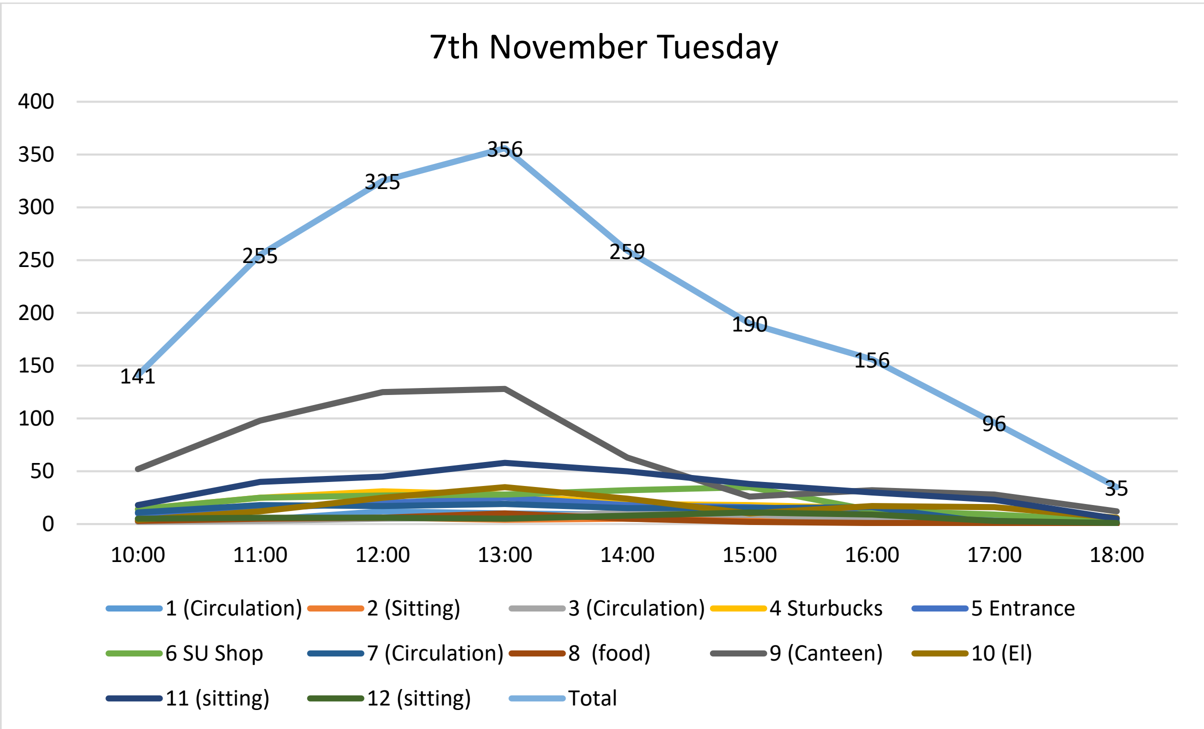


Figure 67. Occupancy data collection, high season, student central building

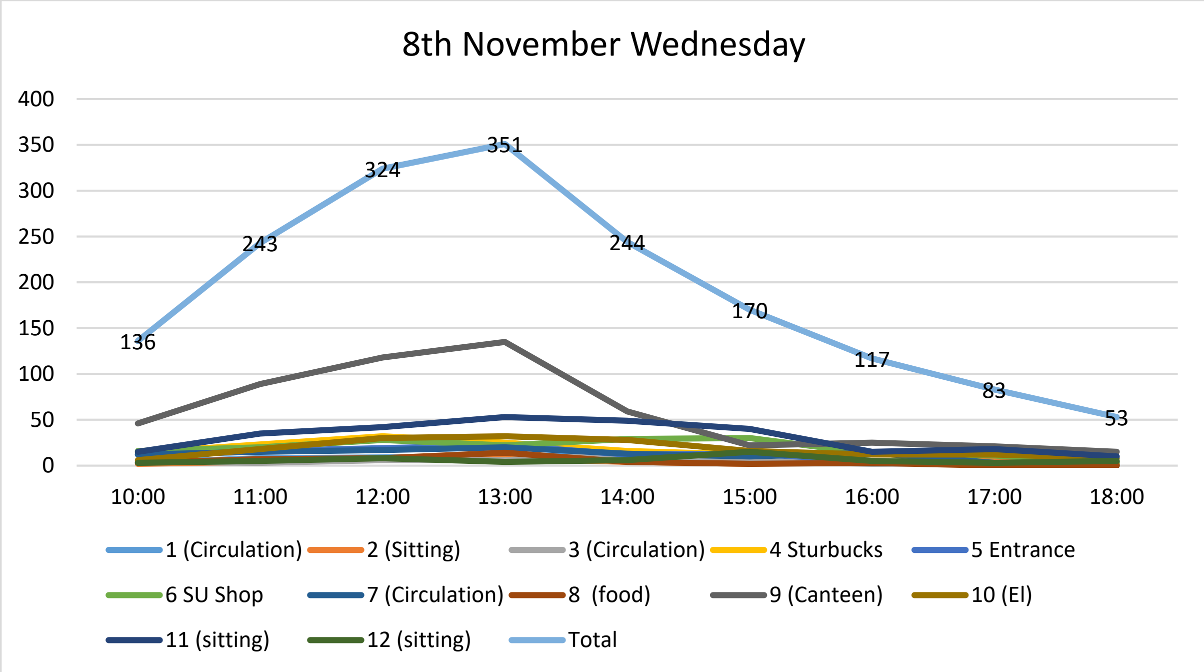


Figure 68. Occupancy data collection, high season, student central building

5.1.4.4. Maximum Occupancy

The occupancy density of the student central building at the University of Huddersfield was conducted during both school semester and non-semester months. In order to integrate the collected occupancy data into DesignBuilder energy simulation tool, the average maximum occupancy density should be assessed. The calculation of maximum occupancy density (people/m^2) for both months (high season and low season) was performed for every zone within the multi-functional space following the below formula which is presented in table 19:

Average number of people at peak hours/ zone area (m^2)= Maximum density (people/m^2)

Zone Function	Area (m^2)	Average Maximum Number of People		Maximum Density (people/m^2)	
		Low Season	High Season	Low Season	High Season
Circulation (1)	81.21	5	10	0.062	0.123
Circulation (3)	59.88	5	9	0.084	0.150
Circulation (7)	178.76	6	21	0.034	0.117

Average maximum occupancy in circulation zones				**0.060**	**0.130**
Entrance (5)	108.96	12	22	**0.110**	**0.202**
Sitting (2)	39.99	5	12	0.125	0.300
Sitting (10)	169.98	16	53	0.094	0.312
Sitting (12)	22.96	6	11	0.261	0.479
Study Area (11)	124.26	10	30	0.080	0.241
Average maximum occupancy in sitting zones				**0.140**	**0.333**
Canteen (9)	245.87	44	128	**0.179**	**0.521**
Starbucks (4)	47.85	10	29	**0.209**	**0.606**
Food shop (8)	110.03	11	12	**0.100**	**0.109**
SU Shop (6)	167.72	14	35	**0.083**	**0.209**

Table 19. Calculation of maximum density for each zone, low season (non-semester) and high season (school semester), student central building

The analysis of the results show that occupancy density during school semester was almost twice the one of non-semester months, which is not considered in energy simulation presumptions. Figure 69 illustrates the gap between the actual average maximum occupancy of each zone within the multi-functional space in Huddersfield student central during both school semester and non-semester months with the standard ASHRAE maximum occupancy.

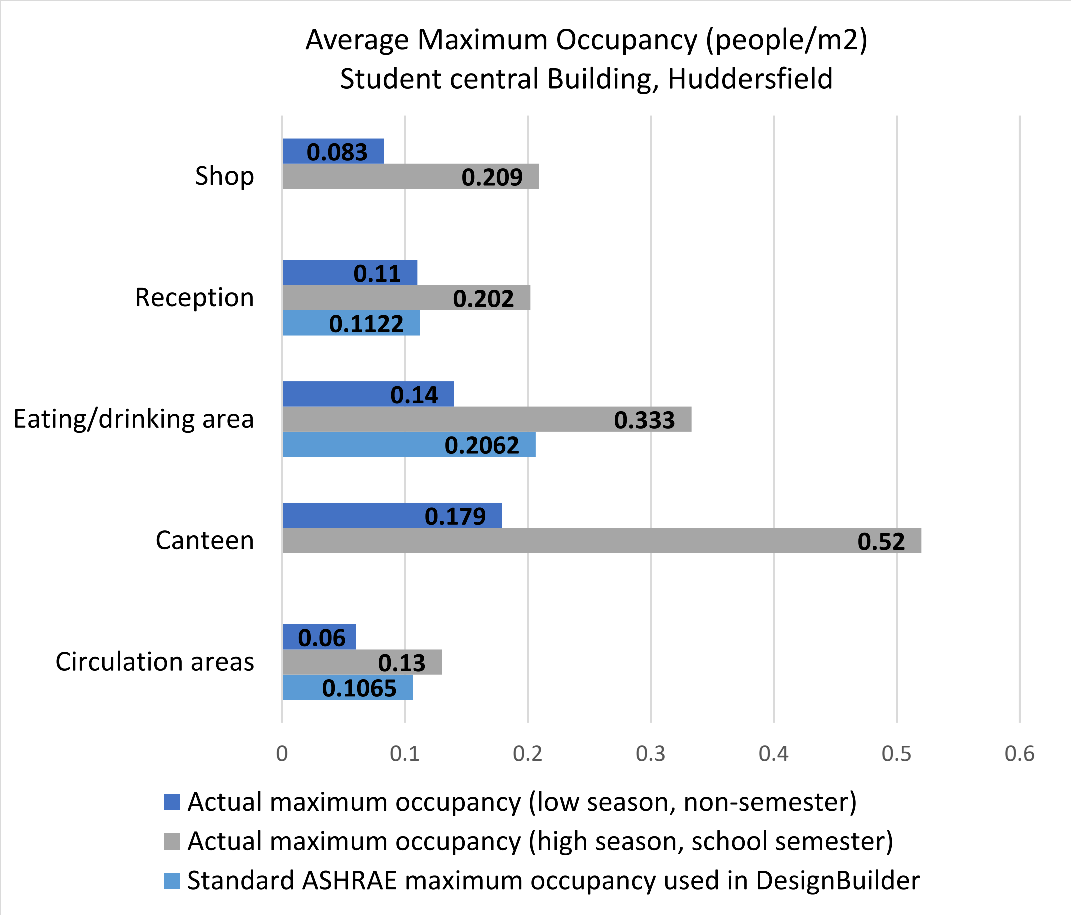


Figure 69. Predicted VS realistic occupancy of student central building, Huddersfield, UK

The analysis of the diagram confirms the following gaps in occupancy presumptions in energy predictions:

- There is a distinct difference between occupancy density in institutional buildings during semester and non-semester months. Depending on the space/zone function, school-semester occupancy density is between 1.8 to 2.9 times more than occupancy density in non-semester months. The occupancy density assumptions in DesignBuilder software (ASHRAE standard) are closer to non-semester occupancy density in Huddersfield student central building.
- The multi-functional spaces in institutional buildings are utilised for various purposes. The function of the space alters as the furniture changes. According to the observation, the presence of a Ping-Pong table in a corner, a temporary performance platform, the availability of electricity sockets and a different arrangement of furniture create new activities and attraction points which changes the occupancy density and consequently, the total energy consumption of the space. The vibrant and dynamic

nature of these spaces makes it difficult to predict the occupancy density accurately. However, the observation of occupancy reveals more realistic patterns, which can be used to develop energy assessment predictions. This study confirms that using data regarding permanent space furniture to estimate the maximum occupancy of each zone improves the accuracy of the occupancy density predictions in multi-functional spaces of public buildings.

- Reception, eating and drinking and circulation areas were the only relevant types of spaces to the multi-functional space of the case in activity section for university buildings in the simulation software. While analysing the energy consumption of the multi-functional space using default software values, reception and eating and drinking areas were not specified clearly on the plans, so the whole zone was considered as circulation areas (See: 5.1.2. Energy Modelling and Simulation (Default)). Designbuilder does not have default values for shops within university buildings.Therefore, one of the challenges during the process of energy assessment of this case before collecting the occupancy data was to select space function for the small retail unit in the multi-functional space. In DesignBuilder, there is a separate category of sales areas (not within university section) called “small shop unit sales area” which was selected for the shop during the initial energy assessment using software default values. This confirms that software presumptions about such spaces are not sufficient and there is a need to expand the list of space functions and activities to have accurate occupancy presumptions for energy consumption prediction of multi-functional spaces of public buildings.

5.1.4.5. Door Opening

Door opening data for Huddersfield student central building was conducted in two weeks during weekdays: low season and high season. Therefore, 17 hours of data was collected in June, which is a non-semester month, and 15 hours of data was conducted in September and November. In central institutional buildings like this case, usually there is a great flow of people entering/ leaving the building constantly and passing within its spaces, which results a very high door opening time percentage.

The main entrance consists of two automatic sliding doors that create a small buffer zone between outside and inside of the building. However, the space between two doors is very small (9.34 m2) and it does not fully function as a thermal buffer zone to reduce unwanted air exchange (Figure 70). In cold seasons, when the door opening percentage is high (school semester peak hours), even availability of an air curtain above the door fails to maintain thermal comfort in spaces connected to the entrance area. For example, in the reception area (called i-point) which is located right in front of the entrance, extra electrical heating devices are used to provide thermal comfort for the full-time staff and part-time student staff who work in this area and all the visitors. In windy days, not only in the spaces such as the reception, café and shop that are immediately linked to the entrance door, but also, in the inner spaces the air exchange can be noticed.

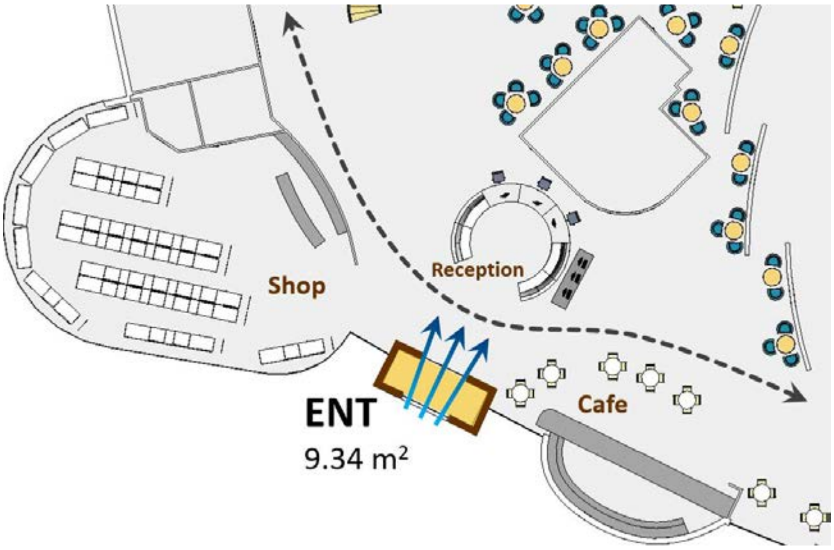


Figure 70. The main entrance, student central building, Huddersfield

The collected data shows that the entrance door in student central building has high opening time percentage both in school semester and non-semester months (Figure 71). In school semester months, between 13:00 to 15:00, the entrance door is always open because of the great number of people entering and leaving the building. Even after the normal working hours, the door opening time percentage is a lot more than software presumptions regarding door opening. The data displayed in figure 71 is the average of door opening time data collected from 10:00 to 20:00 during weekdays in two weeks, rounded to the nearest 5.

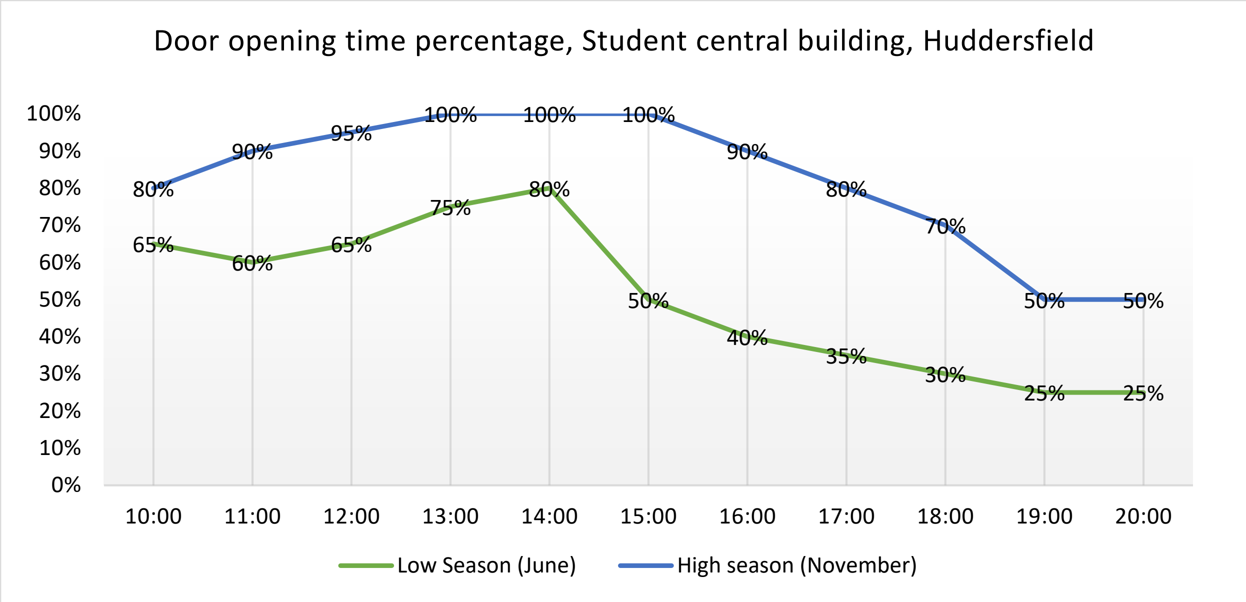


Figure 71. Hourly door opening time percentage during weekdays in low and high seasons rounded to the nearest 5

The analysis of the impacts of door opening on this case suggests that parameters such as design features of entrance space, door opening time setting, the differences between inside and outside air pressure (wind intensity) and temperature, interior layout, in addition to, the frequency of the entrance door utilisation impact occupants thermal comfort and the energy consumption of the building.

5.1.5. Energy Modelling and Simulation (Collected Data)

The initial simulation period for the second case study of this research (Huddersfield student central building) was the coldest week of the year from 17th to 23rd February. The selected period is the so called "winter design week" determined by the weather data in DesignBuilder simulation tool (DesignBuilder). The incorporation of all collected data with energy simulation tool (including zoning, occupancy patter and density and door opening) provides a quantitative comparison between the realistic and predicted energy consumption of the multi-functional space of the case. The simulation results of total energy, heating and electricity consumption using default and collected data are presented in table 20.

- The significant gap between the actual door opening time percentage (average maximum 85%) and software default door opening data (Maximum 5%) caused a great gap between the actual and predicted energy consumption.

Student Central Building, University of Huddersfield Simulation Duration: 17-23 Feb (Winter Design week)				
Simulations	Total Energy Consumption (kWh)	Heating (kWh)	Space Heating (kWh)	Electricity (kWh)
Predicted energy consumption using default inputs (with natural ventilation)	7978.15	3141.04	3103.6	4755.25
Actual door opening data	10177.25	5372.84	5335.4	4755.25
Actual space zoning	12215.22	5523.42	4040.1	5663.63
Actual working hours	No changes in working hours			
Actual space zoning and occupancy density	13993.78	7386.75	5903.43	5663.63
Energy consumption using more realistic inputs (All actual data: door opening, space zoning and occupancy)	15083.01	8590.89	7107.57	5663.63

Table 20. "Winter design week" simulation results: the gap between realistic and predicted energy consumption in Huddersfield student central building

For institutional buildings, there are two distinct patterns of occupancy and human-behaviour-related parameters in school semester and non-semester months. Therefore, another round of energy consumption prediction of the case was performed. Once, using initial software assumptions (referred to as predicted energy consumption), and then, using the actual observed data (realistic energy consumption) from 1 September to 31 May which is the official school semester period. Table 21 and figure 72 present the summary of the energy simulation results.

Simulation Duration		Total Energy Consumption (kWh)	Heating (kWh)	Electricity (kWh)
Predicted	1 Sep to 31 May	257557.04	60118.91	177132.32
Actual	1 Sep to 31 May	491362.72	224939.4	211569.54

Table 21. School semester simulation results: the gap between realistic and predicted energy consumption in Huddersfield student central building

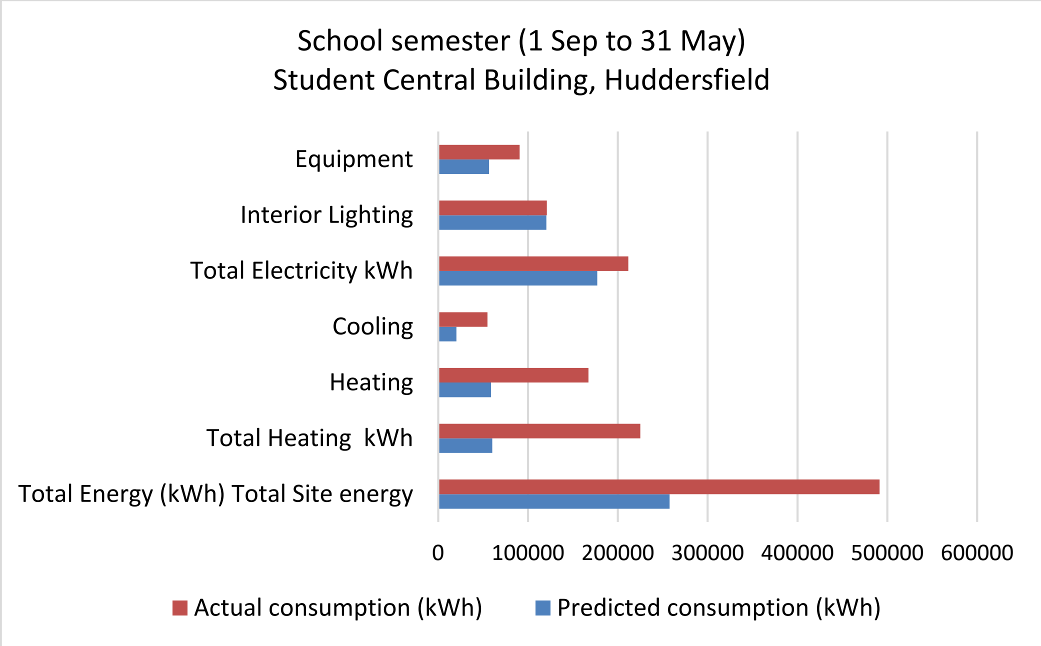


Figure 72. Realistic and predicted energy demand in student central building, University of Huddersfield, categorised by the sources of energy consumption

The analysis of the results suggests a great gap between both simulation results of the studied space.

- The simulation using collected door opening, space zoning and occupancy density data predicts 91% more energy consumption in comparison to the default simulation result.
- The final simulation results show that heating consumption of the space is 274% more than the initial prediction. The gap was caused by unrealistic assumptions regarding door opening, zoning and occupancy.

5.2. Post-Occupancy Stage Case Study: Manchester Art Gallery

5.2.1. Case Study Description

Manchester art gallery, placed in Manchester city centre, is one of the most remarkable galleries and art museums in North England with over half a million visitors per year (Figure 73). It is a publicly owned building managed by Manchester city council and is free to enter. Manchester art gallery was first built in the 19^{th} century (1823). It later expanded to accommodate more galleries and collections which occupy three joined buildings. Two of the three connected buildings are among listed buildings with significant historical values.

Figure 73. Manchester Art Gallery

The building exterior has a simple cubic volume, but, the building interior is more complex containing three floors with various connected spaces and voids (Figure 74). The ground floor consists of: an entrance hall, two exhibition areas, a shop, an information desk (reception) and another entrance area, a café and restaurant with two sitting areas, teaching and learning rooms and services. The first and second floors accommodate various exhibition and gallery spaces and circulation areas. The whole building (except for training and lecture sections and services) can be considered as one energy zone in energy calculations as its different spaces are not fully enclosed by walls.

Figure 74. Manchester art gallery, interior space

The building has two main entrances and one direct entrance to the restaurant and café. One of the main entrances has a wooden historic door connected to an entrance hall, and the other one has a newly built glass revolving door which opens to the receiption and information space. The ground floor is a multi-functional space with various directly connected zones. Figure 75 shows a 3D view of the selected multi-functional space in Manchester art gallery, highlighting its relation to entrances, vertical circulations and staircases and various connected spaces that it contains.

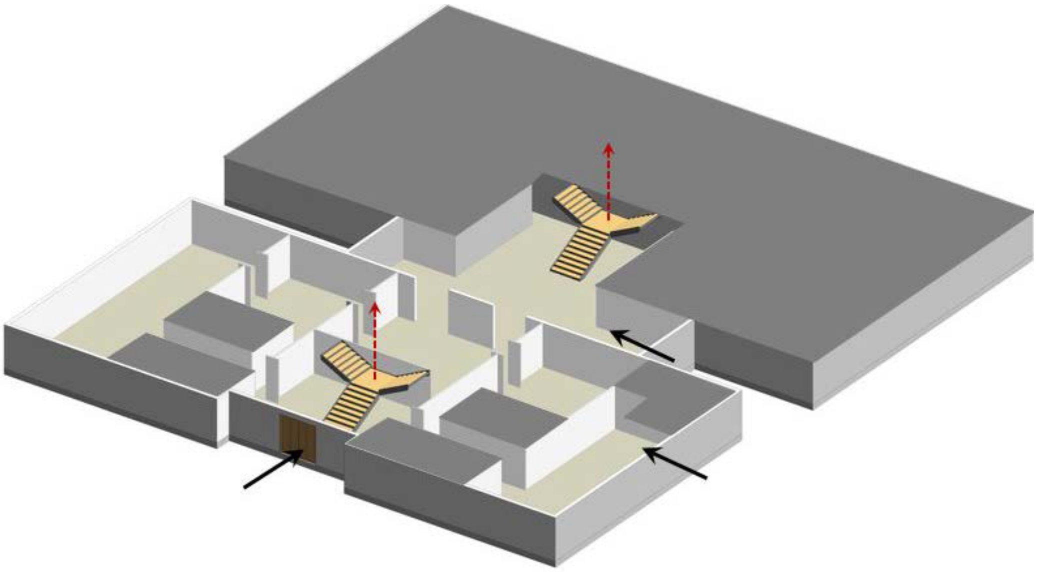


Figure 75. Manchester art gallery ground floor 3d view

5.2.2. Energy Modelling and Simulation (Default)

For the purpose of this study, in order to study the energy consumption of a set of spaces located at the ground floor of Manchester art gallery, the building was modelled in

DesignBuilder energy simulation tool using the available architectural plans. Also, further general information about the building were gathered by contacting various managers at the Manchester art gallery directly. For energy modelling of the case, the ground floor of the building was modelled in details and the building floors were modelled as simple building blocks which allowes to run multiple specific energy calculations on the multi-functional space of the case (Figure 76). The building has a simple volume which made the energy modelling stage less challenging in comparison to other cases.

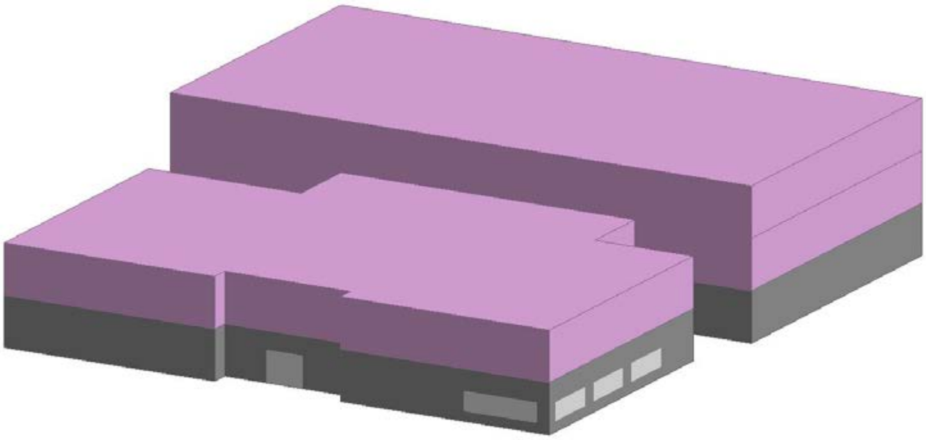


Figure 76. DesignBuilder model of the Manchester art gallery

Similarly, the internal layout and arrangement of various zones within the multi-functional space are very clear. Different spaces are partly disconnected using walls.

Figure 77. Interior layout of the multi-functional space in DesignBuilder model of Manchester art gallery

5.2.3. Data Collection

The preliminary observation of the interaction of occupants in various zones of Manchester art gallery confirmed that occupants' energy consumption behaviours are limited to occupancy and door opening. Therefore, after specifying the function of each zone within the selected multi-functional space, occupancy and door opening were studied during working hours of the building which are discussed in the next sections.

5.2.3.1. Zoning

Following the initial zoning of the spaces in Manchester art gallery using its available architectural plans, the preliminary observation was carried out. As, the internal layout of the case clearly separated various functions by walls with some openings, the observation confirmed the initial zoning. To collect occupancy data in different zones, the observation routes were created for every floor of the building which are illustrated in Figures 76, 77 and

78. The data collection route for the multi-functional space located at the ground floor of the building, for which the detailed energy consumption analysis is perfomed, started from the main entrance (number 1) and ended at the main reception and information point (number 7) where circulations to upper levels are located (Figure 76). The data collection was then extended to floors 1 and 2.

