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Impact of Occupant Behaviour (OB) on building energy use and thermal comfort

From stochastic modelling and occupant profiling to interdisciplinary user engagement

By

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Summary

Occupant behaviour (OB) has been acknowledged to be one of the key factors of uncertainty in prediction of energy consumption in buildings. Building occupants affect building energy use directly and indirectly by interacting with building energy systems such as adjusting temperature set-points, switching lights on/off, using electrical devices and opening/closing windows. Indeed, within the energy and building research community, occupant-centred approaches and analysis are gaining continuously more attention and significant research effort is put on gaining a deeper knowledge on the human interaction with the building systems and envelope. These efforts are mainly focused on reducing estimation uncertainties related to the human factor in building energy analysis and design, as well as the active engagement for a more aware behaviour of the occupants in view of reaching energy efficiency goals.

The introductory chapter (Chapter 1) outlines key aspects of the state-of-art in current behavioural research and highlights **research gaps and shortcomings** in the current research body that have stirred the focus of this dissertation, such as:

(i) Lack of understanding to which extent OB can impact building energy use and thermal comfort in high performing buildings;
(ii) Gap between real and predicted building energy use due to an oversimplification (e.g. fixed schedules) of the human factor in simulation programs;
(iii) Absence of qualitative data and individual characteristics and preferences of building occupants in existing models;
(iv) Lack of reliable and affordable ways to collect large-scale occupant behaviour data;
(v) Lack of innovative solutions for motivating and assessing behavioural change towards energy efficiency goals.

Given these current limitations in existing literature, this doctoral research is aimed at addressing the following **research questions:**

(i) How significant is the impact that OB might have on building energy use and thermal comfort conditions of the occupants, especially in the

context of high performing and technologically optimized buildings, in which the human factor might play an even more significant role than in buildings whose envelope-driven loads dominate the consumption profile?

(ii) Is there an innovative approach to model the stochastic nature of the human-building interaction influenced by key environmental and time-related drivers towards bridging the gap between real and predicted building energy use?

(iii) Which role do qualitative data and individual characteristics of the occupants play (e.g. thermal comfort attitudes) and how can they be introduced in the modelling process?

(iv) Is there a reliable way for profiling OB on a large scale to provide enhanced building simulation input?

(v) How to engage and assess behavioural change to optimise building operation and well-being of the occupants?

In this context, the **methodological framework** of this dissertation is aimed at contributing to new knowledge in occupant behavioural research through the development and implementation of methods for

(i) estimating the **impact of OB** on building energy use and thermal comfort in low energy buildings (Chapter 2);

(ii) exploring the Bayesian Network framework for developing advanced **stochastic OB models** (Chapter 3);

(iii) introducing qualitative data and individual characteristics of the occupants in these models through tailored **OB surveys** (Chapter 4);

(iv) **profiling OB** (daily activities and occupancy) on a **large scale** based on Time Use Survey data (Chapter 5);

(v) developing and evaluating **energy engagement** campaigns in different environments to improve OB and raise user awareness (Chapter 6).

A first step (Chapter 2) consisted in presenting a methodology for investigating to which extent different occupant behaviour lifestyles (low, standard, and high energy consuming) and different household compositions might affect building energy use in high performing buildings. The analysis was based on simulation results of a case study located in Northern Italy whose energy consumption varied significantly when considering high or low consumer profiles. The outcomes also stressed the urgent need for the development of occupant behaviour models that allow for more reliably capturing the stochastic nature of human behaviour inside buildings. In line with this, the next step (Chapter 3) was to demonstrate the applicability of the Bayesian Network (BN) framework for OB analysis, and in particular for predicting window opening/closing behaviour of building occupants based on the measurements in a residential apartment located in Copenhagen, Denmark. This study showed the high predictive power of BN models and identified environmental and time-related factors as key drivers for window control behaviour, but highlighted that next to traditional field measurements of environmental parameters and information on building characteristics, survey-based information can be introduced in the modelling process to obtain a more accurate picture of behavioural patterns. In a next step, these additional factors were investigated by means of a tailored interdisciplinary survey framework for Danish dwellings (Chapter 4) and some of them were included in the modelling process, which highlighted that thermal comfort attitudes and preferences of the occupants have a significant influence on the human-building interaction. Then, the focus was put on enlarging the scale of OB analysis by identifying Time Use Survey data as an essential source for profiling energy-related daily activities of occupants during different seasons and weekdays/weekends and profiling occupancy patterns for different household types. The Danish Time Use Survey served as main data source for this investigation (Chapter 5). A final step consisted in investigating how occupant behaviour can be changed through user awareness and behavioural change programs and how OB can be leveraged towards reducing its impact on energy use and the environment through an interdisciplinary approach – this closes the loop of the methodological framework of this doctoral research (Figure I-1.1).

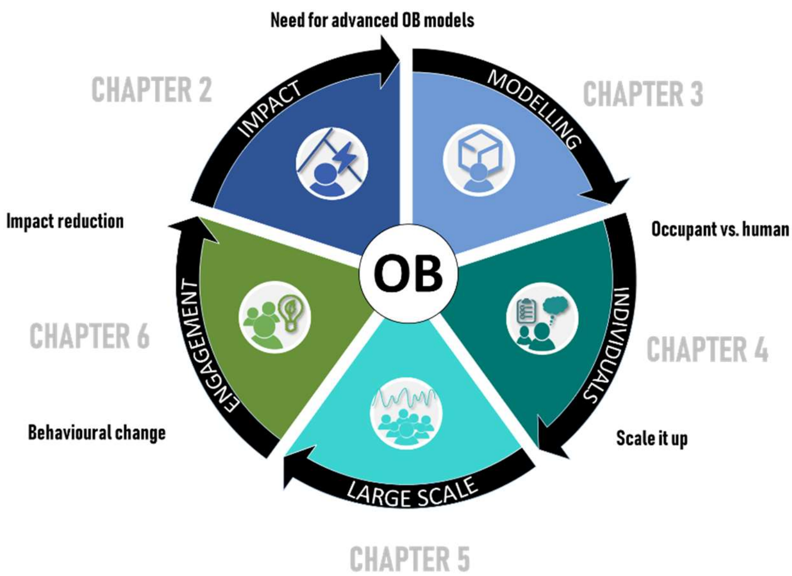

Figure I-1.1 Summary of the methodological framework of the PhD thesis.

Acknowledgment

My PhD path, academically and personally speaking, has been an incredible enrichment for me and would not have been possible without the immeasurable support and back up from many people.

First, I would like to thank my supervisor, Prof. Stefano Paolo Corgnati, who has guided and supported my academic activities for over 7 years – you have opened the world of research to me and offered me incredible opportunities and (life) experiences that were extremely precious for this work and my academic path, but also for my personal growth.

I also would like to thank my wonderful co-supervisors, Yeonsook and Rune. I am truly thankful for your continuous support – you helped me enrichening my knowledge and enlarging my research perspective, and on top you were warmly welcoming when I visited your institutions.

A special thank you goes to all the members of the IEEM research group. Thank you Valentina, for introducing me to the topic of occupant behaviour and –next to being a friend- for being such a pleasant person to work with. A massive thank you also to Cristina, Mara, Daniela, Tiziana, Chiara, Giorgia, Giulia, Giulia, Marvi, Federico – these years would not have been the same without you.

A big thank you goes also to my colleagues and friends that made my stays in Copenhagen and Cambridge joyful. During the development of this work I had the chance to meet so many special people and I will not tempt to list them all. Special thanks though to my "Italian besties", Enrica, Tita, and Marcella, you know why.

A unique thank you goes to my family - in these years, more than ever, I had the chance to really experience the biggest gift of all. Without my parents all this would not have been possible, they mean the biggest support and joy to me and have always shaped my view on things from completely different angles. Thanks to my big brother, Stephan – you are the big brother every little sister should have.

Thanks to my sister heart Berit - always ready with an open ear to share joy and tear. Thanks to my little brother, Tobias – maybe you don't know but you make the world a little brighter.

Last, but not least, I would like to thank Duncan, my wonderwall and soulmate, for endless patience, support, loving care, and happiness – this and you mean the world to me.

To my family.

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Preface

The elaboration of this doctoral research is the result of research activities that I had the chance to carry out within an international research framework and was supported by precious encounters and collaborations with worldwide experts in the field. During the first year of doctoral research, I visited the Architecture Department of the **University of Cambridge** under the supervision of Dr. Yeonsook Heo. This visiting period allowed for developing the methodological framework based on Bayesian Networks for OB analysis (Chapter 3). In this context, I also had the chance to discuss applicative statistical challenges within the Statistical Labs of the Faculty of Mathematics on a regular basis. During the second year of doctoral research, I visited the International Centre for Indoor Environment and Energy (ICIEE) at the **Technical University of Denmark** under the supervision of Dr. Rune K. Andersen. This visiting period allowed for extending the proposed methodological framework and apply it to a larger number of case studies (Chapter 4). Furthermore, I had the chance to profile OB based on Danish Time Use Survey data (Chapter 5); the outcomes were presented at the COBEE 2018 conference in Melbourne, Australia, and conferred with a best paper award. My involvement in international and national research projects, as well as the participation to international conferences, had a big impact on my learning process and allowed me not only to follow investigations in the field, but also to gain a deeper understanding on the big value of research communities and the interaction between experts aiming at pursuing answers to common open research questions, or to formulate the latter together. In particular, I had the chance to participate to most of the IEA-EBC Annex 66 meetings ("*Definition and Simulation of Occupant Behavior in Buildings"),* as well as the new follow-up Annex 79 ("*Occupant-Centric Building Design and Operation*"). Another precious learning experience I would like to highlight is the Horizon 2020 MOBISTYLE project ("*Motivating end-users behavioural change by combined ICT based tools and modular information services on energy use, indoor environment, health and lifestyle*"), as well as some concluded national projects, such as ComfortSense (Chapter 6).

This international studying and working experience – for which I am incredibly thankful - would not have been possible without the support of my supervisor and co-supervisors, as well as the financial support of my home institution.

Chapter 1

Introduction

1.1 The big picture

"Climate change is the challenge of our generation" – this statement has found numerous voices in wide-ranging organizations across the world and its meaning gives the lead to an increasing number of innovative research activities in different fields, to tackle a challenge that requires being addressed strategically and with combined strength. A challenge that is focused on mitigating and reducing a significant increase of greenhouse gas (GHG) emissions due to human-induced activities that has been observed over the past 150 years, and whose harmful consequences have been broadly documented (World Health Organization 2016).

The EU has set itself a long-term goal of reducing GHG emissions by 80-95%, when compared to 1990 levels, by 2050 (European Commission 2012). To achieve this target, it is necessary to tackle main energy consumers and move towards a low-carbon economy. With a large share of total primary energy consumptions (40%) in most developed countries (IEA and UNDP 2013), one of the major consumers of energy – and contributors to global GHG emissions – is the building sector, which therefore has become a main focus for energy consumption efforts.

These efforts oftentimes rely on the technological optimization of building envelope and systems towards reaching the nearly zero energy target. However, nowadays, the building energy research community is aware of the **pivotal role of occupant behaviour** in having a crucial impact on building energy demand as well as the indoor environment (Masoso and Grobler 2010; Yan et al. 2017; Mahdavi 2011) (Figure 1.1-1). Indeed, the building occupants cannot be seen as merely passive recipients of the built environment, but they interact with the latter in search of a personally comfortable condition (Langevin et al. 2016). To meet individual comfort criteria or other necessities, the occupants perform two different categories of actions. The first category are adaptive actions (De Dear and Brager 2002), which means that occupants either adapt the environment to their current needs (e.g. regulate heating/cooling set points, lighting levels, windows and sunscreens, or other installed HVAC systems and building envelope features) – and/or the occupants adapt themselves to the environment (e.g. adjusting clothes, moving through spaces). The second category are non-adaptive actions and refer for example to behavioural patterns related to occupancy or the usage of plug-in devices. It is not difficult to envision the stochastic nature of the human-building interaction, since individuals might perceive the indoor environment in different ways, or have different preferences, priorities, habits or even constraints (e.g. social or economic barriers) when regulating the indoor environment. The following subsections are aimed at providing an introductory overview on the challenges and key research limitations that were addressed in the 5 core chapters of this doctoral thesis.

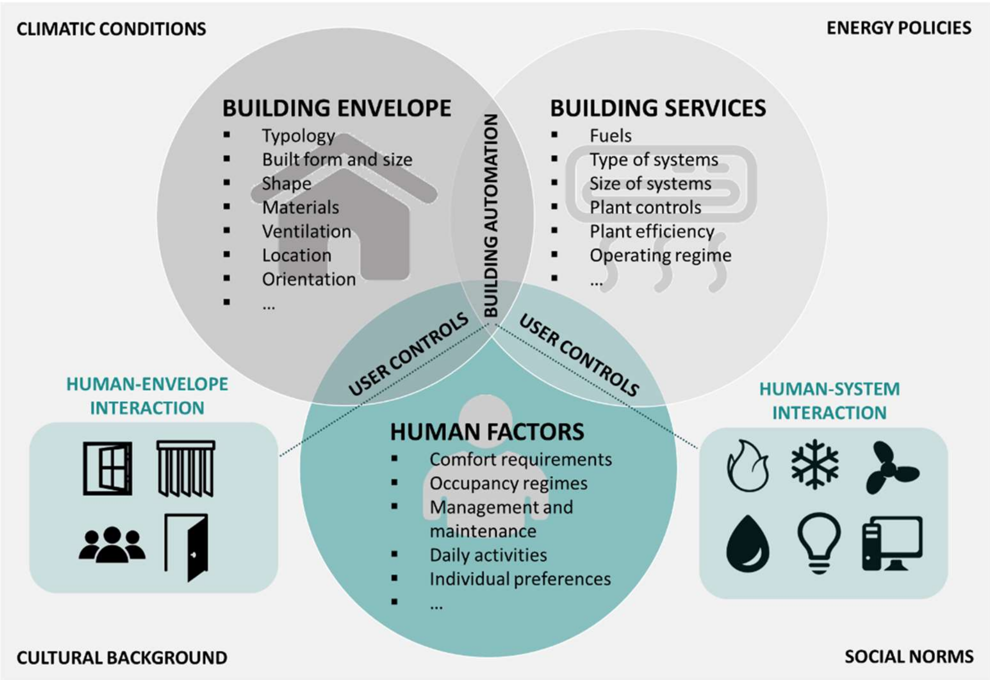


Figure 1.1-1. Influencing factors on building energy use, inspired by El Bakkush et al. (2015).

1.1.1 OB and its impacts: buildings don’t use energy, people do!

“Buildings don’t use energy, people do!” (Janda 2011) – this might be one of the most emblematic headlines in energy-related behavioural research. As already outlined by Janda et al. (2011), a large number of existing studies in the field argue that building occupants play a critical, but often still poorly understood and overlooked role in the built environment. Understanding energy use in buildings is not only a technological challenge, but requires to carefully address aspects related to the human-building interaction. A first step of investigation that has been and is

being addressed by an always increasing number of researchers is trying to understand **to which extent occupant behaviour can impact energy use in buildings**. Investigations on the impact of occupant behaviour on building energy use has been done through direct demonstration in field studies as well as estimations based on simulation results.

Previous field studies measured the impact of occupant-driven parameters on energy consumptions in residential buildings means to data gathering setups and monitoring campaigns. Sidler et al. (2002), for instance, reported a detailed dataset related to the electricity consumption of major end uses in 100 households of four European countries (Denmark, Italy, Portugal, and Greece). The study of Stoecklein et al. (2000) conducted a long-term nationwide investigation into household energy consumption patterns in New Zealand. The outcomes of these studies showed large discrepancies in the effect of occupant behaviour among houses in a community and across communities, with corresponding large impacts on energy use. Other studies have shown that the behaviour of occupants in houses with similar layout and climatic boundary conditions may lead to **differences in energy consumptions of over 300%** (Andersen et al. 2007; Chen and Taylor 2013; Mahdavi 2011)(Figure 1.1-2). In particular, the performance gaps can be due to differences in occupancy patterns, household characteristics, lifestyle, cognitive variables and perception of comfort, physiological characteristics of the occupants, as well as household motivation, attitudes and values (Guerra Santin 2013).

As regards the office environment, Hong and Lin (2013) deployed building energy simulations to show that for a typical single-occupancy office room, compared to the standard or reference workstyle, an austerity workstyle consumes up to 50% less energy, while the wasteful workstyle consumes up to 90% more energy.

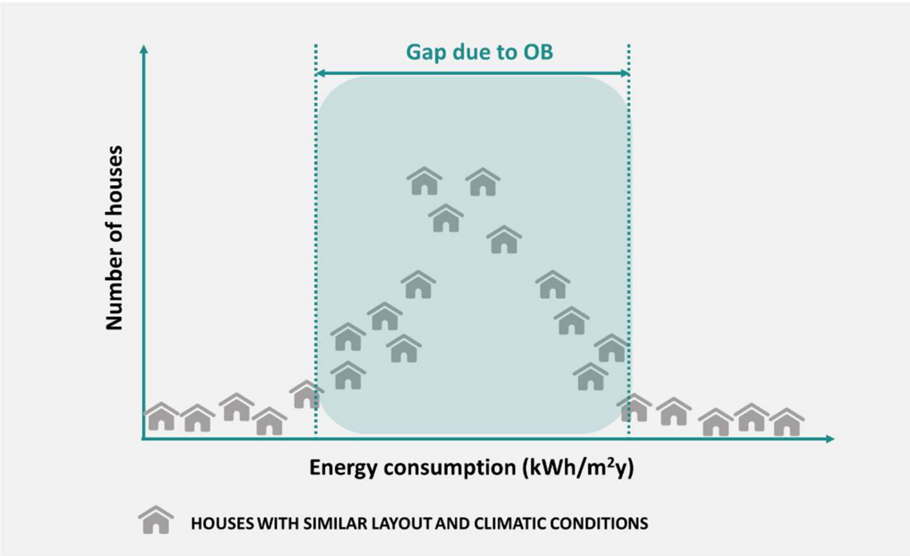


Figure 1.1-2. OB and its impacts: Energy consumption gaps between households with similar layout and climatic conditions, adapted from Andersen et al. (2007)

Additionally, in the last two decades, more stringent energy codes and environmental standards have required the implementation of innovative energy efficiency strategies with the aim of optimizing technical solutions for the building features and reaching nearly zero energy targets in the existing and upcoming building stock (EPBD 2010/31/EC 2010). It seems clear that the success of these strategies is now heavily dependent on how occupants interact with the building system and envelope (Owens and Driffill 2008; Stazi and Naspi 2018). Indeed, **in high performing buildings, the unpredictable loads generated by the occupants might even have a bigger impact on building energy use than in buildings, in which envelope-driven loads dominate the consumption profile** (Brandemuehl and Field 2011). As an example, Bucking et al. (2011) demonstrated that occupant behaviour can significantly deteriorate the overall performance of energy consumption and production in a net-zero energy community and high performing buildings in Montreal, Canada.

However, at the time being, there is still only a small number of studies that thoroughly investigated the impact of occupant behaviour in residential nearly zero energy buildings (Brandemuehl and Field 2011; Gill et al. 2010; Lenoir et al. 2011).

In this context, **Chapter 2** is aimed at contributing to this research gap by investigating potential impacts of occupant behaviour lifestyles on the energy uses and thermal comfort conditions in nearly Zero Energy Buildings.

1.1.2 OB as a key factor of uncertainty: the human dimension in modelling environments

"Bridging the gap" – is the well-known motto of the IEA-EBC Annex 66 "Definition and Simulation of Occupant Behavior in Buildings" (Yan et al. 2017). The gap refers to the significant discrepancies that can be found between real and simulated energy consumption. Building Energy Simulations (BES) are a useful and cost-effective tool to support energy efficient design and operation of buildings. However, when predicting the absolute energy performance of buildings, such tools are still subjected to great uncertainty (Gaetani et al. 2016). Indeed, a major challenge in simulation tools is how to deal with difficulties through large variety of parameters and complexity of factors such as non-linearity, discreteness, and uncertainty (Hopfe and Hensen 2011). ASHRAE (2007) stated that neither the proposed building performance nor the baseline building performance represent actual energy consumption after construction, but that the key items from the listed sources of uncertainty are strictly related to occupancy and building operation. Indeed, international research effort is put on numerically describing the relationship between occupants and buildings in order to eliminate current inconsistencies in building energy simulation (Yan and Hong 2018). Extended literature reviews and state-of-the-art analyses confirm that an **accurate modelling of occupant behaviour is a key factor to bridging the gap between predicted and actual energy performance of buildings** (Marcel Schweiker 2017)(Mahdavi 2011).

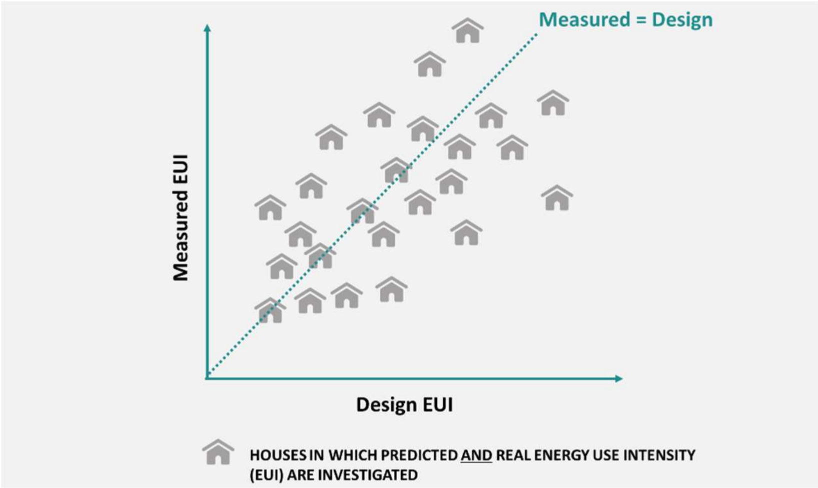


Figure 1.1-3. Measured vs. simulated energy consumption in buildings, adapted from Turner and Frankel (2008) .

Frequently, simulation-based design analysis relies on standard use and operation conditions such as fixed schedules for occupancy levels, light switching, ventilation rates and temperature setting. These assumptions often lead to an oversimplification of the human-related variables creating discrepancies between predicted and real energy use of the building. Thus, in recent years, probabilistic modelling approaches have been applied to capture the stochastic nature of energy-related human behaviour when predicting building energy consumptions in dynamic simulation programs (Gaetani et al. 2016). Probabilistic modelling approaches have been developed to include uncertainty factors into building energy analysis by modelling human-related factors such as **occupancy patterns** (Wang et al. 2005; Page et al. 2008; Erickson et al. 2009; Aerts et al. 2014; Mahdavi and Tahmasebi 2015), **occupants' activities** (Wilke 2013; Tanimoto et al. 2008;Widén et al. 2009), **lighting control** (Hunt 1979; Stokes et al. 2004; Bourgeois et al. 2006; Zhou et al. 2015), **window action control** (Fritsch et al. 1990; Andersen et al. 2013; Yun and Steemers 2008; Haldi and Robinson 2009; Schweiker et al. 2012), **regulation of window blinds/shades** (Reinhart 2004; Haldi and Robinson 2010), **adjustment of the thermostat settings** (D'Oca et al. 2014), **internal heat gains** (Tanimoto et al. 2008), and **usage of plug-in appliances** (Bourgeois et al. 2006).

The majority of these existing studies rely on **logit analysis** (Andersen et al. 2013; Yun and Steemers 2008; D'Oca et al. 2014), **probit analysis** (Hunt 1979), **Markov chain processes** (Page et al. 2008; Haldi and Robinson 2010; Schweiker et al. 2012), **Poisson processes** (Zhou et al. 2015), and **survival analysis** (Haldi and Robinson 2009). More complex modelling frameworks have introduced –often very time-consuming- agent-based and object-oriented models (Erickson et al. 2009; Tanimoto et al. 2008) to model single individuals or objects and their interaction with the building. However, (Yan et al. 2015a) described the current state and future challenges in occupant behaviour modelling and emphasized that there are still many gaps in knowledge and limitations to current methodologies, including model development together with the need for greater rigor in experimental methodologies next to a detailed, honest and candid reporting of methods and results. Furthermore, the authors highlight the importance of moving towards modelling procedures of occupant behaviour, knowing that the latter might be influenced by multiple contextual factors, incorporating qualitative model inputs. This aspect is currently not accurately covered by the above-mentioned existing models. Therefore, it seems crucial to explore further modelling environments that are characterised by a transparent semantic and that are able to include and combine at the same time a number of different types of variables from different sources (quantitative and qualitative data) in the same model.

In this context, **Chapter 3** is aimed at contributing to this research gap by exploring the Bayesian Network framework for stochastically modelling occupant behaviour and to gain a first insight on exploiting this methodology for the creation of more comprehensive OB models.

1.1.3 OB as a challenge for multidisciplinary investigation: occupant vs. human

"Every individual is essentially unique and different from everyone else" – is the principle of the uniqueness theorem of the human being (Varki et al. 2008). Indeed, every human might perceive the indoor environment in different ways due to a multiple set of factors (Figure 1.1-4), have different motivations and habits or can even be conditioned by a series of barriers (e.g. social or economic factors) that restrain them from performing a certain action, even though they feel the need to change the conditions of the indoor environment. Fabi et al. (2012) highlight that much is still unknown about the motivation of building occupants to interact with the building envelope and systems.

Hence, the authors highlight that, next to environmental and time-related factors, it is necessary to take into account "individual" factors of occupants, such as the personal background, energy-related attitudes, perception or personal preferences related to the indoor environment. Also the physiological condition of the occupant plays an important role, such as age, gender or health conditions. Fabi et al. (2012) also stress the importance of social driving forces depending on household composition and the interaction between household members (e.g. which household member determines the thermostat set-point or the opening/closing of windows). Social norms in office environments were investigated by D'Oca et al. (2017) through an extensive survey framework.

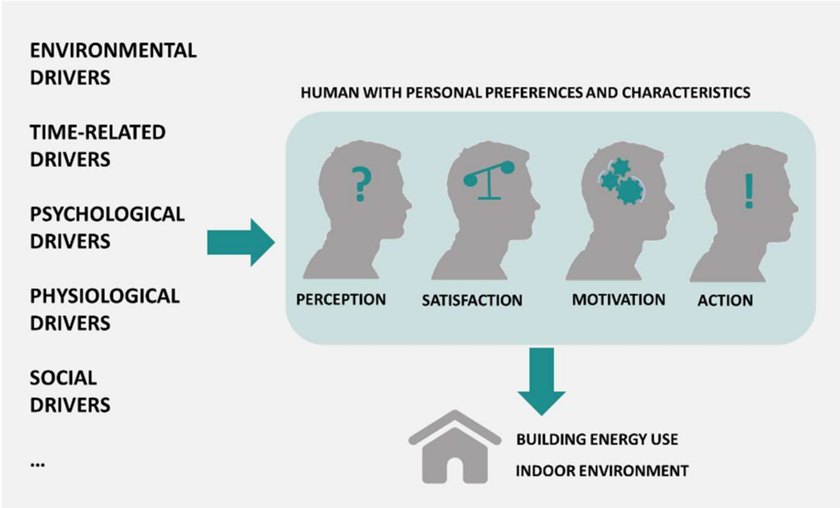


Figure 1.1-4. Drivers influencing occupant behaviour.

Wei et al. (2014) identified 27 drivers that have been evaluated in previous studies on space heating behaviour and showed that at present none of them can be identified confidently as having no influence. Next to physical and time-related drivers, the authors list occupant age, gender, culture/race, educational level, social grade, household size, family income, thermal sensation, perceived IAQ and noise, health, heating price, and energy use awareness as potential driving factors. Schweiker et al. (2016) analysed the influence of (the big-five) personality traits (neuroticism, extraversion, openness, and concepts of general and thermos-specific self-efficacy) on four types of behavioural patterns (clothing adjustment, window opening, blind closing, and interactions with ceiling fan). The authors highlighted that all personality traits led to significant differences between behavioural patterns confirming the need to investigate individual characteristics of the occupants. However, from an interdisciplinary point of view, much is still unknown about occupant behaviour and further exploration is required to gain a deeper knowledge on a comprehensive set of factors that drive the occupants to perform a certain action and how to introduce the latter in modelling environments.

In this context, **Chapter 4** is aimed at developing a theoretical model of OB and exploring a more extensive set of drivers means to the combination of field measurements (quantitative) and survey-based information (qualitative) that were implemented in the same BN-based model environment.

1.1.4 OB on a large scale: Profiling behavioural patterns with Time Use Survey data

"Measuring how people spend their time" (Stinson 1999) on a **large scale** is the key objective of Time Use Surveys (TUS). National time use surveys (TUS) have been carried out at national level since the early 1970s. The first TUS were

conducted in developing countries in Europe. They were designed to understand and assess progress in lifestyles, focusing mainly on time spent for leisure, transport, and work (Figure 1.1-5). The first TUS in developing and transitional countries were conducted in the late 1990s, with the main objective being to measure the gender gap in paid and unpaid work. By 2015, nearly a hundred surveys for 65 countries were available for in-depth analyses (Charmes 2015; Eurostat 2009).

Although TUS data have been used predominantly for answering research questions related to social aspects, work, and economics, they are **becoming an essential data source for energy-related occupant behaviour modelling** as well (Figure 1.1-6).

Indeed, occupants' activities evidently shape the timing of building energy use throughout the day. Diary-based surveys on how occupants spend their time during the day can help to shape occupancy profiles and energy-related activities. As Schipper et al. (1989) first stated, to gain a deeper understanding about the impact of different lifestyles on energy use it is necessary to understand interdependencies between time use and energy consumption. Wilke et al. (2013), for instance, developed stochastic models based on the French TUS to predict time-dependent residential occupancy and activities, relating the use of electrical appliances to the activities performed. Yu et al. (2013) used data collected in a household TUS in Beijing to develop a household time-use and energy-consumption model, which incorporates multiple behavioural interactions. Torriti (2017) used the British TUS to assess how dependent energy-related social practices in the household are in relation to the time of the day. They analysed the 2005 UK TUS and made use of statistically derived time dependence metrics for six social practices, including preparing food, washing, cleaning, washing clothes, watching TV and computer usage. Other studies modelled TUS data to explore the temporal change in laundry practices and related implications on the flexibility of energy demand (Anderson 2016) or to generate myriad schedule data of each inhabitant's behaviour at a fine time resolution for time-series cooling load calculation (Tanimoto et al. 2005; Tanimoto et al. 2008).