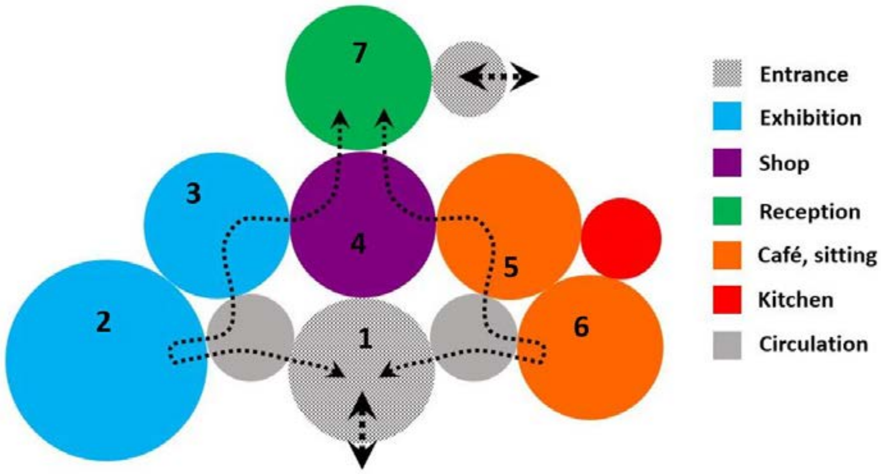


Figure 78. Space function and observation route diagram, ground floor, Manchester art gallery

The first and second floors consist of various galleries, exhibitions and circulation areas (Figures 77 and 78). The observation of these floors was carried out with the aim to link the presence of occupants in the ground floor with their activities on other parts of the building where the main function of the building takes place and to further study occupancy density and patterns of the building.

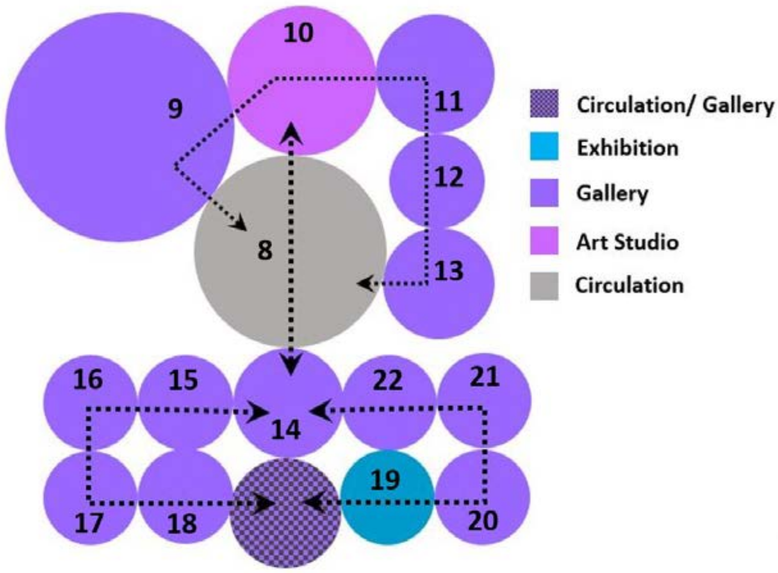


Figure 79. Space function and observation route diagram, 1st floor, Manchester art gallery

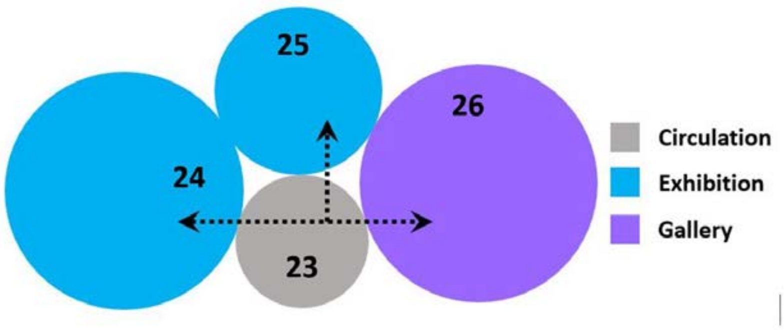


Figure 80. Space function and observation route diagram, 2nd floor, Manchester art gallery

5.2.3.2. Occupancy

In order to analyse occupancy in various zones of Manchester art gallery, three sources of data were used in this study: UK governmental data of monthly visits of 57 museums and galleries (Delaney, 2017), Google "popular times" real-time data and observation (Figure 81).

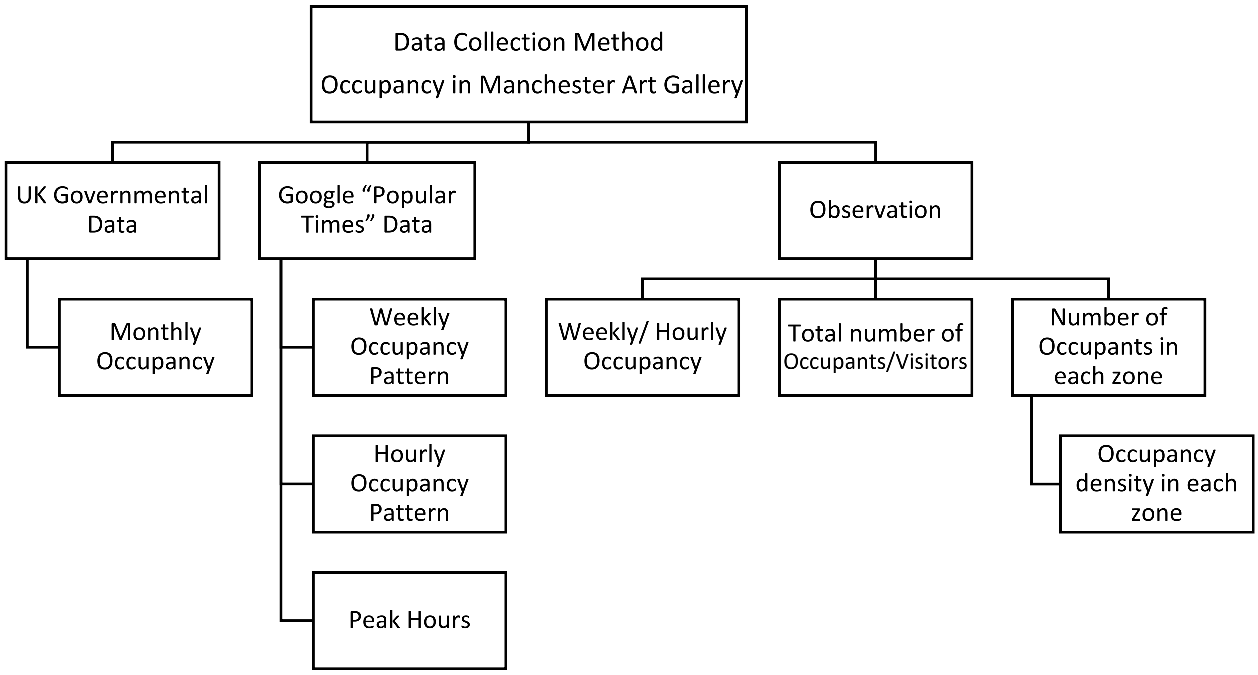


Figure 81. Data collection methods to capture occupancy in different zones of Manchester art gallery

Monthly occupancy patterns of the building are taken from the wide-ranging governmental data regarding total monthly visits of 57 museums and galleries in UK between 2008 and 2017 (Figure 82). The data allows conversion of occupancy data in a month to estimate occupancy in other months throughout the year.

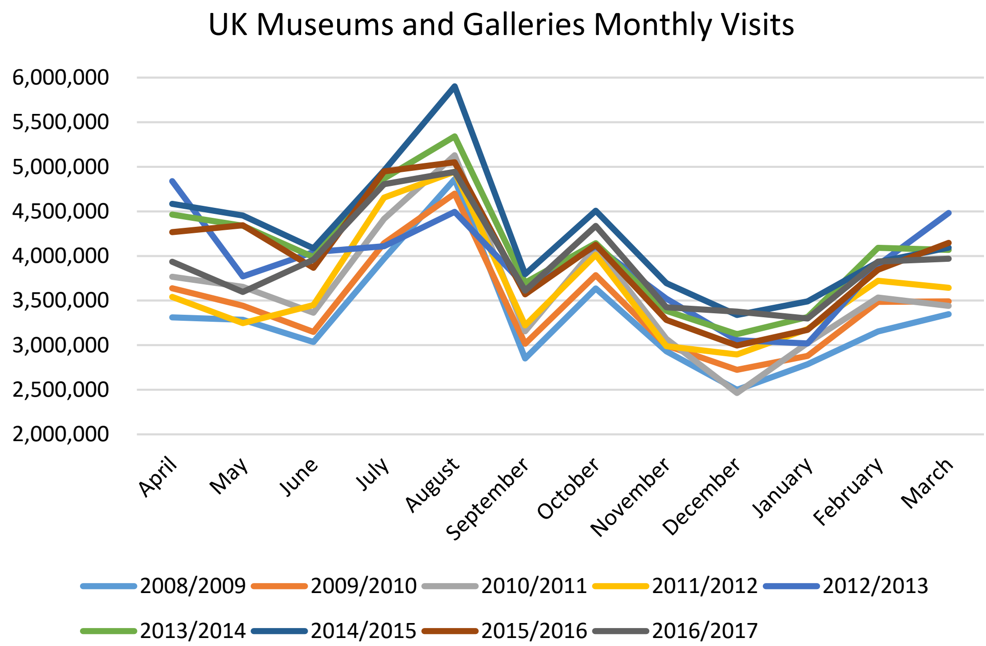


Figure 82. Total museums and galleries monthly visits in UK: 57 centres, source of data: (Delaney, 2017)

The number of visitors in galleries have high monthly variations which are not fully contemplated into default occupancy schedules of energy simulation tools. In some energy simulation tools such as DesignBuilder, the seasonal variations in buildings are only considered by “summer and winter design” schedules. However, the actual monthly visits of galleries and museums follow other distinctive patterns that are shown above. According to the aforementioned UK governmental data regarding the monthly visits of museums and galleries (Delaney, 2017) there is 33% difference between occupancy in high-season and low-season months. According to the data, in 2016-2017 the highest number of visits happened in August and July and the lowest number of visits happened in January, December and November. Table 21 illustrates the ratio of monthly visits of galleries and museums in the UK over the highest monthly visit in August.

2016-2017			
Months	Total Gallery Visitors	Ratio of monthly Occupancy over the highest monthly occupancy (August)	
April	3,935,139	0.80	
May	3,596,291	0.73	
June	3,959,636	0.80	
July	4,805,539	0.97	
August	4,943,777	1	Maximum
September	3,610,540	0.73	
October	4,337,514	0.88	
November	3,424,767	0.69	
December	3,375,506	0.68	
January	3,299,349	0.67	Minimum
February	3,936,889	0.80	
March	3,969,880	0.80	
Total	47,194,827		

Table 22. Total museums and galleries monthly visits in UK (57 centres), 2016-2017

Google has recently provided a service called “Google popular time” which uses location-based mobile services (such as GPS) to launch real-time information about the number of people visiting specific buildings (Silva & Silva, 2018). The great number of people being connected to google at all times or most of the time, gives a high credibility to the data it provides. Another advantage of this open web service is its availability to all users of internet (Toepke, 2017). Therefore, Google popular times data has been used in various recent studies on the estimation of occupancy, population and mobility patterns (Neves et al., 2016; Nunes, Ribeiro, Prandi, & Nisi, 2017; Silva & Silva, 2018; Toepke, 2017). For Manchester art gallery, the availability of “Google popular times” data, provided information regarding occupancy patterns and peak hours (Figure 83).

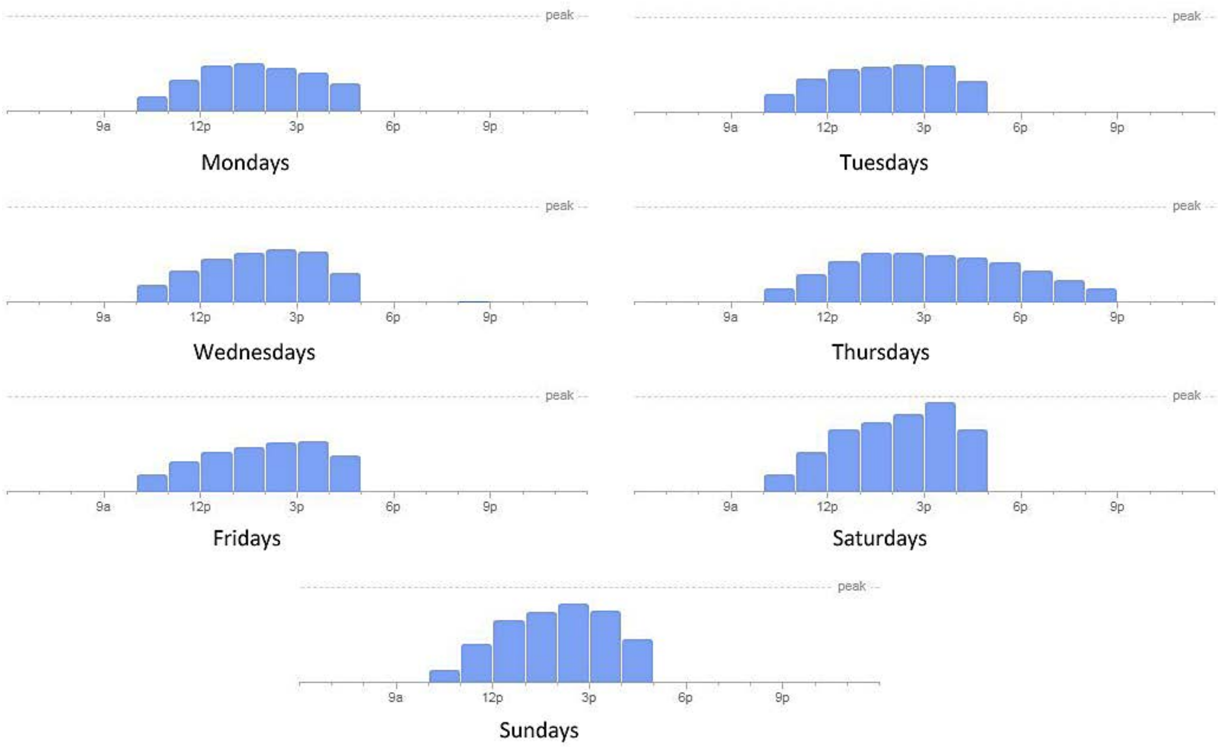


Figure 83. Manchester Art Gallery weekly occupancy, Google “popular times” graph

The hourly occupancy, total numbers of occupants/visitors and the number of occupants in each zone was collected using hourly observation of the zones following the “observation route” (see: Data collection, zoning). The observation of the case was done in 2 weeks: the first week was a pilot study to capture zoning and to modify the observation technique, and in the second week the data was collected during weekdays and weekends. Occupancy density of each zone was then calculated using the number of people in each zone and the area (m2) of each zone. The hourly observation also included hourly measurement of door opening time percentage. In the next section the further analysis of the data is presented (see: Data collection, Occupancy).

5.2.4. Data Analysis

The investigation of the primary and secondary data suggest various gaps between actual and predicted human-behaviour-related factors used in prediction of energy consumption in Manchester art gallery including building working hours, occupancy and door opening. The actual data was also analysed to be used in DesignBuilder energy simulation tool to quantify the gap between actual and predicted energy consumption. The following sections further explain each of the aforementioned parameters.

5.2.4.1. Working Hours

The comparison of software default working hours for exhibition and gallery building types and the actual working hours of Manchester art gallery demonstrates a big difference (Figure 84). Usually, galleries and exhibitions are not only open during weekends, but the most crowded. That is to encourage the majority of visitors who work and study during weekdays, visit cultural buildings at the weekends. Manchester art gallery's working hours is 6 hours less than predicted. Another unrealistic assumption regarding working hours of cultural buildings is their opening times: It is very uncommon to see such buildings open at 8 am.

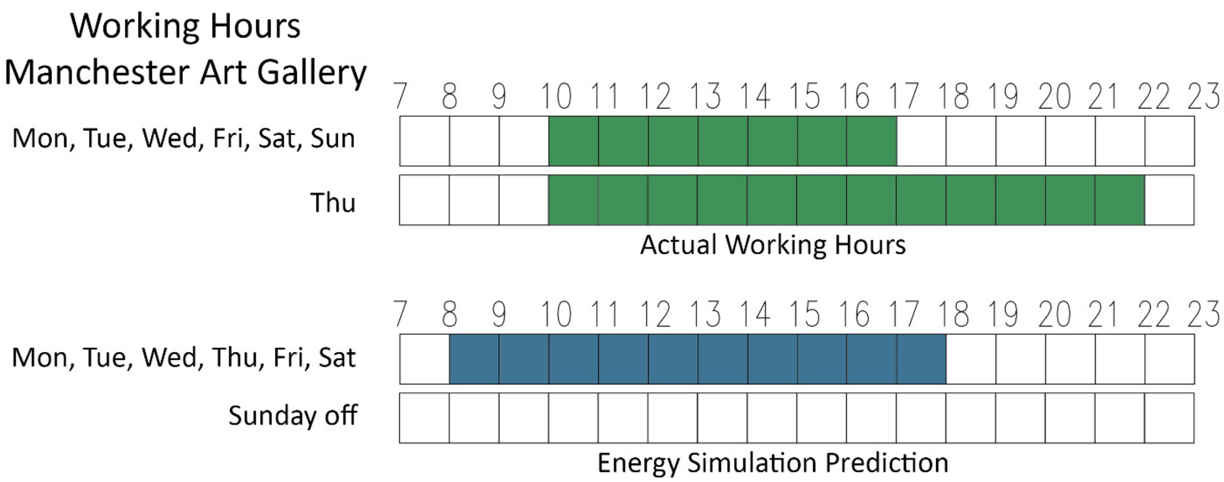


Figure 84. Predicted VS actual working hours, Manchester art gallery, UK

5.2.4.2. Occupancy

The analysis of both observed data and the daily/hourly occupancy data driven from "Google popular times" showed that the maximum daily/hourly occupancy in Manchester art gallery is in midday between 13:00 and 16:00. The highest Daily occupancy of Manchester art gallery is from 15:00 to 16:00 on Saturdays and the lowest occupancy happens on Sunday mornings between 10:00 and 11:00. Table 2 shows the ratio between the daily/hourly occupancy of Manchester art gallery and its maximum occupancy that happens from 15:00 to 16:00 on Saturdays. The comparison between Table 23 and ASHRAE occupancy pattern used in DesignBuilder show the gap between the predicted and actual occupancy pattern of the building (Table 24). The actual occupancy pattern of the case study is illustrated in Table 3 that is the result of data analysis in this research.

Hourly	Weekly/ Daily						
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
10:00 - 11:00	0.18	0.20	0.20	0.16	0.19	0.19	**0.15**
11:00 - 12:00	0.36	0.37	0.37	0.31	0.34	0.44	0.44
12:00 - 13:00	0.52	0.48	0.49	0.46	0.45	0.70	0.70
13:00 - 14:00	**0.55**	0.51	0.56	**0.56**	0.49	0.77	0.80
14:00 - 15:00	0.49	**0.53**	**0.60**	**0.56**	0.55	0.87	**0.89**
15:00 - 16:00	0.44	0.52	0.57	0.53	**0.57**	**1**	0.80
16:00 - 17:00	0.32	0.35	0.33	0.50	0.41	0.69	0.49
17:00 - 18:00	-	-	-	0.45	-	-	-
18:00 - 19:00	-	-	-	0.36	-	-	-
19:00 - 20:00	-	-	-	0.26	-	-	-
20:00 - 21:00	-	-	-	0.16	-	-	-
Average daily occupancy ratio comparison (ranging from 1 to 0)	0.40	0.42	0.44	0.39	0.42	0.66	0.61

Table 23. Manchester Art Gallery, Hourly/daily occupancy ratio comparison

Occupancy pattern in gallery spaces	
Realistic occupancy pattern	Predicted occupancy pattern (DesignBuilder, ASHRAE data)
Schedule:Compact, LibMusGall_Circulation_Occ, Fraction, Through: 31 Dec, For: Weekdays SummerDesignDay, Until: 10:00, 0, Until: 11:00, 0.2, Until: 12:00, 0.35, Until: 16:00, 0.5, Until: 17:00, 0.30, Until: 24:00, 0, For: Weekends, Until: 10:00, 0, Until: 11:00, 0.2, Until: 12:00, 0.45, Until: 13:00, 0.7, Until: 14:00, 0.8, Until: 15:00, 0.9, Until: 16:00, 1, Until: 17:00, 0.6, Until: 24:00, 0,	Schedule:Compact, LibMusGall_CirculationPub_Occ, Fraction, Through: 31 Dec, For: Weekdays SummerDesignDay, Until: 07:00, 0, Until: 08:00, 0.25, Until: 09:00, 0.5, Until: 12:00, 1, Until: 14:00, 0.75, Until: 17:00, 1, Until: 18:00, 0.5, Until: 19:00, 0.25, Until: 24:00, 0, For: Weekends, Until: 07:00, 0, Until: 08:00, 0.25, Until: 09:00, 0.5, Until: 12:00, 1, Until: 14:00, 0.75, Until: 17:00, 1,

For: Holidays, Until: 10:00, 0, Until: 11:00, 0.2, Until: 12:00, 0.45, Until: 13:00, 0.7, Until: 14:00, 0.8, Until: 15:00, 0.9, Until: 16:00, 1, Until: 17:00, 0.6, Until: 24:00, 0, For: WinterDesignDay AllOtherDays, Until: 24:00, 0;	Until: 18:00, 0.5, Until: 19:00, 0.25, Until: 24:00, 0, For: Holidays, Until: 07:00, 0,

Table 24. Realistic and predicted occupancy pattern in DesignBuilder occupancy format

The analysis of the table suggests a distinct gap between the actual and predicted occupancy pattern. Especially during weekends, when the maximum occupancy is twice the maximum occupancy of the weekdays.

5.2.4.3. Maximum Occupancy

The occupancy density of Manchester art gallery was conducted for duration of a week. Using "Google popular times", the peak hours were specified (See: 4.4.2. occupancy and 4.3.1. occupancy). The average maximum occupancy was then calculated considering the ratio between peak hours in each day. For example, the maximum occupancy on Saturdays is 89% of the maximum occupancy on Sunday. The calculated maximum occupancy for each zone is presented in Table 25. For spaces such as exhibitions and galleries

Zone Function	Floor	Maximum number of people	Area (m^2)	Maximum Density (people/m^2)
Entrance	Ground Floor	14	115.1	**0.122**
Shop	Ground Floor	18	115.2	**0.156**
Café	Ground Floor	56	85.95	**0.652**
Café sitting	Ground Floor	9	85.1	**0.106**
Exhibition 1	Ground Floor	43	169.2	0.254
Exhibition 2	Ground Floor	8	85.49	0.094
Exhibition 11	Frist Floor	4	99.96	0.040
Exhibition 17	Second Floor	4	355.2	0.011
Exhibition 18	Second Floor	10	169.3	0.059

Average in Exhibitions		69	879.14	**0.078**
Gallery 3 (18th Century)	Frist Floor	4	99.96	0.040
Gallery 4 (Late 18th Century)	Frist Floor	5	90.92	0.055
Gallery 5 (19th Century)	Frist Floor	10	77.32	0.129
Galley 6 (Romanticism)	Frist Floor	3	85	0.035
Gallery 7 (Pre-Raphaelites)	Frist Floor	14	159.6	0.088
Gallery 8 (19th Century)	Frist Floor	7	85	0.082
Gallery 9 (19th Century)	Frist Floor	8	67.72	0.118
Gallery 10 (Late 19th Century)	Frist Floor	8	79.63	0.100
Gallery 12 (The Edwardians)	Frist Floor	13	355.2	0.037
Gallery 14 Art in the Netherlands	Frist Floor	5	88.02	0.057
Gallery 15 Art in the Netherlands	Frist Floor	2	103.4	0.019
Gallery 16 Lowry and Valette	Frist Floor	4	143.4	0.028
Average in Galleries		83	1435	**0.058**
Clore Art Studio	Frist Floor	21	169.3	0.124
Design Gallery 19	Second Floor	8	335.6	0.024
Balcony	Frist Floor	9	93.38	0.096
Bridge	Frist Floor	3	87.52	0.034

Table 25. Calculation of maximum density for each zone, Manchester Art Gallery

Figure 85 compares the actual average maximum occupancy of each zone within the multi-functional space in Manchester art gallery with the standard ASHRAE maximum occupancy. The data was collected in the month of November to avoid monthly variations. As shown in the diagram (Figure 85), the analysis of the data suggests the following gaps:

- In DesignBuilder, there are default assumptions for reception, eating and drinking areas and services in gallery, exhibition and libraries. However, “display and public areas (public circulation, galleries and exhibitions)” are all defined under one category.

Manchester art gallery contains permanent painting galleries, in addition to, some temporary exhibition areas. Occupancy density in exhibitions was about 25% higher than permanent gallery areas.

- This study shows differences in occupancy density and patterns of the entrance and other circulation areas. All circulation areas in cultural buildings (galleries, exhibitions and libraries) have the same occupancy presumption in energy simulation tools including the main entrance, primary staircases and secondary corridors.
- There are no default assumptions in energy simulation tools for some types of spaces in public buildings. For example, most of the cultural buildings have gift shops. However, retail spaces and shops are not considered in galleries, exhibition and libraries list of spaces. The type of activity and attraction factor in retail units increase occupant’s duration of presence. Consequently, such spaces sometimes have much higher occupancy density rates than other display and public areas in galleries. For instance, in Manchester art gallery, the occupancy in the shop, which is located in the centre of the ground floor, is nearly 5 times higher than circulation areas and 3 times more than galleries.

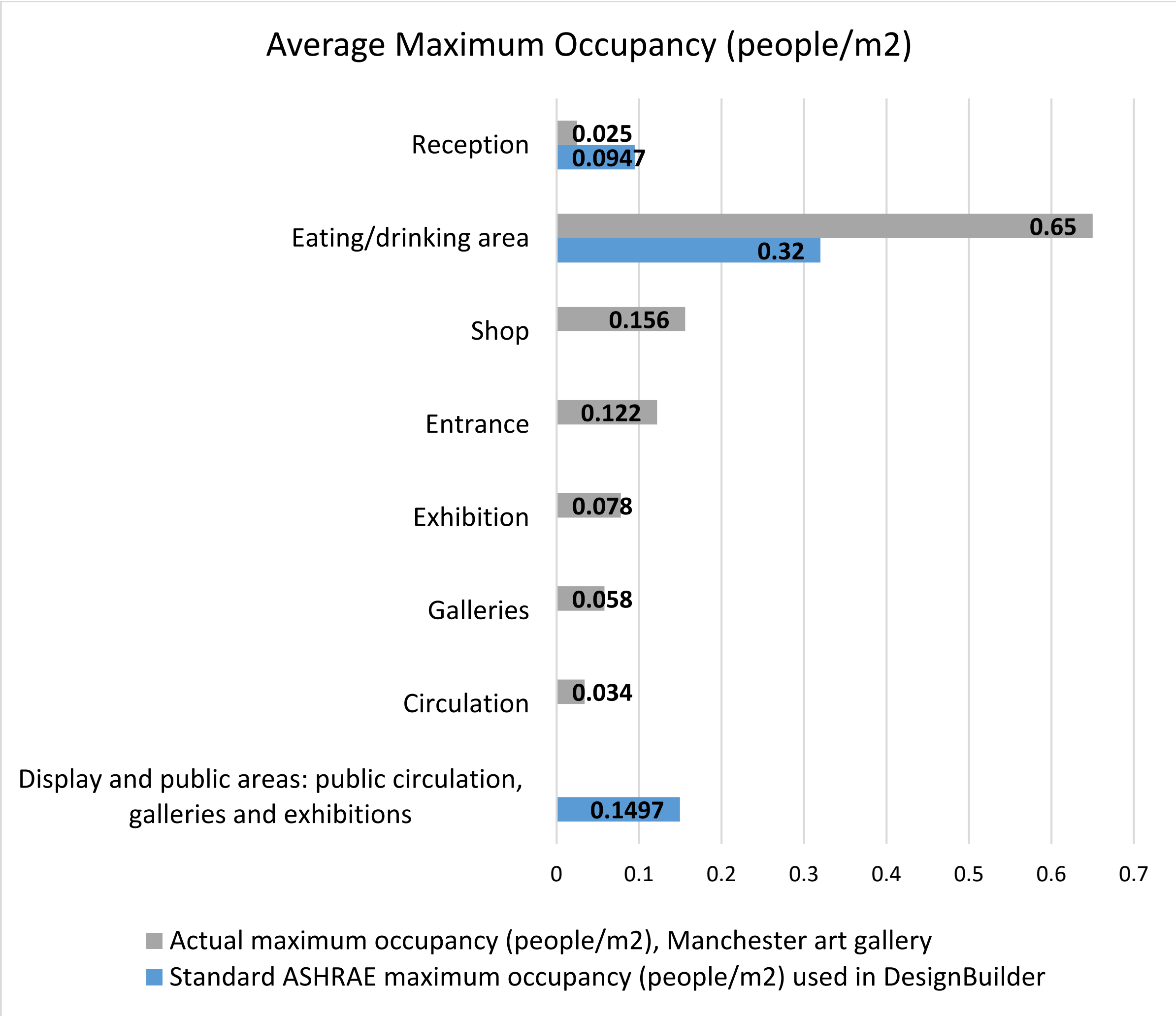


Figure 85. Predicted VS realistic occupancy of Manchester art gallery (November), UK

5.2.4.4. Door Opening

Manchester art gallery is included in “The National Heritage List for England (NHLE)” as a grade 1 listed building. The original main façade and the entrance door have historic importance and are preserved as they are. The heavy wooden entrance door is almost never fully open due to its weight. People just open it to the extent that lets them get in and get out. The door directly opens to the entrance/lobby space. That is why, in cold seasons the lobby area is considerably colder than other spaces. To study the entrance door in Manchester art gallery, 23 sets of cross-sectional hourly data were conducted in November. Table 26 and figure 86 show the analysis of the observed daily/hourly door opening time percentage rounded to the nearest 5. For the purpose of this study, the numbers are rounded to the nearest 5 to be used as an input in energy simulation. During weekdays (Monday to

Friday), door opening time percentage ranges between approximately 10% in the early hours to nearly 50% in peak hours. Door opening peak time is slightly after the occupancy peak hour. That is from 14:00 to 15:00, when a great number of the occupants/visitors leave or enter the building. In general, galleries, exhibitions and museums are visited more during weekends resulting higher occupancy density and door opening time percentage. In peak hours (from 14:00 to 15:00), the entrance door was open nearly 65% of the time.

Door opening time percentage, Manchester art gallery			
Days	Maximum door opening time percentage	Minimum door opening time percentage	Average daily door opening time percentage
Monday to Friday	50 % From 14:00 to 15:00	10 % From 10:00 to 11:00	30 %
Saturday and Sundays	65 % From 14:00 to 15:00	10 % From 10:00 to 11:00	45%

Table 26. Average daily door opening ratio in Manchester art gallery (November)

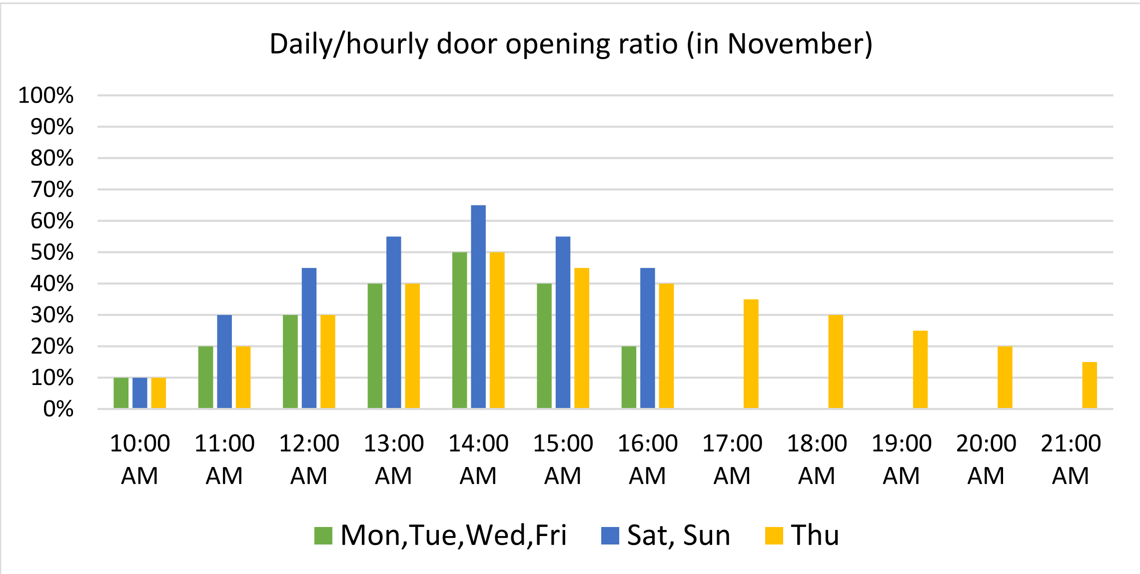


Figure 86. Average hourly/daily door opening time percentage rounded to the nearest 5, Manchester art gallery (November)

5.2.5. Energy Modelling and Simulation (Collected Data)

To avoid the monthly variations of occupancy in gallery buildings, the simulation period for the first case study of this research (Manchester art gallery) was a week from 12th to 18th Feb. This period is identified by DesignBuilder energy simulation tool as “winter design week” which is a week determined by the weather data translator to be the coldest week of the year (DesignBuilder). The integration of all observed data with energy simulation tool (including working hours, occupancy patter and density, door opening and setback temperature) is referred to as the actual energy consumption. The final results of total energy, heating and electricity consumption using default and collected data are shown in table 27.

Manchester art gallery Simulation Duration: 12-18 Feb (Winter Design week)				
Simulations	Total Energy Consumption (kWh)	Total Heating (kWh)	Space Heating (kWh)	Total Electricity (kWh)
Predicted energy consumption using default inputs (with natural ventilation)	4750.13	2557.83	1659.56	2192.3
Actual door opening data	5220.6	3028.3	2130.03	2192.3
Actual space zoning	No changes in zones			
Actual working hours	4604.27	2411.24	1512.97	2162.99
Actual working hours and setback temperature	4848.53	2582.58	1786.87	2162.99
Actual working hours, set-back temperature and occupancy pattern and density	4608.27	2443.88	1545.61	2162.99
Realistic energy consumption	5101.32	2936.1	2037.83	2162.99

Table 27. Final simulation results: the gap between realistic and predicted energy consumption in Manchester art gallery

The quantitative analysis of the simulation results indicates:

The actual working hours of the building are slightly less than predicted which resulted a decrease in the total energy, heating and electricity consumption predictions of the case. Also, the realistic occupancy density and pattern of the spaces was another cause of a decrease in the prediction of the total energy consumption. However, the other factors including setback temperature and door opening, however, increased the total energy consumption prediction of the case. As the multi-functional space had clear boundaries for each function in the construction plans used for the initial energy consumption, therefore, there was no significant difference between the actual and predicted zoning of the multi-functional space of this case. This explains why the results of predicted energy consumption using default software inputs are pretty close to the energy consumption presiction using realisting inputs.

The significant gap between the actual door opening time percentage (average maximum 34%) and software default door opening data (Maximum 5%) caused the most increase in the energy consumption of this case in comparison to other parameters studied.

Because of the historic importance of the displayed paintings in Manchester art gallery, temperature and humidity should be controlled strictly. The same rule applies for all museums and most galleries and libraries. Therefore, when predicting the energy consumption of such buildings, energy modellers should modify the setback temperature inputs. After the working hours, setback temperature set-point controls heating and cooling systems to maintain the desirable temperature at all times. The initial setback temperature assumption of the simulation tool is 12 degree Celsius. In the final energy assessment of the case, the actual setback temperature set-point was adjusted to 20 degree Celsius which increased the energy consumption.

Due to the low occupancy density of most zones within the multi-functional space of this case, integrating the actual occupancy into the energy simulation tool demonstrated a fall in the energy consumption.

The realistic energy consumption is 7% more than the predicted using software default presumptions. Also, the realistic heating consumption is 14% more than the predicted.

Figure 87 illustrates the gap between realistic and predicted energy consumption of the multi-functional space in Manchester art gallery, categorised by the sources of energy consumption.

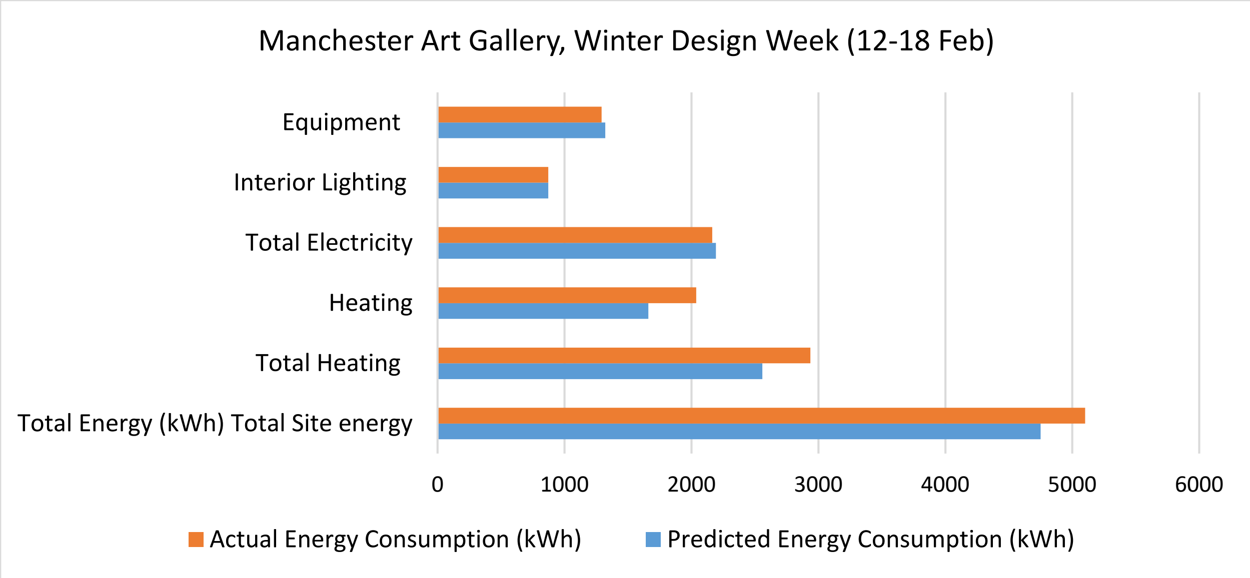


Figure 87. Realistic and predicted energy demand in Manchester art gallery, categorised by the sources of energy consumption

5.3. Chapter Conclusion

In stage 2 of the case study design in this research, a model simulation method is applied on multiple cases at the operation and post-occupancy stages to quantify the gap between energy consumption prediction using the standard (software presumptions) and realistic (collected data) occupant-behaviour-related inputs. Therefore, for stage 2 case studies (student central building, University of Huddersfield and Manchester art gallery), the comprehensive data collection was performed and the gaps between realistic and standard occupant-behaviour-related parameters in building energy consumption prediction were measured. The observation of both cases of this study suggest some of the existing gaps in energy consumption assessment of large multi-functional spaces at the operation stage including: zoning, working hours, occupancy and door opening. The quantitative analysis of both simulation outcomes confirm that using unrealistic occupant-behaviour-related assumptions may result considerable gaps between the actual and predicted energy consumption in multi-functional spaces. This chapter contains case study description, energy modelling and simulation using standard software presumptions, data collection, data analysis and energy simulation using the collected data for both cases. The further analysis and discussions about the findings of this study is presented in the next chapter.

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Discussions and Framework Chapter

Chapter 6: Discussions and Framework

This chapter includes further analysis of the collected data and energy simulation results which were discussed in case study chapters (stages 1 and 2). Following the discussions, the final output of this study is presented in form of a conceptual framework which aims to improve the accuracy of energy consumption assessment in multi-functional spaces by incorporating realistic human-behaviour-related assumptions into energy predictions. This chapter also includes refinement and validation of the framework through incorporating experts' comments. The final framework is constructed after applying experts' comments and is presented in this chapter.

6.1. Discussion

The investigation of building energy modelling and simulation of cases at the design and construction stages which were performed comprehensively in chapter 4 (case study stage 1), demonstrated that human-behaviour-related factors are among the most unknown factors during the energy prediction process of multi-functional spaces. Furthermore, the detailed analysis of building energy simulation results of the two multi-functional case studies of this research at the operation stage (see: case study stage 2 chapter) confirmed that insufficient inputs regarding how the buildings are actually used might result inaccurate energy consumption predictions in multi-functional spaces. According to the findings of this study, the most significant human-behaviour-related gaps in energy assessment of multi-functional spaces are caused by using non-detailed and unrealistic inputs about building working hours, entrance door opening time, occupancy density and pattern and space zoning (Figure 88). Particularly, in building types where occupants' access to building systems are restricted. When predicting the energy consumption of buildings, the energy modellers are usually concerned about providing accurate inputs about building 3D model, material and systems and the aforementioned human-behaviour-related parameters are often overlooked. Unavailability of those data, often urge the energy modeller to rely on simulation software presumptions. This quantitative analysis of the energy simulation results in this study confirm that there may be a considerable gap between energy prediction of multi-functional spaces using software standard presumptions and building energy prediction using realistic data.

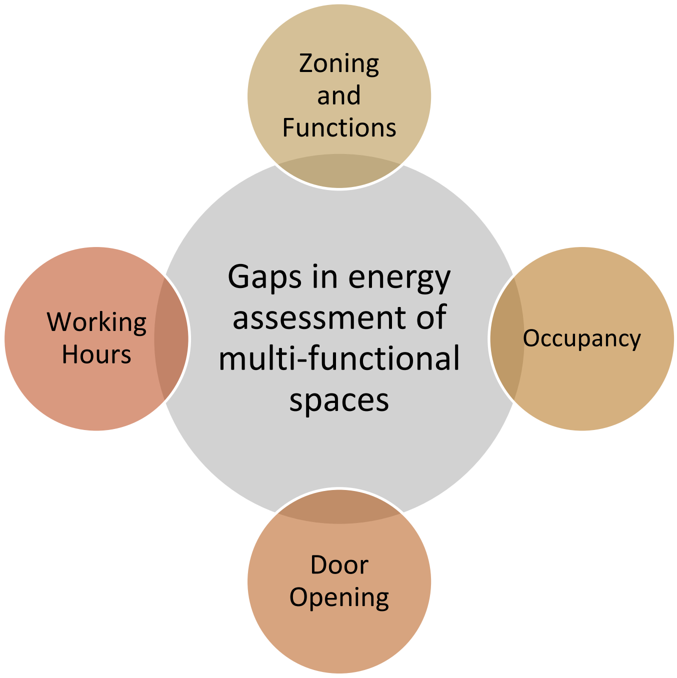


Figure 88. Human-behaviour-related gaps in energy assessment of multi-functional spaces

In the following sub-sections, the findings of this study with regard to the impacts of working hours, zoning, door opening time and occupancy on energy consumption in multi-functional spaces are further discussed.

6.1.1. Working Hours

Working hours which are sometimes referred to as operation hours, directly affect the energy consumption of the buildings. In building energy simulation tools, working hours presumptions, for a building or a space in a building, define the time period that HVAC, electricity and water are expected to fully function. Therefore, the longer the working hours are the more energy consumption is expected to be. The findings of this study confirm that reliance on software assumption regarding building working hours may lead to considerable inaccuracies in energy consumption predictions. Especially, for some building types with more vibrant working hours in different parts of the buildings, specifying the actual working hours for each building zone can be easily overlooked during energy modelling and simulation. The limited number of studies on energy consumption in public buildings such as galleries, museums, libraries and institutional buildings has left noticeable inaccuracies in building energy simulation presumptions regarding the working hours of such building types. In order to have more realistic assumption regarding the building's working hours, this study suggests energy modellers to use working hours of similar building types in the region.

6.1.2. Zoning

Zoning is the act of assigning function to each space, which enables energy simulation tools to have initial assumptions regarding occupants' behaviours and their impacts on building energy consumption. This research proves that space design features and particularly space layout and furniture are amongst the most important factors defining the functions of spaces in multi-functional spaces. Zoning has a substantial importance in energy prediction of multi-functional spaces which is sometimes overlooked. In large multi-functional spaces various functions take place within one physical zone. At design and construction stages, space design and furniture data is sometimes unavailable to the energy modeller. However, even during the process of energy consumption prediction for buildings at the operation and post-occupancy stages, space design and furniture data are not usually amongst the provided information for the energy modeller. This study confirms that frequently there are significant differences between space functions specified through labels on architectural/ construction plans and what actually happens after occupancy which may cause significant gaps between the actual and predicted energy consumption in multi-functional spaces. By underlining the considerable role of space layout and furniture data in energy consumption of multi-functional spaces, this study suggests to include the aforementioned data as required inputs for energy assessment of multi-functional spaces.

6.1.3. Door Opening

Various studies confirm that in public buildings with high flow of people such as commercial and institutional buildings, space heating and ventilation are respectively the major sources of energy consumption in both cold and hot climates (Roetzel, Tsangrassoulis, Dietrich, & Busching, 2010). When the entrance door opening time is high, a great amount of energy is wasted through doors. Even electrical air curtains which are placed on top of entrance doors and are used to block and reduce unwanted air exchange, consume energy (Basarir, 2010). Despite the significant impact of the unwanted airflow caused by entrance door opening on energy consumption in public buildings, it is usually not fully calculated in building energy predictions due to its complicated nature. The design characteristics of building openings such as doors and windows including their size, type of opening (sliding, swinging, revolving, etc.), location on the façade and orientation determine their ventilation rates (Roetzel et al., 2010). The comprehensive observation of both post-occupancy cases of this study show that entrance door opening time ratio depends not only on the number of people entering and leaving the building, but also, on entrance door features including its type (manual or automatic), design and ease of use. In automatic doors, the opening time setting can have a considerable impact on the door opening time duration. In public buildings, occupants and visitors have no control over the above settings. Karlsonn (2013) investigated the energy performance and the air infiltration of different building entrance doors. He established that entrance doors are the main sources of air infiltration, which is affected by the frequency of use. Consequently, different entrances including primary and secondary have different impacts on the energy consumption of the building. Figure 89 shows the parameters influencing entrance door opening time.

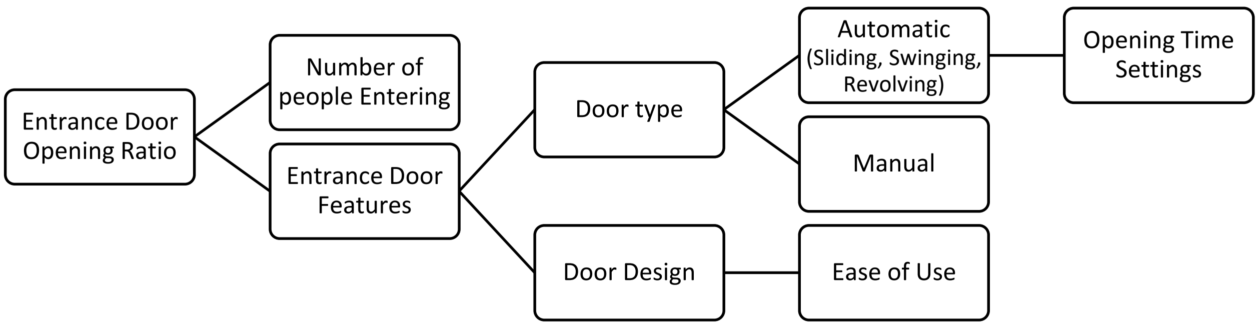


Figure 89. Parameters influencing entrance door opening time

In DesignBuilder, one of the most prominent energy simulation tools associated with EnergyPlus energy prediction engine, airflow caused by external doors are considered through natural ventilation section (DesignBuilder, 2009). The actual effects of door opening will only be calculated if the energy modeller sets natural ventilation setting instead of calculated ventilation which is the software default setting. Besides, the software door opening time percentage presumption is 5% for all building types and spaces. In addition, it considers by default that 50% of the door area is openable. Both door opening time percentage and door openable area percentage are adjustable. Depending on the building and entrance characteristics, unrealistic presumptions about door opening time percentage and openable area may cause a distinct gap between the building actual energy consumption and simulation results. With regard to entrance door opening, the number of people entering the building affect its energy consumption; however, effective design can reduce the negative impacts significantly. Most of the public buildings have double or revolving entrance doors. These types of doors are energy efficient, which reduce the negative impact of high flow of people through entrance doors on building's energy performance. However, the cases studied in this research, did not have energy efficient entrances due to their special design and historical values. The findings of this study demonstrate that type of entrance door and the relationship between the interior layout and the entrance space are amongst influential parameters on entrance door opening time duration, which consequently affects the total energy consumption of the building.

6.1.4. Occupancy

Occupancy is one of the substantial information required for building energy predictions and has been studied broadly (see: 2.4.1. Passive Energy Behaviour: Occupancy). Various parameters influence the occupancy density and pattern in multi-functional spaces. Building attraction factor, target audience and seasonal factors directly affect the number of visitors in multi-functional spaces. For example, the particular historic and cultural importance of a buildings may attract a great number of visitors to the building, which eventually increases the occupancy in various spaces of the building. Also, the location of a building affects its number of visitors which has been pointed out in various studies. Most of the public building types have monthly variations in the number of occupants/ visitors. For example, galleries, exhibitions and institutional buildings have distinct patters of monthly occupancy, in addition to, high and low seasons.

Furthermore, the findings of this study confirm the substantial impacts of space function and the types of activities performed in each zone on the energy consumption in multi-functional spaces. The interior furniture of a space has a considerable impact on its density capacity and maximum occupancy. Other design-related parameters such as comfort level and availability of internet and electricity sockets affect occupant's duration of presence and consequently has impacts on the occupancy density and energy consumption of the space. In specific spaces of buildings, for instance café and eating areas, the availability of free internet and electricity sockets may result notable growth in occupants' duration of presence. In addition, it may change the main function of the space from an eating area to a studying space. Many studies have confirmed the direct link between comfort (particularly, thermal comfort) and occupant's duration of presence in a space. Similarly, the comfort level of space furniture affects occupancy density in a space. This study demonstrates that the duration of activity in each zone which may be fixed or flexible, in addition to, the working hours in each zone within a multi-functional space affect its occupancy density and pattern. Moreover, the findings of this study confirm that there is a direct link between the maximum occupancy density of a space and the density capacity provided of the space furniture.

Figure 90 provides a comprehensive illustration of the factors and sub-factors affecting occupancy in multi-functional spaces which is a combination of the findings of this study and the existing literature on building occupancy.

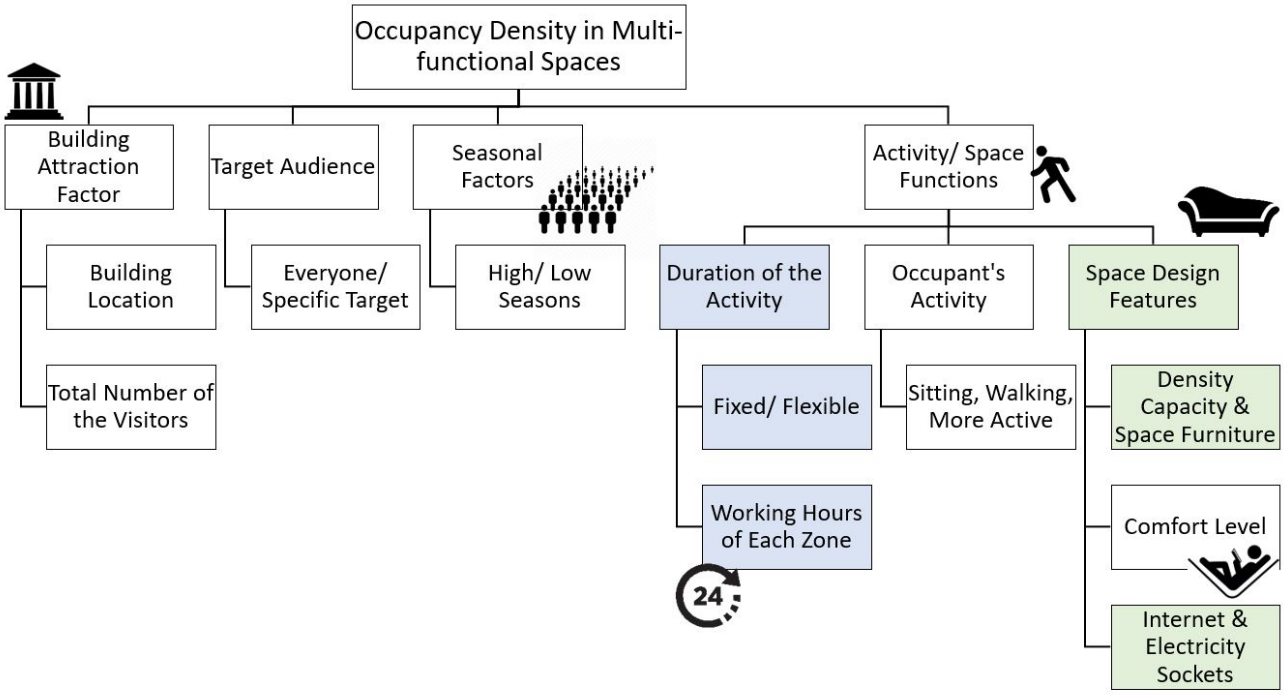


Figure 90. Factors and sub-factors affecting occupancy in multi-functional spaces

6.1.5. Key Findings

This study have pointed out some of the most influential human-behaviour-related parameters including working hours, occupancy, zoning and door opening on energy consumption in multi-functional spaces. Other key findings of this study suggest that considering type of activity in prediction of occupancy is more accurate than type of space. Moreover, estimation of the type of activity is associated with the space function which is determined by furniture and space design. The findings of this study confirm that to assess energy consumption of multi-functional spaces at the operation, post-occupancy and maintenance stages, using actual occupancy data is a necessity, which is often overlooked. Therefore, presumptions of energy simulation tools regarding occupants' behaviours should be adjusted using the available information through data collection, using online resources and the existing literature.

In the next section, after classification, categorisation and integration of the key findings of this study, the final conceptual framework is formulated, validated and refined. The conceptual framework illustrates a guideline for energy modellers to reach more accurate energy consumption predictions for multi-functional spaces during different stages of building's lifecycle.

6.2. Development of the Conceptual Framework

A framework is defined as a systems of rules or concepts used to underlie something (CambridgeDictionary, 2018). A conceptual framework connects key parameters, variables and concepts and constructs their relationships to provide an understanding of the whole system (Miles, Huberman, Huberman, & Huberman, 1994). Jabareen (2009) defines conceptual framework as an interconnected system and chain of concepts that collectively explain a phenomenon. In a comprehensive research study about definitions of conceptual framework and procedures of constructing it, Jabareen (2009) suggests a methodology to create a conceptual framework following 8 stages: 1- categorisation of the data sources, 2- classification of the data, 3- specification of the concepts/ parameters, 4- classification of the concepts/ parameters, 5- integration of concepts/ parameters and their relationships, 6- synthesis (and resynthesize), 7- validation of the framework, 8- construction of the final framework. In this research, the development of the conceptual framework followed three main steps: preparation of the initial framework, validation and refinement and formation of the final framework. In the next sub-sections each of the mentioned steps are explained.

6.2.1. Initial Framework

In order to formulate the initial conceptual framework of this study, first, the results of data analysis were categorised and classified. Then, the human-behaviour-related parameters which were pointed out through analysis of the cases were specified (See: 6.1. Discussion). Finally, the findings of the study were linked with the parameters to create the initial framework. The final output of this study is illustrated as a conceptual framework to help energy modellers perform more accurate energy consumption assessments in multi-functional spaces by integrating occupant-behaviour-related factors into the energy simulation tools (Figure 91).

As energy consumption of buildings are assessed throughout different stages of building's lifecycle, the conceptual framework provides separate guidelines for post-occupancy and maintenance stages, and design and construction stages. It provides guidelines to incorporate the most influential human-behaviour-related parameters, which are highlighted in this study (including: working hours, occupancy, zoning and door opening), into energy consumption assessment of multi-functional spaces.

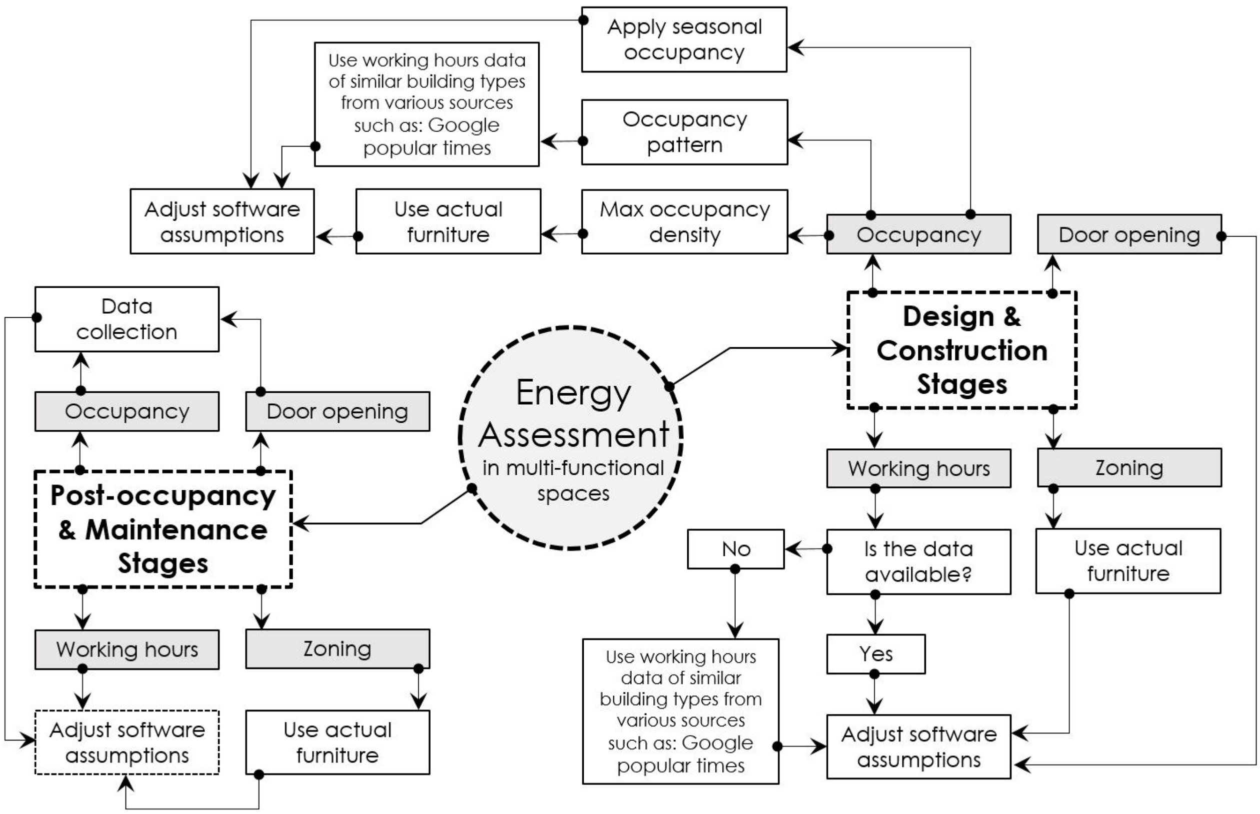


Figure 91. A conceptual framework to improve the accuracy of energy consumption assessment in multi-functional spaces.