Indeed, next to the exploration of TUS data for establishing a link between occupants' activities and energy consumption, time use data have been used most frequently in the development of high resolution occupancy profiles for different countries. Richardson et al. (2008) presented a thorough and detailed method for generating realistic occupancy data for UK households, based upon surveyed time-use data describing what people do and when. The approach presented generates statistical occupancy time-series data with a ten-minute resolution and takes account of differences between weekdays and weekends. The model also indicates the number of occupants that were active within a house at a given time. Aerts et al. (2014) developed a methodology for modelling domestic occupancy patterns based on the Belgian TUS (2005). Buttitta et al. (2017) used the UK 2000 TUS for demonstrating a methodology that permits to generate occupancy patterns that can be representative for different archetype building models.

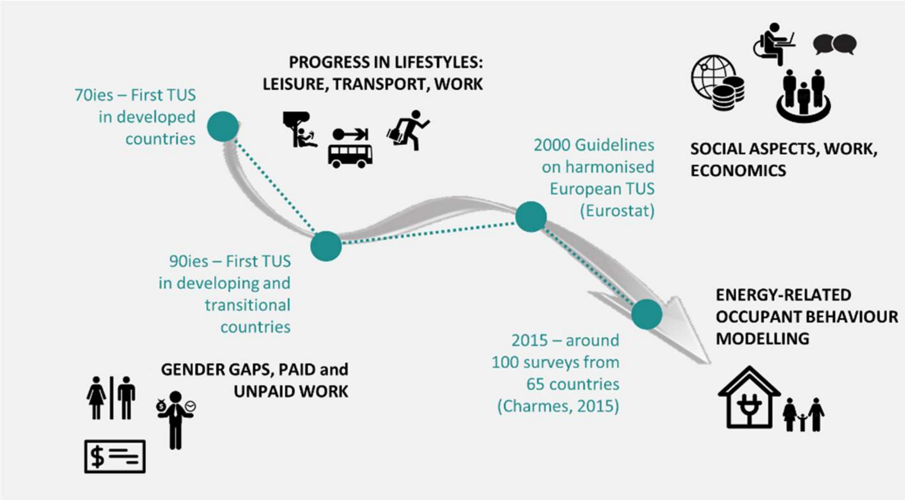


Figure 1.1-5. Time Use Survey data as source for occupant behaviour modelling.

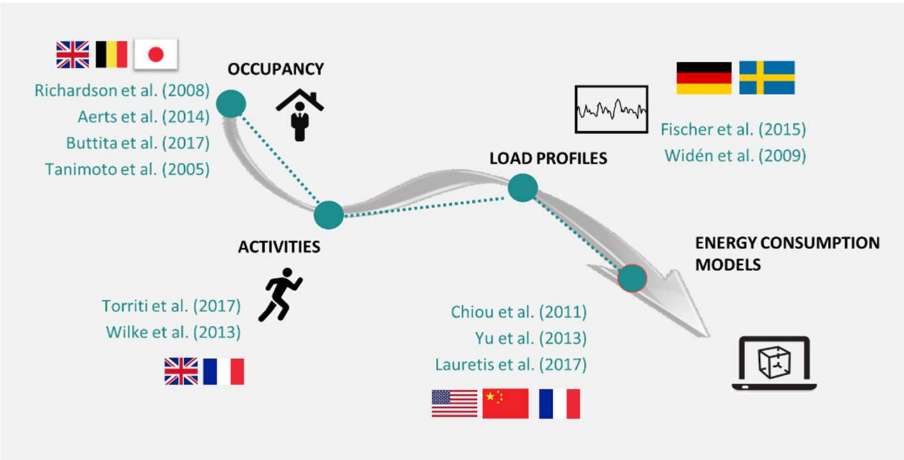


Figure 1.1-6. Time User Survey data as source for enhanced building energy simulation input.

Some of the existing studies show that TUS data represents a significant resource by validating their TUS-based approaches against field measurements. Widén et al. (2009), for instance, modelled time-use data for constructing load profiles for household electricity and domestic hot water based on Swedish TUS data. They also provided validation against detailed, end-use specific electricity measurements in a small sample of households and revealed that the model for household electricity reproduces hourly load patterns with preservation of important qualitative features. Fischer et al. (2015) modelled electric load profiles with high time resolution based on the German TUS and validated their model against field data from 430 households; the results showed an accuracy of 91%.

The range of above-mentioned studies clearly shows how TUS data can be used to model and analyse occupant behaviour on a large scale in the field of building energy use. In countries with growing electricity generation from renewable energy sources, gaining better knowledge of occupants' time use in households and related energy use at a national scale becomes a crucial task in order to respond to challenges related to demand-response modelling.

However, in some nations (e.g. Denmark, Italy), TUS data have not been analysed from the perspective of energy usage. Its potential usability for modelling energy- and behavioural-related processes in this context needs still to be thoroughly explored.

In this context, **Chapter 5** is aimed at profiling occupant behaviour (activities, occupancy) on a large scale based on the Danish Time Use Survey data 2008/2009.

1.1.5 OB within the energy efficiency framework: occupant engagement as a key for reaching energy saving targets

"*Achieving energy efficiency through behaviour change: what does it take?*" is the title of the EEA Technical report (European Environment Agency 2013) that expresses together with a growing body of evidence in academic literature that there is significant potential for energy savings due to measures targeting the human factor and behavioural change (Clarity Sustainability 2015). Indeed, a large number of energy efficiency strategies implemented involve technological interventions, but should equally rely on raising user awareness and adjusting their energy consumption behaviour (Figure 1.1-7). Behavioural change strategies have been recognized as a low-cost and highly efficient measure to reduce building energy consumption, and consequently related environmental impacts and operational costs. Building occupants oftentimes are not truly aware of how their behaviour and interactions with the built environment (negatively or positively) affect energy uses and their own environmental comfort (Judd et al. 2013). The role of occupants in reaching the net-zero target and the importance of institutional behavioural change to enhance building performance is crucial since frequently passive building strategies developed for high performing buildings require that occupants are engaged to actively and smartly interact with the proposed solutions.

Promoting and achieving energy-conscious behaviour among householders is a key issue for reducing energy consumptions in the residential sector (Wood and Newborough 2003). Results from domestic energy awareness campaigns in Italy (D'Oca et al. 2014) and worldwide (Pothitou et al. 2016) verified the energy saving potential (on average among 15 to 20%) of improving occupant behaviour at home.

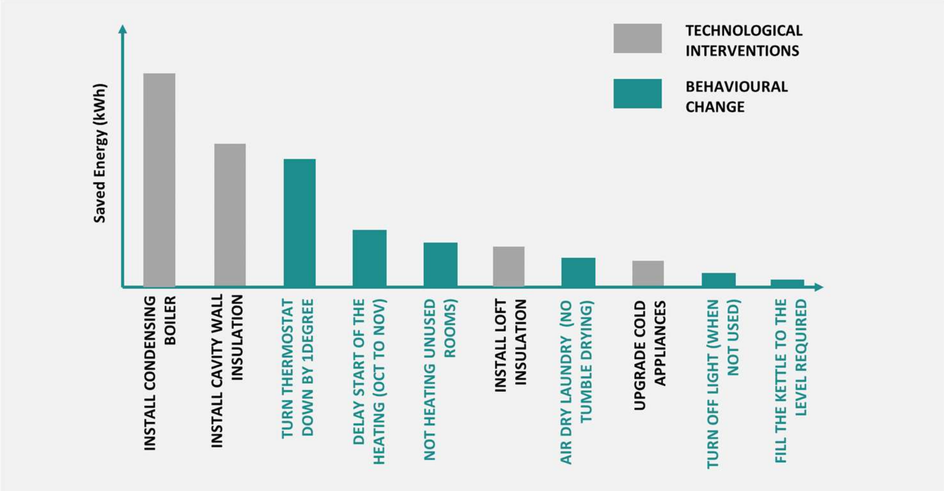


Figure 1.1-7. Energy Savings: Technological interventions vs. behavioural change, adapted by (Clarity Sustainability 2015) .

Engaging behavioural change in commercial buildings and offices is more critical, since the effects of energy (and cost) saving is often not “paid back” to the employees in monetary terms (savings on energy bill). Motivation for employees to engage in energy efficiency behaviours is therefore very different and must rely on corporate and social responsibility objectives and reinforcing societal norms. Moreover, the nature of competition between individual colleagues or different offices can be a more powerful driver than financial gain. Studies focusing on energy engagement in office settings report energy savings ranging from 4 to 10% (Gulbinas et al. 2014; Orland et al. 2014). Most likely for this reason – at the time-being - a larger amount of studies have focused on residential buildings (Ueno et al. 2006; Ueno et al. 2005; Ouyang and Hokao 2009), while fewer investigations have been done for the non-residential sector (Matthies et al. 2011). Efforts related to behavioural change incentives have been done also in the higher education sector (Macarulla et al. 2015) in order to reach the keystone for sustainable development also in university campuses.

Existing literature highlights that most of the user awareness campaigns stimulate behavioural change by providing feedback on the electricity usage and related costs (Brounen et al. 2012). These approaches oftentimes do not consider or leverage on psychological, anthropological, physiological needs or health aspects of the occupants (Darby 2006; Herring 2006). Indeed, motivating occupants to change their behaviour can become a challenging task, especially if they are expected to internalize and adopt the new behaviour on a long term. This means that information and feedback provided to the occupants must be stimulating, easy to understand, and easy to adopt in the daily routine. Further research is necessary to explore the effectiveness of motivational triggers (health and well-being of the occupants) in leading to a behavioural change on a long term (behavioural persistence), also after the conclusion of the engagement campaign. Next to the feedback content itself, it is also crucial to deploy a successful communication strategy with the engaged users. In the field of persuasive technology, various innovative solutions have been realized for leveraging behavioural change, such as ambient displays that show real-time energy consumption (Wood and Newborough 2007), mobile or web applications with the most variate functions, or even serious games that are aimed at changing behaviour with an added pedagogical value of fun and competition (Orland et al. 2014). To address the above-mentioned shortcomings, the European Union introduced several measures to ensure better engagement of the citizens and in which the awareness of the building occupant is a key to achieving the remaining tasks (European Commission 2017). Among other initiatives, the European Commission funded several projects under Horizon 2020 programme aiming to achieve a behavioral change towards energy efficiency through ICT-based solutions. In 2014, the European Commission funded the following projects: EnerGAware, ENTROPY, OrbEEt, GreenPlay, Tribe. In 2015 further projects kicked off, such as PeakAPP, GAIA, and ChArGED, whereas the most recent projects (2016) within this scope are enCOMPASS and MOBISTYLE (European Commission 2018).

In the context of the Intelligent Energy Europe Programme from the European Commission, Dahlbom et al. (2009) developed guidelines for Behavioural Change Programmes and provided an overview of lessons learnt in 41 cases in Europe over the past years. The authors highlight that interventions aimed at changing the behaviour of the occupants are only effective if they are set up in a systematic way and according to a planning and evaluation model. The exploration of methodological frameworks to set up and evaluate effective engagements is therefore a key aspect to reach desired outcomes in terms of energy saving and long-term behavioural change and still needs to be thoroughly explored.

In this context, **Chapter 6** is aimed at demonstrating the development of energy engagement programs that have been part of this doctoral research. Focus is put on (i) innovative approaches that involve new triggers such as health-related aspects and well-being of the occupants (ii) the development of methods for setting up and evaluating an effective engagement campaign.

1.2 Roadmap and methodological framework

This doctoral thesis is divided into five core chapters aimed at contributing to the open research questions highlighted in the previous section. All the chapters present a schematic overview, a description of the developed methodology, key findings, discussion and further investigations as well as perspectives and challenges. Each chapter is aimed at addressing to some extent the challenges highlighted in the previous chapters and therefore this work should be seen as "interactive" framework to address the human factor in buildings (Figure 1.2-1).

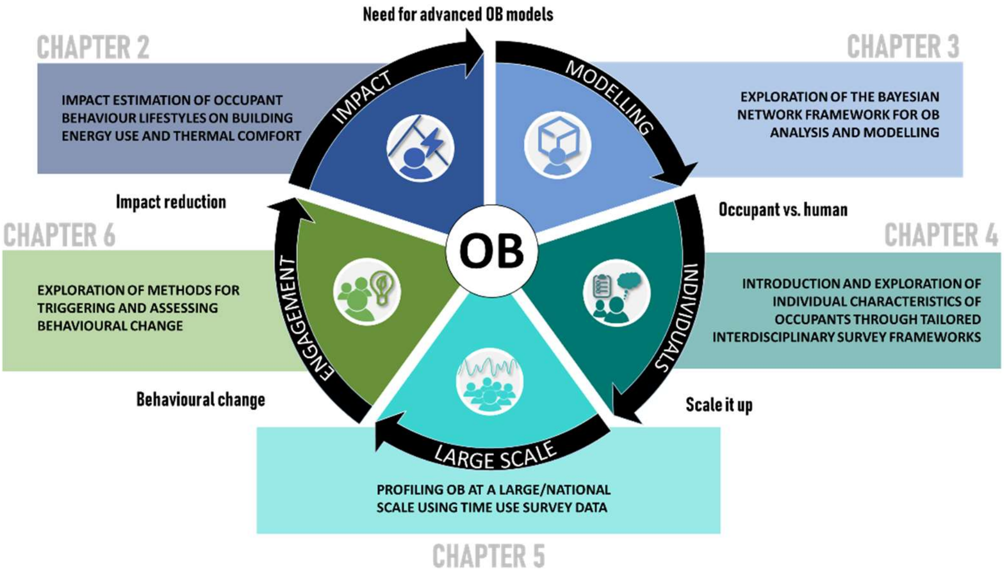


Figure 1.2-1. Methodological framework of the Ph.D. dissertation.

Chapter 2 is aimed at evaluating the impact of different occupant behaviour lifestyles and patterns on the energy use and thermal comfort of a residential nearly-zero energy building. The outcomes of this chapter highlight that there is an urgent need for developing sophisticated models able to capture the stochastic nature of the human-building interaction. Chapter 3 provides an innovative methodology to provide such a model based on the Bayesian Network framework. The outcomes of Chapter 3 lead to the conclusion that in order to build a more comprehensive model, it is necessary to include a larger set of motivational drivers (qualitative and quantitative data). Chapter 4 is indeed aimed at extending the proposed methodological framework by investigating individual characteristics of the occupants through survey-based information (e.g. thermal comfort attitudes, personal preferences) and introducing them into the Bayesian Network model. Chapter 4 also highlights that sophisticated models oftentimes are based on small samples and for some research purposes it is necessary to profile occupant behaviour on a large scale. This challenge is addressed in Chapter 5 by profiling occupants' daily activities and occupancy patterns using national Time Use Survey data. Finally, Chapter 6 is aimed at showing how occupant behaviour can be changed through user awareness and behavioural change programs – this responds to how occupant behaviour lifestyles introduced in Chapter 2 can be driven towards a low consumer behaviour.

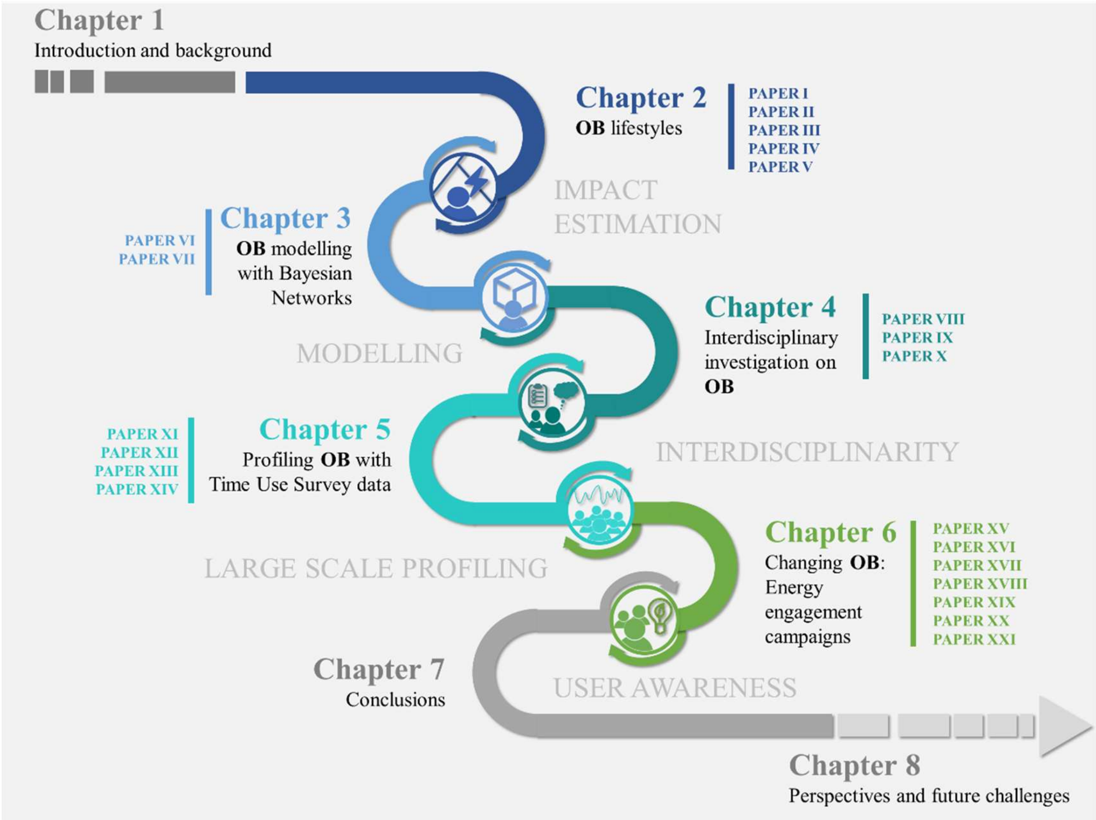


Figure 1.2-2. Roadmap.

This dissertation is structured as a monograph, however, it is important to highlight that most of the Ph.D research outcomes were also object of international scientific journal publications or conference proceedings, which trace the same research path. The latter are cited at the end of each chapter. Table 1.2-1 gives an overview on the papers relevant to this dissertation. In particular, key publications are marked with an "*" and will be digitally added as Annexes.

Table 1.2-1. List of research papers relevant to the Ph.D dissertation.

Chapter	PAPER ID	TITLE
CHAPTER 2	PAPER I*	**Barthelmes, V.M.**, Becchio, C., Corgnati, S.P. (2016), Occupant behavior lifestyles in a residential nearly zero energy building: Effect on energy use and thermal comfort, *Science and Technology for the Built Environment* 22, pp. 960-975.
	PAPER II	**Barthelmes, V.M.**, Becchio, C., Corgnati, S.P. (2018). Il peso del comportamento dell'occupante in edifici ad energia quasi-zero: il caso studio della CorTau House, *Ingenio Informazione tecnica e progettuale* 68, pp. 1-5.
	PAPER III	**Barthelmes, V.M**.; Fabi, V.; Corgnati, S.P. (2016) Impact of behavioural patterns on the energy use of a residential nearly-zero energy building. In: Proceeding of Behave 2016, Coimbra, Portugal, 8-9 September. pp. 1-2.
	PAPER IV*	**Barthelmes, V.M**., Becchio, C., Fabi, V., Corgnati, S.P. (2017). Occupant behaviour lifestyles and effects on building energy use: Investigation on high and low performing building features, *Energy Procedia* 140, pp. 93-101.
	PAPER V*	Fabi, V., **Barthelmes, V.M.**, Schweiker, M., Corgnati, S.P. (2017). Insights into the effects of occupant behaviour lifestyles and building automation on building energy use, *Energy Procedia* 140. pp. 48-56.
CHAPTER 3	PAPER VI*	**Barthelmes, V.M**., Heo, Y., Fabi, V., Corgnati, S.P. (2017). Exploration of the Bayesian Network framework for modelling window control behaviour, *Building and Environment* 126, pp. 318-330).
	PAPER VII	**Barthelmes, V.M.**, Heo, Y., Fabi, V., Corgnati, S.P. The Bayesian Network framework for building energy and occupant behaviour analysis: A critical review (to be submitted to Energy and Buildings, 2019)
CHAPTER 4	PAPER VIII*	**Barthelmes, V.M.**, Andersen, R.K., Heo, Y., Knudsen, H., Fabi, V., Corgnati, S.P. (2018). Introducing thermal comfort attitudes, psychological, social and contextual drivers in occupant behaviour modelling with Bayesian Networks. In: Proceedings of the 10th Windsor conference (Rethinking Comfort) 2018, 12-15 April, Windsor, UK, pp. 1003-1019.
	PAPER IX*	**Barthelmes, V.M.**, Heo, Y., Andersen, R.K., Fabi, V., Corgnati, S.P. (2018). Towards A Comprehensive Model Of Window Control Behaviour: A Survey-based Investigation On Interdisciplinary Drivers In Danish Dwellings. In: Proceedings of the 4th Building Simulation and Optimization Conference (BSO 2018), 11-12 September, Cambridge, UK, pp. 649-656.
	PAPER X*	D'Oca, S., Pisello, A.L., De Simone, M., **Barthelmes, V.M.**, Hong, T., Corgnati, S.P. (2018). Human-building interaction at work: Findings from an interdisciplinary cross-country survey in Italy, *Building and Environment* 132, pp. 147-159.
	PAPER XI	**Barthelmes, V.M**., Li, R., Andersen, R.K., Bahnfleth, W., Corgnati, S.P., Rode, C. (2018). Profiling Occupant Behaviour in Danish Dwellings using Time Use Survey Data – Part I: Data Description and Activity Profiling. In: Proceedings of the 4th International Conference on Building Energy & Environment 2018, 5-9 February, Melbourne, Australia, pp. 97-102.
	PAPER XII	**Barthelmes, V.M.**, Li, R., Andersen, R.K., Bahnfleth, W., Corgnati, S.P., Rode, C. (2018). Profiling Occupant Behaviour

CHAPTER 5		in Danish Dwellings using Time Use Survey Data – Part II: Time-related Factors and Occupancy. In: Proceedings of the 4th International Conference on Building Energy & Environment 2018, 5-9 February, Melbourne, Australia, pp. 103-108.
	PAPER XIII*	**Barthelmes, V.M.,** Li, R., Andersen, R.K., Bahnfleth, W., Corgnati, S.P., Rode, C. (2018). Profiling occupant behaviour in Danish dwellings using time use survey data, *Energy and Buildings* 177, pp. 329-340.
	PAPER XIV	**Barthelmes, V.M.**, Becchio, C., Crespi, G., De Nicoli, M.V., Fabi, V., Corgnati, S.P. (2019). Profiling Occupant Behaviour in Italian Households for enhanced building simulation input: Insights Into A Survey-based Investigation. Paper accepted at the Building Simulation conference, 2-4 September, Rome, Italy.
CHAPTER 6	**PAPER XV***	**Barthelmes, V.M.**, Fabi, V., Corgnati, S.P., Serra, V. (2019). Human Factor and Energy Efficiency in Buildings: Motivating End-Users Behavioural Change, *Advances in Intelligent Systems and Computing* 825, pp. 514-525.
	PAPER XVI	Fabi, V., **Barthelmes, V.M.**, Kingma, B., van Marken Lichtenbelt, W., Heiselberg, P., Corgnati, S.P. (2017). Combining energy, comfort and health data for behavioural change. In: Proceedings of the 10th International Symposium on Heating, Ventilation and Air Conditioning, 19-22 October, Jinan, China.
	PAPER XVII	**Barthelmes, V.M.,** Becchio, C., D'Oca, S., Litiu, A.V., Tisov, A., Vergerio, G., Corgnati, S.P. (2019). A methodological framework to motivate and assess behavioural change: Insights into an interdisciplinary user awareness campaign. Paper accepted at the 51th International AICARR conference, 20-22 February, Venice, Italy.
	PAPER XVIII (Chapter)	Corgnati, S.P., Buso, T., **Barthelmes, V.M**. (2017), Energy management strategies for University Campuses. Chapter in: News from the Front of Sustainable University Campuses, edited by P. Lombardi and G. Sonetti, Edizioni Nuova Cultura, Rome, Italy, pp. 23-44.
	PAPER XIX*	Fabi, V., **Barthelmes, V.M.,** Heo, Y., Corgnati, S.P. (2017). Monitoring and stimulating energy behavioural change in university buildings towards post carbon cities. In: Proceedings of the 15th IBPSA Conference 2017, 7-9 August, San Francisco, USA, pp. 423-429.
	PAPER XX|*	Cottafava, D., Magariello, S., Ariano, R., Arrobbio, O., **Barthelmes, V.M.,** Baruzzo, G., Bonansone, M., Console, L., Contin, L., Corgnati, S.P., Fabi, V., Gambino, P., Gerlero, I., Grillo, P., Guaschino, G., Landolfo, P., Malano, M., Mana, D., Matassa, A., Monterzino, L., Mosca, S., Nuciari, M., Olivetta, E., Padovan. D., Rapp, A., Sanseverino, M., Sciullo, A., Simeoni, R., Vernero, F. (2019). Crowdsensing for a sustainable comfort: behavioural change for energy saving, *Energy and Buildings* 186, pp. 208-220.
	PAPER XXI*	Fabi, V., **Barthelmes, V.M.,** Corgnati, S.P. (2016). Impact of an engagement campaign on user behaviour in office environment. In: Proceedings of the 14th International Conference of Indoor Air Quality and Climate (Indoor Air 2016), Ghent, Belgium, pp. 1-8.

Chapter 2

Occupant behaviour lifestyles: Impacts on building energy use and thermal comfort

2.1 Overview

Chapter 1 introduced occupant behaviour as a key driving factor of uncertainty when predicting energy use in buildings. The way building occupants interact with the building and set their comfort criteria can be extremely different from case to case and therefore impact building energy use to enormously varying extents (Andersen et al. 2007; Mahdavi 2011). Hence, it seems to be a crucial task to gain a better understanding on how different energy-related attitudes and associated occupant behaviour lifestyles can affect building energy use, especially in high performing buildings. Indeed, as technological solutions for building systems and envelopes are optimized, the impact of occupant behaviour gains even more importance.

In line with this, this chapter proposes a methodology for investigating to which extent different occupant behaviour lifestyles (low, standard, and high energy consuming) and different household compositions might affect building energy use and thermal comfort (Figure 2.1-1) in high performing buildings. On the other hand, the outcomes stress the urgent need for the development of occupant behaviour models that allow for more reliably capturing the stochastic nature of human behaviour inside buildings. In particular, based on simulation results of a real case study, this chapter is aimed at contributing to answer the following research questions:

- What impacts can different occupant behaviour lifestyles and household arrangements have on the energy performance of a nearly zero energy building?
- What impacts can different occupant behaviour lifestyles and household arrangements have on the thermal comfort conditions of a nearly zero energy building?
- Which are the key behavioural patterns that should be addressed by decision-makers of behavioural change programs in high performing buildings?
- Do these key behavioural patterns differ in high and low performing buildings?

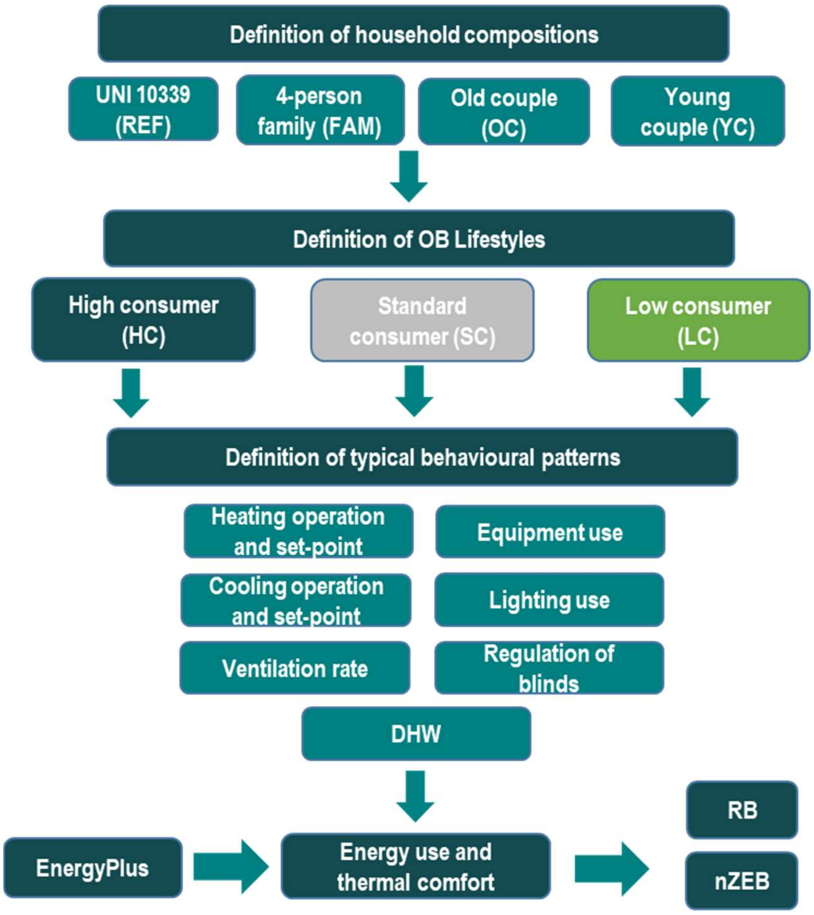


Figure 2.1-1. Overview Chapter 1.