Energy prediction of buildings at **post-occupancy and maintenance stages**	Energy prediction of buildings at **design and construction stages**
• Occupancy should be collected using proper techniques (such as hourly/weekly observation) and used instead of software assumptions. • The realistic zoning of the multi-functional space can be reached using the actual space furniture. • Space working hours data should be collected and used in simulation software. • Similar to occupancy data, the realistic entrance door opening time should be collected to be used in building energy prediction.	• Adjusting software assumptions regarding occupancy, seasonal occupancy should be taken into account, as well as, occupancy pattern and maximum occupancy. • Interior design and furniture data should be used as the basis for space zoning. • Space working hours data should be adjusted either using the actual working hours data or using data from similar building types nearby. • Door opening software assumptions should be adjusted based on the type of building and its predicted occupancy.

Table 28. Description of the initial framework

6.2.2. Validation and Refinement

Depending on the nature of study, various methods may be applied for validation of frameworks such as using existing literature, experts' comments, survey and case studies (Inglis, 2008). To validate the framework in this study, experts from building energy performance research domain and particularly who have experience in energy modelling and simulation were asked to give feedback on the conceptual framework (Table 27). For this purpose, a summarized document of this research study (including research problem, research method, findings and the conceptual framework) was presented to them (Appendix 1). For the validation of the framework, 10 experts were contacted, 6 of them accepted to take part and 4 validated the framework. The profile of experts who took part in the validation of framework is presented in table 29.

Expert no.	Description
V1	• Associate professor in sustainable and energy-efficient buildings • Expert in energy modelling and simulation
V2	• Architect, specialized in sustainable design • Expert in energy modelling and simulation
V3	• Researcher in building energy performance • Expert in occupants 'behaviours and energy consumption research domain • Certified passive-house consultant
V4	• Professor of built environment • Leading researcher and expert in occupant behaviours, adaptive thermal comfort and thermal environment • Skilled at energy modelling and simulation

Table 29. Profile of experts in building energy performance

The experts' comments and their feedback on the framework are presented in the following sub-sections (see: 6.2.2.1. to 6.2.2.4.).

6.2.2.1. Comments from expert V1

V1 found the summarised document interesting and well-structured and did not require any more information to fully understand the framework. V1 made two comments about the types of occupants' behaviours and the missing information during the design stage:

- V1 mentioned that some other aspects of occupants' behaviours, such as the reaction of users to lighting conditions (visual comfort), were not included in the study because of the type of spaces that were investigated. However, the activation (or not) of solar shading / filtering devices by the users, as a reaction to their perception of visual comfort, can alter significantly the actual energy consumption of the building according to the amount of solar radiation that enters the spaces. Depending on the case, there may be other types of occupant's behaviours affecting the energy consumption of the building which is better to be mentioned somewhere in the framework even if no further work has been done about it.
- V1 pointed out that the availability of information during the design stage, undoubtedly generates massive variations in the amount and quality of the inputs

used for building energy performance analysis, however, it is important that the framework covers in more details how the missing information could be retrieved for instance from the existing literature.

6.2.2.2. Comments from expert V2

V2 found the method of the study very interesting and made different questions and then gave some comments about the framework:

- V2 asked which software was used for the study. The name of the software used for energy analysis of the cases was not mentioned in the summarised document, as the framework did not intend to provide guideline for a particular energy simulation tool. However, V2 made a notable comment that although most of the energy simulation tools have more or less similar inputs, but, there are slight differences. Therefore, it will be more accurate to mention that you are giving suggestions particularly based on DesignBuilder software interface.
- V2 suggested to provide a clear definition of zoning and further explain how interior design and furniture data can be used for zoning.
- V2 also mentioned the unclear boundary between design and construction stages of a building, as design phase usually extends till the end of construction phase. V2 suggested to include the definition of design and construction stages.

6.2.2.3. Comments from expert V3

V3, first, suggested a recently published paper by M. M. Ouf, O'Brien, and Gunay (2018) which discussed refinement of occupant-behaviour-related inputs in building energy simulation tools. The paper provides a broader categorization of actions required to improve default assumptions of building energy simulation tools regarding occupants' behaviours. Then, V3 made excellent comments to develop the framework:

- V3 recommended that each stage (design/ construction and Post-occupancy/ maintenance) shall branch out to 3 human-behaviour-related points: occupancy cycle, door control or opening and zoning. In this categorisation, occupancy and working hours are grouped as one.

- V3 suggested to use the term "occupancy cycle" instead of occupancy which includes five main elements:
  1. Seasonal occupancy
  2. Occupancy density
  3. Occupancy pattern (movement, activity and duration spent within zones)
  4. Working hours/occupancy schedule or period
  5. Arrival and departure

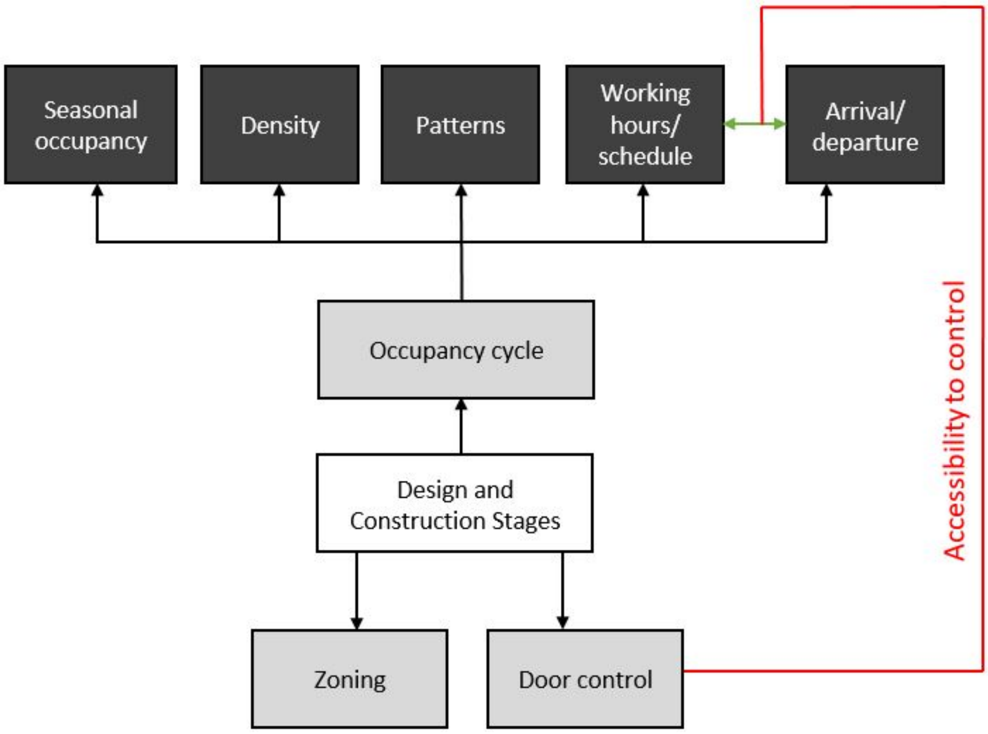


Figure 92. Refinement of framework, V3 comments

- V3 pointed to further expand the framework by adding constraints, as well as, relationships between the human-behaviour-related factors in the framework. For example, accessibility to the control system, in this case, the door control is a constraint and there is a relationship between the occupancy schedules, arrival/departure ad door opening time. Also, for the use of actual furniture, the freedom to adjust interior design and whether the space is private/shared might create constraints (Jakubiec & Reinhart, 2011).
- To improve the table, V3 suggested to mention various techniques for collecting occupancy and control: IOE, use of sensors and monitoring.

6.2.2.4. Comments from expert V4

V4, like V1, made comments about the types of human-behaviour-related factors which are considered in the framework. In the multi-functional spaces investigated in the study, however, occupants have no control over various building systems such as windows which was particularly asked by the expert. V4, also, suggested exploring a study by H. B. Rijal et al. (2007) that used field surveys and simulation to predict occupants' windows opening behaviour and its impacts on thermal comfort and building energy consumption.

6.2.2.5. Analysis of experts' comments

In order to refine the initial framework using the experts' comments, classification and analysis of the comments are performed in this section which is presented below:

- Almost all the experts involved in the validation and refinement of the framework suggested to add more details and definitions to the framework and expand the table.
- A number of the experts suggested to either mention or include other types of occupant's behaviours which might happen in other cases of multi-functional spaces.
- Some of the experts mentioned to improve the framework by providing information about the inter-relationship between its parameters.

6.2.3. Final Framework

After applying experts' comments and suggestions, the final framework of this study is developed and presented in this sub-section. The final framework of this study provides guidelines to improve the accuracy of energy consumption assessment in multi-functional spaces by incorporating realistic occupant-behaviour-related inputs into energy simulation tools (Figure 93). As the focus of this study has been on energy assessment of multi-functional spaces at different stages of the building's lifecycle, the final framework is constructed in two sections: section 1, for the buildings at the design and construction stages, and section 2, for buildings at the operation, post-occupancy and maintenance stages. The main difference between the two sections of the framework is the availability of actual occupant's behaviours data. For buildings at the operation and maintenance stages, collecting occupant-behaviour-related data and adjusting software presumptions is explained in the framework. However, the framework offers more guidelines for buildings at the design and construction stages, explaining how to use the existing data to have more accurate assumptions regarding human-behaviour-related factors. In the following sub-sections (see: 6.2.3.1. and 6.2.3.2.), both sections of the framework are explained broadly.

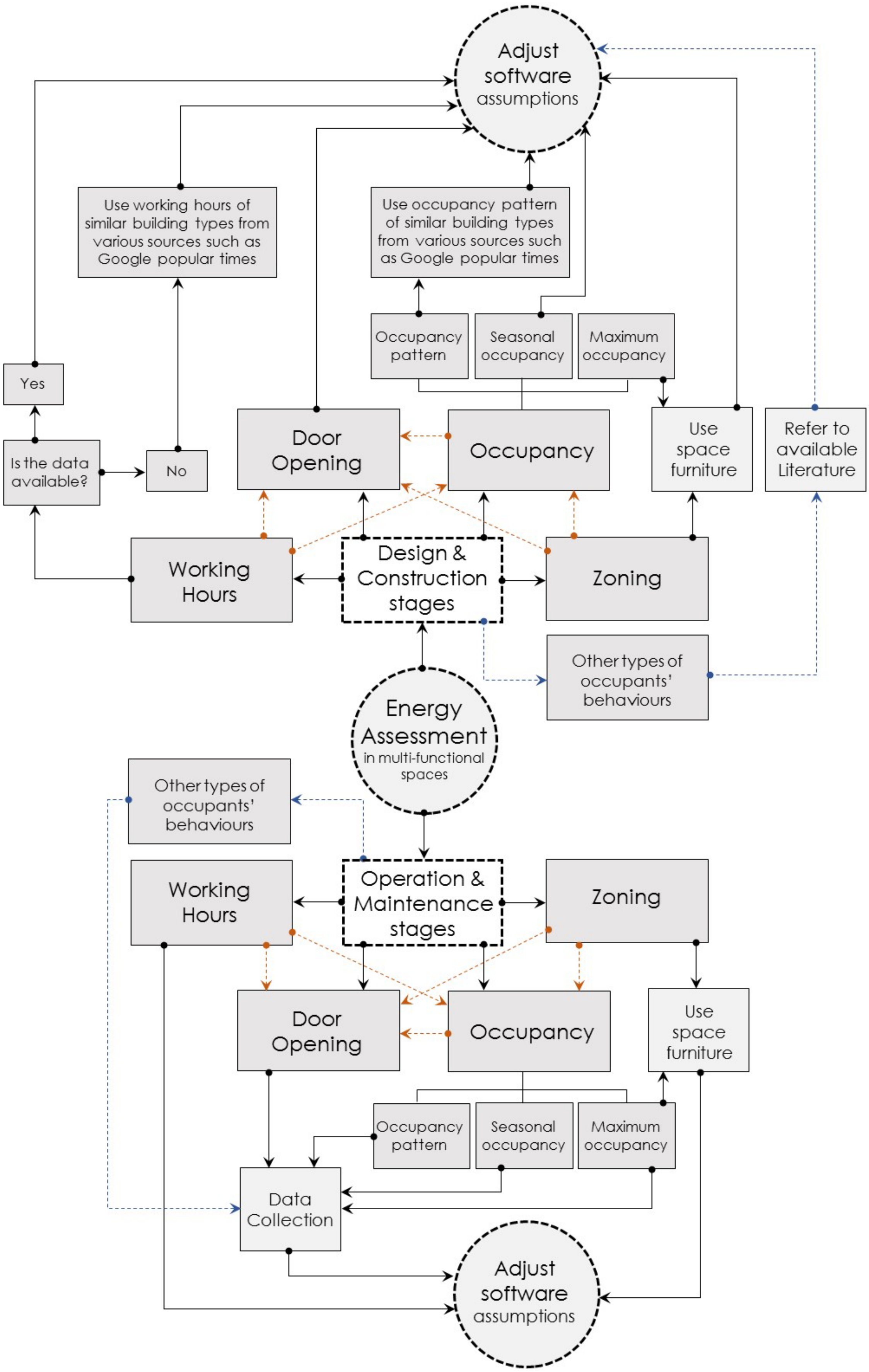


Figure 93. Final framework

6.2.3.1. Final framework: buildings at the operation and maintenance stages

In this research, through investigation of multiple cases of multi-functional spaces in galleries and institutional buildings, the gaps and insufficiency of inputs in energy simulation tools to address occupant-behaviour-related parameters have been pointed out and discussed. The below framework is constructed to attain more realistic inputs for energy analysis of buildings at the operation and maintenance stages (Figure 94). The framework provides guidelines to integrate four human-behaviour-related parameters that have been pointed out in this research into building energy assessment process: working hours, zoning, occupancy and door opening. The relationship between the aforementioned parameters are illustrated in the framework with an orange line.

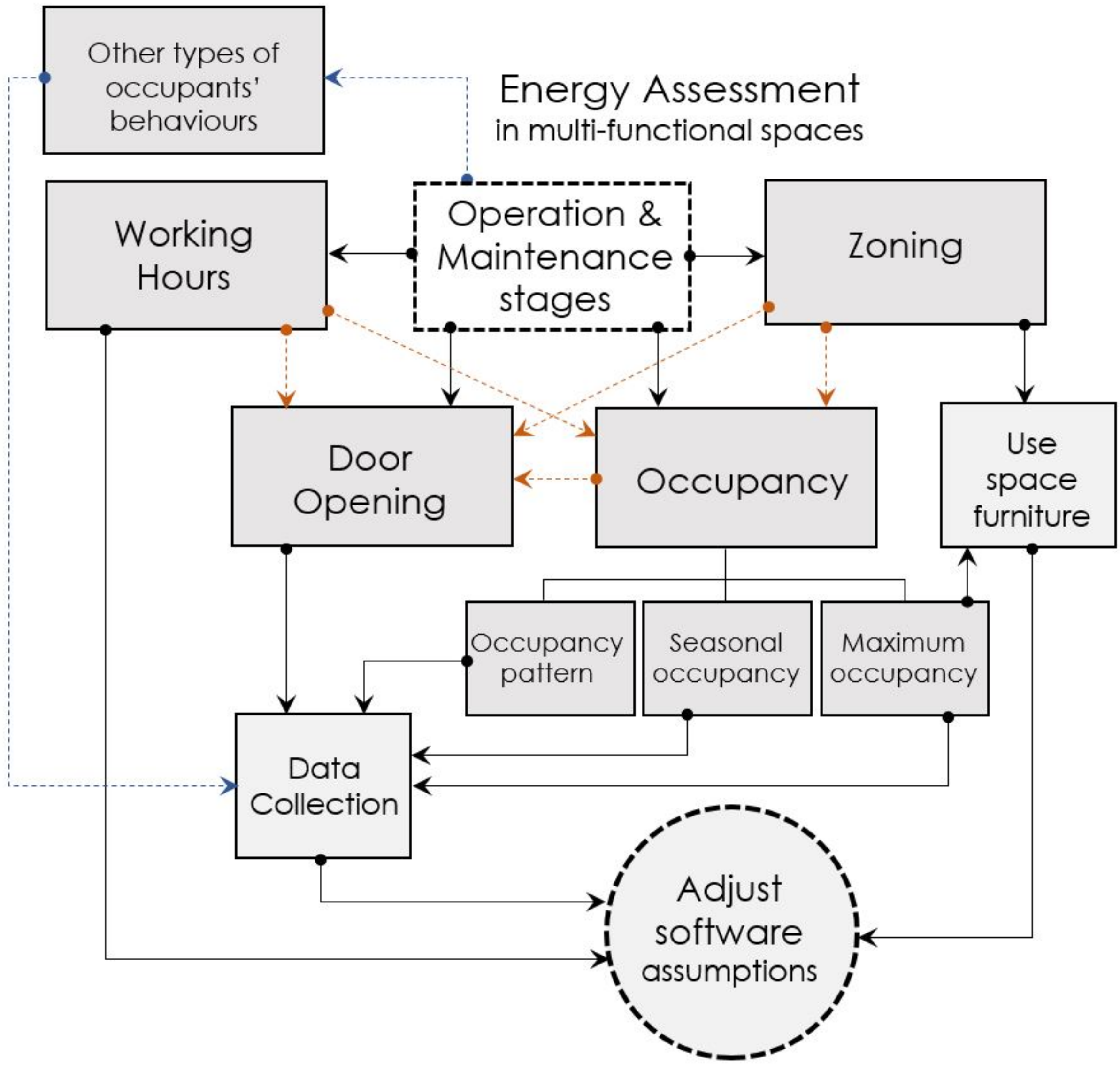


Figure 94. The final framework for buildings at the operation and maintenance stages

The detailed description of each of the parameters in the framework and their relationships are provided in table 30.

Energy prediction of multi-functional spaces at the **operation and maintenance** stages	
Parameter	Description
Working hours	• For energy assessment of multi-functional spaces, not only the actual working hours of the building, but also, the working hours of each space/ or zone should be collected and then used to adjust software assumptions.
Occupancy	• Occupancy is related to working hours and zoning. • To integrate realistic occupancy data into building energy simulation tools, three sets of occupancy-related data should be collected: maximum occupancy density, occupancy pattern and seasonal occupancy. • For buildings at the operation and maintenance stages, all occupancy related data should be collected using proper techniques such as hourly/weekly observation, which is comprehensively presented in this study (see: 5.1.3. and 5.2.3. Data Collection) or other methods like IoE, use of sensors and various monitoring techniques. The collected data should then be used to adjust software assumptions. • To attain maximum occupancy density, for each zone, the space furniture and its maximum capacity should be taken into account.
Door opening	• Entrance door opening time is related to working hours and occupants' arrival and departure. Therefore, the more the occupancy density is, the higher door opening time is expected to be. Entrance door opening time is related to space layout and zoning too. • Similar to occupancy data, the realistic entrance door opening time should be collected and then used to adjust software assumptions (see: 5.1.4.5. and 5.2.4.4.).

Zoning	• Zoning means to specify function to each zone within a space, which allows energy assessment tools to have default occupant-behaviour-related assumptions. To assign the realistic function to each zone, space furniture should be taken into account. • Observation of occupants' activities in different zones within the multi-functional spaces, together with, using space furniture data leads to more realistic zoning. The actual zoning should then be used for the energy assessment. • In multi-functional spaces where more than one main function takes place, the space furniture is a reliable source to specify the type of activity. For example, the presence of some sitting areas in the entrance area or corridor changes the function of the space.
Other types of occupants' behaviours	• In case studies investigated in this research, the human-behaviour-related factors were limited to working hours, occupancy, door opening time and zoning. However, in multi-functional spaces of other types of buildings, occupants may have less restrictions to interact with building systems. In order to provide realistic inputs in energy simulation tools about any other types of occupants' behaviours, data collection should be planned and performed.

Table 30. Description of the framework for buildings at the operation and maintenance stages

6.2.3.2. Final framework: buildings at the design and construction stages

There is no doubt that prediction of energy consumption for buildings at the design and construction stages will always have a certain degree of uncertainty. This is due to unavailability of various types of information which has been broadly discussed in this study (see: 2.1. Energy Consumption in Buildings). However, using more realistic inputs will increase the accuracy of the energy consumption predations and decrease the performance gap between actual and predicted energy consumption in buildings. The final framework of this study is constructed to increase the accuracy of energy consumption prediction of multi-functional spaces by providing guidelines to attain more realistic occupant-behaviour-related inputs. The framework for buildings at the design and construction is slightly more detailed in comparison to the framework section for buildings at the operation and maintenance stages, however there are various similarities between the two sections of the framework. The comprehensive explanation of the parameters in the framework and their relationships are presented in table 31.

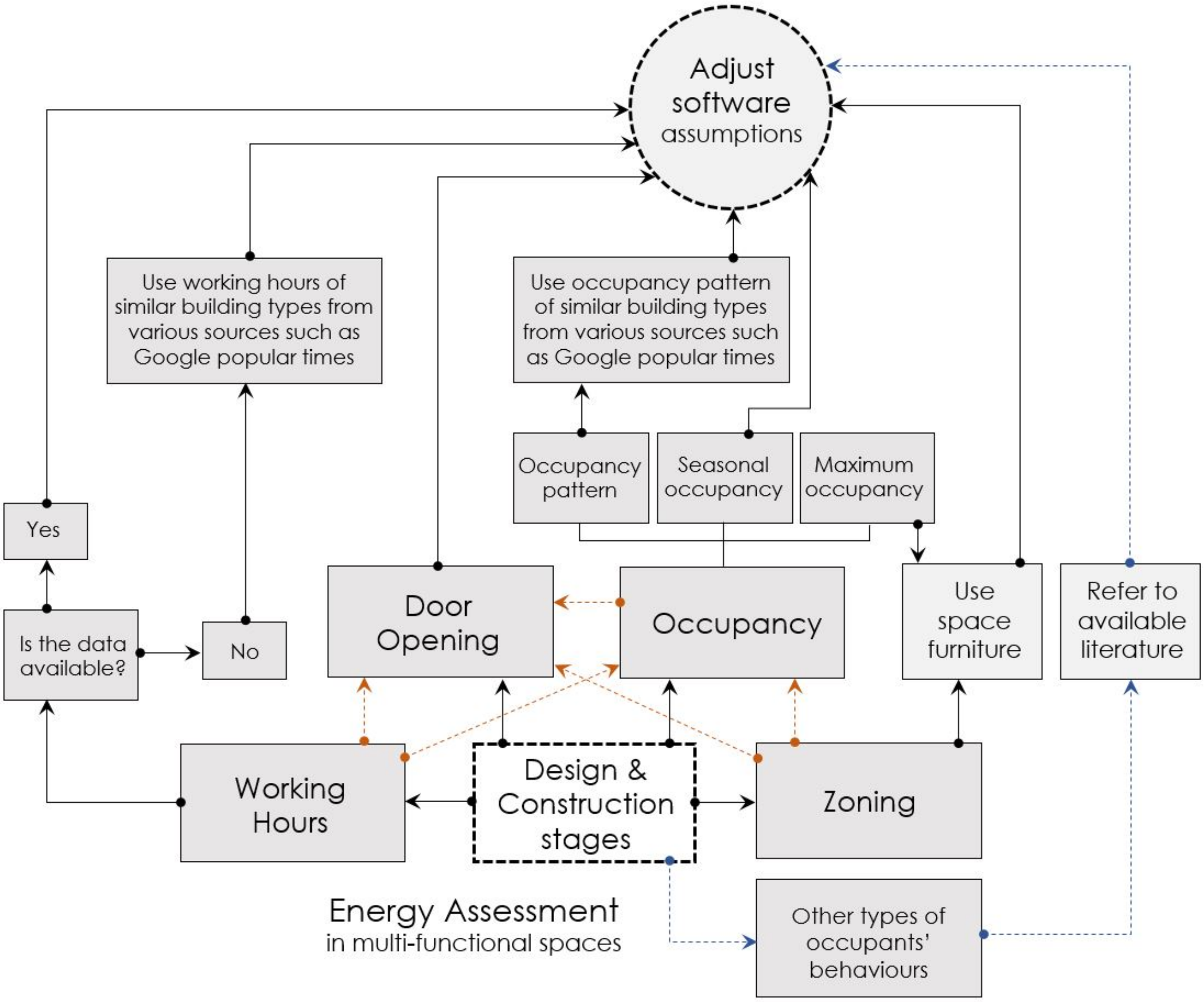


Figure 95. The final framework for buildings at the design and construction stages

Energy prediction of multi-functional spaces at the **design and construction** stages	
Parameter	Description
Working hours	• Working hours of the building, each space or zone are required for energy assessment of multi-functional spaces.

	• If the working hours of the building and its spaces are available, they should be used to adjust software assumptions. • If the working hours of the building and its spaces are unknown or unavailable, the findings of this study suggest to use working hours of similar building types to adjust software working hours presumptions. Various sources such as Google popular times provide real-time data about working hours of different buildings worldwide.
Occupancy	• Occupancy is related to working hours and zoning. • To attain realistic occupancy data for energy consumption prediction of buildings at the design and construction stages, three sets of occupancy-related data should be collected: maximum occupancy density, occupancy pattern and seasonal occupancy. • To achieve maximum occupancy density, for each zone, the space furniture and its maximum capacity should be taken into account. There is a link between the maximum capacity of a space and its furniture. • To predict occupancy pattern, this study suggests to use occupancy pattern of similar building types to adjust software occupancy presumptions. Various sources such as Google popular times provide real-time data about occupancy patterns of different buildings worldwide.
Door opening	• Entrance door opening time is related to working hours, occupancy density and pattern and zoning. • Door opening software assumptions should be adjusted based on the type of building and its predicted occupancy and working hours.
Zoning	• In multi-functional spaces where more than one main function takes place, the space furniture is a reliable source to specify the type of activity.

	• To assign the realistic function to each zone, space furniture should be taken into account. For example, presence of some sitting areas and tables alongside the corridor changes its main function from circulation area to sitting area. In addition to space furniture, other space design features and facilities, such as the availability of electricity sockets can transform the main function of a sitting area to a studying area. • Space furniture data is suggested be requested by the energy modeler before energy simulation.
Other types of occupants' behaviours	• More realistic assumptions about any other types of occupants' behaviours could be retrieved from the existing literature.

Table 31. Description of the framework for buildings at the design and construction stages

6.3. Chapter Conclusion

In this chapter, discussions about research findings and development of the final framework are deliberated. The gaps in existing energy simulation tools to address four human-behaviour-related parameters including working hours, zoning, door opening and occupancy are discussed in this chapter. Furthermore, different stages of framework development are discussed and the final framework is constructed after validation and refinement. In the next chapter final conclusion, research limitations and future work are presented.

The Impact of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

Conclusion Chapter

"It is good to have an end to journey toward; but it is the journey that matters, in the end."

(K. Le Guin, 2017)

Chapter 7: Conclusion

This chapter includes the conclusion, research limitations and future work. The conclusion section provides a summary of research problem and research findings. The research findings section is constructed to follow research objectives and explain how the study have addressed each objective.

7.1. Conclusion

This section includes a summary of this thesis to demonstrate how research objectives are achieved. For this, the summary of research problem and key research findings are discussed below.

7.1.2. Summary of Research Problem

Various statistics show that building sector accounts for approximately 40% of the total yearly energy consumption worldwide. Therefore, building energy assessment has progressively become an essential process during different stages of building's lifecycle, over the last 15 years. Various studies confirm that occupants' behaviours have not been fully reflected into building energy assessment. The gap between the actual and predicted energy consumption in buildings has prompted scholars around the world to investigate the sufficiency of energy simulation software presumptions regarding how the buildings are actually used and occupants' behaviours. In order to calculate the energy consumption of a building with an energy simulation tool, the energy modeller has to provide information regarding the building type, which enables the software to use specific presumptions such as the working hours and schedules. In addition, the function of every space/zone of the building should be defined, as space function enables the energy simulation tools to apply the level of occupancy and type of activity, required lighting and ventilation, comfort temperature, use of hot water and electricity. It is often challenging to specify the space function for large multi-functional spaces in buildings such as public galleries and institutional buildings where various functions take place within one large space. For energy assessment of multi-functional spaces, in order to specify te function of each zone within the multi-functional spaces, space layout design and furniture should be incorporated into building simulation tool which is often overlooked. The focus of this research has been on investigating the impacts of occupants' behaviours on energy consumption in multi-functional spaces (See: 2.5. Research Focus). In addition, the integration of the findings with building energy assessment process has endeavoured to bridge the gap between theory and practice.

7.1.3. Summary of research method

In order to investigate the Impact of occupants' behaviours on energy consumption in multi-functional spaces, multiple cases at different stages of building's lifecycle has been investigated. Case study design of this research consists of two stages. In stage 1, the existing gaps and insufficiency of human-behaviour-related parameters in energy assessment of multi-functional spaces at the design and constructio stages has been studied. In stage 2, a model simulation method was applied on two large multi-functional spaces in a gallery and an institutional building both located in the North England. Human-behaviour-related factors were observed in 38 zones of two cases for 2 weeks. The quantitative analysis and comparison of collected data with the presumptions of one of the most prominent energy simulation tools (DesignBuilder and EnergyPlus) suggested potential causes of inaccuracy in energy consumption prediction of multi-functional spaces. For each of the cases in this study, multiple energy simulation was performed to compare the energy consumption using realistic and standard occupant-behaviour-related inputs. For student central building, the final result of the energy simulation tool using default and realistic occupant-behaviour-related inputs are presented in appendixes 2 and 3, respectively. The final outcome of this research is a conceptual framework to provide guidelines for energy modellers to incorporate realistic occupant-behaviour-related inputs into building energy assessment. The conceptual framework was refined and validated by experts' comments.

7.1.4. Summary of research findings

The summary of key findings of this study is presented in the following sub-sections under each of the research objectives.

7.1.4.1. Objective 1

The first objective of this study was to investigate existing literature on the impacts of occupants' behaviours on energy consumption in buildings. The comprehensive literature review was followed by identification of the existing gaps in the subject area through a comprehensive quantitative analysis and qualitative review (See: 1.2.2. Research Objectives). The most significant gaps in the existing knowledge are presented below:

- The comprehensive literature review demonstrates that approximately 75% of current studies on the impacts of occupants' behaviours on energy consumption in buildings are focused on residential and office buildings. Thus, there are limited studies in this research domain on other building types such as exhibitions, galleries, museums and recreational, institutional and healthcare facilities that require further investigations.
- Most of the existing studies have investigated the impacts of occupants' behaviours on single buildings or flat units. However, inadequate studies have explored the impacts at the macro (such as urban scale) and micro levels (single or multiple zones) forming profoundly recommended research areas.
- Several influential parameters on occupants' energy consumption behaviours have been studied extensively by various scholars. However, understanding the correlation between the aforementioned parameters remains obscure and inadequate that needs further studies. In future research, machine-learning techniques should be applied to combine various influential parameters on occupants' energy consumption behaviours.
- Similarly, various types of occupants' energy consumption behaviours and types of occupants' interactions with building systems (such as opening windows, using appliances and adjusting HVAC set points) have been investigated broadly in existing studies. However, there are inadequate research on the inter-relationship between occupants' various types of energy consumption behaviours. Further studies are required to explore the holistic energy consumption behaviour of occupants to integrate them into building energy predictions.
- The incorporation and integration of the quantitative findings of the existing studies into the building energy simulation tools has yet to be achieved, particularly, to

improve the sufficiency and accuracy of default occupant-behaviour-related assumptions. This will consequently contribute in reducing the gap between predicted and actual energy consumption in buildings.

7.1.4.2. Objective 2

The second objective of this study was to establish research focus and method to study the influence of occupants' behaviours on energy consumption in multi-functional spaces (See: 1.2.2. Research Objectives). Research focus was shaped to contribute in addressing three existing gaps in the knowledge:

- First, the study has focused on multi-functional spaces of galleries and institutional buildings that need further investigations due to insufficiency of knowledge in the existing literature.
- Second, the impacts of space design as an influential parameter on occupants' energy consumption behaviours have been investigated in this study.
- Third, applying model simulation method with the aim to incorporate the findings into energy simulation tools. For this, the realistic observed occupant behaviour data was integrated into DesignBuillder energy simulation tool to highligt the difference between the energy simulation outcomes using standard software assumptions and analysis based on actual observations.

In this research, occupants' energy consumption behaviours and their impacts on energy consumption of buildings were studied through multiple case studies. The cases were large multi-functional spaces at different stages of building's life cycle. Therefore, the case study design of this research study consists of two stages: stage 1, for buildings at the design and construction stages that actual occupant's behaviour data is unavailable, and stage 2, for buildings at the post-occupancy and operation stage.

7.1.4.3. Objective 3

The third objective of this study was to analyse energy consumption of multi-functional cases at different stages of building's lifecycle by comparing default software presumptions regarding human-behaviour-related factors with the realistic collected data (See: 1.2.2. Research Objectives). The comparison between the two aforementioned simulation outcomes enabled further investigation of the potential gaps in energy assessment with regard to occupant-behaviour-related factors. Therefore, four cases at different stages of building's lifecycle were studied. The case study design of this research is developed in two stages.

Stage 1 is applied on cases at the design and construction stages which is presented comprehensively in chapter 4. Therefore, two cases, one, at the design stage and the other one, at the construction stage have been investigated to point out the existing gaps and insufficiency of information in building energy simulation tools to reflect realistic human-behaviour-related parameters. Stage 1 of the case study design consists of three steps including preparation of information, energy modelling and simulation and analysis of the existing gaps. The analysis of the first case confirmed that during design stage, lack of sufficient information about building material, HVAC systems, technical detailing, in addition to, space function, building working hours and occupants' behaviour data may result considerable gaps between the actual and predicted energy consumption on multi-functional spaces. Furthermore, the analysis of the second case suggested that during construction stage, when building material and systems are finalised, still unavailability of occupants' behaviour and space furniture data may cause inaccuracies in energy consumption predictions of multi-functional spaces. The study was then further expanded to investigate energy consumption of multi-functional spaces in buildings at the operation and post-occupancy stages.

Hence, stage 2 of the case study design was developed to explore and quantify the impacts of human-behaviour-related factors on energy consumption in multi-functional spaces of buildings at the operation stage which was pointed out through stage 1 case study analysis (see: chapter 5, case study stage 2). Therefore, a model simulation method consisting of the following steps were applied on two multi-functional spaces: preparation of information, energy modelling and simulation of the cases using default software presumptions, data collection with focus on occupants' energy behaviours, energy simulation of the cases using the realistic collected data, comparison and analysis of the two simulation results (using software default assumptions and the realistic collected data) for both cases. The analysis of the findings of stage 2 case studies indicate that using non-detailed and unrealistic human-behaviour-related inputs, particularly, regarding entrance door opening time, occupancy density and pattern, space zoning and building working hours can result considerable gaps in energy assessment of multi-functional spaces.

7.1.4.4. Objective 4

The fourth objective of this study was to analyse the collected data and the results of the energy simulations to formulate a conceptual framework to improve the accuracy of energy consumption assessment in multi-functional spaces (See: 1.2.2. Research Objectives). The conceptual framework developed in this research provides guidelines for energy modellers to reach more realistic energy consumption predictions in multi-functional spaces by incorporating realistic occupant-behaviour-related inputs into building energy assessment. Further quantitative analysis of the collected data and simulation outcomes pointed out the most significant human-behaviour-related parameters in energy consumption of the cases (See: Chapter 6 Discussions and Framework). After categorisation, classification and specification of the influential parameters and their relationships, the initial conceptual framework was developed.

7.1.4.5. Objective 5

The fifth objective of this study was to validate and refine the initial conceptual framework through experts' comments (See: 1.2.2. Research Objectives). For this, a summarized document of this research study was presented to a group of international experts from building energy performance research domain who are expert or adequately skilled in building energy modelling (See: Chapter 6 Discussions and Framework). The summarized document included research problem, research method, findings and the conceptual framework. The experts' comments were collected, categorised and used to refine the conceptual framework. The final framework was then constructed after applying experts' comments. The final conclusion, research limitations and future work were then investigated and presented in chapter 7.

7.2. Contribution to Knowledge

The findings of this research have various contributions to knowledge, both theoretical and practical (See: 1.4. Contribution to Knowledge, Uniqueness and Novelty) which are further explained in the following sections (7.2.1. and 7.2.2.).

7.2.1. Theoretical Contribution

This study has several theoretical contributions to knowledge as it has addressed some of the existing gaps in the literature:

- Occupant's behaviour is often recognised as a disregarded area in building energy assessment causing inaccuracies in energy predictions. In this study, the impacts of occupants' energy consumption behaviours on energy performance in buildings was studied and investigated comprehensively.
- There is limited and insufficient existing knowledge about energy performance in multi-functional spaces of public buildings (such as galleries, exhibitions and institutional buildings) and the energy consumption behaviours of occupants/users in such spaces. By focusing on the aforementioned spaces and building types, this research has contributed in filling one of the gaps in the literature.
- This research has measured and quantified the potential gap between actual and predicted energy consumption in multi-functional spaces caused by insufficient and inaccurate human-behaviour-related inputs in building energy predictions.
- Despite most of the studies in this research domain that focus on one specific type of activity only (such as window opening and electricity consumption), in this study, the overall energy consumption behaviour of occupants has been investigated. This approach, delivers a more realistic and holistic understanding of the impact of occupants on energy consumption in multi-functional spaces.

7.2.2. Practical Contribution

The practical contributions of this study are beneficial for building energy modelling and simulation industry. The main beneficiaries are building energy simulation software developers and energy modellers, however, it is also useful for researchers, designers and policy makers.

- This research has contributed in improving the accuracy of energy simulation software by highlighting software gaps and insufficiency of information to address occupants' behaviours in multi-functional spaces of public buildings. Therefore, the findings of this study are particularly beneficial for building energy simulation software developers.
- One of the final outcomes of this research is a conceptual framework for energy modellers to reach more realistic energy predictions in multi-functional spaces by integrating realistic human-behaviour-related parameters into the energy modelling and simulation process (see: 6.2.3 Final Framework).

The next sub-section expands on how the conceptual framework is beneficial for energy modellers to produce more reliable human-behaviour-related inputs for their building energy assessment.

7.2.2.1. Practical Contribution: Conceptual Framework

The conceptual framework is constructed in two sections. Depending on the stage of building's lifecycle that the energy modeller is willing to run the energy simulation for a multi-functional space in a public building, they can refer to one of the two sections of the conceptual framework: operation and maintenance stages, and design and construction stages (see: 6.2.3 Final Framework).

The first section is formulated to be used for energy modelling and simulation of the multi-functional spaces of public buildings at the operation and maintenance stages (See: 6.2.3.1 Final framework: buildings at the operation and maintenance stages). By referring to the conceptual framework, the energy modeller finds guidelines to adjust human-behaviour-related inputs before running the energy simulation. Zoning, occupancy, door opening and working hours, are the four main human-behaviour-related factors in multi-functional spaces of public buildings that the conceptual framework has focused on. The framework, also, indicates the interrelationship between the aforementioned human-behaviour-related factors that should be taken into account to have more realistic energy performance assessment inputs. Accordingly, for each of the parameters, the framework suggests some steps. For example, in order to adjust energy simulation software assumption regarding occupancy in a multi-functional space of a public building at the operation and maintenance stages, the framework suggests to collect “maximum occupancy”, “seasonal occupancy” and “occupancy patterns” data from the multi-functional space. The combination of the three occupancy-related sets of data would produce a more realistic occupancy input for the building energy assessment.

The second section is constructed to be used for energy modelling and simulation of the multi-functional spaces of public buildings at the design and construction stages where real-time data is unavailable (See: 6.2.3.2 Final framework: buildings at the design and construction stages). Similar to the first section, in the second section, the conceptual framework contains series of guidelines and suggested steps on how to adjust software assumptions regarding human-behaviour-related factors in multi-functional spaces at the design and construction stages. For example, in order to use more realistic inputs regarding working hours, the conceptual framework suggests to use the available scheduled working hours of the building instead of relying on energy simulation software presumptions. If the working hours data of the building and its spaces are unavailable, the energy modeller is suggested to use working hours of similar building types which can be extracted from various recourses such as “Google popular times” which provides real-time data about public buildings.

Using more realistic inputs for building energy predictions contributes in increasing their accuracy and decreasing the performance gap between actual and predicted energy consumption in buildings.

7.3. Research Limitations

In this research study, four cases at different stages of building’s lifecycle (including design, construction and operation) were investigated. The quantitative findings of this study do not aim to provide a general statement, instead, they point out the possible causes of inaccuracy in energy consumption prediction of multi-functional spaces, the potential gaps and insufficiency of information. However, applying a similar method on a large number of cases may lead to more accurate general assumptions regarding occupancy and occupant-behaviour-related parameters.

In addition to constraints regarding the number of case studies investigated in this research, the duration of data collection was another limitation. The focus of this study was on hourly and daily, however, to predict yearly and monthly energy consumption more accurately, the duration of data collection should be extended, which was not possible because of time limitations in this study.

In accordance with the aim of this study, which is to decrease the gap between actual and predicted energy consumption in multi-functional spaces at different stages of building's lifecycle, the occupants' realistic behaviours were collected and then integrated into the building energy simulation tool (See: 2.1. Research Aim). In similar studies on building energy performance, the actual energy consumption is found through energy bills and/or energy meters. However, unavailability of such data for the multi-functional spaces of the cases , which are specific zones inside the buildings, is a remaining limitation in this study. The comparison between the predicted energy consumption of the cases using collected data with their actual energy consumption could provide further understanding on the impacts of occupants' behaviours on energy consumption in multi-functional spaces. Limited responses from experts in the research domain for validation of the final framework is another limitation in this study which provides an area for future work.

7.4. Future Work

Several gaps in the existing literature on the impacts of occupants on building energy consumption has been pointed out (See: 2.4.4. Existing Gaps in the Literature). This research has focused on three gaps (See: 2.5 Research Focus), which remains other gaps to be investigated in future studies.

For future work, the method of this study can be applied on series of multi-functional spaces in similar building types (such as museums, libraries, galleries, etc.) to enable development of accurate general assumptions.

Different influential factors affecting occupants' energy consumption behaviours in buildings have been pointed out in numorous research studies (See: 2.2.2. Parameters influencing occupants' energy behaviour). Applying machine learning techniques, makes it possible to analyse large and complex occupant's behaviour data by considering and integrating several influential parameters. The knowledge derived from studies such as this research, provide inputs to make machine learning algorithms to predict occupant's energy consumption behaviours. This ultimately leads to more accurate building energy predictions, consequently, minimizing the performance gap between actual and predicted energy consumption.

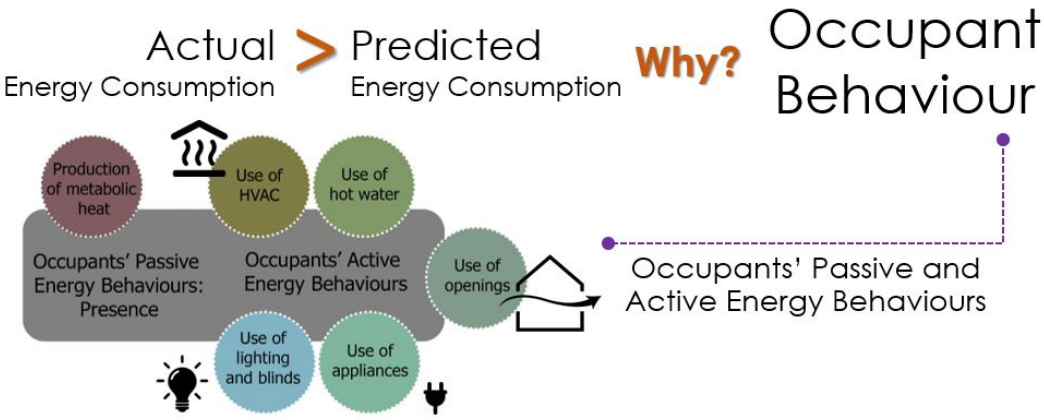
7.5. Final Words

In this chapter, a summary of research problem, method and findings and the key conclusions of this study has been discussed. Also, the chapter demonstrates how the aim and objectives of this study have been achieved. The final outcome of this study is a conceptual framework that provides guidelines to improve the accuracy of energy consumption assessment in multi-functional spaces by incorporating realistic occupant-behaviour-related inputs into energy simulation tools. The limitations of the study are identified and the future research areas are introduced. The study has both theoretical and practical contributions to reduce the gap between predicted and actual energy consumption in multi-functional spaces and has a great potential to be further expanded and developed.

Appendix 1: Research Summary Document Sent to Experts for Validation of the Framework

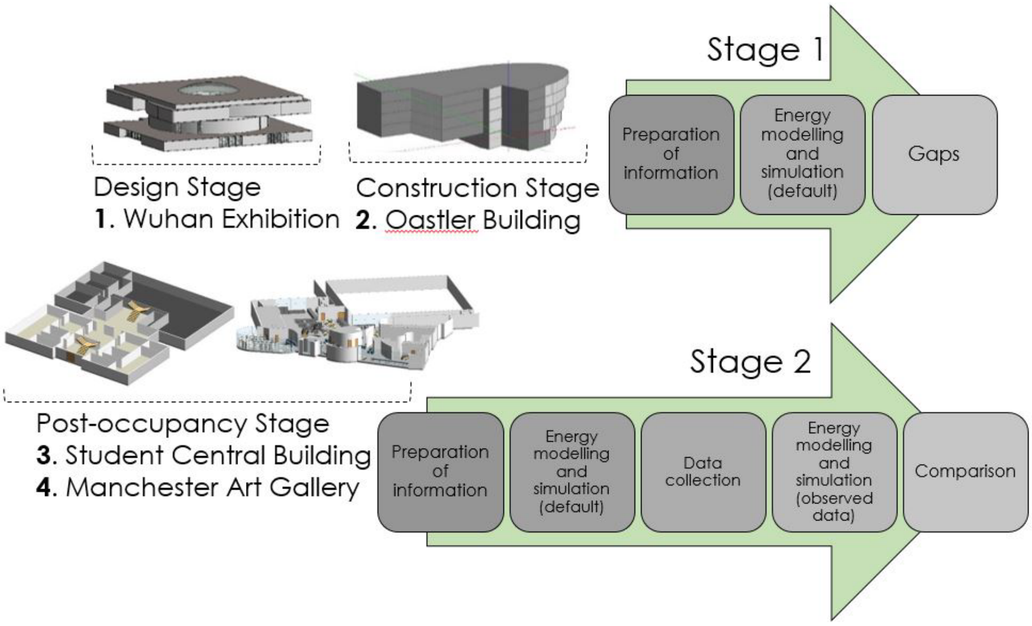
The Impacts of Occupants' Behaviours on Energy Consumption in Multi-Functional Spaces

It has been widely acknowledged in the literature that there is a distinct performance gap between predicted and actual energy consumption of buildings which has attracted scholars across the world to investigate the sufficiency of software inputs and presumptions regarding how the buildings are actually used.



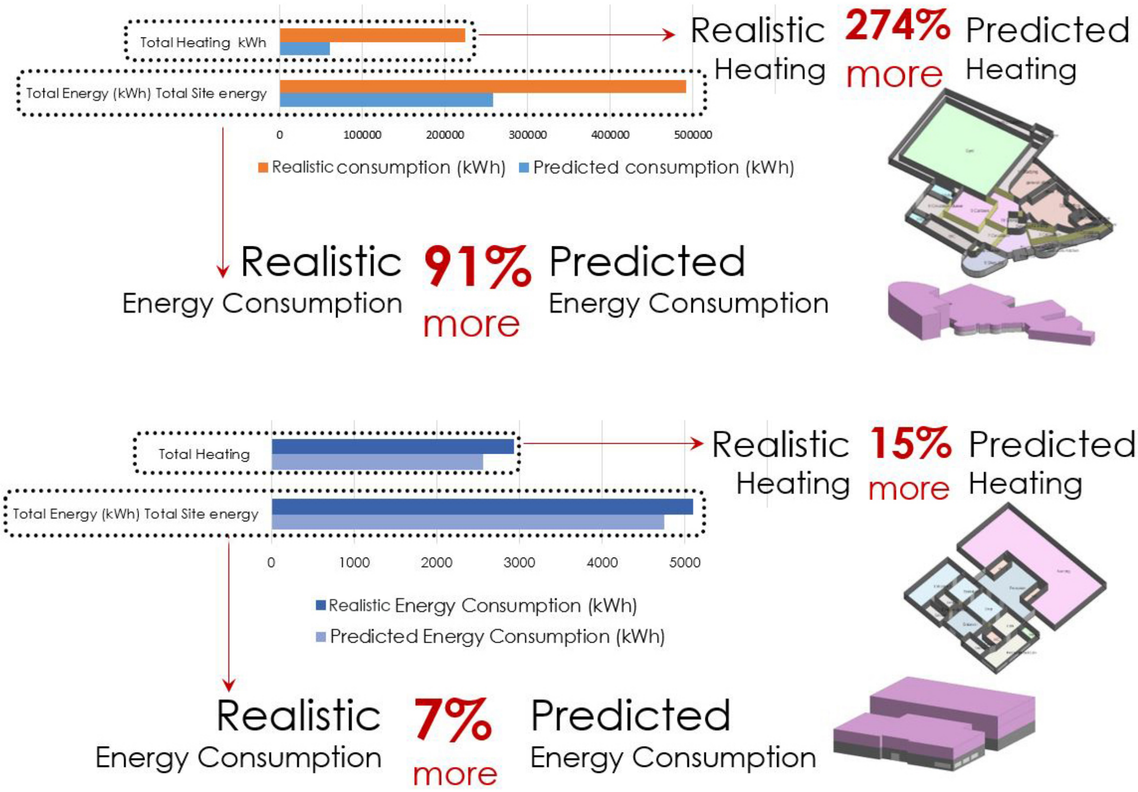
This research intends to develop **a conceptual framework to improve the accuracy of energy consumption assessment in multi-functional spaces at different stages of building's lifecycle by integrating the impacts of occupants' behaviours into building energy predictions** to reduce the gap between actual and predicted energy consumption.

In this quantitative research, a model simulation method is applied on multiple cases at different stages of the building lifecycle including design, construction and post-occupancy.

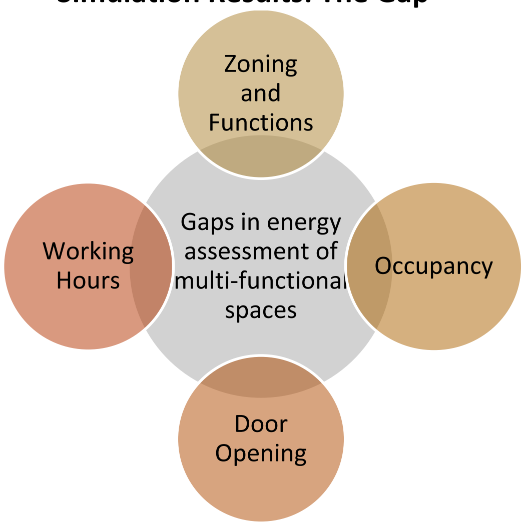


The first two cases are large multi-functional spaces at the design and construction stages, which were studied to address the missing information and potential gaps in energy modelling and simulation (stage 1). The study was then taken forward using case studies at the post-occupancy stage to integrate the actual observed data into the building energy simulation tool. For each of the cases, energy simulation was run twice: first, using default values of the software, and second, using the collected data (Stage 2). The data collection included hourly observation of 38 zones in both cases at the post-occupancy stage for the duration of two weeks, in addition to, using available governmental and real-time statistics.

The analysis of energy simulation results using default software values and collected data highlighted that lack of sufficient information regarding building working hours, space layout and function, occupancy density and schedules, the entrance door opening time and HVAC set-points may result significant performance gaps in energy consumption prediction of multi-functional spaces in institutional buildings and galleries.

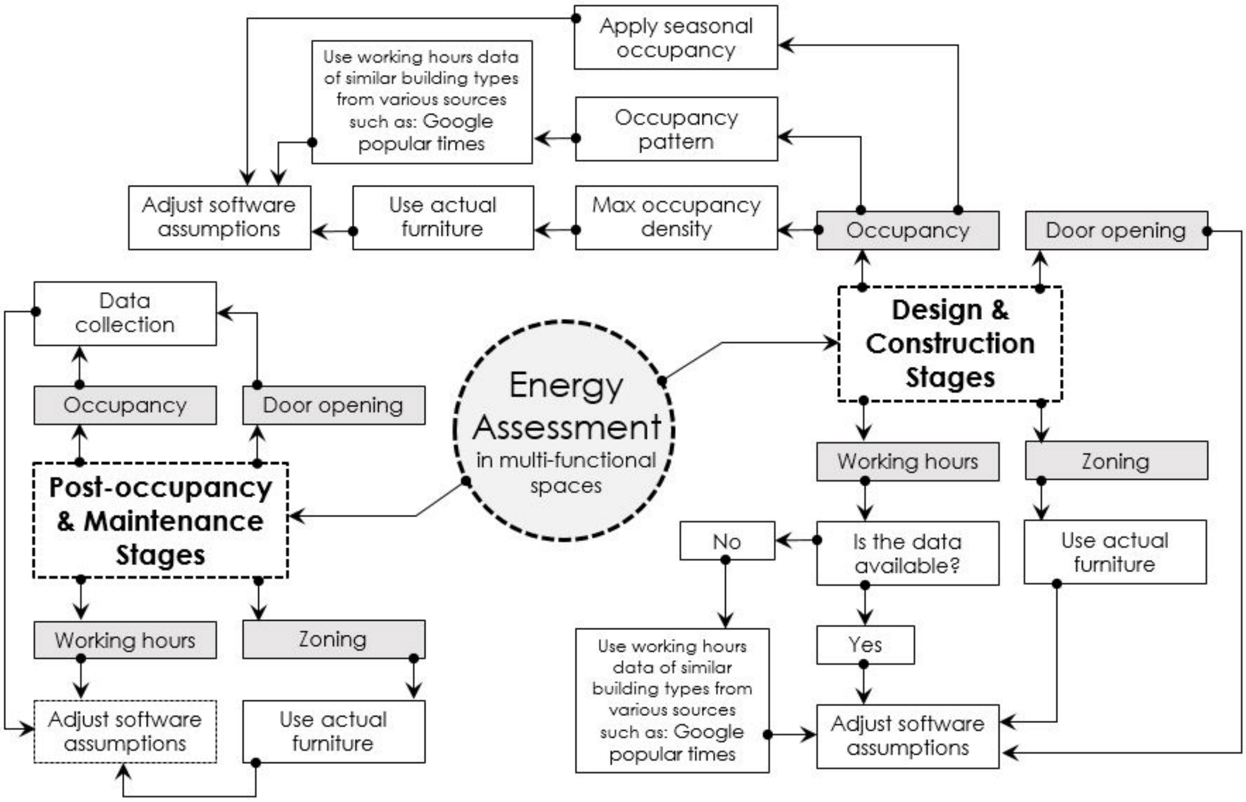


Simulation Results: The Gap



Framework

The conceptual framework provides guidelines to incorporate some of the most influential human-behaviour-related parameters, which are highlighted in this study (working hours, occupancy, zoning and door opening), into energy consumption assessment of multi-functional spaces.



A conceptual framework to improve the accuracy of energy consumption assessment in multi-functional spaces

Energy prediction of buildings at post-occupancy and maintenance stages	Energy prediction of buildings at design and construction stages
• Occupancy and door opening data should be collected using proper techniques (such as hourly/weekly observation) and used instead of software assumptions. • The realistic zoning of the multi-functional space can be reached using the actual space furniture. • Space working hours data should be collected and used in simulation software.	• Adjusting software assumptions regarding occupancy, seasonal occupancy should be taken into account, as well as, occupancy pattern and maximum occupancy. • Interior design and furniture data should be used as the basis for space zoning. • Space working hours data should be adjusted either using the actual working hours data or using data from similar building types nearby. • Door opening software assumptions should be adjusted based on the type of building and its predicted occupancy.

Appendix 2: Student Central Building, Energy Simulation Using Default Data

For each of the cases in this study, multiple energy simulation was performed to compare the energy consumption using realistic and standard occupant-behaviour-related inputs. Appendix 2 presents selected parts of the final results of energy simulation tool for student central building using default software data.

Program Version:**EnergyPlus, Version 8.5.0-c87e61b44b, YMD=2018.06.05 10:32**

Tabular Output Report in Format: **HTML**

Building: **Building**

Environment: **UNTITLED (17-02:23-02) ** FINNINGLEY - GBR IWEC Data WMO#=033600**

Simulation Timestamp: **2018-06-05 10:32:34**

Report: **Annual Building Utility Performance Summary**

Timestamp: **2018-06-05 10:32:34**

Values gathered over 168.00 hours

WARNING: THE REPORT DOES NOT REPRESENT A FULL ANNUAL SIMULATION.

Site and Source Energy

	Total Energy [kWh]	Energy Per Total Building Area [kWh/m2]	Energy Per Conditioned Building Area [kWh/m2]
Total Site Energy	7978.15	1.91	1.91
Net Site Energy	7978.15	1.91	1.91
Total Source Energy	26495.92	6.36	6.36
Net Source Energy	26495.92	6.36	6.36

Site to Source Energy Conversion Factors

	Site=>Source Conversion Factor
Electricity	3.167
Natural Gas	1.084

District Cooling	1.056
District Heating	3.613
Steam	0.250
Gasoline	1.050
Diesel	1.050
Coal	1.050
Fuel Oil #1	1.050
Fuel Oil #2	1.050
Propane	1.050
Other Fuel 1	1.000
Other Fuel 2	1.000

Building Area

	Area [m2]
Total Building Area	4167.04
Net Conditioned Building Area	4167.04
Unconditioned Building Area	0.00

End Uses

	Electricity [kWh]	Natural Gas [kWh]	Additional Fuel [kWh]	District Cooling [kWh]	District Heating [kWh]	Water [m3]
Heating	0.00	0.00	0.00	0.00	3103.60	0.00
Cooling	0.00	0.00	0.00	81.86	0.00	0.00
Interior Lighting	3269.91	0.00	0.00	0.00	0.00	0.00
Interior Equipment	1485.34	0.00	0.00	0.00	0.00	0.00
Water Systems	0.00	0.00	0.00	0.00	37.45	0.59
Total End Uses	4755.25	0.00	0.00	81.86	3141.04	0.59

Note: District heat appears to be the principal heating source based on energy usage.