2.2 Methodology

For exploring and describing the potential impact of different occupant behaviour lifestyles on energy use and thermal comfort conditions in the building, this investigation deploys dynamic energy simulations in Energy Plus (version

8.4)(DOE 2017). In line with the geographical context of the chosen case study described in section 2.2.1, climatic data of Turin (Italy) was used for all simulations. The core idea behind the methodological approach is to investigate the effect of different occupant behaviour lifestyles described through specific occupant-driven variables on (i) building energy use and (ii) thermal comfort conditions inside the building. Since (i) and (ii) can also be heavily dependent on the number of people that occupy the building, a further investigation describes the potential impact of different types of household compositions **(PAPER I, II, III)**.

2.2.1 Case study

The methodological approach presented in this chapter has been tested on a nearly zero-energy building (the so-called "*CorTau House*") located in Northern Italy (Figure 2.2-1). The 147-m^2 family home is considered an innovative design experience in which the refurbishment of a traditional building is combined with high-performing energy solutions for envelope and systems. Next to a design based on bioclimatic principles, the building performance benefits from a strongly insulated building envelope ($U_{wall,ceiling}$ =0.15 W/m^{2}K, U_{slab} =0.19 W/m^{2}K, U_{window} =0.96 W/m^{2}K) and a high performing building primary system. A water-to-water heat pump (COP =4.4, EER=4.2) is combined with radiant floors in all rooms and provides for space heating/cooling and the production of domestic hot water (DHW). Other features are a controlled mechanical ventilation system with heat recovery and dehumidifier, and a 7kW$_{peak}$ grid-connected photovoltaic (PV) system that covers electricity needs for space heating/cooling, ventilation, lighting, electric equipment, and DHW. Detailed information on the envelope characteristics and HVAC systems can be found in (Barthelmes et al. 2014)(Barthelmes et al. 2015).

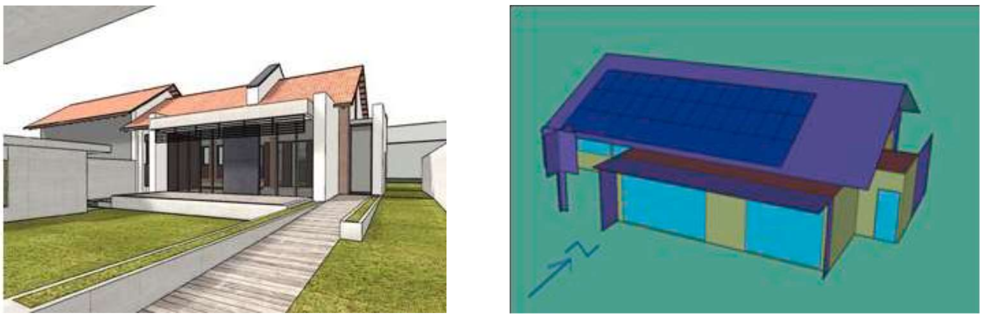


Figure 2.2-1. CorTau House: Project design and Energy Plus model.

2.2.2 Occupant Behaviour Lifestyles

For comprehending how different attitudes and associated lifestyles of the occupants can affect the energy performance of the building, three categories of energy-related occupant behaviour lifestyles were defined: a low consumer (LC), a standard consumer (SC), and a high consumer (HC). These lifestyles are described by a series of key variables shown in Table 2.2-1. Hong and Lin (Hong and Lin 2013) used a similar method to analyse the effects of different workstyles of employees on the energy use in office environments.

The values for heating/cooling set-points and ventilation rates refer to the European Standard EN 15251 (where HC refers to Category I, SC to Category II, and LC to Category III) (Cen 2007). The temperature set-point was assumed to be constant throughout the day in the HC scenario, while the low and standard consumer were assumed to set back the set-point by 2°C during the evening and night hours. According to Italian regulation for Climatic Zone E (in which Turin is located), the heating system was considered to be active from October 15th to April 15th, while the cooling system was set to operate from April 30th to September 30th. The number of occupants per zone floor area was calculated according to the Italian Standard UNI 10339 (0.04 occupants/m^2)(UNI 1995). Lighting and electric equipment power densities refer to ASHRAE Standard 90 (ASHRAE 2013) and mount to 3.88 and 5.89 W/m^2, respectively. The lighting and electric equipment schedules for the standard scenario refer to reference schedules available on the Department of Energy dataset for residential reference buildings (DOE 2018). For assessing the operational levels in the low and high consumer scenario, these standard schedules were increased (HC) or decreased (LC) by 10% (Figure 2.2-2). The lighting use in the low consumer scenario was furthermore optimized through daylight control (continuous/off dimming). The windows blinds were assumed to be always kept open by the high consumer, while the standard and low consumer would close them when a relevant solar radiation engraved on the fenestration surface or through optimized daylight control. The domestic hot water usage differed from 40 l/pers.day (LC) up to 80 l/pers.day (HC).

Table 2.2-1. Key variables describing OB lifetyles

Type of behaviour	Low consumer (LC)		Standard consumer (SC)		High consumer (HC)	
Heating operation and set-point (°C)	5am-11pm	18°C	7am-8pm	20°C	0am-12pm	21°C
	11pm-5am	16°C	8pm-7am	18°C		
Cooling operation and set-point (°C)	5am-11pm	27°C	7am-8pm	26°C	0am-12pm	25.5°C
	11pm-5am	28°C	8pm-7am	27°C		
Ventilation rate (ACH)	0.5		0.6		0.7	
Electric equipment (schedule – see Figure **2.2-2)**	-10% referred to average operational level for electric equipment		Average operational level for electric equipment		+10% referred to average operational level for electric equipment	
Lighting (schedule– see Figure 2.2-2**)**	-10% referred to average operational level for lighting + optimization through daylight control (continuous/off dimming)		Average operational level for lighting		+10% referred to average operational level for lighting	
Blinds	Optimization through daylight control (only if glare index is higher than 22)		Only if solar radiation (higher than 300W/m^2) engraves on fenestration surface, in summer		Always open	
DHW (l/pers.day)	40		60		80	

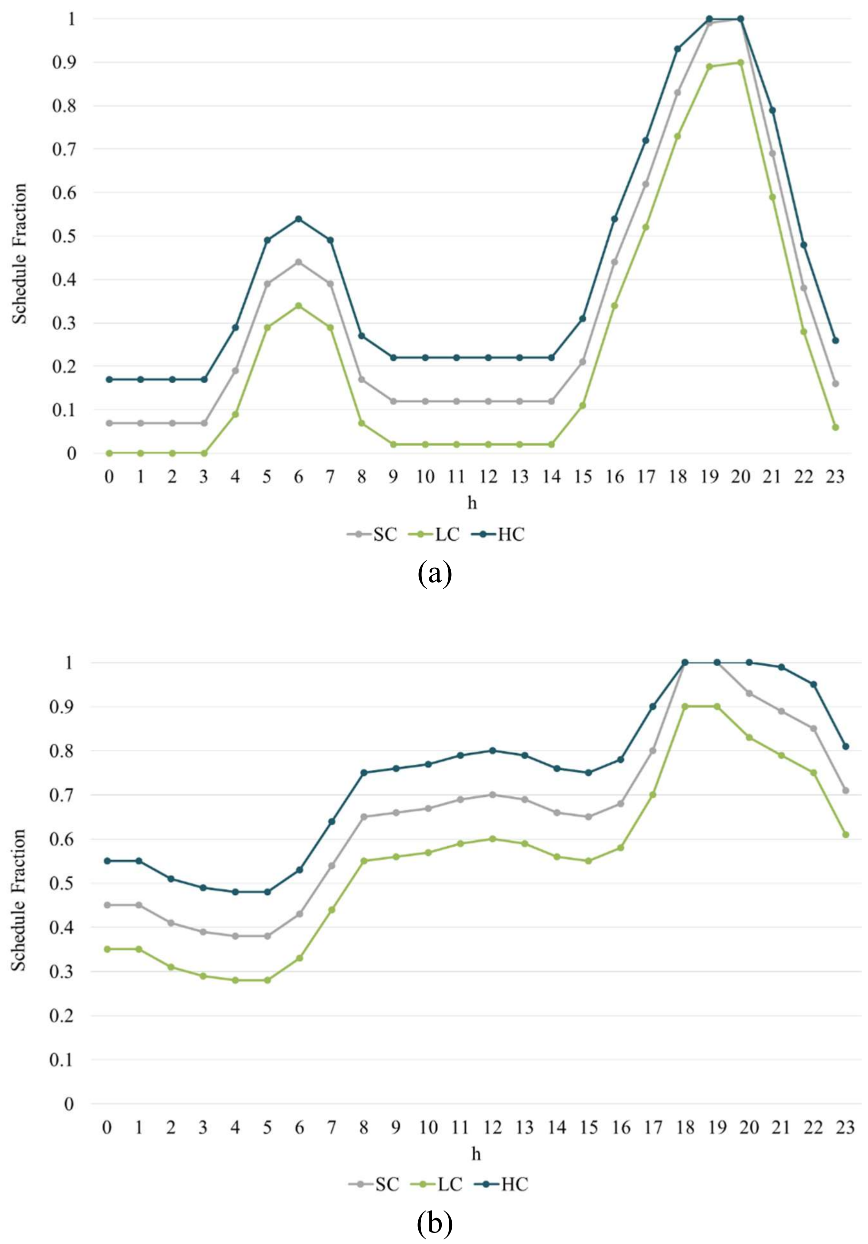
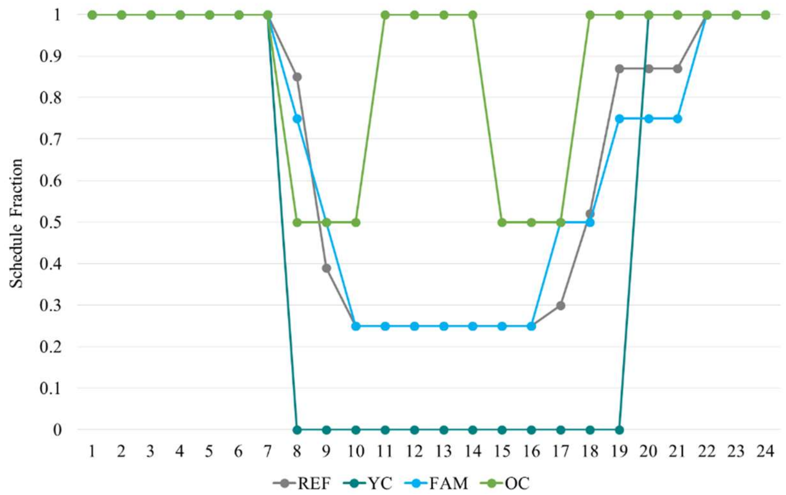


Figure 2.2-2. Schedule variations for (a) lighting and (b) electric equipment.

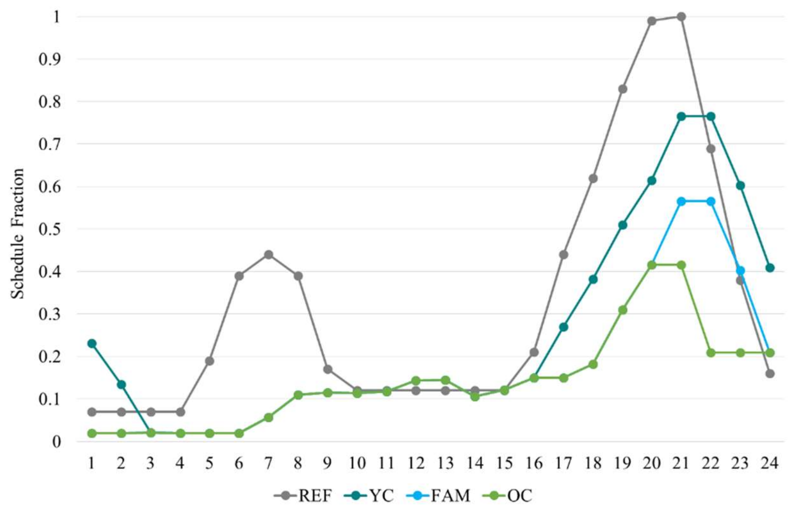
2.2.3 Household compositions

As mentioned in the previous section, up to this point the number of occupants per zone floor area was calculated according to the crowding index provided by the the UNI EN 10339 (0.04 occupants/m^2), which meant that, considering a net conditioned building floor area of 147 m^2, nearly six users occupy the building. This standard therefore clearly might lead to an overestimation of occupants and, consequently, of the energy consumptions in buildings with a large floor area. For this reason, an additional analysis was performed for capturing potential variations of the building energy performance due to different household arrangements. Next to the scenario that considered the standardized number of occupants (REF), additional three types of more "realistic" household compositions were defined based on their high representativeness in the wider population: Family (FAM): 4

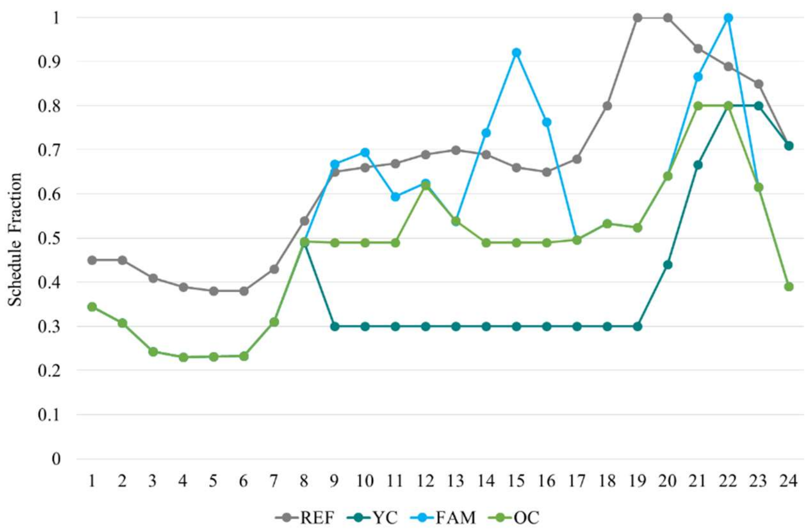
persons – 0.027 pers./m^2); Old couple (OC): 2 persons (0.014 pers./m^2); Young couple (YC): 2 persons (0.014 pers./m^2). Tailored schedules for occupancy, lighting and electric equipment were defined for each household arrangement during weekdays and weekends (Figure 2.2-3). The occupancy schedule for the family profile is still based on the reference schedule, but was modified for considering exact fractions for four occupants (e.g. 1 occupant = 0.25, 2 occupants = 0.5). The old couple was assumed to spend more time at home and to leave home only a few hours during the morning and the afternoon. The young couple was expected to work and therefore stay out most time of the day. Also the schedules for lighting and electric equipment were redefined for the different household compositions. The schedules for the family household were based on typical Italian operation profiles extracted from collected data within the MICENE project (eERG 2004). With respect to the schedule defined for the family scenario, the young couple was expected to have higher power densities in the evening, while the old couple was assumed to have peak operation levels during lunch and the early evening hours.



(a)



(b)



(c)

Figure 2.2-3. Schedule variations for household arrangements: (a) occupancy, (b) lighting, and (c) electric equipment.

2.3 Key findings

2.3.1 Effect on energy performance

The key findings presented in this paragraph highlight how different occupant behaviour lifestyles and household compositions can affect the energy performance of the building. Annual electric energy consumption related to different occupant behaviour lifestyles divided by end uses (space heating/cooling, lighting, electric equipment, pumps and fans, and DHW production) is shown in Figure 2.3-1. The simulation results clearly show that different occupant behaviour lifestyles affect the building performance and eventually lead to an amount of energy use that cannot be covered by the installed renewable energy sources. As an example, the electricity production on site from the PV system (blue dot dashed line) allows for covering a large amount of the total electricity consumption in the low consumer scenario (95%), while it can cover only 73% and 61% in the standard and high consumer scenario, respectively. This analysis also shows that the highest incidences on the total building energy consumptions in all consumer profiles are related to the use of electric equipment (50-58%) and lighting (13-20%). Minor incidences on the total energy consumptions are linked to energy used for space heating (6-8%), space cooling (4%), domestic hot water production (8-10%), fans (9-10%), and pumps (0.3-0.5%).

As a next step, the variation of the total energy performance was analysed by considering three additional types of household compositions described in section 2.2.3. As shown in Figure 2.3-2, the simulation outcomes confirm significant variations of the building energy performance when different household arrangements are considered. The graph depicts percentages of variation of energy uses with respect to the standard consumer scenario (REF-SC). As expected, the results show that the basic scenario (REF) presents the highest energy consumptions, while the latter gradually reduce in correspondence with the assumed (reducing) number of occupants in the building (FAM: -45%; OC:-94%; YC:-102%). Furthermore, significant discrepancies can also be found when comparing different occupant behaviour lifestyles within the same household type category.

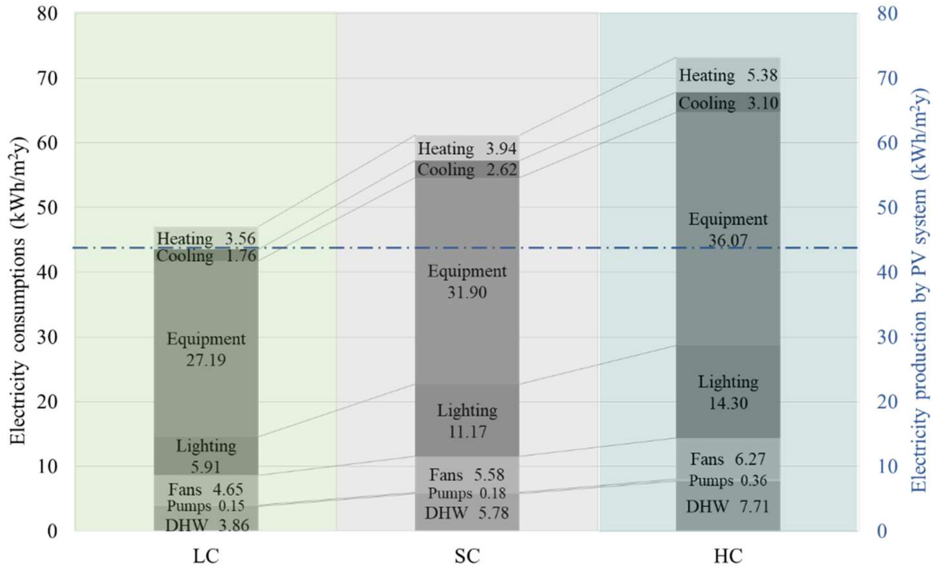


Figure 2.3-1. Electricity consumptions for occupant behaviour lifestyles (LC=Low consumer, SC=Standard consumer, HC=High consumer).

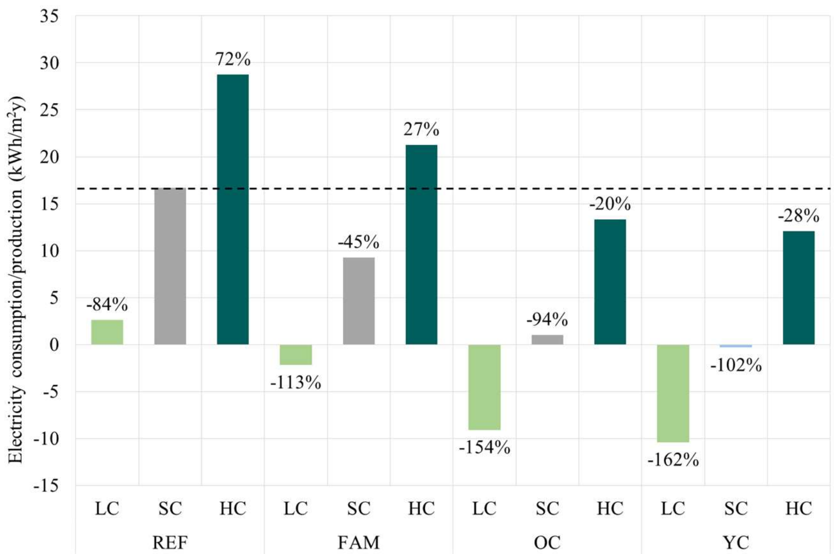


Figure 2.3-2. Total electricity use/production for type of household composition (LC=Low consumer, SC=Standard consumer, HC=High consumer, REF=number of occupants according to standard UNI 10339, FAM=4-person family, OC=old couple, YC= young couple).

The impact of individual behavioural patterns on the total energy consumptions are presented as percentage changes of annual electricity consumptions of the low and high consumer scenario compared to the standard consumer scenario (vertical dashed blue line (Figure 2.3-3). The outcomes of this analysis show that electric equipment and lighting usage have the most important impact on the total energy use. According to these results, a low consumer might save around 28 and 26% of the annual electricity consumptions by operating more responsibly electric devices and lighting appliances in the building. On contrary, an unaware or wasteful user might increase electricity consumption by 25 and 18% for electric equipment and lighting usage, respectively. Behavioural patterns related to the regulation of the heating/cooling set-point are shown to have a less significant impact on the energy consumptions in the low consumer profile (-9%) as well as in the high consumer scenario (+15%). Low and high consumer scenarios related to the regulation of the ventilation rate are accountable for the smallest variation of electricity consumptions (LC: -6%; HC: +6%). The adjustments of blinds has a noticeable impact only in the low consumer scenario (-14%), while it is negligible in the high consumer profile. If all behavioural attitudes are combined for the low and high consumer scenario, respectively, the total performance gap with respect to the standard consumer scenario is -86% for a complete low consumer profile and +73% for a complete high consumer profile.

Additionally, Figure 2.3-4 depicts a similar analysis considering the impact the single occupant-driven variables on the total energy use for different types of household types. In this analysis, the amount of electric energy production by the PC system was not subtracted from the total consumptions in order to obtain reasonable percentage values when highlighting the variation of nearly zero scenarios. The outcomes show that in all scenarios the most influencing patterns are still linked to the electric equipment and lighting use. The adjustment of temperature set-points gain a bigger importance in high consumer profiles of two-persons households (HC-OC: +7%; HC-YC: +8%). The impact of DHW use decreases in two-persons households with respect to the FAM and REF scenarios. If the combined low and high consumer scenarios are considered, the first might allow for saving 21-23% of the total electricity consumptions, while the second might increase them from 20% (REF) up to 27-28% (two-person households).

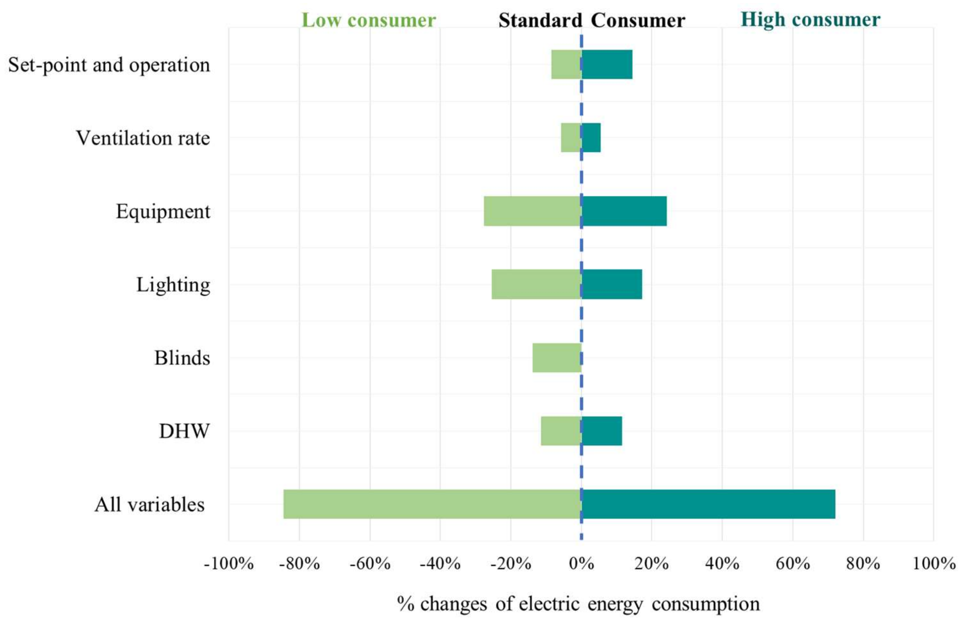


Figure 2.3-3. Impact of single occupant-driven variables on the total energy use (REF).

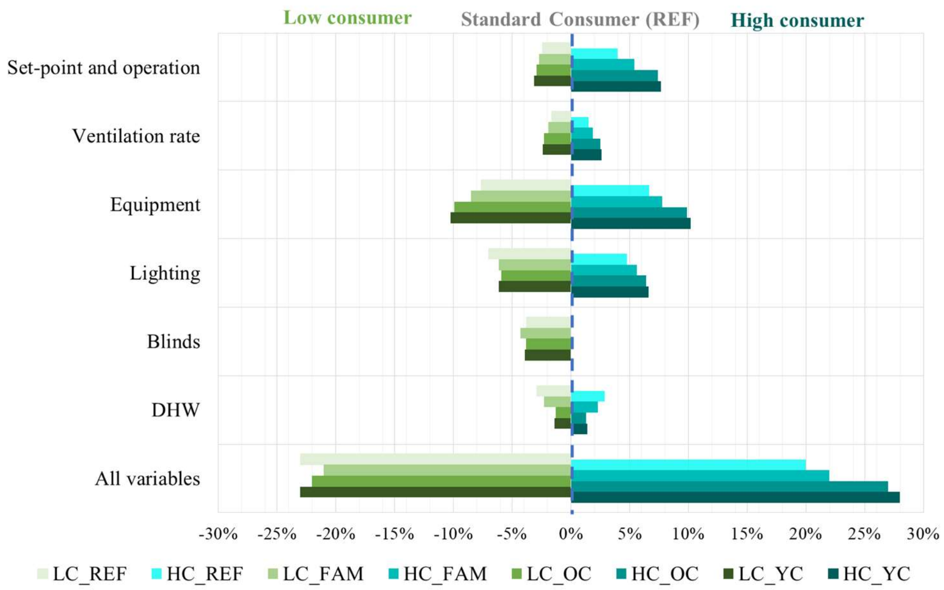


Figure 2.3-4. Impact of single occupant-driven variables on the total energy use for type of household composition.

2.3.2 Effect on thermal comfort conditions

The key findings presented in this paragraph highlight how different occupant behaviour lifestyles and household compositions can affect the thermal comfort conditions of the building occupants inside the building. Comfort classes used in this analysis refer to the European Standard EN15251 (Cen 2007). The threshold values for indoor operative temperature ranges that describe the three comfort categories are shown in Table 2.3-1 and refer to the recommended criteria for the thermal environment in residential buildings. In detail, the outcomes describe the distribution of the hourly indoor operative temperature values were distributed between the abovementioned comfort classes. If no comfort class is achieved, the values were classified as “non-defined” (N.D.). Only hours in which the building was occupied were considered for the analysis. Figure 2.3-5 shows the effects on thermal conditions by different household composition in the living room during the heating period. In all scenarios, the high consumer profile has the highest percentage of values falling within Comfort Class I (76-83%). On the other hand, it does not present the lowest percentage of values that do not fall within any of the defined comfort classes (N.D.). Indeed, the low consumer profiles in all scenarios allow for the highest percentage of values within Comfort Classes I, II and III. This analysis, hence, suggests that low consumer profiles might present advantages in terms of thermal comfort. Occupants can therefore be motivated to assume a more aware energy lifestyle and experience thermal comfort at the same time. Furthermore, they could be motivated to adjust their clothing level in order to optimize their sensation of thermal comfort. A further analysis was carried out to give an idea about how the clothing level might affect the Predicted Mean Vote

(PMV) (CEN (European Committee for Standardization) 2005) during daytime with respect to indoor operative temperatures of 18°C, 20°C, and 21°C (Figure 2.3-6). The other boundary conditions were assumed to be constant (relative humidity: 70%; air velocity: 0.1 m/s; metabolic energy: 1.2 met). The graph highlights that, in order to not exceed the limit of Predicted Percentage of Dissatisfied (PPD) of 10% (Comfort Class II: -0.5 < PMV < +0.5), the thermal insulation of clothing (I_{clo}) according to standard ISO 7730 has to be 1.1 clo (e.g. panties, stockings, blouse, long skirt, jacket, shoes) if the indoor environment is characterized by an operative temperature of 18°C. Perfect thermal neutrality would be achieved only with an unlikely thermal insulation of clothing around 1.5 clo (e.g. underwear with short sleeves and legs, short, trousers, vest, jacket, coat, socks, shoes).

Table 2.3-1. Comfort classes according to Standard EN15251.

Category	Temperature range for heating (°C)	Temperature range for cooling (°C)
I	21-25	23.5-25.5
II	20-25	23-26
III	18-25	22-27

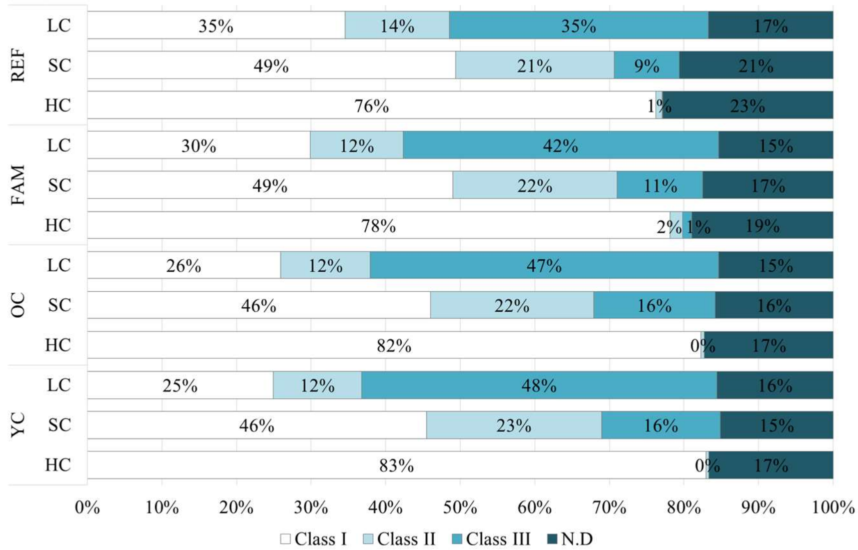


Figure 2.3-5. Classification of thermal environment according to EN15251 in the living area during heating period.