End Uses By Subcategory

	Subcategory	Electricity [kWh]	Natural Gas [kWh]	Additional Fuel [kWh]	District Cooling [kWh]	District Heating [kWh]	Water [m3]
Heating	General	0.00	0.00	0.00	0.00	3103.60	0.00

Cooling	General	0.00	0.00	0.00	81.86	0.00	0.00
Interior Lighting	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:WC#GeneralLights	98.92	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:6ShopSU#GeneralLights	295.50	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:ShopStorage#GeneralLights	2.96	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Services#GeneralLights	27.18	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StudentCentral#GeneralLights	687.26	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OpenOffice#GeneralLights	321.77	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office1#GeneralLights	60.15	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GeneralOffice#GeneralLights	213.96	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen2#GeneralLights	89.21	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Gym#GeneralLights	1023.19	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GymCirculation#GeneralLights	197.63	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Staircase#GeneralLights	17.28	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen#GeneralLights	55.05	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office#GeneralLights	74.49	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Entrance#GeneralLights	6.06	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OfficeInternational#GeneralLights	17.43	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:InternationalOffice#GeneralLights	43.81	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StarbucksKitchen#GeneralLights	38.07	0.00	0.00	0.00	0.00	0.00
Exterior Lighting	General	0.00	0.00	0.00	0.00	0.00	0.00
Interior Equipment	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:WC#05	61.49	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:6ShopSU#05	60.74	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Services#05	10.22	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StudentCentral#05	258.42	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OpenOffice#05	333.90	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office1#05	62.42	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GeneralOffice#05	222.03	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen2#05	159.76	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Staircase#05	6.50	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen#05	98.58	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office#05	77.30	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Entrance#05	2.28	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OfficeInternational#05	18.08	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:InternationalOffice#05	45.46	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StarbucksKitchen#05	68.17	0.00	0.00	0.00	0.00	0.00
Exterior Equipment	General	0.00	0.00	0.00	0.00	0.00	0.00
Fans	General	0.00	0.00	0.00	0.00	0.00	0.00
Pumps	General	0.00	0.00	0.00	0.00	0.00	0.00
Heat Rejection	General	0.00	0.00	0.00	0.00	0.00	0.00
Humidification	General	0.00	0.00	0.00	0.00	0.00	0.00
Heat Recovery	General	0.00	0.00	0.00	0.00	0.00	0.00

Water Systems	DHW StdntCntrlGrndFlr:6ShopSU	0.00	0.00	0.00	0.00	5.59	0.09
	DHW StdntCntrlGrndFlr:GeneralOffice	0.00	0.00	0.00	0.00	13.66	0.21
	DHW StdntCntrlGrndFlr:Kitchen2	0.00	0.00	0.00	0.00	7.53	0.12
	DHW StdntCntrlGrndFlr:Kitchen	0.00	0.00	0.00	0.00	4.65	0.07
	DHW StdntCntrlGrndFlr:InternationalOffice	0.00	0.00	0.00	0.00	2.80	0.04
	DHW StdntCntrlGrndFlr:StarbucksKitchen	0.00	0.00	0.00	0.00	3.21	0.05

Normalized Metrics

Utility Use Per Conditioned Floor Area

	Electricity Intensity [kWh/m2]	Natural Gas Intensity [kWh/m2]	Additional Fuel Intensity [kWh/m2]	District Cooling Intensity [kWh/m2]	District Heating Intensity [kWh/m2]	Water Intensity [m3/m2]
Lighting	0.78	0.00	0.00	0.00	0.00	0.00
HVAC	0.00	0.00	0.00	0.02	0.75	0.00
Other	0.36	0.00	0.00	0.00	0.00	0.00
Total	1.14	0.00	0.00	0.02	0.75	0.00

Utility Use Per Total Floor Area

	Electricity Intensity [kWh/m2]	Natural Gas Intensity [kWh/m2]	Additional Fuel Intensity [kWh/m2]	District Cooling Intensity [kWh/m2]	District Heating Intensity [kWh/m2]	Water Intensity [m3/m2]
Lighting	0.78	0.00	0.00	0.00	0.00	0.00
HVAC	0.00	0.00	0.00	0.02	0.75	0.00
Other	0.36	0.00	0.00	0.00	0.00	0.00
Total	1.14	0.00	0.00	0.02	0.75	0.00

Table of Contents

Report: **Input Verification and Results Summary**

For: **Entire Facility**

Timestamp: **2018-06-05 10:32:34**

General

	Value
Program Version and Build	EnergyPlus, Version 8.5.0-c87e61b44b, YMD=2018.06.05 10:32
RunPeriod	UNTITLED (17-02:23-02)
Weather File	FINNINGLEY - GBR IWEC Data WMO#=033600
Latitude [deg]	53.48
Longitude [deg]	-1.0
Elevation [m]	17.00
Time Zone	0.00
North Axis Angle [deg]	0.00
Rotation for Appendix G [deg]	0.00
Hours Simulated [hrs]	168.00

ENVELOPE

Window-Wall Ratio

	Total	North (315 to 45 deg)	East (45 to 135 deg)	South (135 to 225 deg)	West (225 to 315 deg)
Gross Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Above Ground Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Window Opening Area [m2]	256.41	35.05	8.98	165.59	46.80
Gross Window-Wall Ratio [%]	20.78	12.63	2.29	56.23	17.34
Above Ground Window-Wall Ratio [%]	20.78	12.63	2.29	56.23	17.34

Conditioned Window-Wall Ratio

	Total	North (315 to 45 deg)	East (45 to 135 deg)	South (135 to 225 deg)	West (225 to 315 deg)
Gross Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Above Ground Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Window Opening Area [m2]	256.41	35.05	8.98	165.59	46.80

Gross Window-Wall Ratio [%]	20.78	12.63	2.29	56.23	17.34
Above Ground Window-Wall Ratio [%]	20.78	12.63	2.29	56.23	17.34

Report: **Demand End Use Components Summary**, For: **Entire Facility**

Timestamp: **2018-06-05 10:32:34**

End Uses

	Electricity [W]	Natural Gas [W]	Propane [W]	District Cooling [W]	District Heating [W]	Water [m3/s]
Time of Peak	18-FEB-09:30	-	-	19-FEB-13:00	18-FEB-07:30	18-FEB-11:30
Heating	0.00	0.00	0.00	0.00	58400.18	0.00
Cooling	0.00	0.00	0.00	12535.67	0.00	0.00
Interior Lighting	41333.88	0.00	0.00	0.00	0.00	0.00
Exterior Lighting	0.00	0.00	0.00	0.00	0.00	0.00
Interior Equipment	16049.44	0.00	0.00	0.00	0.00	0.00
Water Systems	0.00	0.00	0.00	0.00	46.37	0.00
Total End Uses	57383.32	0.00	0.00	12535.67	58446.55	0.00

End Uses By Subcategory

	Subcategory	Electricity [W]	Natural Gas [W]	Propane [W]	District Cooling [W]	District Heating [W]	Water [m3/s]
Heating	General	0.00	0.00	0.00	0.00	58400.18	0.00
Cooling	General	0.00	0.00	0.00	12535.67	0.00	0.00
Interior Lighting	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:WC#GeneralLights	1413.14	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:6ShopSU#GeneralLights	4690.49	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:ShopStorage#GeneralLights	45.52	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Services#GeneralLights	242.68	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StudentCentral#GeneralLights	6136.26	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OpenOffice#GeneralLights	5850.32	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office1#GeneralLights	1093.67	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GeneralOffice#GeneralLights	3890.24	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen2#GeneralLights	1512.02	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Gym#GeneralLights	10440.74	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GymCirculation#GeneralLights	1764.52	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Staircase#GeneralLights	154.29	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen#GeneralLights	932.98	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office#GeneralLights	1354.41	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Entrance#GeneralLights	54.07	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OfficeInternational#GeneralLights	316.83	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:InternationalOffice#GeneralLights	796.52	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StarbucksKitchen#GeneralLights	645.18	0.00	0.00	0.00	0.00	0.00
Interior Equipment	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:WC#05	645.80	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:6ShopSU#05	813.02	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Services#05	88.82	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StudentCentral#05	2245.87	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OpenOffice#05	3507.27	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office1#05	655.65	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GeneralOffice#05	2332.20	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen2#05	2057.56	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Staircase#05	56.47	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen#05	1269.60	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office#05	811.97	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Entrance#05	19.79	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OfficeInternational#05	189.94	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:InternationalOffice#05	477.51	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StarbucksKitchen#05	877.96	0.00	0.00	0.00	0.00	0.00
	DHW StdntCntrlGrndFlr:GeneralOffice	0.00	0.00	0.00	0.00	38.49	0.00
	DHW StdntCntrlGrndFlr:InternationalOffice	0.00	0.00	0.00	0.00	7.88	0.00

Report: **Climatic Data Summary**, For: **Entire Facility**, Timestamp: **2018-06-05 10:32:34**

SizingPeriod:DesignDay

	Maximum Dry Bulb [C]	Daily Temperature Range [deltaC]	Humidity Value	Humidity Type	Wind Speed [m/s]	Wind Direction
SUMMER DESIGN DAY IN UNTITLED (17-02:23-02) JUL	24.00	7.00	17.60	Wetbulb [C]	0.00	0.00
WINTER DESIGN DAY IN UNTITLED (17-02:23-02)	-3.80	0.00	-3.80	Wetbulb [C]	15.20	0.00

Time Not Comfortable Based on Simple ASHRAE 55-2004

	Winter Clothes [hr]	Summer Clothes [hr]	Summer or Winter Clothes [hr]
STDNTCNTRLGRNDFLR:WC	50.00	50.00	50.00
STDNTCNTRLGRNDFLR:6SHOPSU	29.50	49.00	18.50

STDNTCNTRLGRNDFLR:SHOPSTORAGE	61.50	65.00	61.50
STDNTCNTRLGRNDFLR:SERVICES	112.00	112.00	112.00
STDNTCNTRLGRNDFLR:STUDENTCENTRAL	100.50	112.00	100.50
STDNTCNTRLGRNDFLR:OPENOFFICE	9.00	53.50	9.00
STDNTCNTRLGRNDFLR:OFFICE1	28.50	55.00	28.50
STDNTCNTRLGRNDFLR:GENERALOFFICE	10.00	55.00	10.00
STDNTCNTRLGRNDFLR:KITCHEN2	59.00	59.00	59.00
STDNTCNTRLGRNDFLR:GYM	98.00	98.00	98.00
STDNTCNTRLGRNDFLR:GYMCIRCULATION	112.00	112.00	112.00
STDNTCNTRLGRNDFLR:STAIRCASE	112.00	112.00	112.00
STDNTCNTRLGRNDFLR:KITCHEN	59.00	59.00	59.00
STDNTCNTRLGRNDFLR:OFFICE	48.00	55.00	48.00
STDNTCNTRLGRNDFLR:ENTRANCE	95.00	103.00	91.00
STDNTCNTRLGRNDFLR:OFFICEINTERNATIONAL	21.00	55.00	21.00
STDNTCNTRLGRNDFLR:INTERNATIONALOFFICE	12.50	55.00	12.50
STDNTCNTRLGRNDFLR:STARBUCKSKITCHEN	31.00	43.50	18.50
Facility	112.00	112.00	112.00

Report: **Outdoor Air Summary**, For: **Entire Facility**, Timestamp: **2018-06-05 10:32:34**
Average Outdoor Air During Occupied Hours

	Average Number of Occupants	Nominal Number of Occupants	Zone Volume [m3]	Mechanical Ventilation [ach]	Infiltration [ach]	AFN Infiltration [ach]	Simple Ventilation [ach]
STDNTCNTRLGRNDFLR:WC	15.05	15.05	565.26	1.144	0.000	0.081	0.000
STDNTCNTRLGRNDFLR:6SHOPSU	16.24	18.27	625.40	0.933	0.000	0.166	0.000
STDNTCNTRLGRNDFLR:SHOPSTORAGE	1.85	1.85	72.73	0.911	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:SERVICES	5.17	5.17	194.14	0.953	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STUDENTCENTRAL	130.67	130.67	4939.56	0.948	0.000	0.019	0.000
STDNTCNTRLGRNDFLR:OPENOFFICE	19.45	30.13	1170.06	0.601	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OFFICE1	3.64	5.63	218.73	0.598	0.000	0.080	0.000
STDNTCNTRLGRNDFLR:GENERALOFFICE	12.93	20.03	778.05	0.600	0.000	0.035	0.000
STDNTCNTRLGRNDFLR:KITCHEN2	5.00	5.78	241.92	1.886	0.000	0.069	0.000
STDNTCNTRLGRNDFLR:GYM	203.94	253.79	5568.39	3.798	0.000	0.006	0.000

STDNTCNTRLGRNDFLR:GYMCIRCULATION	37.58	37.58	1411.62	0.925	0.000	0.173	0.000
STDNTCNTRLGRNDFLR:STAIRCASE	3.29	3.29	123.43	0.953	0.000	0.247	0.000
STDNTCNTRLGRNDFLR:KITCHEN	3.09	3.57	149.28	1.886	0.000	0.215	0.000
STDNTCNTRLGRNDFLR:OFFICE	4.50	6.98	270.88	0.595	0.000	0.143	0.000
STDNTCNTRLGRNDFLR:ENTRANCE	1.15	1.15	43.26	0.952	0.000	13.607	0.000
STDNTCNTRLGRNDFLR:OFFICEINTERNATIONAL	1.05	1.63	63.37	0.599	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:INTERNATIONALOFFICE	2.65	4.10	159.30	0.600	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STARBUCKSKITCHEN	2.13	2.47	121.64	1.603	0.000	0.383	0.000

Minimum Outdoor Air During Occupied Hours

	Average Number of Occupants	Nominal Number of Occupants	Zone Volume [m3]	Mechanical Ventilation [ach]	Infiltration [ach]	AFN Infiltration [ach]	Simple Ventilation [ach]
STDNTCNTRLGRNDFLR:WC	15.05	15.05	565.26	1.136	0.000	0.004	0.000
STDNTCNTRLGRNDFLR:6SHOPSU	16.24	18.27	625.40	0.777	0.000	0.005	0.000
STDNTCNTRLGRNDFLR:SHOPSTORAGE	1.85	1.85	72.73	0.904	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:SERVICES	5.17	5.17	194.14	0.944	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STUDENTCENTRAL	130.67	130.67	4939.56	0.938	0.000	0.001	0.000
STDNTCNTRLGRNDFLR:OPENOFFICE	19.45	30.13	1170.06	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OFFICE1	3.64	5.63	218.73	0.091	0.000	0.003	0.000
STDNTCNTRLGRNDFLR:GENERALOFFICE	12.93	20.03	778.05	0.092	0.000	0.001	0.000
STDNTCNTRLGRNDFLR:KITCHEN2	5.00	5.78	241.92	1.059	0.000	0.002	0.000
STDNTCNTRLGRNDFLR:GYM	203.94	253.79	5568.39	2.339	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:GYMCIRCULATION	37.58	37.58	1411.62	0.916	0.000	0.006	0.000
STDNTCNTRLGRNDFLR:STAIRCASE	3.29	3.29	123.43	0.944	0.000	0.010	0.000
STDNTCNTRLGRNDFLR:KITCHEN	3.09	3.57	149.28	1.059	0.000	0.008	0.000

STDNTCNTRLGRNDFLR:OFFICE	4.50	6.98	270.88	0.091	0.000	0.006	0.000
STDNTCNTRLGRNDFLR:ENTRANCE	1.15	1.15	43.26	0.944	0.000	0.489	0.000
STDNTCNTRLGRNDFLR:OFFICEINTERNATIONAL	1.05	1.63	63.37	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:INTERNATIONALOFFICE	2.65	4.10	159.30	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STARBUCKSKITCHEN	2.13	2.47	121.64	0.899	0.000	0.011	0.000

Appendix 3: Student Central Building, Energy Simulation Using Realistic Data

This section presents selected parts of the final results of energy simulation tool for student central building using realistic data which has been collected in this study.

Program Version:**EnergyPlus, Version 8.5.0-c87e61b44b, YMD=2018.10.04 14:05**

Tabular Output Report in Format: **HTML**

Building: **Building**

(17-02:23-02) ** FINNINGLEY - GBR IWEC Data WMO#=033600

Simulation Timestamp: **2018-06-05 14:06:23**

Report: **Annual Building Utility Performance Summary**

Timestamp: **2018-06-05 14:06:23**

Values gathered over 168.00 hours

WARNING: THE REPORT DOES NOT REPRESENT A FULL ANNUAL SIMULATION.

Site and Source Energy

	Total Energy [kWh]	Energy Per Total Building Area [kWh/m2]	Energy Per Conditioned Building Area [kWh/m2]
Total Site Energy	15083.01	3.62	3.62
Net Site Energy	15083.01	3.62	3.62
Total Source Energy	49853.09	11.97	11.97
Net Source Energy	49853.09	11.97	11.97

Site to Source Energy Conversion Factors

	Site=>Source Conversion Factor
Electricity	3.167
Natural Gas	1.084
District Cooling	1.056
District Heating	3.613
Steam	0.250
Gasoline	1.050
Diesel	1.050
Coal	1.050
Fuel Oil #1	1.050
Fuel Oil #2	1.050
Propane	1.050
Other Fuel 1	1.000
Other Fuel 2	1.000

Building Area

	Area [m2]
Total Building Area	4165.77
Net Conditioned Building Area	4165.77
Unconditioned Building Area	0.00

End Uses

	Electricity [kWh]	Natural Gas [kWh]	Additional Fuel [kWh]	District Cooling [kWh]	District Heating [kWh]	Water [m3]
Heating	0.00	0.00	0.00	0.00	7107.57	0.00
Cooling	0.00	0.00	0.00	828.48	0.00	0.00
Interior Lighting	3297.36	0.00	0.00	0.00	0.00	0.00
Interior Equipment	2366.27	0.00	0.00	0.00	0.00	0.00
Water Systems	0.00	0.00	0.00	0.00	1483.32	23.23
Total End Uses	5663.63	0.00	0.00	828.48	8590.89	23.23

Normalized Metrics

Utility Use Per Conditioned Floor Area

	Electricity Intensity [kWh/m2]	Natural Gas Intensity [kWh/m2]	Additional Fuel Intensity [kWh/m2]	District Cooling Intensity [kWh/m2]	District Heating Intensity [kWh/m2]	Water Intensity [m3/m2]
Lighting	0.79	0.00	0.00	0.00	0.00	0.00
HVAC	0.00	0.00	0.00	0.20	2.06	0.01
Other	0.57	0.00	0.00	0.00	0.00	0.00
Total	1.36	0.00	0.00	0.20	2.06	0.01

Utility Use Per Total Floor Area

	Electricity Intensity [kWh/m2]	Natural Gas Intensity [kWh/m2]	Additional Fuel Intensity [kWh/m2]	District Cooling	District Heating	Water Intensity [m3/m2]

				Intensity [kWh/m2]	Intensity [kWh/m2]	
Lighting	0.79	0.00	0.00	0.00	0.00	0.00
HVAC	0.00	0.00	0.00	0.20	2.06	0.01
Other	0.57	0.00	0.00	0.00	0.00	0.00
Total	1.36	0.00	0.00	0.20	2.06	0.01

Electric Loads Satisfied

	Electricity [kWh]	Percent Electricity [%]
Electricity Coming From Utility	5663.633	100.00
Surplus Electricity Going To Utility	0.000	0.00
Net Electricity From Utility	5663.633	100.00

Setpoint Not Met Criteria

	Degrees [deltaC]
Tolerance for Zone Heating Setpoint Not Met Time	1.11
Tolerance for Zone Cooling Setpoint Not Met Time	1.11

Comfort and Setpoint Not Met Summary

	Facility [Hours]
Time Setpoint Not Met During Occupied Heating	112.00
Time Setpoint Not Met During Occupied Cooling	0.00
Time Not Comfortable Based on Simple ASHRAE 55-2004	112.00

Note 1: An asterisk (*) indicates that the feature is not yet implemented.

Table of Contents

Report: **Input Verification and Results Summary**

For: **Entire Facility**

Timestamp: **2018-10-04 14:06:23**

General

	Value
Program Version and Build	EnergyPlus, Version 8.5.0-c87e61b44b, YMD=2018.10.04 14:05
RunPeriod	UNTITLED (17-02:23-02)
Weather File	FINNINGLEY - GBR IWEC Data WMO#=033600
Latitude [deg]	53.48
Longitude [deg]	-1.0
Elevation [m]	17.00
Hours Simulated [hrs]	168.00

ENVELOPE

Window-Wall Ratio

	Total	North (315 to 45 deg)	East (45 to 135 deg)	South (135 to 225 deg)	West (225 to 315 deg)
Gross Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Above Ground Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Window Opening Area [m2]	256.92	35.05	8.98	166.10	46.80
Gross Window-Wall Ratio [%]	20.83	12.63	2.29	56.40	17.34
Above Ground Window-Wall Ratio [%]	20.83	12.63	2.29	56.40	17.34

Conditioned Window-Wall Ratio

	Total	North (315 to 45 deg)	East (45 to 135 deg)	South (135 to 225 deg)	West (225 to 315 deg)
Gross Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Above Ground Wall Area [m2]	1233.68	277.47	391.82	294.49	269.91
Window Opening Area [m2]	256.92	35.05	8.98	166.10	46.80
Gross Window-Wall Ratio [%]	20.83	12.63	2.29	56.40	17.34
Above Ground Window-Wall Ratio [%]	20.83	12.63	2.29	56.40	17.34

Report: **Demand End Use Components Summary**

	Electricity [W]	Natural Gas [W]	Propane [W]	District Cooling [W]	District Heating [W]	Water [m3/s]

Time of Peak	18-FEB-09:30	-	-	19-FEB-13:00	18-FEB-08:00	18-FEB-13:30
Heating	0.00	0.00	0.00	0.00	121400.83	0.00
Cooling	0.00	0.00	0.00	33224.55	0.00	0.00
Interior Lighting	43334.57	0.00	0.00	0.00	0.00	0.00
Interior Equipment	24455.04	0.00	0.00	0.00	0.00	0.00
Water Systems	0.00	0.00	0.00	0.00	25152.75	0.00
Total End Uses	67789.61	0.00	0.00	33224.55	146553.58	0.00

End Uses By Subcategory

	Subcategory	Electricity [W]	Natural Gas [W]	Propane [W]	District Cooling [W]	District Heating [W]	Water [m3/s]
Heating	General	0.00	0.00	0.00	0.00	121400.83	0.00
Cooling	General	0.00	0.00	0.00	33224.55	0.00	0.00
Interior Lighting	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:WC#GeneralLights	1413.14	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:6ShopSU#GeneralLights	4690.49	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:ShopStorage#GeneralLights	45.52	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:7Circulation#GeneralLights	882.94	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:10Sitting#GeneralLights	1190.53	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Services#GeneralLights	242.68	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:12Sitting#GeneralLights	222.44	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OpenOffice#GeneralLights	5850.32	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office1#GeneralLights	1093.67	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:9Canteen#GeneralLights	1821.48	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:11Studying#GeneralLights	629.08	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GeneralOffice#GeneralLights	3890.24	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:8Circulation Queue#GeneralLights	593.94	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Gym#GeneralLights	10440.74	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GymCirculation#GeneralLights	1764.52	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen2#GeneralLights	1512.02	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Staircase#GeneralLights	154.29	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen#GeneralLights	932.98	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office#GeneralLights	1354.41	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:3Circulation#GeneralLights	340.07	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:5LobbyReception#GeneralLights	1401.49	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Entrance#GeneralLights	54.07	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:4SittingStarbucks#GeneralLights	275.55	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:1Circulation#GeneralLights	370.50	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OfficeInternational#GeneralLights	316.83	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:InternationalOffice#GeneralLights	796.52	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StarbucksKitchen#GeneralLights	645.18	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:2Sitting#GeneralLights	408.94	0.00	0.00	0.00	0.00	0.00
Interior Equipment	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:WC#05	645.80	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:6ShopSU#05	813.02	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:7Circulation#05	323.15	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:10Sitting#05	2725.51	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Services#05	88.82	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:12Sitting#05	509.23	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OpenOffice#05	3507.27	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office1#05	655.65	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:9Canteen#05	4169.97	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:11Studying#05	230.24	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:GeneralOffice#05	2332.20	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:8CirculationQueue#05	217.38	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen2#05	2057.56	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Staircase#05	56.47	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Kitchen#05	1269.60	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Office#05	811.97	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:3Circulation#05	124.46	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:5LobbyReceiption#05	648.89	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:Entrance#05	19.79	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:4SittingStarbucks#05	630.82	0.00	0.00	0.00	0.00	0.00

	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:1Circulation #05	135.60	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:OfficeInternational#05	189.94	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:InternationalOffice#05	477.51	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:StarbucksKitchen#05	877.96	0.00	0.00	0.00	0.00	0.00
	ELECTRIC EQUIPMENT#StdntCntrlGrndFlr:2Sitting#05	936.21	0.00	0.00	0.00	0.00	0.00
	DHW StdntCntrlGrndFlr:10Sitting	0.00	0.00	0.00	0.00	7605.90	0.00
	DHW StdntCntrlGrndFlr:12Sitting	0.00	0.00	0.00	0.00	1421.07	0.00
	DHW StdntCntrlGrndFlr:9Canteen	0.00	0.00	0.00	0.00	11636.86	0.00
	DHW StdntCntrlGrndFlr:GeneralOffice	0.00	0.00	0.00	0.00	96.22	0.00
	DHW StdntCntrlGrndFlr:4SittingStarbucks	0.00	0.00	0.00	0.00	1760.39	0.00
	DHW StdntCntrlGrndFlr:InternationalOffice	0.00	0.00	0.00	0.00	19.70	0.00
	DHW StdntCntrlGrndFlr:StarbucksKitchen	0.00	0.00	0.00	0.00	0.00	0.00
	DHW StdntCntrlGrndFlr:2Sitting	0.00	0.00	0.00	0.00	2612.61	0.00

	Maximum Dry Bulb [C]	Daily Temperature Range [deltaC]	Humidity Value	Humidity Type	Wind Speed [m/s]	Wind Direction

SUMMER DESIGN DAY IN UNTITLED (17-02:23-02) JUL	24.00	7.00	17.60	Wetbulb [C]	0.00	0.00
WINTER DESIGN DAY IN UNTITLED (17-02:23-02)	-3.80	0.00	-3.80	Wetbulb [C]	15.20	0.00

Time Not Comfortable Based on Simple ASHRAE 55-2004

	Winter Clothes [hr]	Summer Clothes [hr]	Summer or Winter Clothes [hr]
STDNTCNTRLGRNDFLR:WC	50.00	50.00	50.00
STDNTCNTRLGRNDFLR:6SHOPSU	22.00	47.50	9.00
STDNTCNTRLGRNDFLR:SHOPSTORAGE	52.50	65.00	52.50
STDNTCNTRLGRNDFLR:7CIRCULATION	2.00	112.00	2.00
STDNTCNTRLGRNDFLR:10SITTING	0.00	84.00	0.00
STDNTCNTRLGRNDFLR:SERVICES	112.00	112.00	112.00
STDNTCNTRLGRNDFLR:12SITTING	0.00	84.00	0.00
STDNTCNTRLGRNDFLR:OPENOFFICE	5.00	46.00	2.50
STDNTCNTRLGRNDFLR:OFFICE1	14.00	55.00	14.00
STDNTCNTRLGRNDFLR:9CANTEEN	0.00	84.00	0.00
STDNTCNTRLGRNDFLR:11STUDYING	79.00	112.00	79.00
STDNTCNTRLGRNDFLR:GENERALOFFICE	5.00	55.00	5.00
STDNTCNTRLGRNDFLR:8CIRCULATIONQUEUE	22.50	112.00	22.50
STDNTCNTRLGRNDFLR:GYM	98.00	98.00	98.00
STDNTCNTRLGRNDFLR:GYMCIRCULATION	112.00	112.00	112.00
STDNTCNTRLGRNDFLR:KITCHEN2	43.00	59.00	43.00

STDNTCNTRLGRNDFLR:STAIRCASE	112.00	112.00	112.00
STDNTCNTRLGRNDFLR:KITCHEN	32.50	59.00	32.50
STDNTCNTRLGRNDFLR:OFFICE	37.00	55.00	37.00
STDNTCNTRLGRNDFLR:3CIRCULATION	1.00	112.00	1.00
STDNTCNTRLGRNDFLR:5LOBBYRECEIPTION	8.50	50.00	8.50
STDNTCNTRLGRNDFLR:ENTRANCE	109.00	112.00	109.00
STDNTCNTRLGRNDFLR:4SITTINGSTARBUCKS	6.00	73.00	0.00
STDNTCNTRLGRNDFLR:1CIRCULATION	13.00	93.50	1.00
STDNTCNTRLGRNDFLR:OFFICEINTERNATIONAL	7.50	53.50	7.50
STDNTCNTRLGRNDFLR:INTERNATIONALOFFICE	2.50	55.00	2.50
STDNTCNTRLGRNDFLR:STARBUCKSKITCHEN	15.00	46.50	6.50
STDNTCNTRLGRNDFLR:2SITTING	13.50	76.50	10.50
Facility	112.00	119.00	112.00

Aggregated over the RunPeriods for Weather

Average Outdoor Air During Occupied Hours

	Average Number of Occupants	Nominal Number of Occupants	Zone Volume [m3]	Mechanical Ventilation [ach]	Infiltration [ach]	AFN Infiltration [ach]	Simple Ventilation [ach]
STDNTCNTRLGRNDFLR:WC	15.05	15.05	565.26	1.144	0.000	0.050	0.000
STDNTCNTRLGRNDFLR:6SHOPSU	29.05	32.68	625.40	1.670	0.000	0.103	0.000
STDNTCNTRLGRNDFLR:SHOPSTORAGE	1.85	1.85	72.73	0.910	0.000	0.000	0.000

STDNTCNTRLGRNDFLR:7CIRCULATION	22.96	22.96	706.35	1.171	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:10SITTING	36.34	52.86	636.70	2.064	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:SERVICES	5.17	5.17	194.14	0.953	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:12SITTING	6.79	9.88	118.63	2.069	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OPENOFFICE	19.45	30.13	1170.06	0.603	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OFFICE1	3.64	5.63	218.73	0.599	0.000	0.054	0.000
STDNTCNTRLGRNDFLR:9CANTEEN	86.82	126.29	971.45	3.231	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:11STUDYING	41.90	41.90	503.26	2.991	0.000	0.019	0.000
STDNTCNTRLGRNDFLR:GENERAL OFFICE	12.93	20.03	778.05	0.600	0.000	0.023	0.000
STDNTCNTRLGRNDFLR:8CIRCULATIONQUEUE	15.44	15.44	475.15	1.169	0.000	0.048	0.000
STDNTCNTRLGRNDFLR:GYM	203.94	253.79	5568.39	3.798	0.000	0.005	0.000
STDNTCNTRLGRNDFLR:GYMCIRCULATION	37.58	37.58	1411.62	0.926	0.000	0.151	0.000
STDNTCNTRLGRNDFLR:KITCHEN2	5.00	5.78	241.92	1.892	0.000	0.057	0.000
STDNTCNTRLGRNDFLR:STAIRCASE	3.29	3.29	123.43	0.953	0.000	0.210	0.000
STDNTCNTRLGRNDFLR:KITCHEN	3.09	3.57	149.28	1.892	0.000	0.161	0.000

STDNTCNTRLGRNDFLR:OFFICE	4.50	6.98	270.88	0.596	0.000	0.097	0.000
STDNTCNTRLGRNDFLR:3CIRCULATION	8.84	8.84	272.05	1.172	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:5LOBBYRECEIPTION	28.31	28.31	560.60	1.812	0.000	0.007	0.000
STDNTCNTRLGRNDFLR:ENTRANCE	1.41	1.41	43.26	1.122	0.000	115.300	0.000
STDNTCNTRLGRNDFLR:4SITTINGSTARBUCKS	8.41	12.23	146.96	2.069	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:1CIRCULATION	9.63	9.63	296.40	1.173	0.000	0.025	0.000
STDNTCNTRLGRNDFLR:OFFICEINTERNATIONAL	1.05	1.63	63.37	0.601	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:INTERNATIONALOFFICE	2.65	4.10	159.30	0.601	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STARBUCKSKITCHEN	2.13	2.47	121.64	1.605	0.000	0.187	0.000
STDNTCNTRLGRNDFLR:2SITTING	12.48	18.16	218.10	2.070	0.000	0.613	0.000

Values shown for a single zone without multipliers

Minimum Outdoor Air During Occupied Hours

	Average Number of Occupants	Nominal Number of Occupants	Zone Volume [m3]	Mechanical Ventilation [ach]	Infiltration [ach]	AFN Infiltration [ach]	Simple Ventilation [ach]
STDNTCNTRLGRNDFLR:WC	15.05	15.05	565.26	1.136	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:6SHOPSU	29.05	32.68	625.40	1.394	0.000	0.002	0.000

STDNTCNTRLGRNDFLR:SHOPSTORAGE	1.85	1.85	72.73	0.903	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:7CIRCULATION	22.96	22.96	706.35	1.159	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:10SITTING	36.34	52.86	636.70	0.744	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:SERVICES	5.17	5.17	194.14	0.944	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:12SITTING	6.79	9.88	118.63	0.746	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OPENOFFICE	19.45	30.13	1170.06	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OFFICE1	3.64	5.63	218.73	0.091	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:9CANTEEN	86.82	126.29	971.45	1.165	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:11STUDYING	41.90	41.90	503.26	2.960	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:GENERALOFFICE	12.93	20.03	778.05	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:8CIRCULATIONQUEUE	15.44	15.44	475.15	1.158	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:GYM	203.94	253.79	5568.39	2.338	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:GYMCIRCULATION	37.58	37.58	1411.62	0.917	0.000	0.001	0.000
STDNTCNTRLGRNDFLR:KITCHEN2	5.00	5.78	241.92	1.063	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STAIRCASE	3.29	3.29	123.43	0.944	0.000	0.002	0.000

STDNTCNTRLGRNDFLR:KITCHEN	3.09	3.57	149.28	1.063	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OFFICE	4.50	6.98	270.88	0.091	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:3CIRCULATION	8.84	8.84	272.05	1.159	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:5LOBBYRECEIPTION	28.31	28.31	560.60	1.794	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:ENTRANCE	1.41	1.41	43.26	1.095	0.000	1.563	0.000
STDNTCNTRLGRNDFLR:4SITTINGSTARBUCKS	8.41	12.23	146.96	0.746	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:1CIRCULATION	9.63	9.63	296.40	1.160	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:OFFICEINTERNATIONAL	1.05	1.63	63.37	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:INTERNATIONALOFFICE	2.65	4.10	159.30	0.092	0.000	0.000	0.000
STDNTCNTRLGRNDFLR:STARBUCKSKITCHEN	2.13	2.47	121.64	0.903	0.000	0.005	0.000
STDNTCNTRLGRNDFLR:2SITTING	12.48	18.16	218.10	0.746	0.000	0.002	0.000

References

Adjaye, D., Allison, P., & Eshun, K. (2006). *Making public buildings*. London: Thames & Hudson.

Agha-Hossein, M. M., El-Jouzi, S., Elmualim, A. A., Ellis, J., & Williams, M. (2013). Post-occupancy studies of an office environment: Energy performance and occupants' satisfaction. *Building and Environment, 69*, 121-130. doi:10.1016/j.buildenv.2013.08.003

Ahmed, V., Opoku, A., & Aziz, Z. (2016). *Research methodology in the built environment: a selection of case studies*. London: Routledge.

Ahn, K.-U., & Park, C.-S. (2016). Correlation between occupants and energy consumption. *Energy & Buildings, 116*, 420-433. doi:10.1016/j.enbuild.2016.01.010

Ahn, K.-U., & Park, C. S. (2016). Different occupant modeling approaches for building energy prediction. *Energy Procedia, 88*, 721-724. doi:10.1016/j.egypro.2016.06.050

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*.

Al-Mumin, A., Khattab, O., & Sridhar, G. (2003). Occupants' behavior and activity patterns influencing the energy consumption in the Kuwaiti residences. *Energy & Buildings, 35*(6), 549-559. doi:10.1016/S0378-7788(02)00167-6

Alaaeddine, R., & Wu, S. (2017). *Application of supervised learning methods to better predict building energy performance.* Paper presented at the International Conference on Sustainable Futures 2017, Bahrain.

Aldossary, N. A., Rezgui, Y., & Kwan, A. (2014). Domestic energy consumption patterns in a hot and humid climate: A multiple-case study analysis. *Applied Energy, 114*, 353-365. doi:10.1016/j.apenergy.2013.09.061

Allard, I., Olofsson, T., Nair, G., Umeå, u., Teknisk-naturvetenskapliga, f., & Institutionen för tillämpad fysik och, e. (2018). Energy evaluation of residential buildings: Performance gap analysis incorporating uncertainties in the evaluation methods. *Building Simulation, 11*(4), 725-737. doi:10.1007/s12273-018-0439-7

American Society of Heating, R., Air Conditioning, E., Ashrae, American Society of Heating, R., Air-Conditioning Engineers, I., & A.S.H.R.A.E. (2009). *2009 ASHRAE handbook fundamentals*. Place of publication not identified: American Society of Heating Refrigerating and Air Conditioning Engineers.

Andersen, P. D., Iversen, A., Madsen, H., & Rode, C. (2014). Dynamic modeling of presence of occupants using inhomogeneous Markov chains. *Energy and Buildings, 69*, 213-223. doi:10.1016/j.enbuild.2013.10.001

Andrews, C. J., Chandra Putra, H., & Brennan, C. (2013). Simulation Modeling of Occupant Behavior in Commercial Buildings. *Center for Green Building at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA.*

Arnheim, R. (2004). *Art and visual perception: a psychology of the creative eye* (Vol. New version.). Berkeley, Calif;London;: University of California Press.

ASHRAE. (2004). Thermal Environmental Conditions for Human Occupancy: American Society of Heating and Air-Conditioning Engineers.

ASHRAE. (2016). ASHRAE 90.1 Standard. USA: ASHRAE.

Augustin, S. (2009). *Place advantage: applied psychology for interior architecture*. Hoboken, N.J: John Wiley & Sons.

Autodesk. (2018). REVIT Built for Building Information Modelling. Retrieved from https://www.autodesk.co.uk/products/revit/overview

Azghandi, M. V., Nikolaidis, I., & Stroulia, E. (2015). *Sensor placement for indoor multi-occupant tracking*.

Barlow, S. (2011). *Guide to BREEAM*. London: RIBA.

Basarir, M. N. (2010). *Energy Appraisal of Retail Units: Assessing the Effect of Door Operation on Energy Consumption and Thermal comfort.* (MPhil), University of Cambridge.

Becchio, C., Bello, C., Corgnati, S. P., & Ingaramo, L. (2016). Influence of Occupant Behaviour Lifestyle on an Italian Social Housing. *Energy Procedia, 101*, 1034-1041. doi:10.1016/j.egypro.2016.11.131

Blight, T. S., & Coley, D. A. (2013). Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings. *Energy and Buildings, 66*, 183-192. doi:10.1016/j.enbuild.2013.06.030

Bluyssen, P. M. (2009). *The indoor environment handbook: how to make buildings healthy and comfortable*. London: Earthscan.

Boafo, F. E., Ahn, J.-G., Kim, J.-H., & Kim, J.-T. (2015). Computing Thermal Bridge of VIP in Building Retrofits using DesignBuilder. *Energy Procedia, 78*, 400-405. doi:10.1016/j.egypro.2015.11.683

Bordass, B., Cohen, R., Standeven, M., & Leaman, A. (2001). Assessing building performance in use 3: energy performance of the Probe buildings. *Building Research & Information, 29*(2), 114-128. doi:10.1080/09613210010008036

Bourgeois, D., Reinhart, C., & A. Macdonald, I. (2005). *Assessing the total energy impact of occupant behavioural response to manual and automated lighting systems* Paper presented at the Ninth International IBPSA Conference, Montréal, Canada.

Boyano, A., Hernandez, P., & Wolf, O. (2013). Energy demands and potential savings in European office buildings: Case studies based on EnergyPlus simulations. *Energy & Buildings, 65*, 19-28. doi:10.1016/j.enbuild.2013.05.039

Burgas, L., Melendez, J., & Colomer, J. (2014). Principal component analysis for monitoring electrical consumption of academic buildings. *Energy Procedia, 62*, 555-564. doi:10.1016/j.egypro.2014.12.417

Burrel, G., & Morgan, G. (1979). *Sociological paradigms and organisational analysis : elements of the sociology of corporate life / Gibson Burrell, Gareth Morgan*. London: Heinemann.

Buxton, P. (2018). *Metric handbook: planning and design data* (Sixth;Sixth; ed.). London: Routledge, Taylor & Francis Group.

Caan, S. (2011). *Rethinking Design and Interiors, Human Beings in the Built Environment*. London: Laurence King.

Cabanac, M. (1971). Physiological Role of Pleasure. *Science, 173*(4002), 1103-1107. doi:10.1126/science.173.4002.1103

Calì, D., Osterhage, T., Streblow, R., & Müller, D. (2016). Energy performance gap in refurbished German dwellings: Lesson learned from a field test. *Energy and Buildings, 127*, 1146-1158. doi:10.1016/j.enbuild.2016.05.020

CambridgeDictionary. (2018). Cambridge Dictionary. Retrieved from https://dictionary.cambridge.org/dictionary/english/multifunctional

Carbontrust. (2005). The UK Climate Change Programme: Potential evolution for business and the public sector. Retrieved from https://www.carbontrust.com/media/84912/ctc518-uk-climate-change-programme-potential-evolution.pdf

Cárdenas, J., Osma, G., Caicedo, C., Torres, A., Sánchez, S., & Ordóñez, G. (2016, 2016). *Building energy analysis of Electrical Engineering Building from DesignBuilder tool: Calibration and simulations*.

Carpino, C., Mora, D., Arcuri, N., & De Simone, M. (2017). Behavioral variables and occupancy patterns in the design and modeling of Nearly Zero Energy Buildings. *Building Simulation, 10*(6), 875-888. doi:10.1007/s12273-017-0371-2

Carriere, M., Schoenau, G. J., & Besant, R. W. (1999). Investigation of some large building energy conservation opportunities using the doe-2 model. *Energy Conversion and Management, 40*(8), 861-872. doi:10.1016/S0196-8904(98)00152-6

Chen, J., & Ahn, C. (2014). Assessing occupants' energy load variation through existing wireless network infrastructure in commercial and educational buildings. *Energy and Buildings, 82*, 540-549. doi:10.1016/j.enbuild.2014.07.053

Chen, J., Wang, X., & Steemers, K. (2013). A statistical analysis of a residential energy consumption survey study in Hangzhou, China. *Energy and Buildings, 66*, 193-202. doi:10.1016/j.enbuild.2013.07.045

Chen, S., Yang, W., Yoshino, H., Levine, M. D., Newhouse, K., & Hinge, A. (2015). Definition of occupant behavior in residential buildings and its application to behavior analysis in case studies. *Energy and Buildings, 104*, 1-13. doi:10.1016/j.enbuild.2015.06.075

Chow, T. T., Fong, K. F., Givoni, B., Lin, Z., & Chan, A. L. S. (2010). Thermal sensation of Hong Kong people with increased air speed, temperature and humidity in air-conditioned environment. *Building and Environment, 45*(10), 2177-2183. doi:10.1016/j.buildenv.2010.03.016

Christensen, K., Melfi, R., Nordman, B., Rosenblum, B., & Viera, R. (2014). Using existing network infrastructure to estimate building occupancy and control plugged-in devices in user workspaces. *International Journal of Communication Networks and Distributed Systems, 12*(1), 4-29. doi:10.1504/IJCNDS.2014.057985

Coakley, D., Raftery, P., & Keane, M. (2014). A review of methods to match building energy simulation models to measured data. *Renewable and Sustainable Energy Reviews, 37*, 123-141. doi:10.1016/j.rser.2014.05.007

COMNET. (2016a). Appendix B. Retrieved from https://comnet.org/appendix-b-modeling-data

COMNET. (2016b). Appendix C. Retrieved from https://comnet.org/appendix-c-schedules

Cool Choices. (2016). Retrieved from https://coolchoices.com/

Cottrell, M. (2012). *Guide to the LEED AP homes exam* (1. Aufl. ed. Vol. 40). Hoboken, N.J: Wiley.

Crawley, D. B., Lawrie, L. K., Winkelmann, F. C., Buhl, W. F., Huang, Y. J., Pedersen, C. O., . . . Glazer, J. (2001). EnergyPlus: creating a new-generation building energy simulation program. *Energy & Buildings, 33*(4), 319-331. doi:10.1016/S0378-7788(00)00114-6

CRCResearch. (2018). Multi-functional Spaces. Retrieved from https://crcresearch.org/solutions-agenda/multi-functional-spaces

Crocker, R., & Lehmann, S. (2013). *Motivating change: sustainable design and behaviour in the built environment*. Abingdon, Oxon: Routledge.

D'Oca, S. (2012). *Influence of occupants' behavior on heating energy consumption and thermal comfort in residential buildings.* Politecnico di Torino.

D'Oca, S., & Hong, T. (2014). A data-mining approach to discover patterns of window opening and closing behavior in offices. *Building and Environment, 82*, 726-739. doi:10.1016/j.buildenv.2014.10.021

D'Oca, S., Fabi, V., Corgnati, S. P., & Andersen, R. K. (2014). Effect of thermostat and window opening occupant behavior models on energy use in homes. *Building Simulation, 7*(6), 683-694. doi:10.1007/s12273-014-0191-6

Dall'O', G., Galante, A., & Torri, M. (2011). A methodology for the energy performance classification of residential building stock on an urban scale. *Energy & Buildings, 48*, 211-219. doi:10.1016/j.enbuild.2012.01.034

Dascalaki, E. G., Droutsa, K., Gaglia, A. G., Kontoyiannidis, S., & Balaras, C. A. (2010). Data collection and analysis of the building stock and its energy performance—An example for Hellenic buildings. *Energy & Buildings, 42*(8), 1231-1237. doi:10.1016/j.enbuild.2010.02.014

Day, J. K., & Gunderson, D. E. (2015). Understanding high performance buildings: The link between occupant knowledge of passive design systems, corresponding behaviors, occupant comfort and environmental satisfaction. *Building and Environment, 84*, 114-124. doi:10.1016/j.buildenv.2014.11.003

de la Torre, S., & Yousif, C. (2014). Evaluation of Chimney Stack Effect in a New Brewery Using DesignBuilder-energyPlus Software. *Energy Procedia, 62*, 230-235. doi:10.1016/j.egypro.2014.12.384

De Meester, T., Marique, A.-F., De Herde, A., & Reiter, S. (2013). Impacts of occupant behaviours on residential heating consumption for detached houses in a temperate climate in the northern part of Europe. *Energy and Buildings, 57*, 313-323. doi:10.1016/j.enbuild.2012.11.005

de Wilde, P. (2014). The gap between predicted and measured energy performance of buildings: A framework for investigation. *Automation in Construction, 41*, 40-49. doi:10.1016/j.autcon.2014.02.009

Delaney, L. (2017). *Statistical data set: museums and galleries monthly visits*. UK Government Retrieved from https://www.gov.uk/government/statistical-data-sets/museums-and-galleries-monthly-visits#summary.

Deloitte, J. (2010). *Employment densities guide*. UK Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/378203/employ-den.pdf.

Delzendeh, E., & Wu, S. (2017). *The Influence of Space Layout Design on Occupant's Energy Behaviour.* Paper presented at the LC3 Lean and Computing in Construction Congress - Joint Conference on Computing in Construction.

Delzendeh, E., Wu, S., & Alaaeddine, R. (2018). *The role of space design in prediction of occupancy in multi-functional spaces of public buildings.* Paper presented at the 2018 Building Performance Analysis Conference and SimBuild, Chicago, IL.

Delzendeh, E., Wu, S., Lee, A., & Zhou, Y. (2017). The impact of occupants' behaviours on building energy analysis: A research review. *Renewable and Sustainable Energy Reviews, 80*, 1061-1071. doi:https://doi.org/10.1016/j.rser.2017.05.264

Demanuele, C., Tweddell, T., & Davies, M. (2010). *Bridging the gap between predicted and actual energy performance in schools*. Paper presented at the World Renewable Energy Congress XI, Abu Dhabi, UAE.

DesignBuilder. Simulation period. Retrieved from http://www.designbuilder.co.uk/helpv2/Content/Simulation_Period.htm

DesignBuilder. (2009). *DesignBuilder 2.1 User's Manual*. Retrieved from http://www.designbuildersoftware.com/docs/designbuilder/DesignBuilder_2.1_Users-Manual_Ltr.pdf

DesignBuilder. (2018a). DesignBuilder Revit – gbXML Tutorial. Retrieved from http://www.designbuilder.co.uk/downloads/db_revit_tutorial_v1.pdf

DesignBuilder. (2018b). Import 3-D BIM Data. Retrieved from https://www.designbuilder.co.uk/helpv4.2/Content/Import_3-D_CAD_Data.htm

Dudovskiy, J. (2018). *The Ultimate Guide to Writing a Dissertation in Business Studies: A Step-by-Step Assistance*

Duignan, O. (2016). A Dictionary of Business Research Methods (Vol. 1): Oxford University Press.

EEA, E. E. A. (2015). *Final energy consumption by sector and fuel*. European Environment Agency.

eia. (2016). *International Energy Outlook*. U.S. Energy Information Administration Retrieved from https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf.

Ekici, C. (2016). Measurement Uncertainty Budget of the PMV Thermal Comfort Equation. *International Journal of Thermophysics, 37*(5), 1-21. doi:10.1007/s10765-015-2011-3

Endler, N. S. (1993). Desire for control. Personality, social and clinical perspectives (Vol. 15, pp. 361-361): Elsevier Ltd.

EnergyPlus. (2018). energyPlus. Retrieved from https://energyplus.net/

EngineeringToolBox. (2003). Building Area per Person. Retrieved from https://www.engineeringtoolbox.com/number-persons-buildings-d_118.html

Erba, S., Causone, F., & Armani, R. (2017). The effect of weather datasets on building energy simulation outputs. *Energy Procedia, 134*, 545-554. doi:10.1016/j.egypro.2017.09.561

EUROSTAT. (2015). *Consumption of energy*. http://ec.europa.eu/: EUROSTAT.

Fabi, V., Andersen, R. V., Corgnati, S., & Olesen, B. W. (2012). Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. *Building and Environment, 58*, 188-198. doi:10.1016/j.buildenv.2012.07.009

Fabi, V., Andersen, R. V., Corgnati, S. P., & Olesen, B. W. (2013). A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings. *Building Simulation, 6*(4), 415-427. doi:10.1007/s12273-013-0119-6

Fabi, V., Andersen, R. V., Corgnati, S. P., Olesen, W. B., & Filippi, M. (2011). *Description of occupant behaviour in building energy simulation: state-of-art and concept for improvements.* Paper presented at the 12th Conference of International Building Performance Simulation Association, Sydney.

Fanger, P. O. (1972). *Thermal comfort, analysis and applications in environmental engineering*. New York U6 - ctx_ver=Z39.88-2004&ctx_enc=info%3Aofi%2Fenc%3AUTF-8&rfr_id=info%3Asid%2Fsummon.serialssolutions.com&rft_val_fmt=info%3Aofi%2Ffmt%3Akev%3Amtx%3Abook&rft.genre=book&rft.title=Thermal+comfort%2C+analysis+and+applications+in+environmental+engineering&rft.au=Fanger%2C+P.+O&rft.date=1972-01-01&rft.pub=McGraw-Hill&rft.externalDBID=n%2Fa&rft.externalDocID=190776&paramdict=en-US U7 - Book: McGraw-Hill.

Fathalian, A., & Kargarsharifabad, H. (2018). Actual validation of energy simulation and investigation of energy management strategies (Case Study: An office building in

Semnan, Iran). *Case Studies in Thermal Engineering, 12*, 510-516. doi:10.1016/j.csite.2018.06.007
Federspiel, C., Zhang, Q., & Arens, E. (2002). Model-based benchmarking with application to laboratory buildings. *Energy & Buildings, 34*(3), 203-214. doi:10.1016/S0378-7788(01)00092-5
Feng, X., Yan, D., & Hong, T. (2015). Simulation of occupancy in buildings. *Energy and Buildings, 87*, 348-359. doi:10.1016/j.enbuild.2014.11.067
Fet, N., Handte, M., Wagner, S., & Marrón, P. J. (2013). *LOCOSmotion: An acceleration-assisted person tracking system based on wireless LAN*.
Freed, M. A. (1998). *Simulating Human Performance in Complex, Dynamic Environments.* (Doctor of Philosophy), Northwestern University, Evanston, Illinois.
Fumo, N., & Chamra, L. M. (2010). Analysis of combined cooling, heating, and power systems based on source primary energy consumption. *Applied Energy, 87*(6), 2023-2030. doi:10.1016/j.apenergy.2009.11.014
Gandhi, P., & Brager, G. S. (2016). Commercial office plug load energy consumption trends and the role of occupant behavior. *Energy & Buildings, 125*, 1-8. doi:10.1016/j.enbuild.2016.04.057
gbXML. (2018). gbXML. Retrieved from http://www.gbxml.org/About_GreenBuildingXML_gbXML
Gelo, O., Braakmann, D., & Benetka, G. (2008). Quantitative and Qualitative Research: Beyond the Debate. *Integrative Psychological and Behavioral Science, 42*(3), 266-290. doi:10.1007/s12124-008-9078-3
Gilani, S., O'Brien, W., Gunay, H. B., & Carrizo, J. S. (2016). Use of dynamic occupant behavior models in the building design and code compliance processes. *Energy & Buildings, 117*, 260-271. doi:10.1016/j.enbuild.2015.10.044
Gill, Z. M., Tierney, M. J., Pegg, I. M., & Allan, N. (2010). Low-energy dwellings: the contribution of behaviours to actual performance. *Building Research & Information, 38*(5), 491-508. doi:10.1080/09613218.2010.505371
Goldstein, R., Tessier, A., & Khan, A. (2011). *Space layout in occupant behavior simulation*. Paper presented at the 12th Conference of International Building Performance Simulation Association, Sydney.
GOV.UK. (2001). Environmental taxes, reliefs and schemes for businesses. Retrieved from https://www.gov.uk/green-taxes-and-reliefs/climate-change-levy
Guerra Santin, O. (2010). *Actual Energy Consumption in Dwellings : The Effect of Energy Performance Regulations and Occupant Behaviour*. Amsterdam: IOS Press.
Gul, M. S., & Patidar, S. (2015). Understanding the energy consumption and occupancy of a multi-purpose academic building. *Energy & Buildings, 87*, 155-165. doi:10.1016/j.enbuild.2014.11.027
Gulbinas, R., Khosrowpour, A., & Taylor, J. (2015). Segmentation and Classification of Commercial Building Occupants by Energy-Use Efficiency and Predictability. *IEEE Transactions on Smart Grid, 6*(3), 1414-1424. doi:10.1109/TSG.2014.2384997
Gunay, H. B., O'Brien, W., Beausoleil-Morrison, I., & Huchuk, B. (2014). On adaptive occupant-learning window blind and lighting controls. *Building Research & Information, 42*(6), 739-756. doi:10.1080/09613218.2014.895248
Hansen, R., Olafsson, A. S., van der Jagt, A. P. N., Rall, E., & Pauleit, S. (2017). Planning multifunctional green infrastructure for compact cities: What is the state of practice? *Ecological Indicators*. doi:https://doi.org/10.1016/j.ecolind.2017.09.042

Harish, V. S. K. V., & Kumar, A. (2016). A review on modeling and simulation of building energy systems. *Renewable and Sustainable Energy Reviews, 56*, 1272-1292. doi:10.1016/j.rser.2015.12.040

Heydarian, A., Carneiro, J. P., Gerber, D., & Becerik-Gerber, B. (2015). Immersive virtual environments, understanding the impact of design features and occupant choice upon lighting for building performance. *Building and Environment, 89*, 217-228. doi:10.1016/j.buildenv.2015.02.038

Hong, T., D'Oca, S., Turner, W. J. N., & Taylor-Lange, S. C. (2015). An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework. *Building and Environment, 92*, 764-777. doi:10.1016/j.buildenv.2015.02.019

HUB, Z. C. (2015). *Post-occupancy Evaluation, Rowner Research Project Phase Two*. Zero Carbon HUB.

Indraganti, M., Ooka, R., & Rijal, H. B. (2015). Thermal comfort in offices in India: Behavioral adaptation and the effect of age and gender. *Energy and Buildings, 103*, 284-295. doi:10.1016/j.enbuild.2015.05.042

Indraganti, M., & Rao, K. D. (2010). Effect of age, gender, economic group and tenure on thermal comfort: A field study in residential buildings in hot and dry climate with seasonal variations. *Energy & Buildings, 42*(3), 273-281. doi:10.1016/j.enbuild.2009.09.003

Inglis, A. (2008). Approaches to the validation of quality frameworks for e-learning. *Quality Assurance in Education, 16*(4), 347-362. doi:10.1108/09684880810906490

Jabareen, Y. (2009). Building a Conceptual Framework: Philosophy, Definitions, and Procedure. *International Journal of Qualitative Methods, 8*(4), 49-62. doi:10.1177/160940690900800406

Jain, R. K., Taylor, J. E., & Culligan, P. J. (2013). Investigating the impact eco-feedback information representation has on building occupant energy consumption behavior and savings. *Energy and Buildings, 64*, 408-414. doi:10.1016/j.enbuild.2013.05.011

Jakubiec, J. A., & Reinhart, C. (2011, 2011). *The 'adaptive zone' - A concept for Assessing glare throughout daylit spaces*.

Janda, K. B. (2011). Buildings don't use energy: people do. *Architectural science review, 54*(1), 15-22.

Jang, H., & Kang, J. (2016a). A stochastic model of integrating occupant behaviour into energy simulation with respect to actual energy consumption in high-rise apartment buildings. *Energy & Buildings, 121*, 205-216. doi:10.1016/j.enbuild.2016.03.037

Jang, H., & Kang, J. (2016b). A stochastic model of integrating occupant behaviour into energy simulation with respect to actual energy consumption in high-rise apartment buildings. *Energy and Buildings, 121*, 205-216. doi:10.1016/j.enbuild.2016.03.037

Ji, Y., Lomas, K. J., & Cook, M. J. (2009). Hybrid ventilation for low energy building design in south China. *Building and Environment, 44*(11), 2245-2255. doi:10.1016/j.buildenv.2009.02.015

Johnson, B. J., Starke, M. R., Abdelaziz, O. A., Jackson, R. K., & Tolbert, L. M. (2014, 2014). *A method for modeling household occupant behavior to simulate residential energy consumption*.