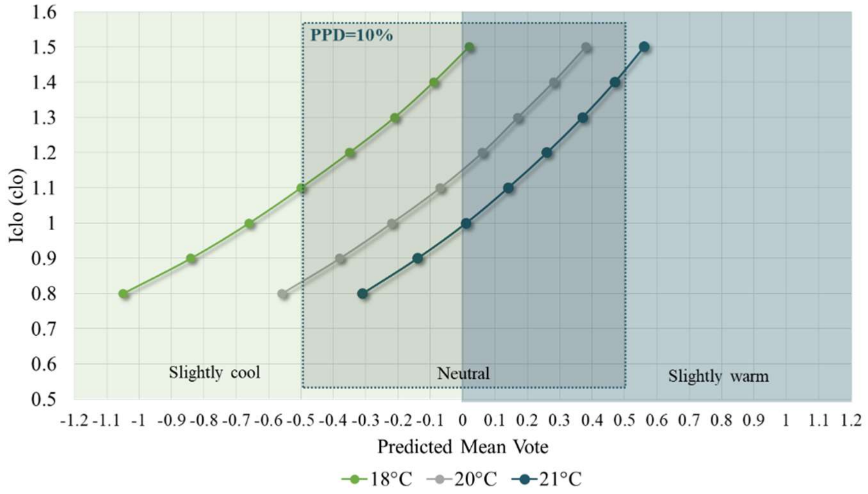


Figure 2.3-6. Effect of indoor temperature settings on lifestyle in terms of clothing level in winter and PMV evaluation.

2.4 Discussion and further investigations

2.4.1 "Truly" reaching the nZEB target: Low energy consumers in high performing buildings

The results obtained in this study reveal that the energy-related occupant behaviour lifestyles significantly influence the energy performance of the analysed residential nearly-zero energy building. With respect to the basic standard consumer scenario (REF-SC), the energy consumptions vary from -83% for the low consumer scenario up to +76% for the high consumer one. Furthermore, this study revealed that the energy performance is also heavily dependent on the type of post-occupancy household arrangements; with respect to the basic scenario (REF, people per floor area: 0.04 pers/m^2), two-person household compositions might imply significant reductions in energy consumptions (-102%). Indeed, the variation of different types of households additionally increases the discrepancy of the final energy consumptions in the several scenarios (~240%). This percentage is in line with literature values regarding the variation of the energy uses due to occupant-driven interactions with the building envelope and systems (~300%) (R. V. Andersen, Olesen, and Toftum 2007). Furthermore, the influence of occupant behaviour on energy consumptions in the specific case of a nearly-zero energy buildings seems to gain even more importance. Indeed, in these kinds of buildings, in which technical solutions regarding the building envelope and HVAC system configurations have been optimized, the influence of the energy-related attitude of the occupants is translated into high percentage variations of the energy consumptions due to the very low values of these last ones. As an example, the high consumer scenario of the young couple household consumes 12.3 kWh/m^{2}y, while the low consumer young couple is a plus energy scenario (-10.3 kWh/m^{2}y). Hence, **a building can only truly be considered a nearly-zero energy building if zero-capital actions related to the behavioural change of the occupants become as important as technological high performing solutions for the building features.**

Indeed, if the behaviour of the inhabitants is energy wasting, it might be unmanageable to reach the nearly-zero energy target, even if the building itself is defined “high performing”; the occupants need to be proactive in saving energy as well. Understanding the potential impact of technology-based and occupant behaviour-based strategies – and the combination of the two – is therefore a key to learning how to make high performing buildings commonplace and how to reduce spread in energy consumption.

The most influencing occupant-driven variables on final energy consumptions are related to the electric equipment use in first place (from -28% up to +25%) and secondly to the lighting use (from -26% up to +18%). Indeed, the unpredictable loads related to these variables gain greater influence than in low performing buildings whose envelope-driven loads most likely dominate the consumptions profile.

2.4.2 Investigation on high and low performing building features

To support statements made in 2.4.1, the proposed methodology and key findings in section 2.2 and 2.3 encouraged further investigations for gaining a better knowledge on the impact of occupant behaviours lifestyles on building energy use. In detail, a further analysis consisted in deploying the same methodological framework for describing the effect of (the same) occupant-driven variables on the building energy performance of the residential nearly-zero energy building compared to a “traditional” Reference Building (RB) **(PAPER IV)**.

The characteristics of the RB were established by using the same geometrical model of the nZEB, but assuming different performance levels of the building envelope and the HVAC systems. A description of the building features assumed for the nZEB and the RB can be found in Table 2.4-1. The energy performance requirements for the building envelope of the RB were established to meet the requirements of the Italian directive for Climatic Zone E (Italian Ministry of Economic Development 2010). Figure 2.4-1 shows the primary energy consumptions for the (i) nZEB and the (ii) RB occupant behaviour lifestyle scenarios. As outlined in 2.3.1, the graph highlights that in all the nZEB scenarios the most relevant incidence on the total energy consumptions is related to electric equipment and lighting use. In the RB scenario, instead, the incidence of the energy use for space heating gains much more importance (23-29%) with respect to the high performing building scenario. Indeed, there is a large gap between primary energy consumptions for space heating and cooling in the low and high performing scenarios and higher variations due to occupant behaviour lifestyles in the RB scenario. Furthermore, the graph depicts the amount of energy consumption covered by the energy production by the PV system (dotted blue line). In the nZEB scenario full cover can be guaranteed only with a low consumer profile: the nZE target might, hence, not be truly reached if the behaviour of the occupants is energy wasting.

Table 2.4-1. Description of the building features assumed for the (i) nZEB and (RB) scenario.

Building characteristics	Description	(i) nZEB	(ii) RB
Envelope U values (W/m2K)	External wall	0.15	0.27
	Ceiling	0.15	0.24
	Slab	0.19	0.26
	Window	0.96	1.8
HVAC system	Heating	Water heat pump (coefficient of performance = 4.4) + radiant floors	Condensing boiler (nominal efficiency = 0.95) + radiant floors
	Cooling	Water heat pump (energy efficiency ratio = 4.2) + radiant floors	Multi split system
	Ventilation	Controlled mechanical ventilation (CMV) with heat recovery	Natural ventilation
	PV system	7 kW_{peak}	2.62 kW_{peak}

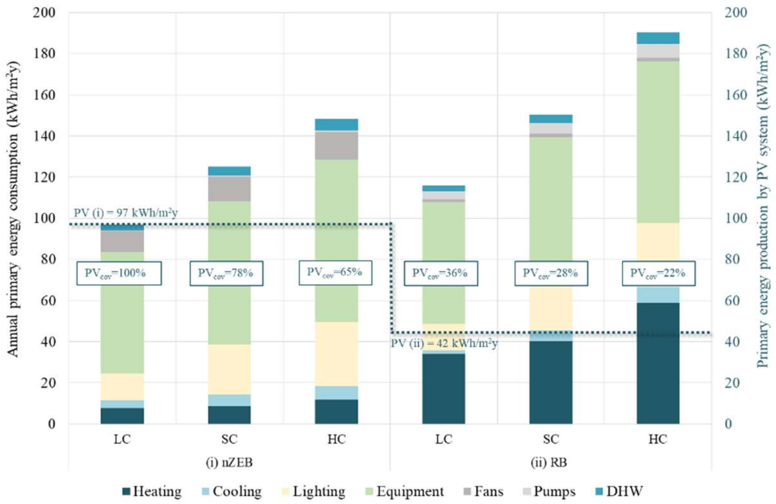


Figure 2.4-1. Primary energy consumptions for (i) nZEB and (ii) RB scenarios.

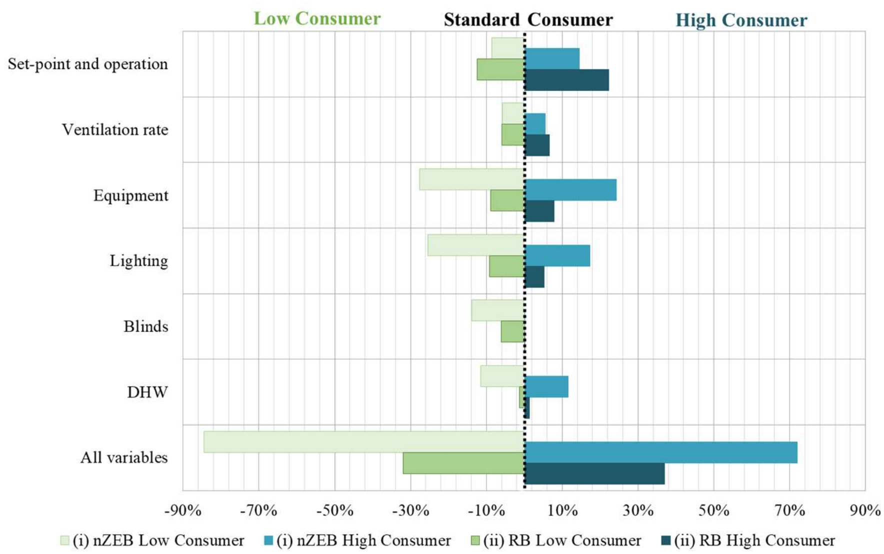


Figure 2.4-2. Impact of single key variables on building energy use of a (i) nZEB and a (ii) RB.

Also in this analysis, the impact of single behavioural patterns on the total energy consumptions is shown as percentage changes of the annual primary energy consumptions (Figure 2.4-2). The results highlight that the most significant impact on consumptions is given by different key variables in the (i) nZEB and the (ii) RB scenario. As regards the first, the highest variation of building energy use is due to the occupants' interaction with electric equipment and lighting (see 2.3.1). In the RB scenario, instead, the highest variation is due to behavioural patterns related to the regulation of the heating/cooling set-point and operation profiles of the systems. The results show that the regulation of the set-point might lead to an increase of the building energy use by 22%. The electric equipment and lighting settings, instead, have a lower incidence with respect to the nZEB scenario. These outcomes stress that once the building design and the technological solutions for the building envelope and systems have been optimized, the effect of the occupants' lifestyle and interaction with the building gains even more importance. In line with these outcomes, Table 2.4-2 provides a ranking of the behavioural patterns that mostly effect the building energy consumption in the (i) nZEB scenario and in the (ii) RB scenario and, therefore, highlights the key behavioural patterns that (according to the results of this particular case study) should be particularly stressed in energy engagement programs. For further details, the reader is invited to refer to (Barthelmes et al. 2017).

Table 2.4-2. Ranking of behavioural key variables for scenario (i) nZEB and (ii) RB.

Rank of key variables	(i) nZEB	(ii) RB
1	Electric equipment use	Temperature set-points and operation
2	Lighting use	Electric equipment use
3	Temperature set-points and operation	Lighting use
4	DHW use	Ventilation rate
5	Adjustment of window blinds	Adjustment of window blinds
6	Ventilation rate	DHW use

2.4.3 Insights on OB lifestyles and building automation

A further investigation assessed how and to what extent the implementation of occupant behaviour lifestyles combined with automated building systems may affect the energy performance within the home **(PAPER V)**. For this analysis different levels of Building Automation Controls (BAC) were explored and combined with a standard lifestyle (SC) and a low consumer lifestyle (LC) scenario, considering the same case study introduced in 2.2.1. In particular, EN 15232 (CEN (European Committee for Standardization) 2007) defines four different building automation and controls classes (A, B, C, D) of functions for non-residential and residential buildings:

- Class D corresponds to non-energy efficient BACs – BACs is in class D if the minimum functions of class C are not implemented;

- Class C corresponds to standard BACS – minimum functions shall be implemented (e.g. emission control, control of distribution network, interlock between heating and cooling control of emission and/or distribution);
- Class B corresponds to advanced BACs with some specific functions and Technical Building Management (TBM);
- Class A corresponds to high-energy performance BACS and TBM – Technical building management function shall be implemented in addition to class B. Room controllers shall be able to demand control building services (e.g. adaptive set point based on sensing of occupancy, air quality, etc.) including additional integrated functions for multi-discipline interrelationships among the various building services (e.g. HVAC, lighting, solar shading, appliances).

From the energy simulations, it emerged that if a standard user is matched with an automated system, the energy savings are even more considerable and it is possible to reduce energy consumptions for space heating/cooling, lighting, ventilation and electric equipment. By implementing advanced levels of automation, even higher energy performance may be achieved. The sustainable lifestyle consumer (LC) defined for Class B of automation systems permits to obtain significant energy savings with respect to Class C. This study showed that savings in homes can be obtained either by considering a more conscious behaviour of the user or the implementation of building automation systems. Combining these two aspects, automation/control and aware user behaviour, permits to achieve important energy savings, to reduce energy demand and consequently to truly guarantee high building performance.

2.5 Perspectives and challenges

To outline perspectives and challenges that this study is aimed at bringing to surface, it is necessary to mention some limitations of the proposed approach. Precisely, simplified deterministic input values were used for defining the energy-related behaviour of the inhabitants; further investigations in this thesis will therefore include the stochastic nature of occupant behaviour models in order to analyse more accurately their influence on energy uses (see Chapter 3 and 4). In second place, the assumed high consumer profiles took into account an energy-wasting attitude related to the occupant-driven variables on consumptions, but some occupants might even reach higher energy consumptions. On the other hand, the low consumer profile could be even more energy-saving, as well, and smarter energy-related attitudes could be assumed. Although if this approach is based on solely one case study and results might not be generalized, it gives an idea on how significant the effect of occupant behaviour can be on building energy use in buildings. This study, hence, highlights **the compelling necessity of reference models of occupant behaviour lifestyles and related behavioural patterns to bridge the gap between predicted and real building energy consumptions**, in particular for nZEBs. Other upcoming studies related to other dwellings and to other different building typologies are required to strengthen the statements made in this chapter. Moreover, this requires also the necessity to put in place complex monitoring campaigns to capture occupant behavioural patterns in (nearly-zero energy) buildings, residential or not, in order to obtain large field data sets that permit to assess data-based behavioural profiles and related building energy uses. The latter might represent the starting point for more accurate occupant behaviour lifestyle models in low energy buildings that can be stochastically implemented in simulation programs. Although the research community around occupant behaviour puts in continuous and thorough effort, still a lot of work has to be done in order to further understand human behaviour and to define reference models related to human behavioural issues that permit to more reliably predict the influence of occupant behaviour on energy consumptions in buildings, and in particular in those that have a nearly-zero energy consumption.

2.6 Publications

PAPER I **Barthelmes, V.M.**, Becchio, C., Corgnati, S.P. (2016), Occupant behavior lifestyles in a residential nearly zero energy building: Effect on energy use and thermal comfort, *Science and Technology for the Built Environment* 22, pp. 960-975.

PAPER II **Barthelmes, V.M.**, Becchio, C., Corgnati, S.P. (2018). Il peso del comportamento dell'occupante in edifici ad energia quasi-zero: il caso studio della CorTau House, *Ingenio Informazione tecnica e progettuale* 68, pp. 1-5.

PAPER III **Barthelmes, V.M**.; Fabi, V.; Corgnati, S.P. (2016) Impact of behavioural patterns on the energy use of a residential nearly-zero energy building. In: Proceeding of Behave 2016, Coimbra, Portugal, 8-9 September. pp. 1-2.

PAPER IV **Barthelmes, V.M**., Becchio, C., Fabi, V., Corgnati, S.P. (2017). Occupant behaviour lifestyles and effects on building energy use: Investigation on high and low performing building features, *Energy Procedia* 140, pp. 93-101.

PAPER V Fabi, V., **Barthelmes, V.M.**, Schweiker, M., Corgnati, S.P. (2017). Insights into the effects of occupant behaviour lifestyles and building automation on building energy use, *Energy Procedia* 140. pp. 48-56.

Chapter 3

Exploration of the Bayesian Network (BN) framework for OB analysis

3.1 Overview

In line with existing literature, the previous chapter outlined the urgent need for reliably modelling occupant behaviour in buildings in order to bridge the gap between predicted and real energy performance in buildings. Similar to the approach in Chapter 2, frequently, simulation-based design analysis relies on standard use and operation conditions such as fixed schedules for occupancy levels, light switching, ventilation rates and temperature settings. These assumptions often lead to an oversimplification of the human dimension in buildings and might lead to inaccurate outcomes of the dynamic building energy simulations. For this reason, in recent years, stochastic modelling approaches have been developed to more reliably capture energy-related human behaviour when simulating building energy use and environmental comfort conditions. The interaction with the windows has a significant impact on the building performance, as well as on the indoor environmental quality (IEQ), by changing the amount of fresh air to the building. An increasing number of studies have been carried out to develop stochastic models for predicting the occupant's interaction with windows. Generally, the latter are based on statistical algorithms for predicting the probability of a specific condition or event, such as the window state or the window opening/closing action, given a set of environmental or other influential factors. Most popularly methods include logit analysis (Nicol 2001; Andersen et al. 2013; Rijal et al. 2008b; Yun and

Steemers 2008), probit analysis (Zhang and Barrett 2012), and Markov chain processes (Haldi and Robinson 2009).

In this chapter, the capabilities of the Bayesian Network framework to model occupant behaviour in the context of thermal comfort and building energy analyses towards bridging the gap between real and simulated outcomes are investigated. In comparison to the above-mentioned regression-based models, BN-based approaches are able to flexibly model complex relationships between diverse explanatory variables and window control behaviour by constructing a joint probability distribution over different combinations of the domain variables. Indeed, the BN model permits to easily model joint conditional dependencies of the entire set of variables through a graphical representation of the model structure (Korb and Nicholson 2010). The BN model also allows for structuring a variety of explanatory variables and multiple target variables in a hierarchical manner. In addition, BNs are demonstrated to yield good prediction accuracy even with small datasets (Mylly Aki et al. 2002). They also have capabilities to handle incomplete datasets by using Expectation-Maximization (EM) algorithms (Lauritzen 1995) in which missing data can be marginalized by integrating over all the possibilities of the missing values. Furthermore, the BN model provides a clear semantic representation of relationships between variables, which facilitates flexibly structuring a model and training it against available data in wider and interdisciplinary research communities.

This study presented in this chapter is aimed at demonstrating the applicability of the Bayesian Network (BN) framework for predicting window opening/closing behaviour of building occupants based on the measurements in a residential apartment located in Copenhagen, Denmark. In particular, five key research questions related to developing a BN model for predicting window-use patterns were addressed. The first set of three research questions addresses general issues relevant to modelling window control behaviour:

- Which variables are key drivers that determine window control behaviour?
- What is the most suitable target variable of window control behaviour?
- What level of correlations resides between variables and should they be captured in the BN model?

The second set of research questions addresses modelling challenges related to the applicability of the BN framework for modelling occupants' window control behaviour:

- How to handle mixed data in the BN framework?
- How to validate stochastic BN models?

A key question regards how to deal with mixed data in the BN framework. Traditional BN approaches to treat either discrete variables or continuous variables are not suited to modelling window control behaviour as datasets typically consist of both continuous variables (e.g., indoor temperature, CO_2 concentration) and noncontinuous variables (e.g., binary control actions, time of the day). This study tries to overcome this problem by proposing a modelling procedure that allows for handling mixed data, particularly with use of the *bnlearn* package (Scutari 2010) in the statistical software environment *R* (Nagarajan 2013). The prediction accuracy of the model is evaluated through a series of methods suitable to validate stochastic models. The steps that were used for the BN modelling approach in this chapter are summarized in Figure 3.1-1.

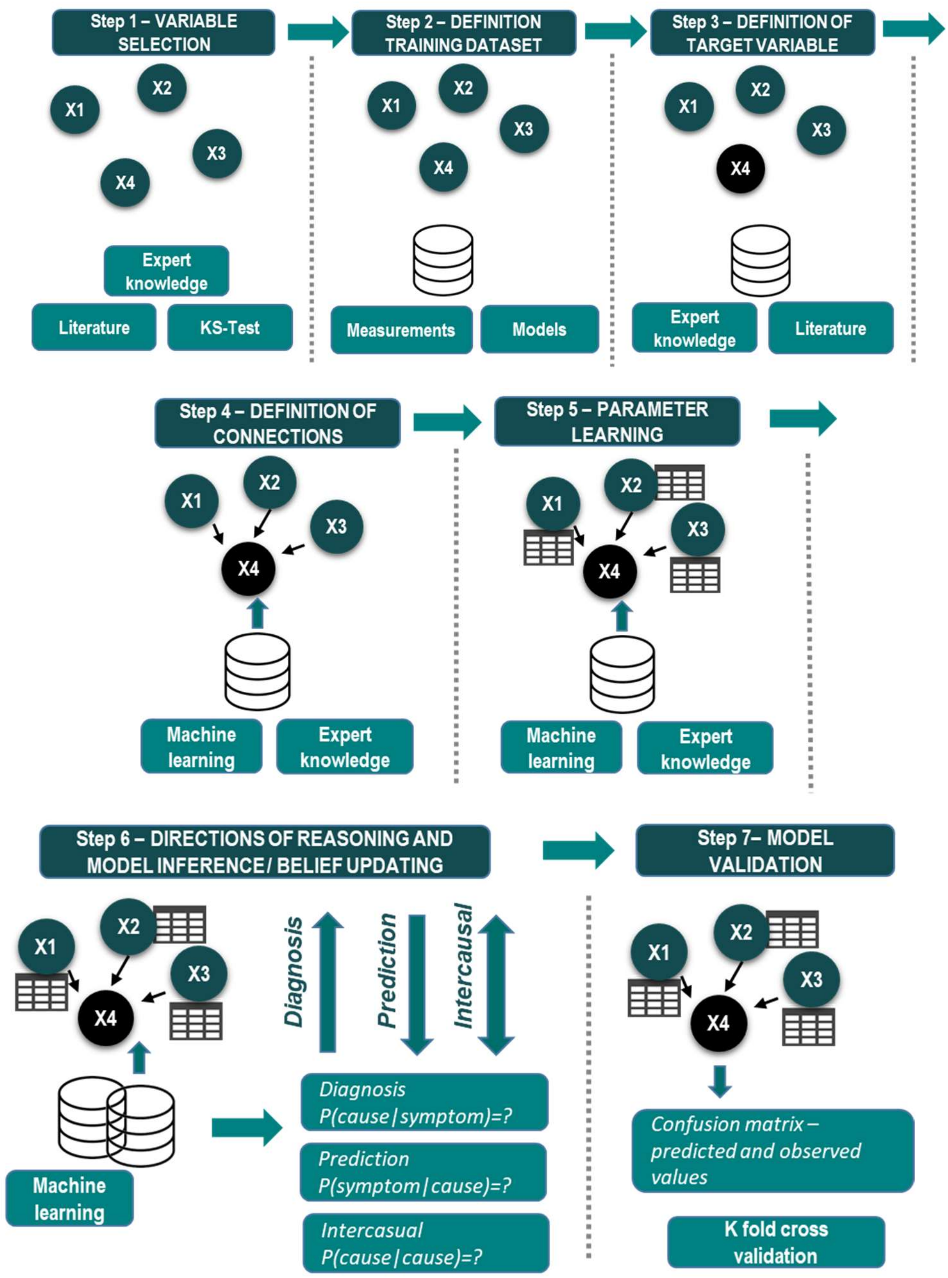


Figure 3.1-1. Overview Chapter 3.

3.2 Methodology

3.2.1 Bayesian Networks

A Bayesian Network (BN) is a Directed Acyclic Graph (DAG) or belief network that is used to represent the relationship among a predefined group of discrete and continuous variables (X_i) (Neapolitan 2004; Korb and Nicholson 2010). BNs consist of two parts: a graphical model and an underlying conditional probability distribution. In detail, nodes represent the variables, and the dependencies between variables are depicted as directional links corresponding to conditional probabilities. Hence, the construction of a BN consists of determining the structure, as well as the probability distribution associated with these relations (see section 3.3.3). The relationships between nodes can be explained by employing a family metaphor: a node is a parent of a child, if there is an arc from the former to the latter. For instance, in case there is an arc from X_1 to X_3 then node X_1 is a parent of node X_3 (Figure 3.2-1). The Markov property of the BNs implies that all the probabilistic dependencies are graphically shown via arcs and that child nodes only depend on the parent nodes. To calculate the joint probability distributions the following chain rules are used for the discrete case (equation 3.1) and the continuous case (equation 3.2), respectively:

$$\textit{Discrete case} \qquad P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \qquad (3.1)$$

$$\textit{Continuous case} \qquad f(X_1, \dots, X_n) = \prod_{i=1}^{n} f(X_i|Parents(X_i)) \qquad (3.2)$$

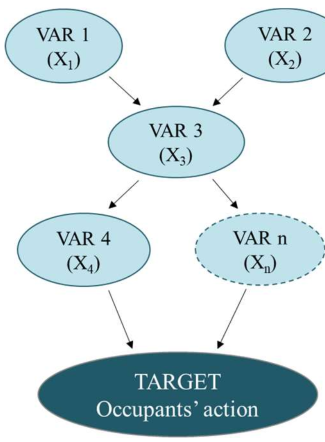


Figure 3.2-1. Example of a BN: Probabilistic dependencies between occupant behaviour and possible explanatory variables (VARs)/drivers

In the discrete case, conditional joint probabilities are represented by the so-called Conditional Probability Tables (CPTs) since all variables are characterized by discrete data. In this case, all intervals for each discrete variable are treated as independent variables, and there is no mechanism to capture the effect of continuous variables such as temperature and relative humidity as a continuous trend. On the other hand, the continuous case assigns each variable X_i with a Gaussian probability density function $f(X_i)$ conditional on the values of its parent nodes. As datasets collected for model development often consist of different data types, many existing studies discretize continuous data for obtaining homogeneous datasets. A key limitation of discretization is a significant loss of information, which has a big impact on the predictive power of resulting BN models and the interpretability of BN models to understand relationships between variables. In fact, data collected for occupant behaviour modelling typically includes both categorical or binary variables (such as window control actions and time-of-day) and continuous variables (such as the indoor/outdoor environmental variables). Hence, it is important to develop a BN framework that allows for appropriately handling mixed data for occupant behaviour modelling, which will be carefully investigated in Section 3.3.4.

3.2.2 BN modelling approach

This paragraph describes how the BN model for window control behaviour in this study was developed. The development of the statistical model consists in a series of steps (Figure 3.1-1) **(PAPER VI)**:

Step 1: Variable selection

The first step is to identify variables that are considered relevant for the analysis. The variable selection encodes a number of specific existing findings into the model through the process of target and explanatory variable choice (see Step 3). Generally, variable selection can be based on outcomes from existing literature combined with expert knowledge and ad-hoc statistical analysis based on field measurements or models.

Borgeson and Brager (2008) elaborated an extensive literature review on studies aimed at modelling window control behaviour of building occupants. In the majority of the cited studies, temperature was found to be the most important driver (Rijal et al. 2008a; Warren and Parkins 1984), although there is no consensus about whether indoor or outdoor temperature is dominant in determining the behaviour. Other models found time-related factors such as the time of the day and season or the current window state to be key variables to predict window control actions (Pfafferott and Herkel 2007; Haldi and Robinson 2008; Yun and Steemers 2008). Review of the existing literature confirmed that the dataset used for this study (see Table 3.2-1) includes key explanatory variables (e.g. indoor and outdoor environmental variables and time-related factors) that were found to impact window control behaviour.

Next to the definition of key variables found in literature, a two-sample Kolmogorov-Smirnov test (K-S test) was carried out to test which variables are main drivers that trigger window control actions. The two-sample K-S statistic quantifies a distance between the empirical distribution functions of two samples to evaluate whether two samples come from the same probability distribution function (Conover 1971). This method is useful to test whether a certain explanatory variable impacts window control actions by comparing the distribution of variable values when window opening or closing actions is different from that in the entire dataset. First, the entire dataset, including all explanatory variables and window control variable, was generated as a baseline (Figure 3.2-2). Then, from (i) the entire dataset, two subsets were generated depending on the window control action: (ii) data only when window opening actions were monitored and (iii) only data when window closing actions were monitored. Hence, (i) provides the distribution of explanatory variable values regardless the window control action, while (ii) and (iii) provide the specific distribution depending on the window control action (opening and closing, respectively). Then, the two-sample K-S test was applied to a pair of samples – (i) and (ii) for the window opening behaviour and (i) and (iii) for the window closing behaviour - for each environmental and time-related variable to examine how different the two samples are. For instance, if the distribution of the indoor air temperature substantially differs between the samples (i) and (ii), it indicates that the indoor air temperature has a significant impact on window opening actions. The statistical significance of differences between the two samples is represented by the p-value; the lower the p-value is, the more the two samples differ. The significance threshold of the p-value is typically 0.05, which is also used in this study to exclude unimportant variables from further analysis.

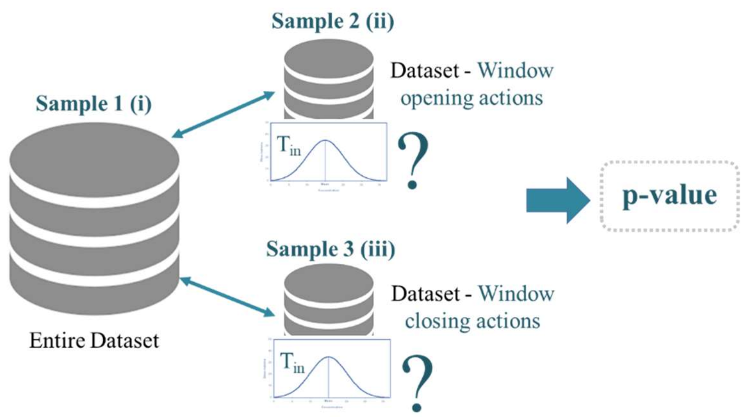


Figure 3.2-2. K-S test: Definition of the samples.