Juodis, E., Jaraminiene, E., & Dudkiewicz, E. (2009). Inherent variability of heat consumption in residential buildings. *Energy & Buildings, 41*(11), 1188-1194. doi:10.1016/j.enbuild.2009.06.007

K. Le Guin, U. (2017). The Left Hand of Darkness (pp. 674-676).

Kalman, A. (2012). *Calculation of energy consumption in dwellings: theory and field data*. Paper presented at the 5th meeting of IEA Annex 53, The Netherlands.

Karatas, A., Stoiko, A., & Menassa, C. C. (2016). Framework for selecting occupancy-focused energy interventions in buildings. *Building Research & Information, 44*(5-6), 535-551. doi:10.1080/09613218.2016.1182330

Karjalainen, S. (2016). Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption. *Energy Efficiency*, 1-14. doi:10.1007/s12053-015-9422-7

Kavousian, A., Rajagopal, R., & Fischer, M. (2013). Determinants of residential electricity consumption: Using smart meter data to examine the effect of climate, building characteristics, appliance stock, and occupants' behavior. *Energy, 55*, 184-194. doi:10.1016/j.energy.2013.03.086

Kazmi, H., D'Oca, S., Delmastro, C., Lodeweyckx, S., & Corgnati, S. P. (2016). Generalizable occupant-driven optimization model for domestic hot water production in NZEB. *Applied Energy, 175*, 1-15. doi:10.1016/j.apenergy.2016.04.108

Khoshbakht, M., Gou, Z., & Dupre, K. (2018). Energy use characteristics and benchmarking for higher education buildings. *Energy and Buildings, 164*, 61-76. doi:https://doi.org/10.1016/j.enbuild.2018.01.001

Khosrowpour, A., Gulbinas, R., & Taylor, J. E. (2016). Occupant workstation level energy-use prediction in commercial buildings: Developing and assessing a new method to enable targeted energy efficiency programs. *Energy and Buildings, 127*, 1133-1145. doi:10.1016/j.enbuild.2016.05.071

Kieras , D., & Meyer, D. (1997). An Overview of the EPIC Architecture for Cognition and Performance With Application to Human-Computer Interaction. *Human-computer Interaction, 12*, 391-438.

Knauth, S., Jost, C., & Klapproth, A. (2009). *iLOC: A localisation system for visitor tracking & guidance*.

Kočí, V., Kočí, J., Maděra, J., & Černý, R. (2019). Effect of applied weather data sets in simulation of building energy demands: Comparison of design years with recent weather data. *Renewable and Sustainable Energy Reviews, 100*, 22-32. doi:10.1016/j.rser.2018.10.022

Kovács, G., & Spens, K. M. (2005). Abductive reasoning in logistics research. *International Journal of Physical Distribution & Logistics Management, 35*(2), 132-144. doi:10.1108/09600030510590318

Lan, L., Lian, Z., Liu, W., & Liu, Y. (2008). Investigation of gender difference in thermal comfort for Chinese people. *European Journal of Applied Physiology, 102*(4), 471-480. doi:10.1007/s00421-007-0609-2

Langevin, J., Gurian, P. L., & Wen, J. (2013). Reducing energy consumption in low income public housing: Interviewing residents about energy behaviors. *Applied Energy, 102*, 1358-1370. doi:10.1016/j.apenergy.2012.07.003

Langevin, J., Gurian, P. L., & Wen, J. (2015). Tracking the human-building interaction: A longitudinal field study of occupant behavior in air-conditioned offices. *Journal of Environmental Psychology, 42*, 94-115. doi:10.1016/j.jenvp.2015.01.007

Langevin, J., Wen, J., & Gurian, P. L. (2015). Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors. *Building and Environment, 88*, 27-45. doi:10.1016/j.buildenv.2014.11.037

Langevin, J., Wen, J., & Gurian, P. L. (2016). Quantifying the human–building interaction: Considering the active, adaptive occupant in building performance simulation. *Energy & Buildings, 117*, 372-386. doi:10.1016/j.enbuild.2015.09.026

Larsen, T. S., Knudsen, H., Kanstrup, A. M., Christiansen, E., Gram-Hanssen, K., Mosgaard, M., . . . Rose, J. (2010). *Occupants influence on the energy consumption of Danish domestic buildings*. Department of Civil Engineering. Aalborg University.

Lee, E., Allen, A., & Kim, B. (2013). Interior Design Practitioner Motivations for Specifying Sustainable Materials: Applying the Theory of Planned Behavior to Residential Design. *Journal of Interior Design, 38*(4), 1-16. doi:10.1111/joid.12017

Lee, S., Alzoubi, H. H., & Kim, S. (2017). The Effect of Interior Design Elements and Lighting Layouts on Prospective Occupants' Perceptions of Amenity and Efficiency in Living Rooms. *Sustainability, 9*(7), 1119. doi:10.3390/su9071119

Lee, S. H., Hong, T., Piette, M. A., Sawaya, G., Chen, Y., & Taylor-Lange, S. C. (2015). Accelerating the energy retrofit of commercial buildings using a database of energy efficiency performance. *Energy, 90*, 738-747. doi:10.1016/j.energy.2015.07.107

Lee, W.-S. (2008). Benchmarking the energy efficiency of government buildings with data envelopment analysis. *Energy & Buildings, 40*(5), 891-895. doi:10.1016/j.enbuild.2007.07.001

Li, N., Li, J., Fan, R., & Jia, H. (2014). Probability of occupant operation of windows during transition seasons in office buildings. *Renewable Energy, 73*, 84-91. doi:10.1016/j.renene.2014.05.065

Liao, C., & Barooah, P. (2010, 2010). *An integrated approach to occupancy modeling and estimation in commercial buildings*.

Lilley, D. (2009). Design for sustainable behaviour: strategies and perceptions. *Design Studies, 30*(6), 704-720. doi:10.1016/j.destud.2009.05.001

Lindberg, R., Binamu, A., & Teikari, M. (2004). Five-year data of measured weather, energy consumption, and time-dependent temperature variations within different exterior wall structures. *Energy & Buildings, 36*(6), 495-501. doi:10.1016/j.enbuild.2003.12.009

Liu, Y., Stouffs, R., Tablada, A., Wong, N. H., & Zhang, J. (2017). Comparing micro-scale weather data to building energy consumption in Singapore. *Energy & Buildings, 152*, 776-791. doi:10.1016/j.enbuild.2016.11.019

Lord, B., & Piacente, M. (2014). *Manual of museum exhibitions*. UK: Rowman & Littlefield.

Lundström, L. (2017). Adaptive Weather Correction of Energy Consumption Data. *Energy Procedia, 105*, 3397-3402. doi:10.1016/j.egypro.2017.03.778

Mahdavi, A., & Tahmasebi, F. (2015). Predicting people's presence in buildings: An empirically based model performance analysis *Energy & Buildings*, 349- 355. doi:10.1016/j.enbuild.2014.10.027

Maier, T., Krzaczek, M., & Tejchman, J. (2009). Comparison of physical performances of the ventilation systems in low-energy residential houses. *Energy & Buildings, 41*(3), 337-353. doi:10.1016/j.enbuild.2008.10.007

Manu, S., Shukla, Y., Rawal, R., Thomas, L. E., & de Dear, R. (2016). Field studies of thermal comfort across multiple climate zones for the subcontinent: India Model for Adaptive Comfort (IMAC). *Building and Environment, 98*, 55-70. doi:10.1016/j.buildenv.2015.12.019

Marshall, A., Fitton, R., Swan, W., Farmer, D., Johnston, D., Benjaber, M., & Ji, Y. (2017). Domestic building fabric performance: Closing the gap between the in situ measured and modelled performance. *Energy & Buildings, 150*, 307-317. doi:10.1016/j.enbuild.2017.06.028

Martin, M., Afshari, A., Armstrong, P. R., & Norford, L. K. (2015). Estimation of urban temperature and humidity using a lumped parameter model coupled with an EnergyPlus model. *Energy & Buildings, 96*, 221-235. doi:10.1016/j.enbuild.2015.02.047

Martinaitis, V., Zavadskas, E. K., Motuziene, V., & Vilutiene, T. (2015). Importance of occupancy information when simulating energy demand of energy efficient house: A case study. *Energy and Buildings, 101*, 64-75. doi:10.1016/j.enbuild.2015.04.031

Martinaitis, V., Zavadskas, E. K., Motuzienė, V., & Vilutienė, T. (2015). Importance of occupancy information when simulating energy demand of energy efficient house: A case study. *Energy & Buildings, 101*, 64-75. doi:10.1016/j.enbuild.2015.04.031

Martinez-Gil, J., Freudenthaler, B., & Natschlaeger, T. (2013, 2013). *Modeling User Behavior through Electricity Consumption Patterns*.

Masoso, O. T., & Grobler, L. J. (2010). The dark side of occupants' behaviour on building energy use. *Energy & Buildings, 42*(2), 173-177. doi:10.1016/j.enbuild.2009.08.009

Masoudifar, N., Hammad, A., & Rezaee, M. (2014-2015, 2014;2015;). *Monitoring occupancy and office equipment energy consumption using real-time location system and wireless energy meters*.

Melfi, R., Rosenblum, B., Nordman, B., & Christensen, K. (2011, 2011). *Measuring building occupancy using existing network infrastructure.* Paper presented at the Int. Green Conput.

Milan, A., Schindler, K., & Roth, S. (2013). *Detection- and Trajectory-Level Exclusion in Multiple Object Tracking*.

Miles, M. B., Huberman, A. M., Huberman, M., & Huberman, A. (1994). *Qualitative data analysis: an expanded sourcebook* (2nd ed.). Thousand Oaks, Calif;London;: Sage.

Mohamed, A. M. A., Al-Habaibeh, A., Abdo, H., & Elabar, S. (2015). Towards exporting renewable energy from MENA region to Europe: An investigation into domestic energy use and householders' energy behaviour in Libya. *Applied Energy, 146*, 247-262. doi:10.1016/j.apenergy.2015.02.008

Moxon, S. n. (2012). *Sustainability in interior design* (Vol. 1). London: Laurence King.

Nasar, J. L., Stamps, A. E., & Hanyu, K. (2005). Form and function in public buildings. *Journal of Environmental Psychology, 25*(2), 159-165. doi:https://doi.org/10.1016/j.jenvp.2005.03.004

Neufert, E., Neufert, P., & Kister, J. (2012). *Architects' data* (Vol. 4th). Chichester: Wiley-Blackwell.

Neves, Y., Sindeaux, M., Souza, W., Kozievitch, N., Loureiro, A., & Silva, T. (2016, 2016). *Study of Google Popularity Times Series for Commercial Establishments of Curitiba and Chicago*.

Nicol, J. F., & Humphreys, M. A. (2002). Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy & Buildings, 34*(6), 563-572. doi:10.1016/S0378-7788(02)00006-3

Nunes, N., Ribeiro, M., Prandi, C., & Nisi, V. (2017, 2017). *Beanstalk: a community based passive wi-fi tracking system for analysing tourism dynamics*.

O'Brien, W., & Gunay, H. B. (2015). Mitigating office performance uncertainty of occupant use of window blinds and lighting using robust design. *Building Simulation, 8*(6), 621-636. doi:10.1007/s12273-015-0239-2

Ormerod, R. J. (2010). Rational inference: deductive, inductive and probabilistic thinking. *The Journal of the Operational Research Society, 61*(8), 1207-1223. doi:10.1057/jors.2009.96

Oseland, N. (2009). The impact of psychological needs on office design. *Journal of Corporate Real Estate, 11*(4), 244-254. doi:10.1108/14630010911006738

Ouf, M., Issa, M., & Merkel, P. (2016). Analysis of Real-Time Electricity Consumption in Canadian School Buildings. *Energy and Buildings*. doi:10.1016/j.enbuild.2016.07.022

Ouf, M. M., O'Brien, W., & Gunay, H. B. (2018). Improving occupant-related features in building performance simulation tools. *Building Simulation, 11*(4), 803-817. doi:10.1007/s12273-018-0443-y

Ouyang, J., & Hokao, K. (2009). Energy-saving potential by improving occupants' behavior in urban residential sector in Hangzhou City, China. *Energy & Buildings, 41*(7), 711-720. doi:10.1016/j.enbuild.2009.02.003

OxfordDictionaries. (2018). Oxford Dictionaries. Retrieved from https://en.oxforddictionaries.com/definition/multifunctional

Page, J., Robinson, D., Morel, N., & Scartezzini, J. L. (2008). A generalised stochastic model for the simulation of occupant presence. *Energy & Buildings, 40*(2), 83-98. doi:10.1016/j.enbuild.2007.01.018

Stochastic simulation of occupant presence and behaviour in buildings, (2007).

Park, J. S., & Kim, H. J. (2012). A field study of occupant behavior and energy consumption in apartments with mechanical ventilation. *Energy and Buildings, 50*, 19-25. doi:10.1016/j.enbuild.2012.03.015

Pearce, D. (2006). The political economy of an energy tax: The United Kingdom's Climate Change Levy. *Energy Economics, 28*(2), 149-158. doi:10.1016/j.eneco.2005.10.001

Pellegrino, M., Simonetti, M., & Chiesa, G. (2016). Reducing thermal discomfort and energy consumption of Indian residential buildings: Model validation by in-field measurements and simulation of low-cost interventions. *Energy and Buildings, 113*, 145-158. doi:10.1016/j.enbuild.2015.12.015

Peng, C., Yan, D., Wu, R., Wang, C., Zhou, X., & Jiang, Y. (2012). Quantitative description and simulation of human behavior in residential buildings. *Building Simulation, 5*(2), 85-94. doi:10.1007/s12273-011-0049-0

Pisello, A. L., Castaldo, V. L., Piselli, C., Fabiani, C., & Cotana, F. (2016). How peers' personal attitudes affect indoor microclimate and energy need in an institutional building: Results from a continuous monitoring campaign in summer and winter conditions. *Energy and Buildings, 126*, 485-497. doi:10.1016/j.enbuild.2016.05.053

Polinder, H., Schweiker, M., Schakib-Ekbatan, K., Fabi, V., Andersen, R., Morishita, N., . . . Heiselberg, P. (2013). *Total energy use in buildings: analysis and evaluation methods, Final Report Annex 53*. Retrieved from

Pollard, B. (2011). Mind the Gap: Predicted vs. Actual Performance of Green Buildings. *Environment Design Guide*(66), 1-10.

Rafsanjani, H. N., & Ahn, C. (2016). Linking Building Energy-Load Variations with Occupants' Energy-Use Behaviors in Commercial Buildings: Non-Intrusive Occupant Load Monitoring (NIOLM). *Procedia Engineering, 145*, 532-539. doi:10.1016/j.proeng.2016.04.041

Rahman, M. M., Rasul, M. G., & Khan, M. M. K. (2010). Energy conservation measures in an institutional building in sub-tropical climate in Australia. *Applied Energy, 87*(10), 2994-3004. doi:10.1016/j.apenergy.2010.04.005

Reeves, T., Olbina, S., & Issa, R. (2015). Guidelines for Using Building Information Modeling for Energy Analysis of Buildings. *Buildings, 5*(4), 1361.

Reinhart, C. F. (2004). Lightswitch-2002: a model for manual and automated control of electric lighting and blinds. *Solar Energy, 77*(1), 15-28. doi:10.1016/j.solener.2004.04.003

Rempel, A. R., Rempel, A. W., Cashman, K. V., Gates, K. N., Page, C. J., & Shaw, B. (2013). Interpretation of passive solar field data with EnergyPlus models: Un-conventional wisdom from four sunspaces in Eugene, Oregon. *Building and Environment, 60*, 158-172. doi:10.1016/j.buildenv.2012.11.006

Rijal, H. B. (2014). Investigation of Comfort Temperature and Occupant Behavior in Japanese Houses during the Hot and Humid Season. *Buildings, 4*(3), 437-452. doi:10.3390/buildings4030437

Rijal, H. B., Honjo, M., Kobayashi, R., & Nakaya, T. (2013). Investigation of comfort temperature, adaptive model and the window-opening behaviour in Japanese houses. *Architectural Science Review, 56*(1), 54-69. doi:10.1080/00038628.2012.744295

Rijal, H. B., Humphreys, M., & Nicol, F. (2015). Adaptive Thermal Comfort in Japanese Houses during the Summer Season: Behavioral Adaptation and the Effect of Humidity. *Buildings, 5*(3), 1037-1054. doi:10.3390/buildings5031037

Rijal, H. B., Tuohy, P., Humphreys, M. A., Nicol, J. F., & Samuel, A. (2011). An algorithm to represent occupant use of windows and fans including situation-specific motivations and constraints. *Building Simulation, 4*(2), 117-134. doi:10.1007/s12273-011-0037-4

Rijal, H. B., Tuohy, P., Humphreys, M. A., Nicol, J. F., Samuel, A., & Clarke, J. (2007). Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy & Buildings, 39*(7), 823-836. doi:10.1016/j.enbuild.2007.02.003

Rijal, H. B., Tuohy, P. G., Nicol, J. F., Humphreys, M. A., Samuel, A. A. A., & Clarke, J. A. (2008). *Development of adaptive algorithms for the operation of windows, fans and doors to predict thermal comfort and energy use in Pakistani buildings.*

Roetzel, A., Tsangrassoulis, A., Dietrich, U., & Busching, S. (2010). A review of occupant control on natural ventilation. *Renewable and Sustainable Energy Reviews, 14*(3), 1001-1013. doi:10.1016/j.rser.2009.11.005

Romero, R. A., Bojórquez, G., Corral, M., & Gallegos, R. (2013). Energy and the occupant's thermal perception of low-income dwellings in hot-dry climate: Mexicali, México. *Renewable Energy, 49*, 267-270. doi:10.1016/j.renene.2012.01.017

Ryu, S. H., & Moon, H. J. (2016). Development of an occupancy prediction model using indoor environmental data based on machine learning techniques. *Building and Environment*. doi:10.1016/j.buildenv.2016.06.039

Salawitch, R. J., Canty, T. P., Hope, A. P., Tribett, W. R., & Bennett, B. F. (2017). *Paris Climate Agreement: Beacon of Hope*. Cham: Springer International Publishing.

Salcido, J. C., Raheem, A. A., & Issa, R. R. A. (2016). From simulation to monitoring: Evaluating the potential of mixed-mode ventilation (MMV) systems for integrating natural ventilation in office buildings through a comprehensive literature review. *Energy and Buildings, 127*, 1008-1018. doi:10.1016/j.enbuild.2016.06.054

Saunders, M., & Lewis, P. (2012). *Doing research in business and management: an essential guide to planning your project*. Harlow: Financial Times Prentice Hall.

Saunders, M., Lewis, P., & Thornhill, A. (2012). *Research methods for business students* (Vol. 6th). Harlow: Pearson.

Saunders, M., Lewis, P., & Thornhill, A. (2016a). *Research methods for business students* (Vol. Seventh). Harlow: Pearson Education.

Saunders, M., Lewis, P., & Thornhill, A. (2016b). *Research methods for business students* (Seventh ed.). Harlow: Pearson Education.

Schakib-Ekbatan, K., Çakici, F. Z., Schweiker, M., & Wagner, A. (2015). Does the occupant behavior match the energy concept of the building? - Analysis of a German naturally ventilated office building. *Building and Environment, 84*, 142-150. doi:10.1016/j.buildenv.2014.10.018

Schweiker, M., & Shukuya, M. (2011). Investigation on the effectiveness of various methods of information dissemination aiming at a change of occupant behaviour related to thermal comfort and exergy consumption. *Energy Policy, 39*(1), 395-407. doi:10.1016/j.enpol.2010.10.017

Scofield, J. H. (2009). Do LEED-certified buildings save energy? Not really. *Energy & Buildings, 41*(12), 1386-1390. doi:10.1016/j.enbuild.2009.08.006

Sekaran, U., & Bougie, R. (2010). *Research methods for business: a skill-building approach* (Vol. 5th). Chichester: Wiley.

Sekki, T., Andelin, M., Airaksinen, M., & Saari, A. (2016). Consideration of energy consumption, energy costs, and space occupancy in Finnish daycare centres and school buildings. *Energy and Buildings, 129*, 199-206. doi:10.1016/j.enbuild.2016.08.015

Shabunko, V., Lim, C. M., & Mathew, S. (2018). EnergyPlus models for the benchmarking of residential buildings in Brunei Darussalam. *Energy & Buildings, 169*, 507-516. doi:10.1016/j.enbuild.2016.03.039

Shi, X., Tian, Z., Chen, W., Si, B., & Jin, X. (2016). A review on building energy efficient design optimization rom the perspective of architects. *Renewable and Sustainable Energy Reviews, 65*, 872-884. doi:10.1016/j.rser.2016.07.050

Shih, C.-Y., Chen, L.-H., Chen, G.-H., Wu, E. H. K., & Jin, M.-H. (2012). *Intelligent radio map management for future WLAN indoor location fingerprinting*.

Silva, L., & Silva, T. (2018). *Extraction and Exploration of Business Categories Signatures*. Curitiba, PR, Brazil.

Slavković, B. (2017). Application of the double skin façade in rehabilitation of the industrial buildings in Serbia. *Thermal Science, 21*(6 Part B), 2945-2955. doi:10.2298/TSCI160524179S

Steemers, K., & Yun, G. Y. (2009). Household energy consumption: a study of the role of occupants. *Building Research & Information, 37*(5), 625-637. doi:10.1080/09613210903186661

Strachan, P., Svehla, K., Heusler, I., & Kersken, M. (2016). Whole model empirical validation on a full-scale building. *Journal of Building Performance Simulation, 9*(4), 331-350. doi:10.1080/19401493.2015.1064480

Streckienė, G., & Polonis, E. (2014). Analysis of Energy Demand for Low-Energy Multi-Dwelling Buildings of Different Configuration. *Mokslas: Lietuvos Ateitis, 6*(4), 414-420. doi:10.3846/mla.2014.57

Sullivan, L. H. (1947). *Kindergarten chatsand other writings (revised 1918)*

Tetlow, R. M., van Dronkelaar, C., Beaman, C. P., Elmualim, A. A., & Couling, K. (2015). Identifying behavioural predictors of small power electricity consumption in office buildings. *Building and Environment, 92*, 75-85. doi:10.1016/j.buildenv.2015.04.009

Tian, W., Heo, Y., de Wilde, P., Li, Z., Yan, D., Park, C. S., . . . Augenbroe, G. (2018). A review of uncertainty analysis in building energy assessment. *Renewable and Sustainable Energy Reviews, 93*, 285-301. doi:10.1016/j.rser.2018.05.029

Toepke, S. (2017). *Investigation of Geospatially Enabled, Social Media Generated Structure Occupancy Curves in Commercial Structures*. Paper presented at the International Conference on Geographical Information Systems Theory, Applications and Management.

ToolBox, T. E. Buildings area per person. Retrieved from http://www.engineeringtoolbox.com/number-persons-buildings-d_118.html

Trust, E. S. (2008). *Measurement of Domestic Hot Water Consumption in Dwellings*. Retrieved from

Ulusoy, B., & Nilgün, O. (2017). Understanding responses to materials and colors in interiors. *Color Research & Application, 42*(2), 261-272. doi:10.1002/col.22072

Ulusoy, B., & Olguntürk, N. (2016). Effects of Color Pairs on Warmth Perception in Interiors. *Society for Imaging Science and Technology*, 126-135(110). doi:https://doi.org/10.2352/ISSN.2169-2629.2017.32.126

Vasser, C. P., & Vasser, C. P. (2009). *Kyoto Protocol: Economic Assessments, Implementation*. New York: Nova Science Publishers, Inc.

Vlasenko, I., Nikolaidis, I., & Stroulia, E. (2015). The Smart-Condo: Optimizing Sensor Placement for Indoor Localization. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 45*(3), 436-453. doi:10.1109/TSMC.2014.2356437

von Grabe, J. (2016). How do occupants decide their interactions with the building? From qualitative data to a psychological framework of human-building-interaction. *Energy Research & Social Science, 14*, 46-60. doi:10.1016/j.erss.2016.01.002

Wang, S., Yan, C., & Xiao, F. (2012). Quantitative energy performance assessment methods for existing buildings. *Energy and Buildings, 55*, 873-888. doi:10.1016/j.enbuild.2012.08.037

Wang, W., Chen, J., & Hong, T. (2018). Modeling occupancy distribution in large spaces with multi-feature classification algorithm. *Building and Environment, 137*, 108-117. doi:10.1016/j.buildenv.2018.04.002

Wang, Z., & Ding, Y. (2015). An occupant-based energy consumption prediction model for office equipment. *Energy and Buildings, 109*, 12-22. doi:10.1016/j.enbuild.2015.10.002

Wang, Z., Zhao, Z., Lin, B., Zhu, Y., & Ouyang, Q. (2015). Residential heating energy consumption modeling through a bottom-up approach for China's Hot Summer-Cold Winter climatic region. *Energy and Buildings, 109*, 65-74. doi:10.1016/j.enbuild.2015.09.057

Wetter, M., Bonvini, M., & Nouidui, T. S. (2016). Equation-based languages – A new paradigm for building energy modeling, simulation and optimization. *Energy & Buildings, 117*, 290-300. doi:10.1016/j.enbuild.2015.10.017

Wilkes, E., & Goodright, V. (2015). *Energy Consumption in the UK (2015)*. London: Department of Energy & Climate Change.

Wilson, G. T., Lilley, D., & Bhamra, T. A. (2013). *Design feedback interventions for household energy consumption reduction*. Paper presented at the 16th Conference of the European Roundtable on Sustainable Consumption and Production (ERSCP) & 7th Conference of the Environmental Management for Sustainable Universities (EMSU).

Wu, S., & Delzendeh, E. (2016). *A conceptual framework to simulate building occupancy using crowd modelling techniques for energy analysis.* Paper presented at the 33rd CIB W78 Conference, Australia.

Yan, D., & Hong, T. (2016). *Definition and Simulation of Occupant Behavior in Buildings, ANNEX 66*. Retrieved from www.iea-ebc.org

Yan, D., O'Brien, W., Hong, T., Feng, X., Burak Gunay, H., Tahmasebi, F., & Mahdavi, A. (2015). Occupant behavior modeling for building performance simulation: Current state and future challenges. *Energy & Buildings, 107*, 264-278. doi:10.1016/j.enbuild.2015.08.032

Yang, J., Santamouris, M., & Lee, S. E. (2015). Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings. *Energy and Buildings*. doi:10.1016/j.enbuild.2015.12.019

Yang, J., Santamouris, M., & Lee, S. E. (2016). Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings. *Energy & Buildings, 121*, 344-349. doi:10.1016/j.enbuild.2015.12.019

Ye, L., Cheng, Z., Wang, Q., Lin, W., & Ren, F. (2013). Overview on Green Building Label in China. *Renewable Energy, 53*, 220-229. doi:10.1016/j.renene.2012.11.022

Yin, R. K. (2014). *Case study research: design and methods* (Vol. 5th). Los Angeles, California: SAGE.

Yu, C.-R., Wu, C.-L., Lu, C.-H., & Fu, L.-C. (2006). *Human Localization via Multi-Cameras and Floor Sensors in Smart Home*.

Yu, Z., Li, J., Li, H. Q., Han, J., & Zhang, G. Q. (2015). A novel methodology for identifying associations and correlations between household appliance behaviour in residential buildings. *Energy Procedia, 78*, 591-596. doi:10.1016/j.egypro.2015.11.024

Yu Zhun Jerry, Z. J., Haghighat, F., Fung, B. C. M., Morofsky, E., & Yoshino, H. (2011). A methodology for identifying and improving occupant behavior in residential buildings. *Energy, 36*(11), 6596-6608. doi:10.1016/j.energy.2011.09.002

Yun, G. Y., Choi, J., & Kim, J. T. (2014). Energy performance of direct expansion air handling unit in office buildings. *Energy and Buildings, 77*, 425-431. doi:10.1016/j.enbuild.2014.03.039

Yun, G. Y., & Steemers, K. (2008). Time-dependent occupant behaviour models of window control in summer. *Building and Environment, 43*(9), 1471-1482. doi:10.1016/j.buildenv.2007.08.001

Zeisel, J. (2006). *Inquiry by design: environment/behavior/neuroscience in architecture, interiors, landscape, and planning* (Vol. Rev.). London;New York, N.Y;: W.W. Norton.

Zhang, Y., & Barrett, P. (2012). Factors influencing occupants' blind-control behaviour in a naturally ventilated office building. *Building and Environment, 54*, 137-147. doi:10.1016/j.buildenv.2012.02.016

Zhao, J., Lasternas, B., Lam, K. P., Yun, R., & Loftness, V. (2014). Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining. *Energy and Buildings, 82*, 341-355. doi:10.1016/j.enbuild.2014.07.033

Zhao, J., Xin, Y., & Tong, D. (2012). Energy consumption quota of public buildings based on statistical analysis. *Energy Policy, 43*, 362-370. doi:10.1016/j.enpol.2012.01.015

Zhu, Y., Ouyang, Q., Cao, B., Zhou, X., & Yu, J. (2016). Dynamic thermal environment and thermal comfort. *Indoor Air, 26*(1), 125-137. doi:10.1111/ina.12233

Zou, P. X. W., Wagle, D., & Alam, M. (2019). Strategies for minimizing building energy performance gaps between the design intend and the reality. *Energy & Buildings, 191*, 31-41. doi:10.1016/j.enbuild.2019.03.013

Zou, P. X. W., Xu, X., Sanjayan, J., & Wang, J. (2018a). A mixed methods design for building occupants' energy behavior research. *Energy & Buildings, 166*, 239-249. doi:10.1016/j.enbuild.2018.01.068

Zou, P. X. W., Xu, X., Sanjayan, J., & Wang, J. (2018b). Review of 10 years research on building energy performance gap: Life-cycle and stakeholder perspectives. *Energy & Buildings, 178*, 165-181. doi:10.1016/j.enbuild.2018.08.040