Step 2: Definition of a training dataset

Based on the identified relevant variables in Step 1, it is necessary to retrieve an adequate training dataset that contains variables of interest. Generally, the training dataset includes samples of the chosen target and explanatory variables and can be based on field measurements, survey data, existing models or simulation data. It can be used to support structure and parameter learning in Step 3 and Step 4. Before this, most studies apply discretization techniques, which means that the training dataset containing continuous variables is transformed into a purely discretized domain for the BN model (Pfafferott and Herkel 2007). Some software environments allow to directly discretize continuous variable sets of the training dataset during Step 3 or 4. The discretization of the domain of the training dataset allows the Bayesian Network model to capture rough characteristics of the distribution of the continuous variables, but often corresponds to a significant loss of information. This will be discussed in the following sections.

The modelling process in this study is based on a training dataset with measurements of one natural-ventilated, rented two-persons apartment located in Copenhagen, Denmark (Andersen et al. 2013). Table 3.2-1 summarises measurements related to the indoor and outdoor environment conditions, occupants' interaction with the windows, and time-related factors such as the time of the day or the day of the week. These measurements were collected in 10-minutes intervals continuously for approximately 3 months (February–May). The outdoor environmental measurements were acquired from a meteorological measuring station located near the apartment. The same time resolution was used for analysis. One thing to point out is that this study treats window states as a binary variable (0=closed, 1=open) and does not take into account the degree of opening (angle of the shutter with respect to the window frame). Windows are a two-wing window type, manually controlled by the building occupants. In total, the occupants performed 215 window opening actions during the monitoring phase.

Table 3.2-1. Available target and explanatory variables.*

Potential VARs	Abbreviation	Unit	Min	Max	Mean	Median	St. Dev.
Indoor Environment							
Dry bulb temperature	T_{in}	°C	12.1	25	21	21	3
Relative humidity	RH_{in}	%	26	66	38	38	5
Illuminance	Lux	lux	1	8360	95	43	171
CO_2 concentration	$CO_{2,in}$	ppm	101	2261	608	580	161
Outdoor Environment							
Air Temperature	T_{out}	°C	-5	24	7	6	5
Relative humidity	RH_{out}	%	25	100	73	74	18
Wind speed	Wind	m/s	0	13	3	2	2
Global solar radiation	SR	W/m^2	0	904	184	63	230
Occupant Behaviour		**Range of values**					
Window position/state	WS*	0/1 (closed/open)					
Window opening/closing action	WOA*/WCA*	0/1 (no action/action)					
Other		**Range of values**					
Time of the day	Hour	1-24					
Weekday	WD	Monday-Sunday					

Step 3: Definition of target variable

The third step is the definition of the most suitable target variable that best allows for predicting the human behaviour in the building, and in particular for predicting occupants' window control actions. Previous models have computed the probability of windows being open or closed (Haldi and Robinson 2009) or to the probability of occupants taking window opening or closing actions (Andersen et al. 2013; D'Oca et al. 2014). In this study, different BN models were created and tested using these two variables as a target variable predicted as the function of the indoor air temperature in order to investigate which target variable is most suitable.

Step 4: Definition of connections

The next step is to define the connections or rather the relationships between the selected variables in the BN. Determining the structure of a BN is at least as important as determining the conditional probabilities linking the variables, since the output of the network is more sensitive to changes in the structure than to changes in conditional probabilities. This step preceding the parameter learning step, hence, is crucial for defining an adequate model structure and consequently obtain reliable outcomes. The connections can be learned by machine learning algorithms (see Step 5) that extract information from the training dataset defined in Step 2, but should always be accurately verified by experts, since automated learning processes often lead to random and not realistic arc directions and connections between nodes.

Additionally, this study applies the Kendall rank correlation coefficient to relatively evaluate the importance of correlations between the measured variables and accordingly structure the arcs between the explanatory variables in the BN model in an efficient manner. In particular, the Kendall rank correlation coefficient, commonly referred to as Kendall's tau coefficient, is a statistic used to measure the ordinal association between two measured quantities (Abdi 2007).

The Kendall τ coefficient is calculated as follows:

let ($VAR_{x,1}$, $VAR_{y,1}$), ($VAR_{x,2}$, $VAR_{y,2}$), …, ($VAR_{x,n}$, $VAR_{y,n}$) be a set of observations of the joint random variables VAR_x and VAR_y respectively, such that all the values of ($VAR_{x,i}$) and ($VAR_{y,i}$) are unique. Any pair of observations ($VAR_{x,i}$, $VAR_{y,i}$) and ($VAR_{x,j}$, $VAR_{y,j}$) are said to be concordant if the ranks of both variables agree; that is, if both $VAR_{x,i} > VAR_{x,j}$ and $VAR_{y,i} > VAR_{y,j}$ or if both $VAR_{x,i} < VAR_{x,j}$ and $VAR_{y,i} < VAR_{y,j}$. Otherwise, they are said to be discordant. Equation 3.3 defines the Kendall τ coefficient and n is the total number of combinations:

$$\tau = \frac{(\text{number of concordant pairs}) - (\text{number of discordant pairs})}{n(n-1)/2} \tag{3.3}$$

Step 5: Parameter learning and model fitting

The BN model is trained by determining all the probabilities for the nodes, and the conditional probabilities for the arcs. In this step, based on the underlying training dataset, frequencies of each possible value for the nodes are counted. Then, these frequencies are used to calculate the conditional probabilities of the arcs based on Equation (3.1) for discrete data and (3.2) for continuous data. Traditionally, BNs were constructed from the knowledge of human experts, this first approach is also called “eclitation” (Shipworth 2010). This approach can be still useful for cases in which field survey data or measurements are not available. However, during the last decade, several methods have been developed to build BNs directly from databases. Indeed, this second approach is based on machine learning algorithms that extract a structure and estimate probability distributions from datasets. These two approaches can be combined: for example, defining the structure of the network based on expert knowledge and learning probability distributions in the BN model from available datasets (Figure 3.2-3).

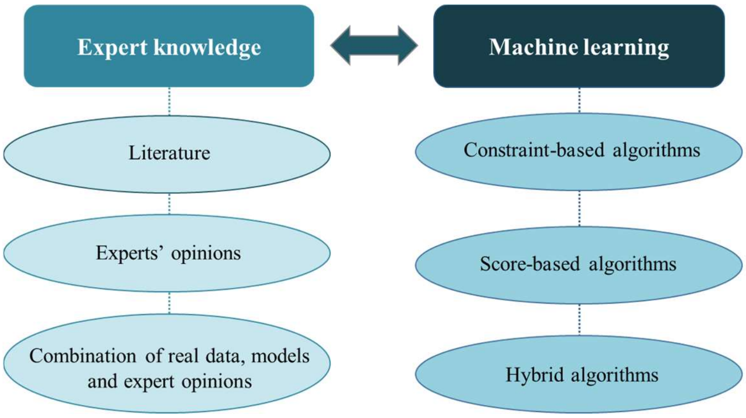


Figure 3.2-3. Learning the structure of a BN: Combination of expert knowledge and machine learning.

Several machine learning algorithms have been developed to extract the structure of BNs from the dataset. Constraint-based algorithms learn the structure of a Bayesian Network by first running local hypothesis tests to identify a dependency model containing independence assertions that hold in the training data. Constraint-based algorithms (conditional independence learners) are all optimized derivatives of the Inductive Causation algorithm (Pearl and Verma 1995). These algorithms use the conditional independence tests to detect the Markov blankets of the variables, which in turn are used to compute the structure of the Bayesian network. Constraint-based algorithms for structure learning are designed to accurately identify the structure of the distribution underlying the data and, therefore, the causal relationships. The main drawback of constrained-based algorithms is their poor robustness, which means that there can be large effects on the output of the structure of the BN for small errors in the independence tests. If all the variables in the network are highly correlated, it might be problematic to define neat independencies among them. The second class of algorithms, called search-and-score, is characterized by a higher robustness and searches over possible Bayesian Network structures to find the best factorization of the joint distribution implied by the training data. These score-based learning algorithms are general purpose heuristic optimization algorithms which rank network structures with respect to a goodness-of-fit score. This process assigns a score to each candidate BN, typically one that measures how well that BN describes the dataset. A score-based algorithm attempts to maximize this score, e.g. Bayesian Information Criterion score (BIC score)(Nagarajan 2013), which represents a useful tool for optimizing the complexity of the model. Equations 3.4 and 3.5 for the discrete and continuous cases represents a useful tool for optimizing the model in terms of both its predictive power and complexity.

$$\textit{Discrete case} \qquad BIC = \sum_{i=1}^{n} logP_{X_i}\left(X_i | \prod X_i\right) - \frac{d}{2}\log n \tag{3.4}$$

$$\textit{Continuous case} \qquad BIC = \sum_{i=1}^{n} logf_{X_i}\left(X_i | \prod X_i\right) - \frac{d}{2}\log n \tag{3.5}$$

where d is the number of variables included in the BN network and n is the sample size. With the determined BN structure, parameter learning is carried out to train unknown parameters associated with conditional distributions in the BN against the dataset. Typically, in this process, the usability of the model is evaluated by the BIC score, and the importance of the variables is evaluated by the strengths of the arcs connected between the variables (Nagarajan 2013). The BIC score is a criterion used to select the best model among a given set of models in terms of the predication accuracy and the model complexity; the lower the BIC score is, the better the model is. The arc strength measures the importance of individual parent nodes on predicting the state of their child node. The strength is measured by the score gain or loss as the result of removing one arc while keeping the rest of the network fixed. Negative strength values indicate decreases in the network score due to the arc's removal, and positive values indicate increases in the network score; the lower the arc strength is, the stronger the relationship between the two variables linked by the arc is.

Finally, hybrid algorithms combine the former types of algorithms as they use conditional independence tests and network scores at the same time.

In this study, parameter learning is carried out with a search-and-score-based algorithm, and in particular the Hill-climbing algorithm, available from the bnlearn package in R (Scutari 2010).

Step 6: Model-based inference and directions of reasoning

Once the model is trained, it is possible to infer the model and ask questions about the nature of the data. In particular, this step permits to carry out predictive analysis, diagnostic analysis and the investigation on relationships between individual nodes of the network. Bayesian Networks provide full representations of probability distributions over their variables and can be defined intuitively as both a knowledge model and an inference engine. That implies that they can be conditioned upon any subset of their variables, supporting any direction of reasoning (Figure 3.2-4). Indeed, once the BN is structured and parameters are learned, it is possible to ask questions about the nature of the data inside the BN. Thus, one can define a single probabilistic model and examine it in different ways to perform prediction and diagnosis, revision of hypotheses, carry out ''what if?'' reasoning, and ''ruling out'' hypotheses. The BN permits to perform diagnostic reasoning, which could for example mean trying to understand which variables (VARs) influence the target node and in which manner. This type of reasoning occurs in the opposite direction to the network arcs. On the other hand, it is also possible to perform predictive reasoning, in this case reasoning is from new information about causes to new beliefs about effects, following the directions of the network arcs. Finally, a further form of reasoning involves reasoning about the mutual causes of a common effect, this has been called intercausal reasoning by Korb and Nicholson (2010). Since any nodes may be query nodes and any may be evidence nodes, sometimes the reasoning does not fit neatly into one of the types described above. Indeed, the above types of reasoning can be combined in any way in the same model.

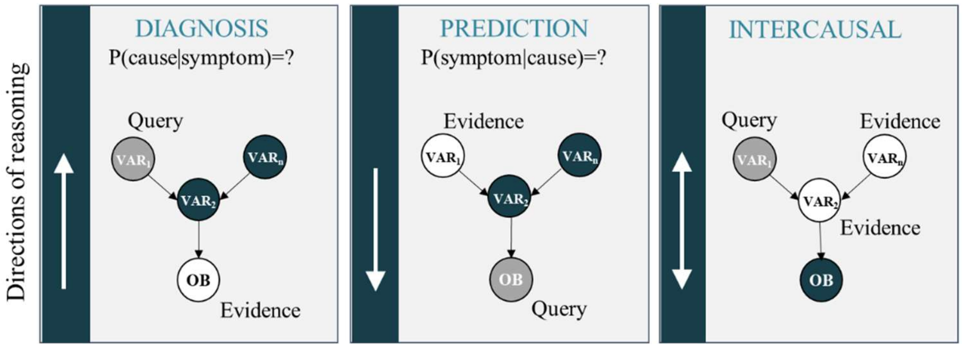


Figure 3.2-4. Types of reasoning with Bayesian Networks.

In this study, the main aim is to carry out diagnostic (which are the main drivers for window control behaviour?) and predictive (how likely is the occupant to open the window given certain conditions?) analysis. The model is, hence, inferred mainly with respect to two directions of reasoning.

Step 7: Model validation

This section investigates validation approaches, which is a crucial step to test the predictive power of stochastic models. In particular, this research step validates and tests the predictive power of the final BN model described in the previous sections. For model validation, cross-validation is a standard way to obtain unbiased estimates of a model's goodness of fit by partitioning the dataset into training and testing subsets. K-fold cross-validation in the bnlearn package is applied to randomly partition the entire dataset into k equally sized subsamples. Out of the k subsamples, a single subsample is retained as the validation data for testing the accuracy of the trained model, and the remaining k-1 subsamples are used as training data. In this case study, the dataset was split into 10 subsets, and the BN model was trained against 9 subsets and tested against 1 subset.

In cross-validation for classification problems similar to the context of predicting binary control actions, the prediction error of a stochastic model is commonly calculated by a loss function that compares the predicted label of the target variable against measurements through the testing dataset. It is worth mentioning that as the original dataset is very unbalanced (0.3% of the dataset corresponding to "window opening = TRUE" events and 99.7% of the dataset corresponding to "window opening = FALSE" events), the low classification error does not guarantee that the model reliably predicts the window opening action.

A tailored approach for model validation is applied to examine the model predictability in detail with considering the imbalance of the dataset. This approach consisted of the following steps:

1. Creation of a testing dataset containing 215 samples of “window opening = TRUE” and 215 samples of “window opening = FALSE”;
2. Computation of model predictions by the BN model for given response variable values in the testing dataset;
3. Creation of a confusion matrix of observed and predicted WOAs and NOAs.

Steps 1 and 2 were repeated approximately 100 times to obtain the probabilistic distribution of prediction accuracy.

3.3 Key findings

3.3.1 Variable selection

Table 3.3-1 shows the K-S test results used to rank the most influencing variables for the window opening and closing behaviour. For the window action behaviour, the results highlight that the six most influencing variables in the case study analysed are the time of the day, CO_2 concentration, solar radiation, indoor and outdoor air temperature and indoor relative humidity. All the variables with a p-value higher than 0.05 were excluded from the analysis. One thing to note is that the day of the week (WD) does not influence the window opening action (WOA) at all (p-value=1). Furthermore, the K-S test results reveal that the six most influencing variables are identical for the window opening and window closing actions, while their ranking varies slightly. The most important variable is the time of the day for both actions. Indeed, exploratory data analyses also showed that the windows were opened and closed in certain times of the day (morning and late afternoon hours). The window closing actions were also influenced by the wind speed and the illuminance level.

Table 3.3-1. K-S test: Variable selection.

Rank	WINDOW OPENING ACTION (WOA)		WINDOW CLOSING ACTION (WCA)	
	VAR	p-value	VAR	p-value
1	Hour	5.754×10^{-12}	Hour	2.2×10^{-16}
2	$CO_{2,in}$	8.668×10^{-11}	SR	2.2×10^{-16}
3	SR	3.226×10^{-6}	$CO_{2,in}$	0.000102
4	T_{in}	0.0001399	T_{in}	0.0001399
5	T_{out}	0.005	Tout	0.003193
6	RH_{in}	0.008602	RH_{in}	0.008602
7	Lux	0.15	Wind	0.01012
8	Wind	0.2212	Lux	0.03478
9	RH_{out}	0.335	RH_{out}	0.335
10	WD	1	WD	1

3.3.2 Target variable definition

Figure 3.3-1 shows results from using the window state and the window opening action as a target variable predicted as the function of the indoor air temperature. Figure 3.3-1(a) depicts the counterintuitive trend of the probability of windows being open increasing as the indoor air temperature decreases. This misrepresentation is due to strong bi-directional interactions between the indoor environmental variables and the window state. When the window state is 1 (open window), cool air flows into the room, lowering the indoor air temperature and the CO_2 concentration. Hence, using the window state as a target variable may lead to unreliable outcomes indoor environmental variables are used as explanatory variables. Andersen et al. (2013) also pointed out that it is problematic to infer the window state based on indoor environment conditions (e.g. indoor temperature) since these are directly influenced by the state of the window. Figure 3.3-1(b) highlights that using the window opening action (WOA) as a target variable instead of the window state overcomes this problem by taking into account the values of the indoor environmental variables only when the window is actually being opened (or closed). It is worth mentioning that using the WOA rather than the WS may lead to weaker arc strengths in the BN model since much less data is used for training the model (e.g., 215 data points when WOA took place out of the entire set of 65335 data points).

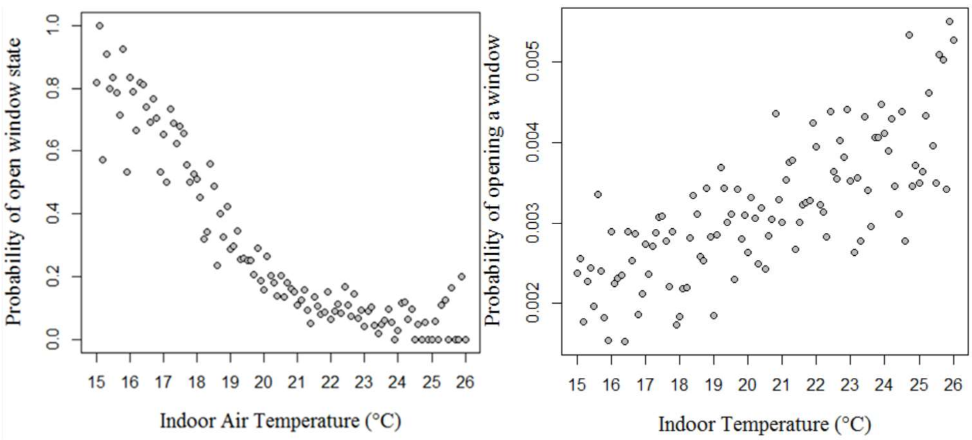


Figure 3.3-1. Probability of (a) an open window (WS) and (b) a window opening action (WOA) depending on the indoor air temperature.

3.3.3 Correlation between variables

Table 3.3-2 shows the ranking of the most correlated variables with the six important drivers and associated Kendall coefficient values. Overall, highly strong correlations between the selected variables are not observed. Mild correlations are observed among the indoor air temperature (T_{in}), the outdoor air temperature (T_{out}), and the solar radiation (SR). As expected, correlations are found between the indoor temperature and relative humidity (T_{in} and RH_{in}) and the outdoor temperature and relative humidity (T_{out} and RH_{out}). Furthermore, minor correlations are found between the time of the day (Hour), the outdoor air temperature (T_{out}), and the solar radiation (SR). These correlations between the selected variables will be represented in the BN model by adding arcs between the identified pairs with correlations. It is worth noting that this analysis intends to evaluate all the correlations between the variables in a relative manner without specific numerical thresholds to define the importance of correlation.

Table 3.3-2. Kendall's Tau: Non-linear correlation between the most influencing variables on window action behaviour and the other variables.

Ranking	Hour		$CO_{2,in}$		SR		T_{in}		T_{out}		RH_{in}	
1	T_{out}	0.16	T_{out}	0.17	Lux_{in}	0.38	RH_{in}	0.39	RH_{out}	0.40	T_{in}	0.39
2	SR	0.16	Hour	0.13	T_{out}	0.36	T_{out}	0.36	T_{in}	0.36	RH_{out}	0.25
3	$CO_{2,in}$	0.13	RH_{in}	0.10	T_{in}	0.21	RH_{out}	0.23	SR	0.36	$CO_{2,in}$	0.10
4	T_{in}	0.11	Lux_{in}	0.08	Wind	0.20	SR	0.21	$CO_{2,in}$	0.17	SR	0.09
5	Wind	0.10	WD	0.02	Hour	0.16	Hour	0.11	Hour	0.16	Wind	0.09
6	RH_{in}	0.06	SR	0.02	$CO_{2,in}$	0.02	Lux_{in}	0.03	Wind	0.09	Lux_{in}	0.07
7	Lux_{in}	0.03	Wind	0.02	WD	-0.01	Wind	0.02	RH_{in}	0.06	WD	0.06
8	WD	0.01	T_{in}	0.02	RH_{in}	-0.09	$CO_{2,in}$	0.02	WD	0.04	T_{out}	0.06
9	RH_{out}	-0.22	RH_{out}	0.02	RH_{out}	-0.45	WD	0.01	Lux_{in}	0.00	Hour	0.06

3.3.4 A BN model for predicting window opening behaviour

Figure 3.3-2 shows the proposed Bayesian Network for predicting window opening actions developed on the basis of the analysis results in paragraphs 3.3.1-3. As outlined in 3.3.1, the key variables that most influence the window control behaviour are the time of the day, indoor CO_2 concentration, solar radiation, indoor air temperature, indoor relative humidity, and outdoor air temperature. We highlight that this study is based on measurements from one residential unit with the four-month of measurements and consequently the proposed model may not include potentially significant drivers that impact window opening actions, such as the season, ventilation type, room type, occupants (e.g., age, gender, smoker/non-smoker), building characteristics, noise level, and security issues. On the basis of the outcomes in 3.3.3, the pairs of the variables with stronger correlations are linked by arcs. As the correlation results do not provide causal relationships between the variables, the directions of the arcs are determined based on building physics. Following the findings in Section 3.3.2, the target variable is the window opening action instead of the window state. As an extension, the window closing action (WCAs) can be included in the same model. As the proposed BN structure can be applied for both discrete and continuous cases, this study compares the BN model based on a fully discrete dataset (Models A, C and E) and on a fully continuous dataset (Models B, D and F). Furthermore, the proposed BN structure (Models E and F) is compared against the structure derived only by machine learning (Models A and B) and the Naïve BN where WOA is the only child node and there is no arc between the other variables (Models C and D). For the discrete case, the continuous data is discretised into equal intervals of values based on logical reasoning as shown in Table 3.3-3.

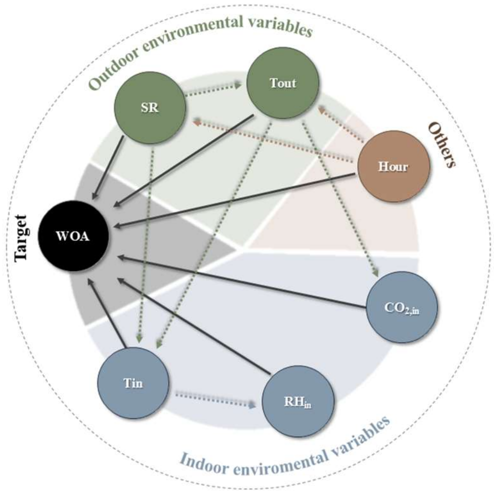


Figure 3.3-2. Proposal of a Bayesian Network for window opening behaviour.

Table 3.3-3. Discretization of the continuous VARs.

VAR	Discrete values
T_{in}	<14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25
T_{out}	-5-0, 1-5, 6-10, 11-15, 16-20, 21-25,
SR	0-250, 251-500, 501-750, 751-1000
RH_{in}	<35, 35-40, 41-45, 46-50, 51-55
$CO_{2,in}$	0-500,501-1000, 1001-1500, 1501-2000, 2001-2500

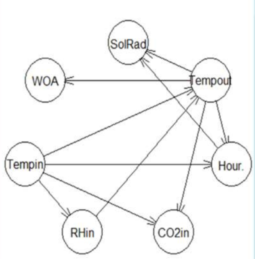
Figure 3.3-3 summarises the BIC score and arc strengths of different BN models. Models A and B show that the learning algorithm alone is not able to derive the BN structure that correctly captures relationships between the physical variables. The arcs automatically created by the learning algorithm do not represent the real physical dynamics beyond correlations between the variables. In addition, comparison between Models D and F highlights that the correlations between the explanatory variables are very high but the effect of modelling correlations between the variables on the model predictive power is very minor as the BIC score of Model F does not change much from that of Model D. The models based on the discrete data (Models C and E) are not able to quantify probabilistic dependencies between the explanatory variables and the WOA, while the continuous data (Models D and F) allows for identifying probabilistic dependencies between them. Indeed, the discretization of the dataset leads to a significant loss of information. Different discretization techniques have been developed to maintain substantial information embedded in the continuous dataset in the discretisation process. Suzuki (Suzuki 2014), for instance, proposed a scoring method that incrementally discretises the

continuous data at finer resolution and evaluates the predictive power of the resulting models. On the other hand, the continuous data cases hold all information, but they do not appropriately handle categorical variables (e.g., time of the day) and binary variables (e.g., window control actions). Recent studies, such as (Dojer 2016) developed methods for learning BNs from datasets joining continuous and discrete variables, but they are not readily available for the wider research community.

DISCRETE DATASET | **CONTINUOUS DATASET**

ONLY MACHINE LEARNING

Model A

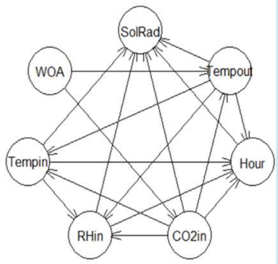


BIC Score
-443,240

Arc strengths

Arc	from	to	Strength
1	Hour	SolRad	-20,141
2	T_{in}	RH_{in}	-21,944
3	T_{in}	T_{out}	-17,647
4	RH_{in}	T_{out}	-7,618
5	T_{out}	SolRad	-6,550
6	T_{out}	Hour	-4,274
7	T_{in}	$CO_{2,in}$	-6,379
8	T_{out}	$CO_{2,in}$	-4,034
9	T_{in}	Hour	-3,675
10	T_{out}	WOA	-1,410

Model B



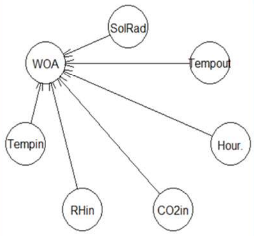
BIC Score
-1,495,630

Arc strengths

Arc	from	to	Strength
1	T_{in}	RH_{in}	-15,880
2	T_{out}	SolRad	-8,824
3	T_{out}	T_{in}	-8,745
4	$CO_{2,in}$	RH_{in}	-2,917
5	T_{out}	RH_{in}	-2,674
6	$CO_{2,in}$	Hour	-1,587
7	T_{out}	Hour	-1,402
8	$CO_{2,in}$	T_{out}	-1,331
9	RH_{in}	SolRad	-1,041
10	$CO_{2,in}$	T_{in}	-548
11	$CO_{2,in}$	SolRad	-279
12	RH_{in}	Hour	-264
13	T_{in}	SolRad	-194
14	T_{in}	Hour	-149
15	Hour	SolRad	-26
16	WOA	$CO_{2,in}$	-20
17	WOA	T_{out}	-5

NAIVE BN

Model C

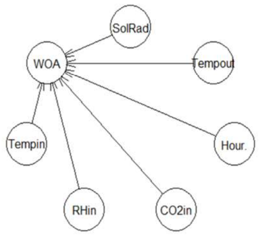


BIC Score
-INF

Arc strengths

Arc	from	to	Strength
1	T_{in}	WOA	-Inf
2	T_{out}	WOA	-Inf
3	SolRad	WOA	-Inf
4	Hour	WOA	-Inf
5	$CO_{2,in}$	WOA	-Inf
6	RH_{in}	WOA	-Inf

Model D



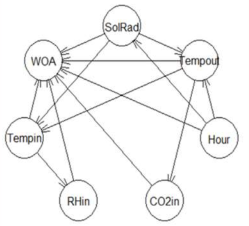
BIC Score
-1,539,440

Arc strengths

Arc	from	to	Strength
1	T_{in}	WOA	5
2	Hour	WOA	5
3	RH_{in}	WOA	5
4	SolRad	WOA	3
5	T_{out}	WOA	-5
6	$CO_{2,in}$	WOA	-25

MACHINE LEARNING + EXPERT KNOWLEDGE

Model E

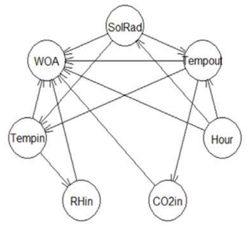


BIC Score
-INF

Arc strengths

Arc	from	to	Strength
1	Hour	SolRad	-21,959
2	T_{in}	RH_{in}	-21,944
3	T_{out}	T_{in}	-14,487
4	SolRad	T_{out}	-6,550
5	Hour	T_{out}	-4,130
6	SolRad	T_{in}	-2,423
7	T_{out}	$CO_{2,in}$	-1,602
8	T_{in}	WOA	-Inf
9	RH_{in}	WOA	-Inf
10	$CO_{2,in}$	WOA	-Inf
11	Hour	WOA	-Inf
11	SolRad	WOA	-Inf
13	T_{out}	WOA	-Inf

Model F



BIC Score
-1,503,114

Arc strengths

Arc	from	to	Strength
1	RH_{in}	T_{in}	-13,788
2	SolRad	T_{out}	-10,524
3	T_{out}	T_{in}	-7,618
4	T_{out}	$CO_{2,in}$	-1,325
5	Hour	Tout	-1,028
6	Hour	SolRad	-700
7	SolRad	T_{in}	-74
8	$CO_{2,in}$	WOA	-24
9	T_{out}	WOA	-3
10	SolRad	WOA	3
11	Hour	WOA	5
11	T_{in}	WOA	5
12	RH_{in}	WOA	5

Figure 3.3-3. Exploration of BNs for modelling window opening behaviour.

3.3.5 Treatment of mixed data

This section proposes a BN modelling procedure that properly treats mixed data. This capability is crucial especially for the context of window control behaviour in which the main target variable is often binary (open/close) and key response variables are continuous. In particular, the target node "WOA" and time of the day are discrete variables while all the indoor and outdoor environmental variables are continuous. Currently, most available statistical analysis packages, including the *bnlearn* package (R environment), support either discrete or continuous variables. The *bnlearn* package offers more flexibility as it does not support the dependence of discrete variables on continuous variables but support the other way around. Hence, it is possible to build a bottom-up model in which the arcs are reversely connected from the discrete target variable to the continuous response variables (Figure 3.3-4). The semantic representation of this model might seem less intuitive, but since the BN model supports any direction of reasoning, it still can correctly infer the window opening action given the set of variable values. The BIC score of the model suggests that appropriately handling the mixed data improves the predictive power of the model in comparison to Models C and D. Furthermore, Model G yields the ranking of the response variables that well aligns with the outcomes of the K-S test described in section 3.3.1. In contrast, the continuous case (Model D) results in a much lower arc strength value for the time of the day as it does not correctly treat this variable as a categorical variable and instead expects a consistent trend between this variable and its child node. This comparison clearly illustrates the importance of appropriately treating mixed data to yield a reliable BN model and correctly analyse the effect of different variables on control actions.

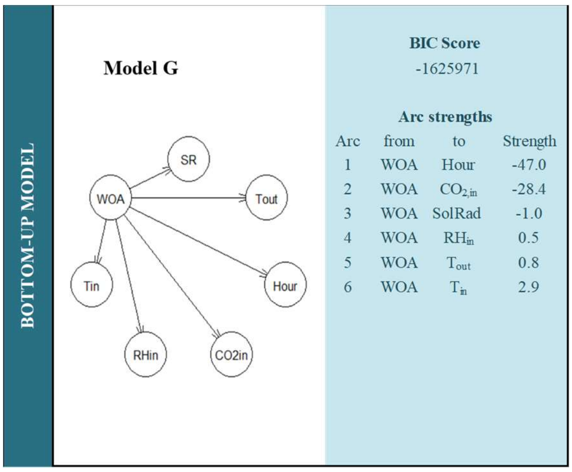


Figure 3.3-4. Treatment of mixed data: Bottom-up (BU) model.

3.3.6 Model-based inference

Figure 12 depicts the outcomes of the queries related to the probability of a window opening action given the main key response variables (Model G). As regards the main influencing driver, the time of the day (Figure 3.3-5a), the results show that the probability of performing a window opening action is higher during the morning and late afternoon/evening hours. Furthermore, also found in the existing literature (Andersen et al. 2013; Yun and Steemers 2008), the results indicate that the probability of opening a window increases in correspondence of a higher CO_2 concentration (Figure 3.3-5b), indoor air temperature (Figure 3.3-5c), and outdoor air temperature (Figure 3.3-5d).

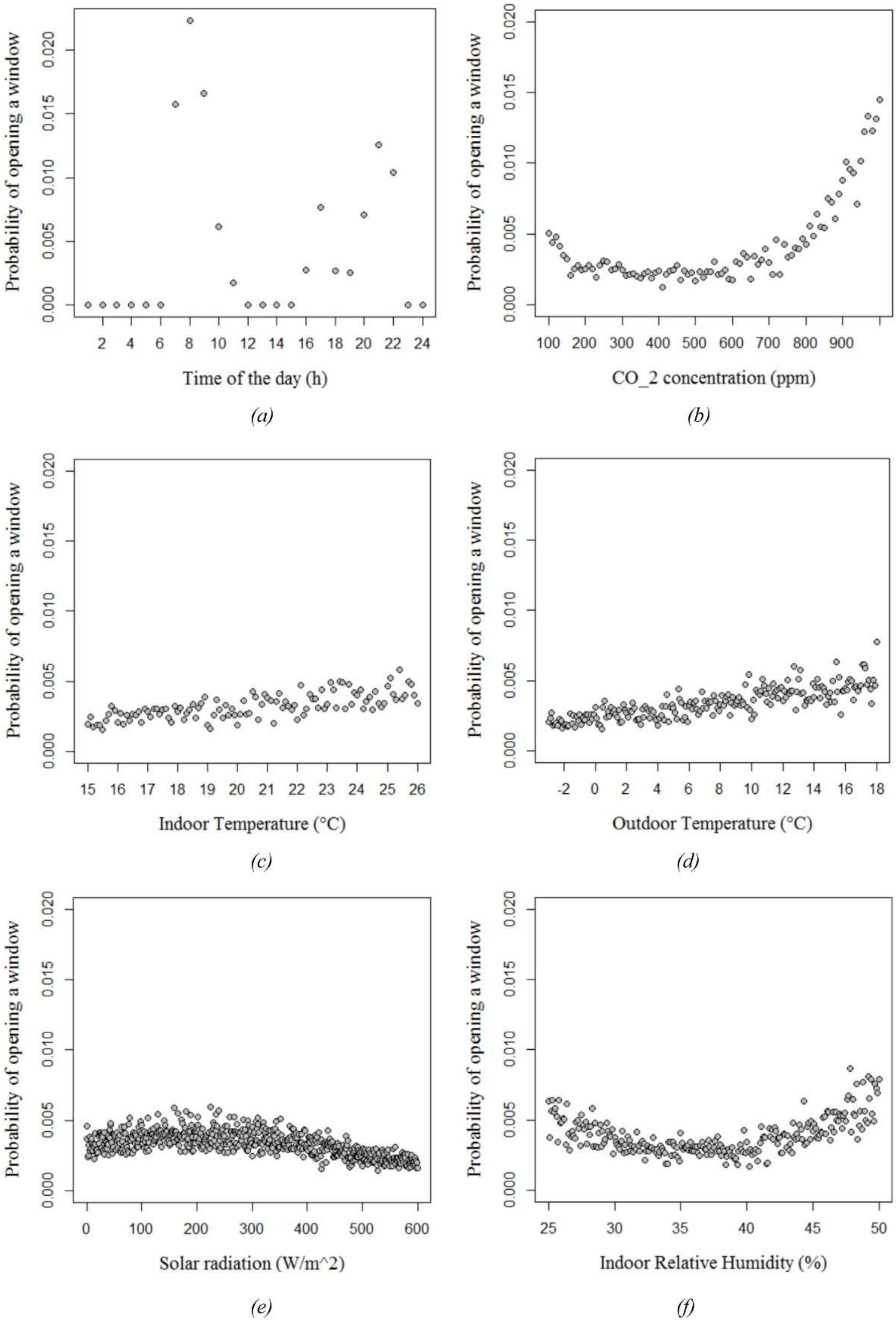


Figure 3.3-5. Probability of a window opening action given (a) time of the day, (b) CO2 concentration, (c) indoor temperature, (d) outdoor temperature, (e) solar radiation, and (f) indoor relative humidity.

3.3.7 Model validation

The confusion matrix in Figure 3.3-6 indicates that there is a good match between observed and predicted window opening actions (WOA), and observed and predicted no opening actions (NOA). In detail, following the tailored validation procedure presented in 3.2.2 (Step 7), the accuracy of the model to predict the window opening action and no opening action is in average 93% and 98%, respectively. The expected loss value obtained with the balanced data is 5%, which confirms the strong predictive power of the BN model.

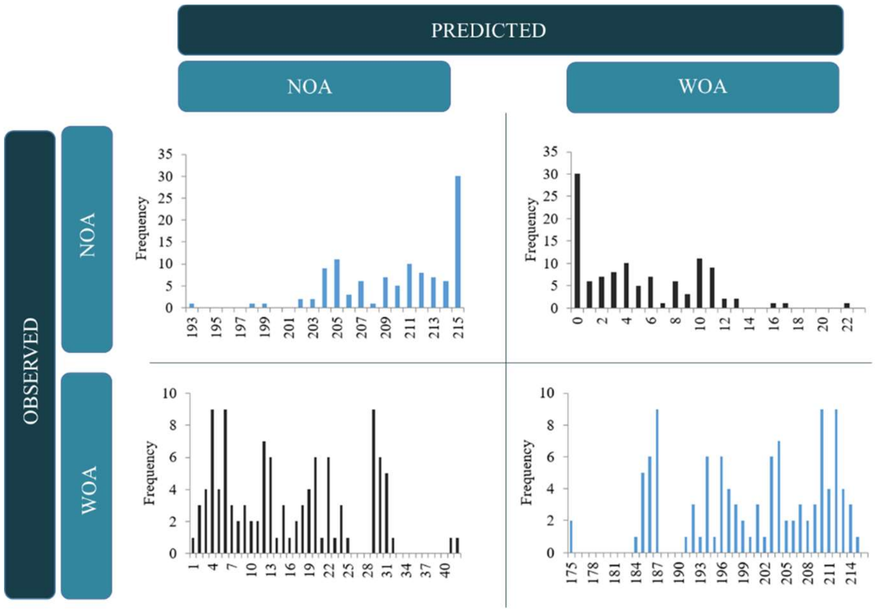


Figure 3.3-6. Confusion matrix of observed and predicted WOAs and NOAs.

3.4 Discussion and further investigations

3.4.1 BN framework: a promising approach for OB modelling?

The Bayesian Network modelling presented in this chapter well represents the stochastic nature of occupants' interaction with the windows in relation to a variety of explanatory variables and consequently provides predictions with high confidence. The BN framework can be considered a promising approach for OB modelling given the following characteristics:

- Clear semantic representation of the model;
- Combination of different sources of knowledge (expert knowledge + information learnt from data);
- Automatic structure and parameter learning feature;
- Flexible applicability permits to include a large variety of variables in one model;

- Joint probability distributions between variables;
- Easy belief updating when new data becomes available;
- Handling of small datasets;
- Handling of incomplete datasets;
- Fast responses.

However, it is necessary to highlight some challenges that need to be taken into account when using the proposed approach. The case study demonstrated that the proposed BN approach yields a probabilistic prediction model with higher confidence and better interpretability by fully exploiting information from the mixed dataset in comparison to the typical BN approaches. In all BN models, however, the joint distribution of all variables (global distribution) is factorised into local probability distributions, which reduces computational requirements for complex networks and increases power for parameter learning On the other hand, this also means that the local probability distribution between two nodes only explain the effect of the parent node on the child node, but does not take into account parameter interaction effects (Scutari and Jean-Baptiste 2014). In order to account for parameter interaction effects, Andersen et al. (2013) developed a multivariate logistic regression model with parameter interaction terms. Although if this study showed the high predictive power of the BN model without accounting for parameter interactions, it is not sufficient to conclude the effect of parameter interactions on the model predictive power. Further investigation is necessary to test the importance of parameter interactions in the context of window control behaviour modelling.

The BN-based approach, in principle, allows for modelling complex hierarchical relationships between a large number of continuous and discrete variables through a clear semantic graphical representation. Moreover, the graphical representation is a valuable conceptual benefit since the structure and its underlying probabilistic dimension are easily interpretable for modellers in the building simulation community. However, owing to the limitation of the existing statistical packages, BN approaches used in existing studies with mixed data are based on discretized data of continuous and discrete variables, which may likely result in a significant loss of information (Dojer 2016). As the first step to overcome this limitation, a bottom-up modelling approach is proposed that handles mixed data when the target node is discrete and depends on continuous and/or discrete explanatory variables. However, it presents a challenge to extend the proposed approach to model a hierarchical complex structure that links continuous and discrete explanatory variables in multiple layers. In fact, occupants take a specific action or combination of actions among many control actions, such as thermostat settings, light dimming, blind control, to maintain their thermal comfort level, and modelling a series of control actions has been identified as one of the future needs for occupant behaviour modelling (Yan et al. 2015b). A Bayesian hierarchical network model can provide a mathematical framework for holistically modelling such adaptive actions in relation to environmental and contextual variables.

3.4.2 BN framework in the field of building energy analysis

The suitability of the BN framework for occupant behaviour and in the field of building energy analysis was further investigated by providing a critical literature review on studies that have employed BNs in their methodological framework **(PAPER VII)**. In particular, the literature survey identified the following areas in the field of building energy analysis in which BNs have been applied during the research process:

i. Indoor Environmental Quality (IEQ) and Thermal Comfort Analysis
ii. Building occupancy detection and other behavioural patterns
iii. Design and operation of building components under uncertainty
iv. Estimation of building energy consumptions at different scales and in smart grids

A fifth area of investigation is related to the application of BNs for renewable energy systems, for an extended literature review on these applications the authors refer the reader to Borunda et al. (2016). Their study provides an extended literature review on BNs applied in renewable energy systems showing that most of the applications are devoted to wind and hydroelectric energy and the less applied and studied areas are geothermal, solar thermal and photovoltaic energies as well as biomass and energy storage.

A first approach for using BNs is related to the analysis of Indoor Environmental Quality (IEQ) and thermal comfort. High Indoor Environmental Quality and an adequate thermal comfort is crucial for the productivity and wellbeing of the building occupants. In line with the needs related to an optimized indoor environment, BNs are well suited for estimating the effects of the indoor climate on the performance of occupants, since they take into account the uncertainty that inevitably will be present when trying to estimate human output as a function of the indoor environment. Jensen et al. (2009) developed a Bayesian Network approach that can compare different building designs by estimating the effects of the thermal indoor environment on the mental performance of office workers. The authors introduced a Performance Index for comparing the several building designs by assessing the total economic consequences of the indoor climate. Also Wu et al. (2007) used BNs for estimating the relationship between occupant behaviours and indoor environmental parameters aiming at minimizing energy consumptions and maximizing occupant productivity. A personalized thermal comfort model was proposed by Auffenberg et al. (2015), which uses a BN to learn and adapt to user’s individual preferences by predicting their optimal temperature at any given time. This research highlights the big advantage of BN models to infer information about expected user feedback, optimal comfort temperatures and thermal sensitivity at the same time. Ghahramani et al. (2015) introduced an online learning approach for modelling and quantifying personalized thermal comfort. In this approach, the authors fit a probability distribution to each comfort condition (i.e., uncomfortably warm, comfortable, and uncomfortably cool) data set and define the overall comfort of an individual through combing these distributions in a Bayesian network. Finally, Shipworth (2010) defined a BN to model and predict living room temperatures in the residential environment.

Another investigated topic is related to the application of BNs for building occupancy detection to determine when and where people occupy the building, which is a key component of building energy management and security. Dodier et al. (2006) developed a universal analysis framework in which occupancy information is collected by a network of multiple independent and redundant sensors and is then processed using the Bayesian probability theory to estimate future occupancy patterns. The Bayesian Network approach presented by Petzold et al. (2005) is used to predict the occupant's next location based on the sequence of their previous locations and the current time of day and day of the week. Next to occupancy detection, BNs have also been applied for the investigation of other behavioural patterns. Harris and Cahill (2005), for example, used a BN into support prediction of user behaviour patterns related to a Context-Aware Power Management (CAPM) with special regard to the power management of users' stationary desktop PCs in an office environment. The study of Hawarah et al. (2010) dealt with the problem of the user behaviour prediction in home automation systems and their method relied on a BN to predict and diagnose user's behaviour in housing. In particular, the aim of this study was to compute at each hour the probability of starting of each energetic service in the building. Tijani et al. (2015) proposed a new general approach based on a BN to model human behaviour in order to predict the rate of CO_2 concentration in an office depending on the door opening.

The third and yet less explored topic regards the design of building components under uncertainty. Indeed, the adoption of new and more sustainable construction technologies, especially in complex building systems, is sometimes difficult, due to the lack of adequate knowledge to properly perform rough sizing of such systems in the professional environment. The shortage of proper simulation programs for the preliminary design of sustainable construction prevents in fact the application of these systems in the contemporary construction market, oftentimes producing higher design costs and construction durations that exceed those of comparable standard buildings. For instance, Naticchia et al. (2007) used the BN framework intended as an expert system for the design of buildings equipped with roof ponds. Thanks to the explicit causal structure of Bayesian Networks, they are able to model also the very complex thermal behaviour of roof ponds, due to their changeable properties varying with seasons, building characteristics and climatic parameters. This probabilistic model is able to cope with several building configurations, and provides architects with a tool for multi-criteria decision-making. Furthermore, Zhao et al. (2013) proposed a generic intelligent fault detection and diagnosis strategy to simulate the actual diagnostic thinking of chiller experts.

A last but very promising approach for using BNs in the domain of building energy analysis is the estimation of energy use at the single building level, on a large scale and in smart grids. O'Neill and O'Neill (2016), for instance, developed a BN model to predict HVAC hot water consumptions based on the time of the day and the outdoor air temperature. Tarlow et al. (2009) estimated energy consumption over a large building stock of the Walt Disney Company, which is characterized by unusual operational patterns and policies that traditional energy simulation tools have difficulty to represent faithfully without extensive calibration. In this study, BNs were applied to automatically learn plausible models of energy consumptions by extracting the information contained in the data of one building in such a way that it can be used for calibration and improving real-world energy consumptions estimates in other similar buildings. Indeed, the authors are focused on developing a highly scalable, data-driven approach based on the BN framework, able to calibrate and share information between a large number of buildings at once. Furthermore, Vlachopoulou et al. (2012) focused on the transition to the new generation power grid, which requires novel ways of using and analysing data collected from the grid infrastructure. The authors showed that the BN model accurately tracks the load profile curves related to the aggregated water heaters under different testing scenarios. Huang et al. (2016) developed a BN model for forecasting cooling loads in educational facilities showing that the model can accurately capture the trend of the cooling load even with a limited size of training data. Finally, the study of Nanda et al.(2016) proposed, developed and validated a Bayesian model for the thermal load forecast in a smart grid environment, which is crucial for optimizing energy production and developing effective demand response strategies on a larger scale.

PAPER VII gives a more detailed critical review of the mentioned studies in view of how the several modelling steps were approached by the researchers.

3.5 Perspectives and challenges

To outline perspectives and challenges that this study is aimed at bringing to surface, it is necessary to mention some limitations of the proposed approach. As the case study in this study is based on measurements from one Danish residential apartment, statistical results from the case study are limited to draw generalizable findings due to the small sample size. Nevertheless, the case study serves as an adequate and useful testbed to investigate the applicability of the BN framework for modelling window control behaviour and demonstrate the statistical methods used for variable selection and model validation in the modelling process. A next step is to use an **extensive dataset from a larger number of residential buildings** to develop a generalizable model. The case study analysed in this chapter focused on environment- and time-related variables for predicting window control actions. In the further work, it is necessary to investigate other building-related factors that may yield different patterns of window control behaviour, such as different ventilation strategies (i.e., presence of controlled mechanical ventilation), room type, and building design characteristics. More importantly, as substantial variation is observed in the window control behaviour due to individual users (Fabi et al. 2012; Schweiker 2017; Stazi et al. 2017), **further work is needed to include contextual information, as well as individual characteristics of the occupants,** such as occupant types (e.g. age, gender, smokers/non-smokers), social factors (energy-related knowledge and attitudes), and psychological and physiological factors.

3.6 Publications

PAPER VI **Barthelmes, V.M**., Heo, Y., Fabi, V., Corgnati, S.P. (2017). Exploration of the Bayesian Network framework for modelling window control behaviour, *Building and Environment* 126, pp. 318-330).

PAPER VII **Barthelmes, V.M.,** Heo, Y., Fabi, V., Corgnati, S.P. The Bayesian Network framework for building energy and occupant behaviour analysis: A critical review (to be submitted to Energy and Buildings, 2019)

Chapter 4

Interdisciplinary investigation on OB through surveys

4.1 Overview

Chapter 3 explored the Bayesian Network framework for modelling window control behaviour in the residential context based on a number of time-related and environmental variables. However, in order to model window control behaviour – or occupant behaviour in general – in a comprehensive manner, it is necessary to explore a more extensive set of factors that drive the occupant to perform a certain action (Schweiker 2017). In this context, this in this chapter a theoretical model of occupant's window control behaviour with an extensive set of drivers is proposed, and discusses ways to develop such models, particularly with use of Bayesian Networks based on extensive field measurements and survey-based information collected in Danish dwellings. The contextual information was collected through a tailored survey framework that included questions for understanding occupants' individual comfort attitudes and preferences, physiological factors, social factors and norms, perceived control and psychological factors, motivations and habits related to window control behaviour, and preferences on adaptive opportunities (e.g. sequence of actions that occupants perform when they feel hot/cold). Then, field measurements were combined with survey-based information of individual household members collected in 14 Danish town houses. Based on the collected dataset, the Bayesian Network (BN) framework was applied to capture underlying relationships between these factors and window control actions. In particular, this chapter is aimed at contributing to the following research questions:

- How and which background information and individual characteristics/preferences of the occupants relevant to OB, and in particular window control behaviour, should be collected?
- How can these factors be introduced in the modelling process and does the latter confirm that are they relevant?

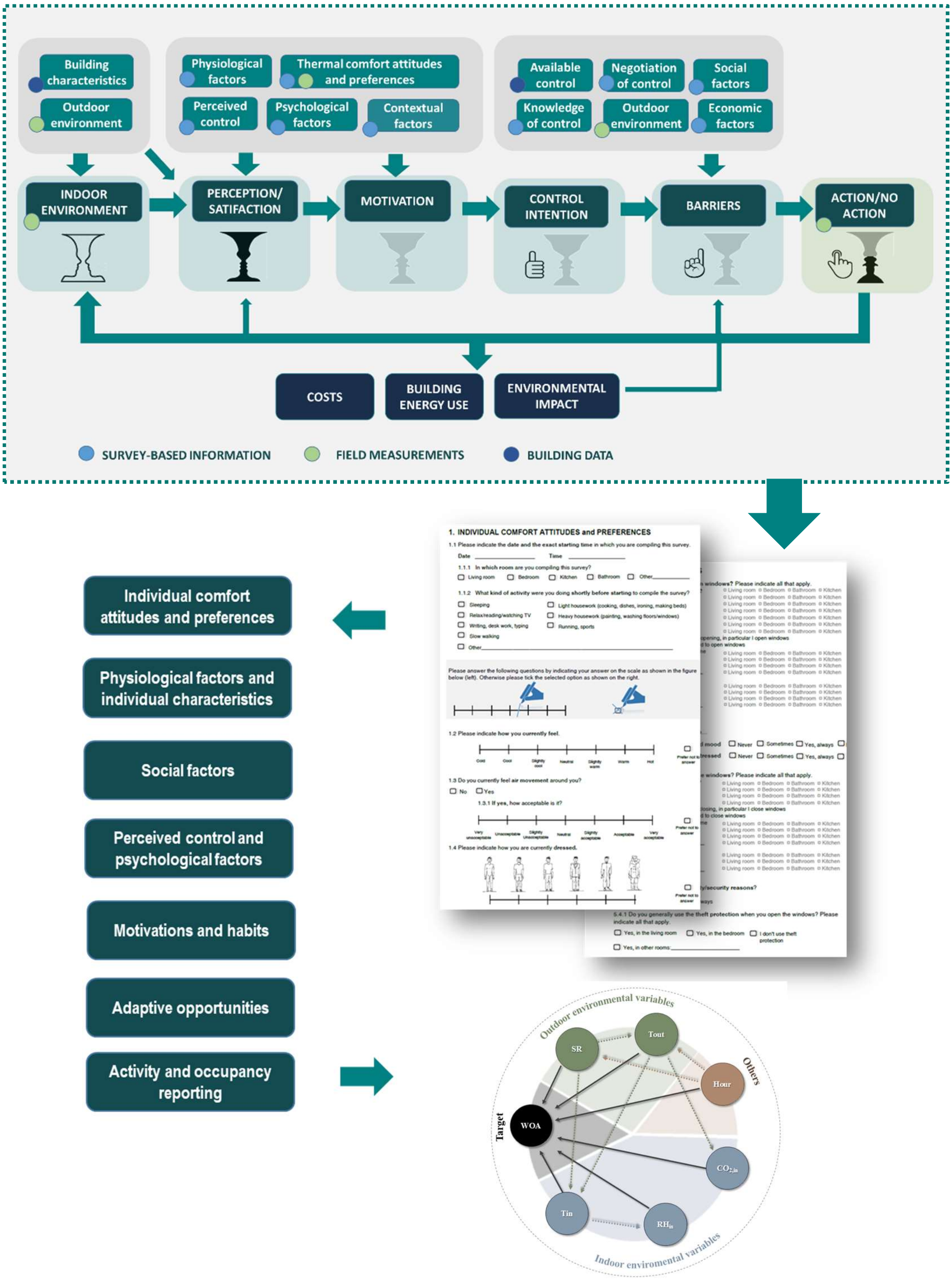


Figure 4.1-1. Overview Chapter 4.

4.2 Methodology

4.2.1 Survey Framework

As mentioned previously, most existing studies directly correlate occupants' interactions with the building envelope and systems to physical parameters, such as environmental variables, or time-related parameters (e.g. time of the day). As shown in Figure 4.1-1, the behavioural process is influenced by a number of other factors – or "drivers" (Fabi et al. 2012) (Schweiker and Shukuya 2009) – that have effect on an individual's perception and satisfaction of the indoor environment and on their motivation to change the indoor environmental conditions. The control intention, for instance, can also be conditioned by social and economic factors or norms, or the limited knowledge of how to interact with the building controls (Ajzen and Madden 1986)(D'Oca et al. 2017)(Mulville et al. 2017)(Chatterton 2011). Next to traditional field measurements of environmental parameters and information on building characteristics, survey-based information can be introduced in the modelling process to obtain a more accurate picture of behavioural patterns. In this study, these additional factors are investigated by means of a tailored interdisciplinary survey framework for 47 Danish Dwellings.

The interdisciplinary survey framework was assessed to collect detailed information on the occupants regarding: (1) individual comfort attitudes and preferences, (2) physiological factors and individual characteristics (e.g. gender, age, height, weight, smoking habits), (3) social factors (e.g. education, household composition, household income), (4) perceived control and psychological factors (e.g. satisfaction of control options, knowledge of control options, interaction frequency with controls, safety), (5) motivations and habits related to window control behaviour, and (6) adaptive opportunities (e.g. sequence of actions that occupants perform when they feel hot/cold). Since building system characteristics and ethnical origin were similar in all households, information related to these factors were excluded from the survey framework. The results of survey responses shown in this study refer to a reduced sample size of 35 individuals. Furthermore, it is worth noting that the survey was distributed in Danish language, in this chapter only translations of the questions to English language are shown **(PAPER VIII)**. The English version of the survey can be found in **Annex A.**

Individual comfort attitudes and preferences

The first section of the survey addresses the occupants' perception of the indoor environment and their individual preferences. The respondents were requested to indicate their perception and satisfaction of thermal, visual, and acoustic environment and Indoor Air Quality (IAQ). The perception was indicated on a continuous seven-point scale, similar to the Predicted Mean Vote (PMV) thermal scale (Cen, 2007), and the respondents' satisfaction was indicated on a Visual Analogue Scale (VAS) with "Very unacceptable" on one end and "Very acceptable" on the other. This subjective data will be analysed together with field measurements in order to investigate differences in individual perception of the indoor environment due to individual physiological characteristics. Furthermore, the preferences of individual occupants were elicited by asking them how much they agree or disagree with comparative statements. Table 4.2-1 summarises the survey questions of the first section.

Table 4.2-1. Survey section 1: Individual comfort attitudes and preferences.

Code	Survey question	Scale
1.1	Please indicate the date and the exact starting time in which you are compiling the survey	-
1.1.1	What kind of activity were you doing shortly before starting to compile the survey?	Multiple choice
1.2	Please indicate how you currently feel	Cold-hot continuous 7-point scale
1.3	Do you currently feel air movement around you?	Yes/No
1.3.1	If yes, how acceptable is it?	VAS Very unacceptable-very acceptable
1.4	Please indicate how you are currently dressed	Nude-winter clothes 7 point scale
1.5	Please describe the lighting level around you	Very dim-very bright - continuous 7-point scale
1.6	How satisfied are you with the amount of light around you?	Very unsatisfied - very satisfied – VAS
1.7	Please describe the air around you	Very stuffy - very fresh - continuous 7-point scale Very humid – very dry - continuous 7-point scale
1.8	How satisfied are you with the air quality around you?	Very unsatisfied - very satisfied – VAS
1.9	Please describe the noise level around you	Very silent – very noisy - continuous 7-point scale
1.9.1	If it is noisy, where does the noise come from?	Multiple choice
1.10	How satisfied are you with the noise level around you?	Very unsatisfied - very satisfied – VAS
1.11	Finally, please indicate your current overall satisfaction with the indoor environment	Very unsatisfied - very satisfied – VAS
2	**How important are the following to you:**	
2.1	Not being too cold or too warm	Very unimportant – very important - continuous 7-point scale
2.2	Absence of drafts	Very unimportant – very important- continuous 7-point scale
2.3	To have good lighting conditions	Very unimportant – very important - continuous 7-point scale
2.4	Absence of noise	Very unimportant – very important - continuous 7-point scale
2.5	To have fresh air	Very unimportant – very important - continuous 7-point scale
2.6	**How much do you agree/disagree with the following statements**	
2.6.1	“When it is cold outside, I rather feel a little cold to get some fresh air”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.2	“I can accept some noise from outdoors to have some fresh air”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.3	“I rather feel a little cold in order to save some on the heating bill”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.4	“When I open windows, I think about higher energy costs for heating”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.5	“I can accept a slightly bad indoor air quality in order to save some energy costs”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.6.	“My first priority is being comfortable with the temperature and air quality, I don’t worry so much about energy costs”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.7	“When I open/close windows and adjust the thermostat, I think about my environmental impact”	Strongly disagree – strongly agree - continuous 5-point scale
2.6.8	“When I open the windows, I usually turn down the heating”	Strongly disagree – strongly agree - continuous 5-point scale

Physiological factors

The second section of the survey aims to gain a deeper knowledge on the physiological characteristics of the occupants. A number of existing studies found that occupants' gender and age influence the individuals' perception of the indoor environment and comfort attitudes (Kingma and Van Marken Lichtenbelt 2015; Wei et al. 2014). However, consensus has not been reached about whether gender difference has an impact on the perception of thermal environment (Fanger 1973). As a health-related question, the occupants were asked if they had any smoking habits, but no further questions about illnesses or other health-related conditions were made due to privacy reasons. The questions related to this section are summarised in Table 4.2-2.

Table 4.2-2. Survey section 2: Physiological factors.

Code	Survey question	Scale
3.1	Please indicate your gender	Multiple choice
3.2	Please indicate your age	
3.3	Please indicate your height	-
3.4	Please indicate your weight	-
3.5	Do you smoke?	Multiple choice
3.5.1	Do you smoke inside your house?	Multiple choice
3.5.2	Do you open windows to get rid of tobacco smoke?	Multiple choice

Social and economic factors

This section provides a deeper insight on energy-related social norms in the household, the household composition itself and economic factors, such as household income and job categories. Extensive studies have shown that the economic level of occupants showed significant effect on the thermal sensation, preference, acceptance and neutrality (Indraganti and Rao 2010; Wei et al. 2014). The effect of social and economic norms on thermal comfort will be investigated on the basis on the data collected by the questions summarised in Table 4.2-3.

Table 4.2-3. Survey section 3: Social and economic factors.

Code	Survey question	Scale
4.1	In a typical month, for how long do you live in the household this survey was sent to?	Multiple choice
4.2	Please indicate the total number of adults (including yourself) that in a typical month live in the household (Always, more than half of the time, ca. half of the time, less than half of the time)	-
4.3	Please indicate the total number of children that in a typical month live in the household (Always, more than half of the time, ca. half of the time, less than half of the time)	-
4.4	Please describe your education	Multiple choice
4.5	Please describe your job category	Multiple choice
4.6	Please indicate the monthly household net income	Multiple choice
4.7	Who usually controls the temperature settings in your home?	Multiple choice
4.8	Who usually opens the windows in your home?	Multiple choice
4.9	Who usually closes the windows in your home?	Multiple choice
4.10	Which and how many of the following domestic appliances are used in your home?	Multiple choice

Perception, satisfaction, and activeness of control

This section of the survey addresses control-related information. In this survey, no further information on available controls was required since control layouts were similar in all households. The respondents were asked if they had any difficulties in operating the control systems or, alternatively, they could indicate that they did not know how to use them. Several studies have shown that perception and satisfaction of control options directly influence perception and satisfaction of the indoor environment (Ajzen and Madden 1986; Toftum 2010; Wei et al. 2014). Questions in this section can be found in Table 4.2-4.

Table 4.2-4. Survey section 4: Perception, satisfaction, and activeness of control.

Code	Survey question	Scale
5.1	**How difficult is it for you to use the…?**	
5.1.1	Thermostat	Very difficult – very easy – 7 point continuous scale
5.1.2	Windows	Very difficult – very easy – 7 point continuous scale
5.1.3	Shading devices	Very difficult – very easy – 7 point continuous scale
5.2	**How satisfied are you with the control options of the…?**	
5.2.1	Thermostat	Very unsatisfied – very satisfied – 7 point continuous scale
5.2.2	Windows	Very unsatisfied – very satisfied – 7 point continuous scale
5.2.3	Shading devices	Very unsatisfied – very satisfied – 7 point continuous scale
5.3	Overall, how satisfied are you with the control options in your home?	Very unsatisfied – very satisfied – 7 point continuous scale
5.4	**In the last 14 days, how often did you operate the...?**	
5.4.1	Thermostat	Multiple choice
5.4.2	Windows	Multiple choice
5.4.3	Shading devices	Multiple choice
5.4.4	Ventilation slots	Multiple choice

Motivation and habits for window control behaviour

In this section, the occupants were asked about their motivations or usual habits when they perform a window control action (Table 4.2-5) in relation to certain activities (e.g. sleeping, cooking, shower) and certain times of the day (e.g. leaving home, coming back home). This included psychological factors, such as closing the windows for safety reasons and the use of theft protection.

Table 4.2-5. Survey section 5: Motivation and habits for window control behaviour.

Code	Survey question	Scale
6.1	Why and where do you usually open windows?	Multiple choice for different rooms
6.2	Why and where do you usually close windows?	Multiple choice for different rooms
6.2.1	Do you close windows for safety reasons?	Multiple choice for different rooms

Adaptive opportunities

This section addresses adaptive opportunities that respondents would undertake if they found themselves in particular environmental conditions. In detail, the occupants were asked to indicate if and in which sequence they would perform certain adaptive actions to improve their condition of discomfort (feeling too hot or too cold) (Table 4.2-6).

Table 4.2-6. Survey section 6: Adaptive opportunities.

Code	Survey question	Scale
7.1	Think of a situation in your home, in which you felt feel too hot and it is cool outside. (e.g. a cool summer day), which action would you perform first? Please number the actions you performed in sequence (only the ones that apply) (e.g. __First action, __second action).	Multiple choice
7.2	Think of a situation in your home, in which you feel too cold, and it is cool outside (e.g. a cool summer day), which action would you perform first? Please number the actions you performed in sequence.	Multiple choice
7.3	Think of a situation in your home, in which you feel too hot and it is warm outside (e.g. a warm summer day), which action would you perform first? Please number the actions you performed in sequence.	Multiple choice
7.4	Think of a situation in your home, in which you feel too cold and it is warm outside (e.g. a warm summer day), which action would you perform first? Please number the actions you performed in sequence.	Multiple choice

4.2.2 Development of a theoretical model for window control behaviour

Figure 8 shows a multi-layered theoretical model that introduces individual preferences, psychological, social and other drivers investigated by means of the above presented survey questions (codes are indicated in Figure 4.2-1 and Tables) for modelling occupant behaviour in a more comprehensive manner. In particular, the layers that compose the theoretical model structure are the following:

- "Horizontal" survey-based layers related to comfort attitudes, preferences, perception and satisfaction of the indoor environment
    - Physiological characteristics of the occupants
    - Individual preferences on the indoor environment
    - Perception of the indoor environment
    - Satisfaction of the indoor environment

- "Vertical" field measurement-based layers
    - Indoor environmental variables
    - Outdoor environmental variables
    - Time-related factors
    - Occupant-related factors (clothing level, activity level)

- Other influencing factors layer with an extensive set of drivers/barriers
    - Habits
    - Building characteristics
    - Social and economic factors
    - Psychological factors

- Control systems layer
    - Knowledge of control
    - Perceived control

  - Satisfaction of control
  - Interaction level with controls

- Adaptive opportunities layer

- "Target": Action layer
  - Window opening control
  - Window closing control

The perception layer includes votes of the respondents on the thermal, visual and acoustic environment as well as on the Indoor Air Quality. The votes on the indoor environmental quality are influenced by a number of factors from the measurement layer, such as indoor/outdoor environmental variables, occupant-related variables, and time-related factors. As an example, the Thermal Sensation Vote depends on influencing factors as indicated in the EN15251 standard (Cen, 2007), which include environmental factors (air temperature, mean radiant temperature, air speed and humidity) and occupant-related factors (metabolic rate and clothing level). Additionally, in this model, the perception layer also depends on physiological characteristics (e.g. gender, age, weight) of the occupants and individual preferences on environmental comfort, as well as the relation of the occupant with the control systems (knowledge of control, perceived control, satisfaction of control, and interaction level with controls)(Paciuk, 1990). Based on the perception votes of the indoor environment, the occupants express levels of satisfaction in terms of thermal, IAQ, visual, and acoustic environment. The level of satisfaction with the indoor environmental quality is a key factor that drives the occupant to perform a certain action, such as a window opening or closing control action (target action layer). At the same time, next to the perception and satisfaction of the indoor environment, a layer containing other influencing factors, such as habits, building characteristics, psychological factors, and social/economic factors might influence the occupant to interact/or not to interact with the window. These factors, in turn, can also be influenced by factors located on the measurements layer. As an example, habits of window control behaviour during certain activities (e.g. sleeping, cooking) can be related to certain times of the day. Finally, the decision of performing a window control action is influenced by the possibility of ceasing different adaptive opportunities (e.g. active body adaptation, thermoregulation, environmental direct control) according to personal preferences and control options. In line with this, it is worth noting that next steps should extend the action layer to include additional control options, such as thermostat control or window blinds regulation.

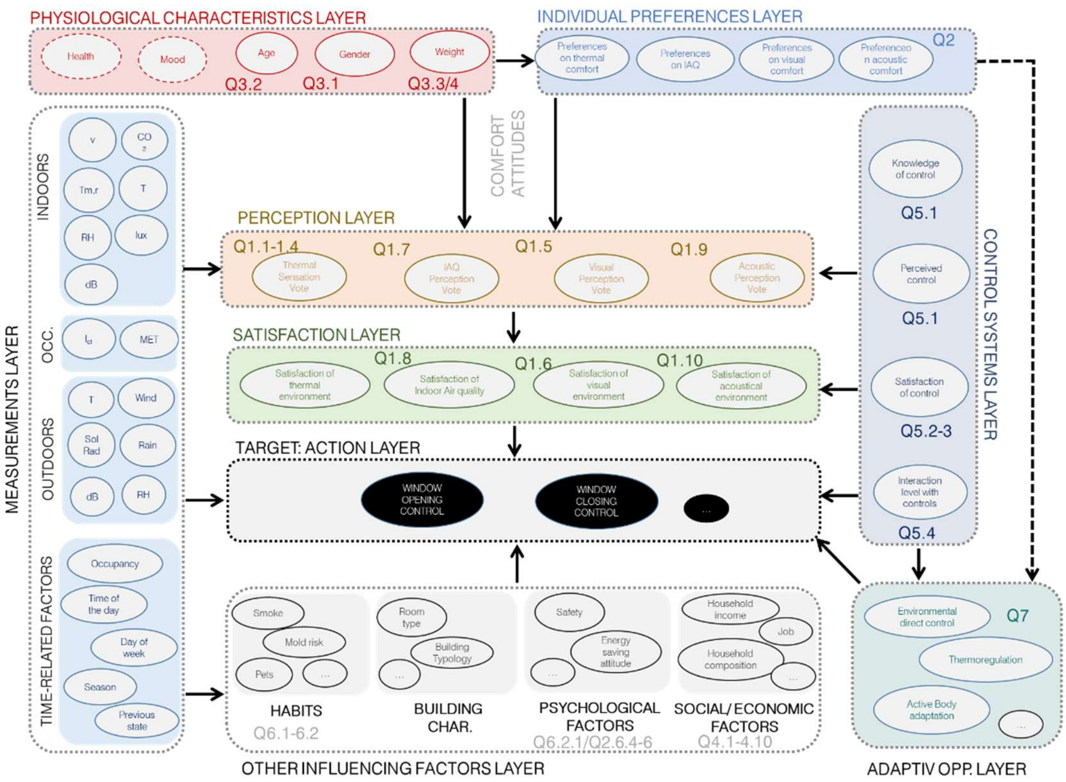


Figure 4.2-1. Proposal of a multi-layered theoretical model for window control behaviour.

4.2.3 Towards a comprehensive BN model: Combining field mesaurements and survey-based information

Field measurements

The field measurements were taken in 14 naturally-ventilated apartments located in a same neighbourhood close to Copenhagen, Denmark. Table 4.2-7 summarises measurements related to the indoor and outdoor environment conditions, occupants' interaction with the windows in the living room, and time-related factors. A time resolution of 15-min intervals was used for the analysis, which considers measurements for one month during the heating season (November 2017).

For the acquisition of window state and movement, windows were equipped with wireless sensor tags. The outdoor environmental measurements were acquired from a sensor located in a representative area for the neighbourhood. For the description of sensors and the monitoring campaign, more information can be found in Henriksen and Olsen (2018).

Table 4.2-7. Measured target and explanatory variables.

Variable	Abbreviation	Unit
Indoor environment		
Air temperature	T_{in}	°C
Relative humidity	RH_{in}	%
CO_2 concentration	$CO_{2,in}$	ppm

Outdoor environment		
Outdoor temperature	T_{out}	°C
Time-related		
Time of the day	Hour	h
Target		
Window opening action	WOA	0/1

Individual thermal comfort attitudes

In the survey, the respondents were requested to indicate their perception of the thermal environment and other factors that influence their thermal sensation (clothing. activity level, perception of drafts). The perception was indicated on a continuous seven-point scale, similar to the Predicted Mean Vote (PMV) thermal scale (CEN 2007). This subjective data was analysed together with field measurements taken during the compilation of the survey in order to establish the thermal comfort attitudes of the occupants according to the procedure depicted in Figure 4.2-2 **(PAPER IX)**.

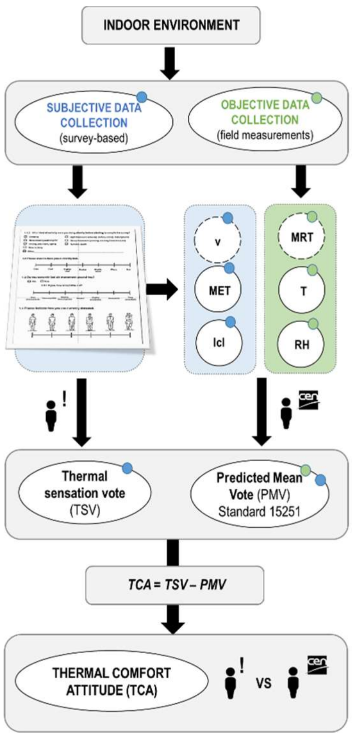


Figure 4.2-2. Definition of Thermal Comfort Attitudes (TCAs), where v=air speed, MET=metabolic rate, Icl=clothing insulation, MRT=mean radiant temperature, T=air temperature, RH=relative humidity.

The influencing factors on the PMV according to EN15251 standard include environmental factors (air temperature, mean radiant temperature, air speed and humidity) and occupant-related factors (metabolic rate and clothing level). Since mean radiant temperature was not measured in the case studies, it was assumed equal to the indoor air temperature. Also air speed was not directly measured in the case studies, but was assumed based on survey answers. If respondents perceived air movement around them, the air speed was set to 0.2 m/s, in other cases without perceived drafts, the air speed was set to 0.1 m/s.

To take into account individual perceptions of the thermal environment of different occupants, thermal comfort attitudes (TCAs) were introduced that were defined as the numerical difference between the calculated PMV values and thermal sensation vote provided by the individual respondents under the same environmental conditions. Hence, if the TCA < 0, then respondents felt colder with respect to the sensation vote calculated according to EN15251; on the other hand, if TCA > 0, then respondents felt warmer than the sensation vote calculated according to the same standard. These values were assumed to be constant throughout the analyses. In case of 2-person households, the average value of TCAs was considered.

Individual preferences

The individual preferences of occupants were elicited by asking them how much they agreed or disagreed with comparative statements. In particular, the aim was to identify preferences in terms of thermal comfort (TC), indoor air quality (IAQ) and energy savings (SAV). For this analysis, we considered the responses to the following statements related to window control behaviour (originally in Danish language):

- Statement 1 (TC-IAQ): "When it is cold outside, I would rather feel a little cold to get some fresh air";
- Statement 2 (TC-SAV): "I would rather feel a little cold in order to save on the heating bill";
- Statement 3 (IAQ-SAV): "I can accept a slightly bad indoor air quality in order to save the heating bill".

The respondents could indicate their opinion around these statements on a continuous 5-point scale (from "I strongly disagree" to "I strongly agree").

Based on these statements, the preference of each occupant (PREF) can assume three states: TC (respondent's priority is thermal comfort), IAQ (respondent's priority is indoor air quality), and SAV (respondent's priority is saving on heating bill). The state of PREF was defined by:

- PREF=IAQ if S1 was in agreement and S3 was in disagreement;
- PREF=TC if S1 and S2 were in disagreement;
- PREF=SAV if S2 and S3 were in agreement;

where Sn is the number of the statement.

4.3 Key findings

4.3.1 Thermal comfort attitudes and individual preferences

Thermal comfort attitudes

Figure 4.3-1 summarises the calculated TCA values for the respondents at the moment of the compilation of the survey.

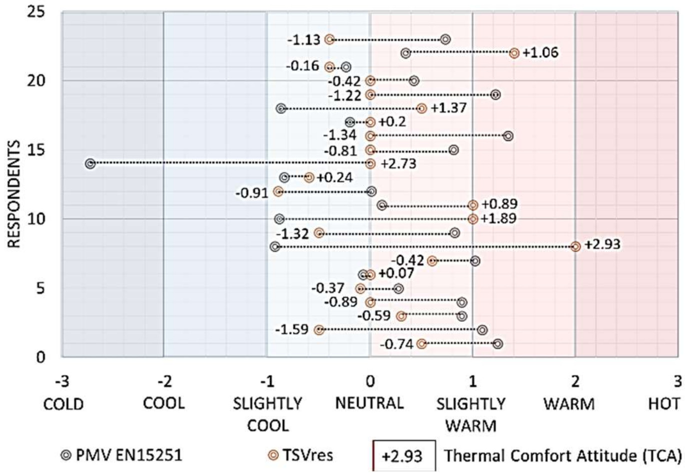


Figure 4.3-1. Definition of TCAs of 23 respondents in 14 households.

Individual preferences

As shown in Figure 4.3-2, 70% of the respondents preferred to have good indoor air quality and feel a little bit cold, while the priority of 17% of the respondents was to have adequate thermal comfort conditions. At least 87% of the respondents preferred to have a pleasant thermal environment and an adequate indoor air quality, rather than saving on the heating bill (Figure 4.3-3 and Figure 4.3-4). This procedure allowed classifying the households according to their preferences. In particular, 71% of the households were classified as PREF=IAQ, 22% as PREF=TC, and only 7% as PREF=SAV.

Figure 4.3-2. Statement 1 (TC - IAQ).

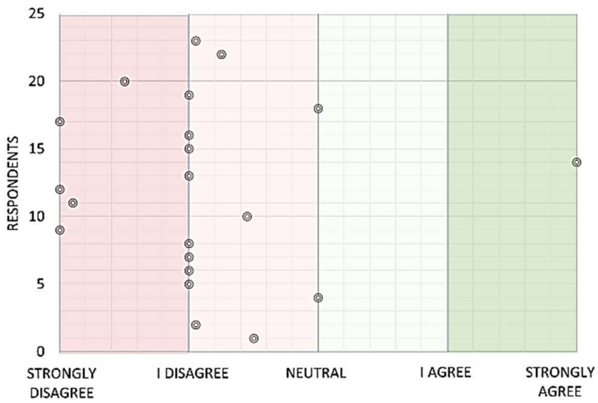


Figure 4.3-3. Statement 2 (TC-SAV).

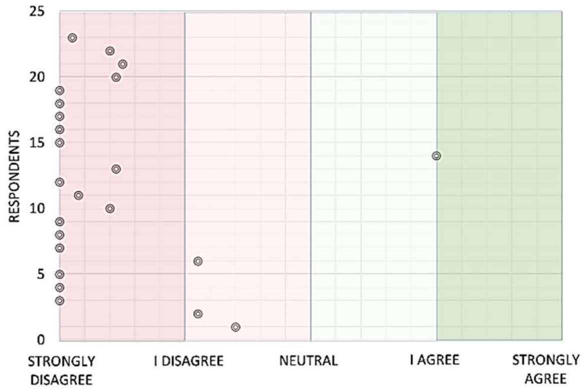


Figure 4.3-4. Statement 3 (IAQ-SAV).

4.3.2 A "personalized" BN model

This section proposes the results of the BN modelling procedure that investigated relationships between window opening behaviour and (i) a set of "common" environmental and time-related drivers (indoor temperature, relative humidity, and CO_2 concentration, outdoor temperature, time of the day), and (ii) individual characteristics of the occupants in terms of thermal comfort attitude and preferences. Figure 4.3-5 depicts the naïve (only one class node) bottom-up model that allows for treating mixed data in the same network and avoiding loss of information that usually occurs when discretizing continuous variables. Table 4.3-1 summarises the arc strengths between the target and explanatory variables. This analysis showed that the strongest probabilistic dependencies were found between window opening actions and preferences, thermal comfort attitude, indoor relative humidity, and indoor CO_2 concentration. The strong relationship between window opening behaviour and relative humidity might be explained by cooking activities in open-plan living rooms.

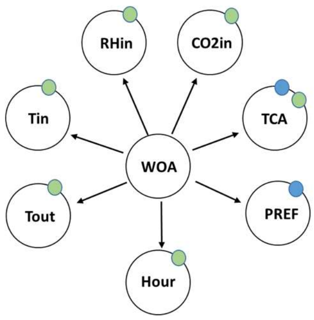


Figure 4.3-5. Bottom-up BN model for modelling window opening actions (WOA) - green dots refer to field measurements while blue dots refer to survey-based information.

Table 4.3-1. Arc strengths.

N°arc	from	to	arc strength
1	WOA	PREF	-151.90
2	WOA	TCA	-125.63
3	WOA	RHin	-99.56
4	WOA	CO2in	-95.55
5	WOA	Hour	-18.62
6	WOA	Tout	-4.63
7	WOA	Tin	-1.24

The BN model was inferred to define probabilities of a window opening action given the single explanatory variables. The outcomes of the queries can be summarised as follows:

- Environmental variables: in line with existing literature, the results indicate that the probability of opening a window increases in correspondence of a higher CO2 concentration, indoor air temperature, and outdoor air temperature (Figure 4.3-6);
- Time-related factors: the probability of opening a window increased from the early morning hours to noon, and then decreased again until the late evening hours (Figure 4.3-7);
- Preferences: the results show that the probability of opening a window is very reduced in households that were classified with a “TC” preference, or rather the priority to maintain adequate thermal comfort conditions (Figure 4.3-8);
- Thermal comfort attitudes: interestingly, the outcomes of this analysis clearly shows that the probability of a window opening action increases with higher thermal comfort attitude values (Figure 4.3-9). This means that the window is more likely to be opened if during the compilation of the survey, the respondents indicated higher thermal sensation votes (felt warmer) with respect to the ones calculated according to Standard EN15251.

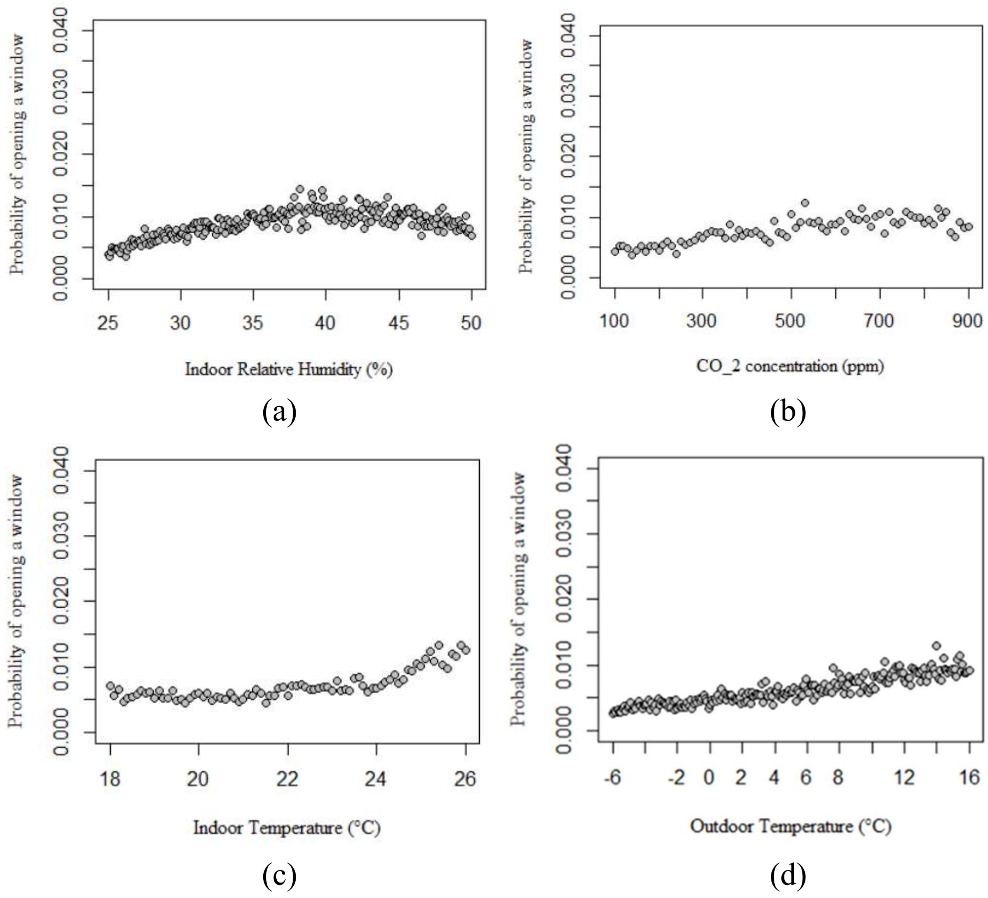


Figure 4.3-6. Probability of opening a window given (a) indoor relative humidity, (b) CO2 concentration, (c) indoor air temperature, and (d) outdoor air temperature.

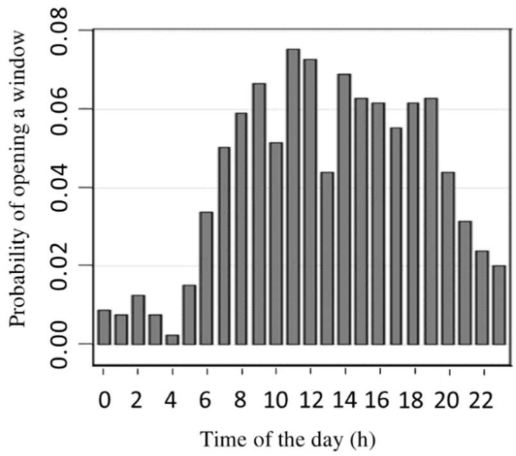


Figure 4.3-7. Probability of opening a window given the time of the day.

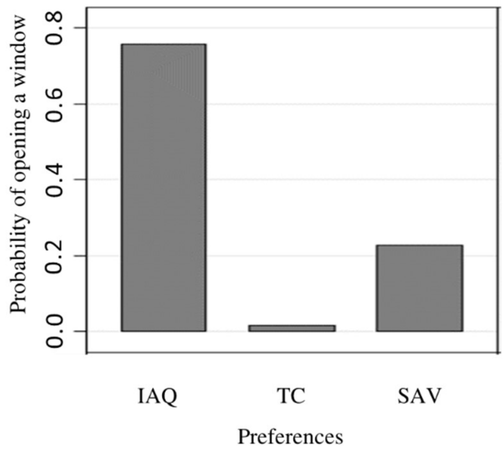


Figure 4.3-8. Probability of opening a window given preferences in terms of indoor air quality (IAQ), thermal comfort (TC), and energy cost savings (SAV).

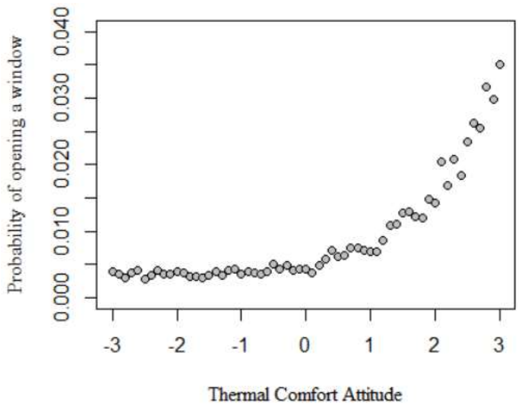


Figure 4.3-9. Probability of opening a window given the Thermal Comfort Attitude (TCA).

4.4 Discussion and further investigations

4.4.1 Towards a comprehensive hierarchical BN model: a first approach

In this study, a naïve Bayesian network (only one class node) is proposed to capture probabilistic dependencies among environmental, time-related and individual drivers that influence window control behaviour. In order to fully exploit the capabilities of the Bayesian Network approach, it is possible to further extend the model to explore (i) other interdisciplinary drivers (e.g. social or economic factors), (ii) other control actions (e.g. thermostat control, window blinds adjustment, light switching), or (iii) the capability of the network to structure influencing factors in a hierarchical manner. As an example, we found that in this case study the thermal comfort attitude (TCA) was linked to individual physiological characteristics of the respondents, such as age, weight, and height. This was done by developing a Bayesian Network as shown in Figure 4.4-1. The probabilistic queries of this BN model are shown in Figure 4.4-2 and investigated the probability that the respondents' thermal comfort attitude was less than 0, or rather the probability of feeling colder with respect to values calculated with Standard EN15251. The results show that the respondents felt colder than the calculated PMV values with increasing age, lower weight, and lower height. No significant differences were found for the gender. Further work will include the exploration of "sub-networks" that can be integrated in the existing network to create one extensive and hierarchical model.

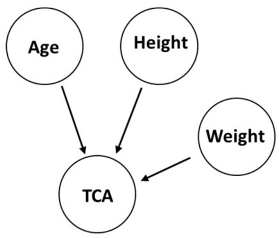
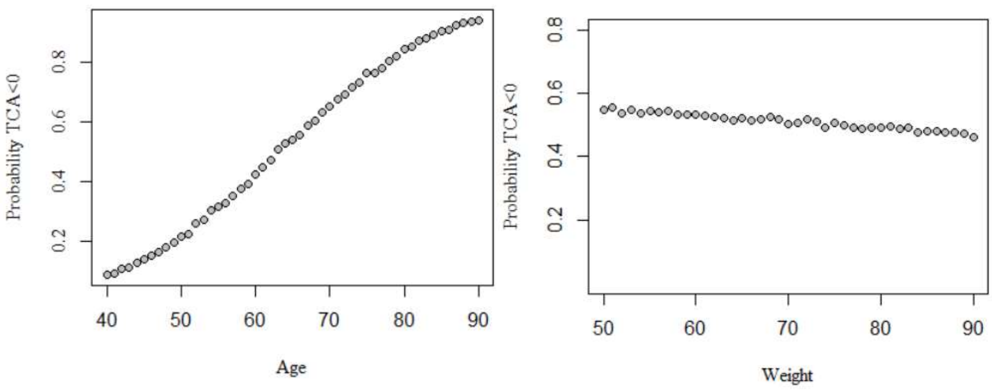
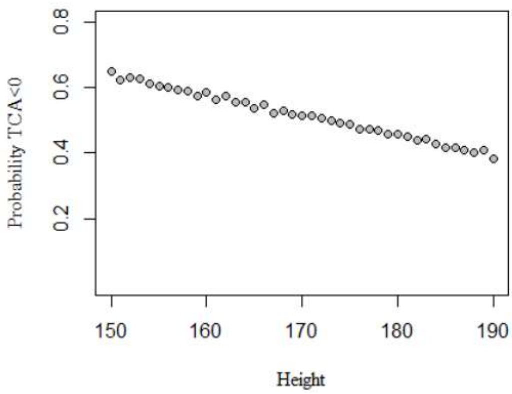


Figure 4.4-1. BN model for exploring probabilistic dependencies between TCA (target) and physiological characteristics of the occupants.



(a) (b)



(c)

Figure 4.4-2. Probability that TCA<0 (respondents feel colder with respect to the PMV) given (a) age, (b) weight, and (c) height.

Figure 4.4-3 shows a preliminary example of how the BN structure shown in Figure 4.4-1 could be extended to include a more extensive set of drivers and target variables.

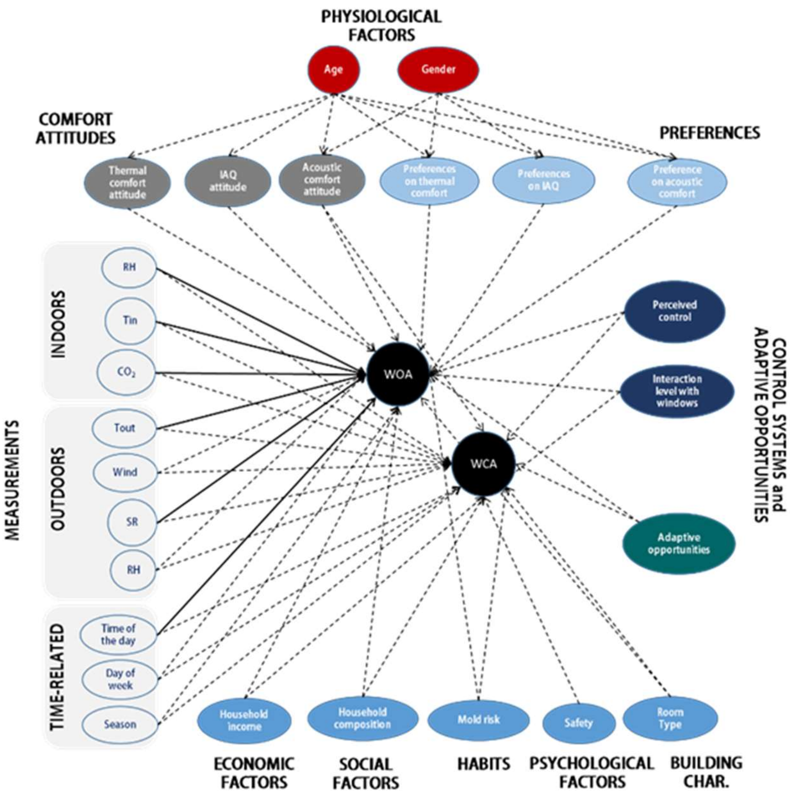


Figure 4.4-3. Preliminary proposal for further exploration: Example of an extensive BN model for window control behaviour. Further investigation is needed for variable selection and definition of connections between variables.

4.4.2 Cross-country survey investigation on human-building interaction in offices

A further investigation was conducted within the Annex 66 framework with the aim to assess contextual and behavioural factors driving occupants' interaction with building and systems in offices across different countries. First outcomes were presented in the context of three different Mediterranean climates in Italy – in Turin (Northern climate), Perugia (Central climate), and Rende (Southern climate) **(PAPER X)**. The survey instrument was grounded in an interdisciplinary framework that bridges the gap between building physics and social science environments on the energy- and comfort-related human-building interaction in the workspace. Outcomes of the survey questionnaire provide insights into four key learning objectives: (1) individual occupant's motivational drivers regarding interaction with shared building environmental controls (such as adjustable thermostats, operable windows, blinds and shades, and artificial lighting), (2) group dynamics such as perceived social norms, attitudes, and intention to share controls, (3) occupant perception of the ease of use and knowledge of how to operate control systems, and (4) occupant-perceived comfort, satisfaction, and productivity. This study attempted to identify climatic, cultural, and socio-demographic influencing factors, as well as to establish the validity of the survey instrument and robustness of outcomes for future studies. Also, the study aimed at illustrating why and how social science insights can bring innovative knowledge into the adoption of building technologies in shared contexts, thus enhancing perceived environmental satisfaction and effectiveness of personal indoor climate control in office settings and impacting office workers' productivity and reduced operational energy costs.

4.5 Perspectives and future challenges

In this chapter a BN-based modelling procedure for window control behaviour was proposed that included not only environmental and time-related factors, but also a preliminary set of individual characteristics of the respondents, such as thermal comfort attitude and preferences. The study was based on a combination of field measurement and survey-based investigations in 14 Danish town houses. In this case study, the outcomes revealed significant probabilistic dependencies between individual thermal comfort attitudes and window control behaviour. This exploration highlighted that the Bayesian network framework represents a powerful approach towards a more comprehensive model of occupant behaviour. However, as outlined in Chapter 3, further investigation is needed in order to fully exploit the potential of this framework by adding even a larger number of potential drivers in a hierarchical BN structure. It is worth noting key challenges and aspects for the model construction. To reduce the complexity of a final model, it is necessary to select a reduced set of key explanatory variables by means of a preliminary survey analysis or additional statistical analysis (e.g. Kolmogorov-Smirnov test). For example, the preliminary survey analysis showed that a number of variables could be excluded from the model, such as window control behaviour related to pets or smoking behaviour (almost all survey respondents did not report any habits related to these aspects). Also, further analysis on the relationship between influencing factors and aggregated window control behaviour data (e.g. total number of window openings/closings) might provide a first idea on important explanatory variables.

In practice, it is challenging to collect survey-based information at finer time resolution as field measurements. In this case study, survey-based information is collected once at a specific time step during the heating period, while field measurements were collected in increments of minutes during a full year. It is therefore necessary to assume survey responses (e.g. comfort attitudes, preferences and habits) constant during the data collection period. Based on this assumption, thermal comfort attitudes (TCA) were defined by comparing thermal sensation votes at the time of response to the PMV calculated by standard EN15251 at the measured environmental conditions.

In Chapter 3, and in line with other studies (Andersen et al., 2013), it is highlighted that window control action is more suitable as a target variable to model window control behaviour than the window open/close state. Indoor environment variables such as indoor CO_2 concentration level and indoor temperature were identified as key variables that change the window state, but at the same time, the indoor environment conditions are directly influenced immediately after a window control action takes place. Hence, when the window state is used as a target variable, indoor environment variables as predictors may not correctly represent relationships between the indoor variables and window control behaviour. A next step is developing an extended Bayesian Network based on the proposed theoretical model with **multiple target layers**, such as window opening action (WOA) and window closing action (WCO). Further work to develop **a comprehensive model for predicting major control actions** (e.g., thermostat control, window blinds control or light switching) will depend on **comprehensive monitoring campaigns** that permit to collect data on a range of control actions altogether. Setting up such comprehensive monitoring campaigns is very difficult and hardly possible on a large scale. At the time-being, the outcomes of stochastic models are very valuable to gain a better understanding on the human-building interaction, but mostly are based on relatively small samples. The definition and implementation of **reliable and affordable ways to collect large-scale occupant behaviour data** remains a challenging task and will be addressed in the next Chapter.

4.6 Publications

PAPER VIII **Barthelmes, V.M.,** Andersen, R.K., Heo, Y., Knudsen, H., Fabi, V., Corgnati, S.P. (2018). Introducing thermal comfort attitudes, psychological, social and contextual drivers in occupant behaviour modelling with Bayesian Networks. In: Proceedings of the 10th Windsor conference (Rethinking Comfort) 2018, 12-15 April, Windsor, UK, pp. 1003-1019.

PAPER IX **Barthelmes, V.M.**, Heo, Y., Andersen, R.K., Fabi, V., Corgnati, S.P. (2018). Towards A Comprehensive Model Of Window Control Behaviour: A Survey-based Investigation On Interdisciplinary Drivers In Danish Dwellings. In: Proceedings of the 4th Building Simulation and Optimization Conference (BSO 2018), 11-12 September, Cambridge, UK, pp. 649-656.

PAPER X D'Oca, S., Pisello, A.L., De Simone, M., **Barthelmes, V.M**., Hong, T., Corgnati, S.P. (2018). Human-building interaction at work: Findings from an interdisciplinary cross-country survey in Italy, *Building and Environment* 132, pp. 147-159.

Chapter 5

Modelling Time Use Survey (TUS) data for OB profiling

5.1 Overview

Chapter 3 and 4 focused on the development of stochastic occupant behaviour models based on collected data in selected case studies. The previous chapters outlined the necessity of extending the sample size of the data underlying the analysis in order to obtain results at a larger scale. In this context, the present study is aimed at providing a methodological framework for profiling occupant behaviour using large-scale surveys, or rather national Time Use Surveys (TUS). In general, TUS are statistical surveys aimed at reporting data on how, on average, people spend their time. The overall objective of these kinds of surveys is to identify, classify and quantify the main types of activities in which the respondents engage during a certain time period. TUS therefore represents a valuable resource for understanding occupants' energy-related daily activities and occupancy patterns that clearly shape the timing and magnitude of energy demand in households.

This study modelled data gathered in the diary-based Danish Time Use Survey (TUS) 2008/09 of 9640 individuals from 4679 households. Individuals' daily activities were logged in 10-min time increments for 24 h, starting and ending at 04:00, during both weekdays and weekends. The aims of this study were to (i) profile energy-related daily activities of occupants during different seasons and weekdays/weekends (ii) investigate time-related characteristics of activities such as starting and ending times and durations, and (iii) profile occupancy patterns for weekdays/weekends for different household types. The outcomes provide valuable input for building energy simulation for bridging the gap between simulated and real energy consumption in the Danish residential sector; typical occupancy profiles for different household types for different days of the week are freely available online (DTU Civil Engineering 2018). This chapter is aimed at contributing to the following research questions:

- Is TUS data a useful source for profiling OB on a large (national) scale?
- How can TUS questions be clustered into useful knowledge on OB (energy-related activities and occupancy)?
- How can this information be translated into enhanced input for building energy simulation?
- What are the outcomes (activity and occupancy profiling) in the Danish context?
- Do occupancy profiles based on the Danish TUS data differ from conventional profiles?

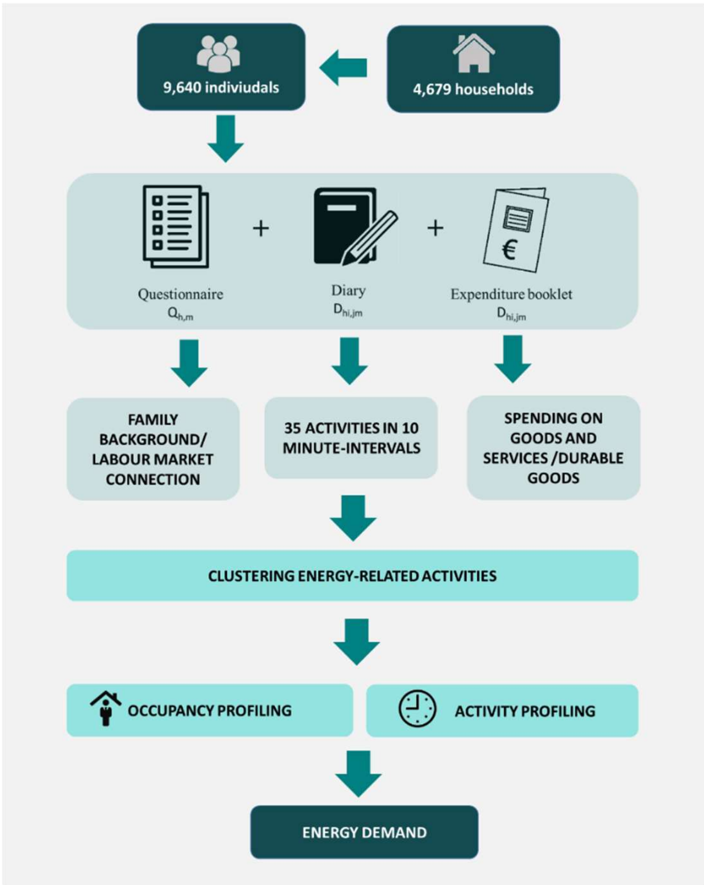


Figure 5.1-1. Overview Chapter 5.

5.2 Methodology

5.2.1 Survey Framework

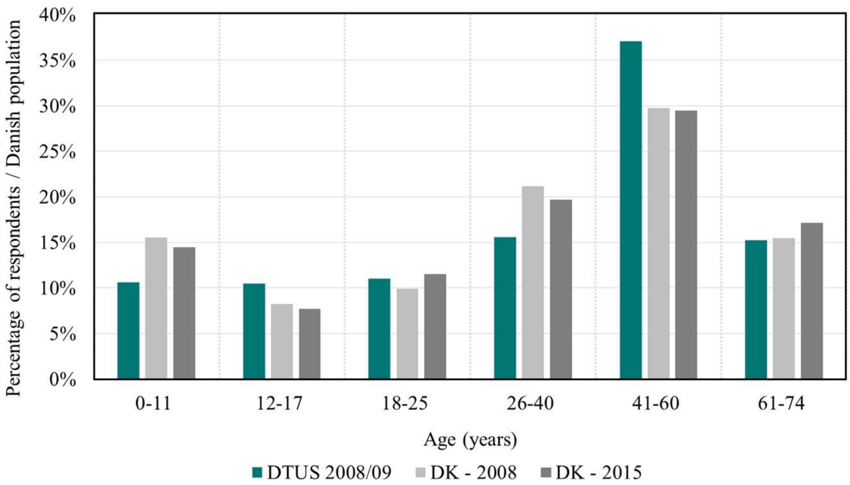
The analysis was based on the Danish TUS (2008/2009), which consisted of responses from 9,640 individuals from 4,679 households drawn randomly from a part of the Danish population aged between 18 and 74 years (Jens Bonke 2016). The questionnaire included 50 questions about general information on the respondents such as family background, incomes, and labour market connection. Respondents were asked to complete two forms for daily time use – one for a specific weekday and one for a specific weekend day. If respondents in the 18-74 age group had a spouse or cohabiting partner and/or children aged 12-17, the latter were also asked to complete the forms for time use. The main respondent of the family completed surveys for children under 12. Finally, a booklet with information about the previous month's spending on goods and services and about regular costs and durable goods bought within the previous year was filled out for all household members.

As shown in Figure 5.1-1, the Danish TUS included three different instruments: Q_{hm}; $D_{hi\ jm}$; E_{hm}, where Q is the questionnaire, D the diary, E the Booklet – expenditures for the household. Subscript h represents the household, i the individuals/household members, j the diary day – weekday or weekend day – and m the method used – telephone or web.

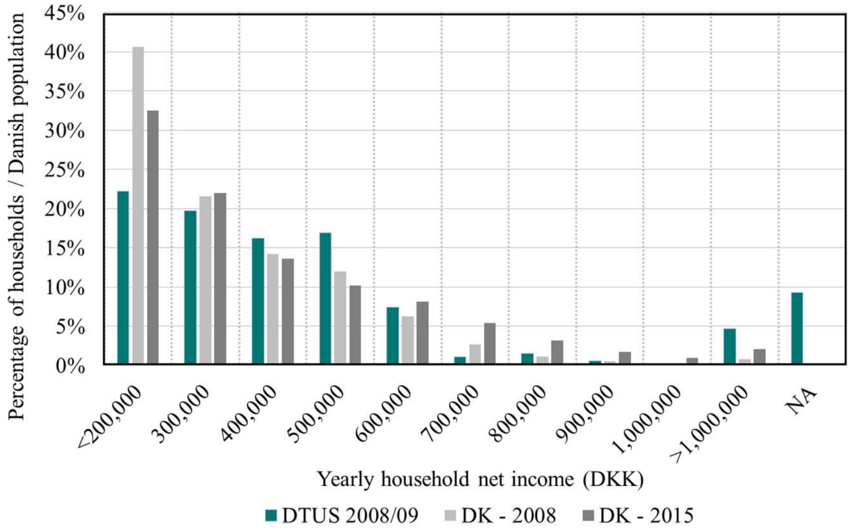
A pre-coding system for different types of activities was used in the diary for enabling the respondents to easily compile the TUS and to facilitate data analysis. The day was divided into 10-minute intervals (in total 144 intervals). The time spent on a given activity in the course of a day therefore becomes the sum of 10-minute sequences, where these activities occur. This was intended to ensure more consistent processing of the responses. Interviews were conducted at regular intervals over twelve months, covering the period of March 2008 to March 2009. A detailed description of the survey can be found in (J. Bonke 2002) and (Jens Bonke and Fallesen 2010) where the response rates and other information are specified.

5.2.2 Representativeness of the Danish TUS

This methodological step is aimed at providing a more detailed description of the main characteristics of the respondents in order to establish if the background information on respondents of the Danish TUS was comparable to national statistics. This pre-analysis was hence aimed at excluding significant sampling errors of the TUS sample with respect to the entire Danish population. In detail, the background information of the respondents collected in the questionnaire (Danish TUS 2008/09) was compared to the same type of statistical data available for research at the national level in 2008 (DK-2008) and 2015 (DK-2015)(Labour, income and wealth - Statistics Denmark n.d.). These two years were chosen for the comparison in order to provide a reference during the year in which the survey was compiled (2008) and to investigate whether the trend significantly changed in recent times (2015). In general, the age distribution of the respondents and the Danish population had a similar trend with a slight overrepresentation of 41–60 years old respondents (Figure 5.2-1a). Both amongst the respondents and in the Danish population, one- and two- member households were the most frequent, while a smaller fraction lived in households of three to six people (Figure 5.2-1b). There was a balanced gender ratio of 51% male to 49% female among the respondents. The trend in the surveyed yearly household net income (DKK) was slightly smoother than the trend of DK-2008, which clearly peaked at incomes lower than 200,000 DKK (Figure 5.2-1c). Nevertheless, the trends were comparable and the Danish TUS can be considered representative for the Danish population. In general, the highest percentage of the respondents was employees (27%) and students (16%). Both retired survey respondents and skilled workers represented 10% of the total respondents; all the other categories represented a lower percentage of the total sample size (Figure 5.2-2).



(a)



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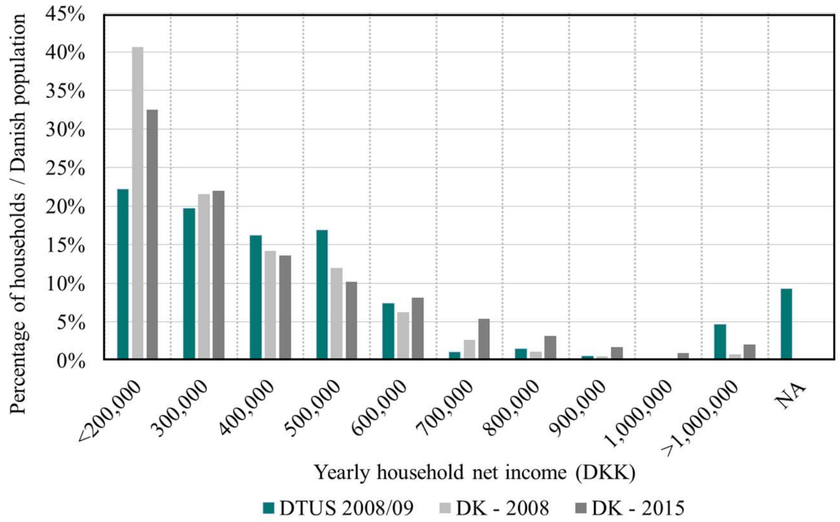


(c)

Figure 5.2-1. Danish TUS data (2008) compared to statistical data on Danish population (2008 and 2015): (a) age, (b) household composition, and (c) yearly household net income.

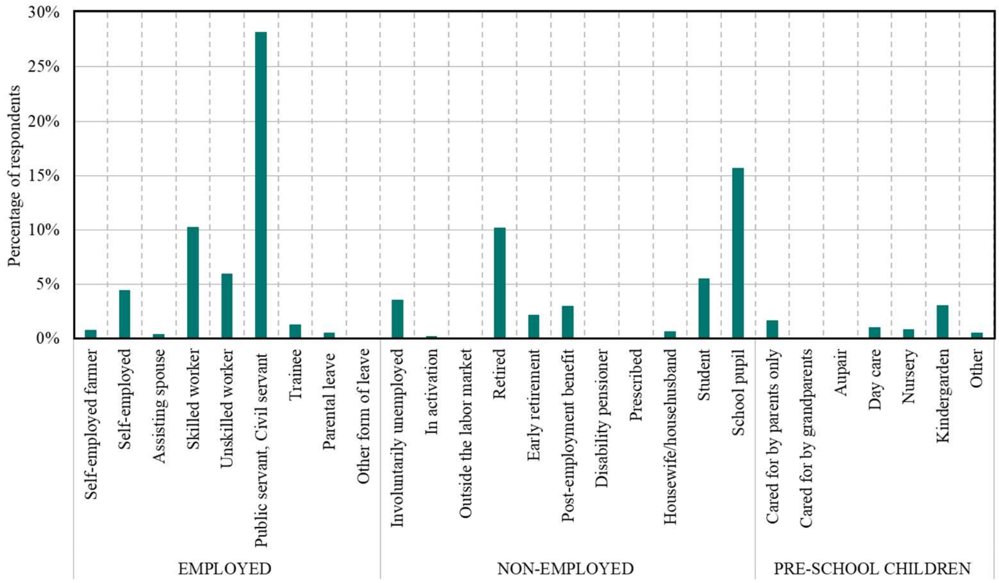


Figure 5.2-2. Work status of the survey respondents.

5.2.3 Profiling energy-related activities (i)

The Danish TUS framework pre-coded and included over 35 primary activities, which were selected by the respondents for describing in 10-minute intervals how they spent their day. In this study, the activities in the original survey framework were consolidated into a set of 10 energy- and occupancy-related activity clusters valuable for occupant behaviour analysis in the residential sector. The new set of 10 clustered activities is shown in Table 5.2-1. Since the focus of the study was to model occupant behaviour in dwellings, activities taking place outside the domestic environment were all placed in category: no. 9 “not at home”. Moreover, the definition of a category “not at home” allowed for development of detailed occupancy profiles (see section 5.2.5). Based on this updated set of activities, the first step of analysis consisted of shaping daily activity profiles of the building occupants throughout the day.

Table 5.2-1. Activity clustering.

No.	New clusters	Activities included in the Danish TUS 2008/09
1	Sleeping	Sleeping
2	Toilette	Toilette
3	Eating	Eating
4	Cooking/Washing dishes	Cooking/Washing dishes
5	Cleaning/Washing clothes	Cleaning/Washing clothes
6	Practical Work	Other work, do-it-yourself work, garden work
7	Family care/Free time	Child care, reading with children, family care, reading, hobby, social gathering, phone conversations
8	Relaxing/TV/IT	TV/radio/music, IT, relaxing
9	Not at home	Work, lunch break, transportation as part of work, transport to and from work education, education, transport to and from education, shopping, errands, visiting public offices, pick up/bring children, association activities, voluntary work and similar, exercise/sport, entertainment/culture, restaurant/café
10	Others	Others

5.2.4 Investigation on time-related factors (ii)

Distribution of activity durations

This methodological step is aimed at understanding typical durations of the identified energy-related activities throughout the day. The Kaplan-Meier estimate, which is a non-parametric method for describing the fraction of activities persisting for a certain amount of time (Kaplan and Meier 1958). The Kaplan-Meier estimate (Kishore et al. 2010) involves computing probabilities of occurrence of event after a certain amount of time. To create a survival curve that yielded the time durations of the activities, the survival probability was calculated for each activity according to Equation 5.1:

$$\hat{S}_t = \prod_{t_i \le t} \left(1 - \frac{d_i}{n_i}\right) \tag{5.1}$$

where S_t is the probability of survival at time t, d_i is the number of ceased activities at time t_i and n_i is the number of continued (surviving) activities at time t_i.

Transition states

A further analysis was aimed at investigating the starting and ending times of the activities during weekdays and weekends. For this, transition states (activity started, activity ended) were defined for eight activities and then accumulated on an hourly basis. Table 5.2-2 shows an example of transition states for activity 2. In this case, a survey respondent performed activity 2 for half an hour; the starting and the ending time of this activity were described by the transition states “activity started” and “activity ended”, respectively. Activity 9 (“not at home”) was analysed separately in section 5.2.5 regarding the definition of occupancy profiles and activity 10 (“others”) was not considered relevant for the analysis.

Table 5.2-2. Transition states of activity 2.

Time	Activity state (survey response)	Transition state “activity started”	Transition state “activity ended”
00:00	0	0	0
00:10	3	1	0
00:20	3	0	0
00:30	3	0	0
00:40	0	0	1
00:50	0	0	0

5.2.5 Occupancy patterns (iii)

The definition of representative occupancy profiles for the Danish residential sector during weekdays and weekends was addressed by analysis of the clustered activity 9 (“not at home”). Activity 9 provided information on when occupants were absent from home, while all the other activities took place in the domestic environment. A departure event occurred when activity 9 was started and a returning event occurred when activity 9 ended. In detail, activity 9 included activities performed outside the house.

The probability of leaving home (LH) and returning home (RH) in the next hour at a given time of day n was calculated according to Equations 5.2 and 5.3, respectively:

$$P(LH)(n) = \frac{Number\ of\ departure\ events\ \ at\ time\ step\ n}{Number\ of\ \ respondents\ at\ home\ at\ time\ step\ n-1} \tag{5.2}$$

$$P(RH)(n) = \frac{Number\ of\ returning\ events\ at\ time\ step\ n}{Number\ of\ respondents\ away\ from\ home\ at\ time\ step\ n-1} \tag{5.3}$$

5.3 Key findings

5.3.1 Shaping daily activity profiles (i)

The percentage of respondents carrying out each of the ten identified activities throughout the day is shown in Figure 5.3-1. Sleeping was clearly the dominant late evening – early morning activity with 90% of the survey respondents being asleep between 00:40 and 06:00. There were two evident peaks in “eating”, corresponding to lunchtime (ca.12:30) and, dinnertime (ca. 18:30). Two other large portions of the graph represent the activities “Not at home” (Activity 9) and “Relaxing/TV/IT” (Activity 8). The largest percentage of survey respondents were out of home around 11:20 and returned during the afternoon hours. A large percentage of respondents were at home during the whole or a large extent of the day. This might be due to the fact that Figure 3 was based on the same number of weekdays and weekend days during which respondents tended to stay home longer (see Figure 4). The full percentage of total respondents at each time step corresponds to 9,518-9,521 respondents for weekdays and from 9,607 to 9,640 respondents for weekends. As regards the activity related to relaxing and the use of TV and IT devices, a peak can be observed between 19:00 (after dinnertime) and 23:00. In particular, the identified patterns related to (a) cooking/washing dishes, (b) occupancy (at home/not at home) and (c) use of TV and IT devices provided valuable energy-related information with respect to occupant behaviour and its impact on building energy use.

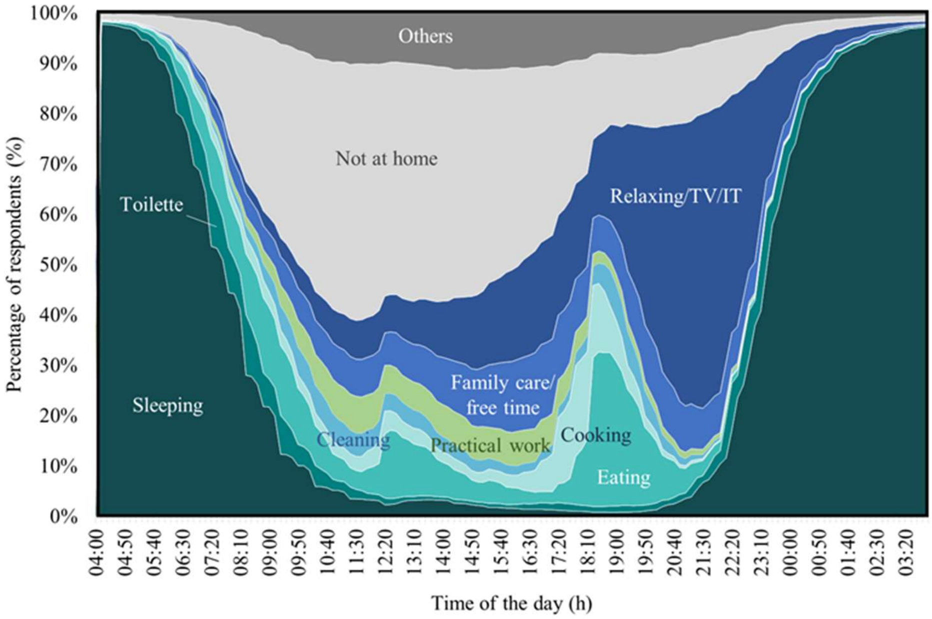


Figure 5.3-1. Daily activity profiles based on the Danish TUS 2008/2009 (all days).

It is important to highlight that Figure 5.3 1 combined all of the collected survey responses in one graph, without distinguishing activities with respect to different seasons of the year or different days of the week. Figure 5.3-2 compared the daily activity profiles during different seasons and on weekdays (WD) and weekends (WE). No noticeable differences were found respectively between the spring/autumn and the summer/winter period. As a consequence, Figure 5.3-2 only shows outcomes related to summer (June, July and August) and wintertime (November, December and January).

The key results of this analysis were:

- longer sleeping times during weekends (8h39m – 9h1m) with respect to weekdays (8h-8h17m);
- longer sleeping times in winter than in summer on both weekdays (8h17 and 8h, respectively) and weekends (9h1m and 8h39m, respectively);
- more time spent on practical and garden work in summer (43m-1h) than in winter (19-22m);
- more time spent out of home during weekdays (6h30m-6h41m) than on weekends (3h51m-4h9m);

- longer relaxing times on weekends (3h59m-4h14m) than on weekdays (3h6m-3h32m);
- small difference in time spent for toilette (ca.40m) and cooking/washing (ca.40m) for different seasons and/or day types;
- in broad-ranging activities, such as “not at home”, “others” or “relaxing/free time”, the values of standard deviation indicated high variability and spread of the data due to occupant diversity - while more specific activities, such as sleeping, eating or toilette were characterised by a lower variability among occupants.

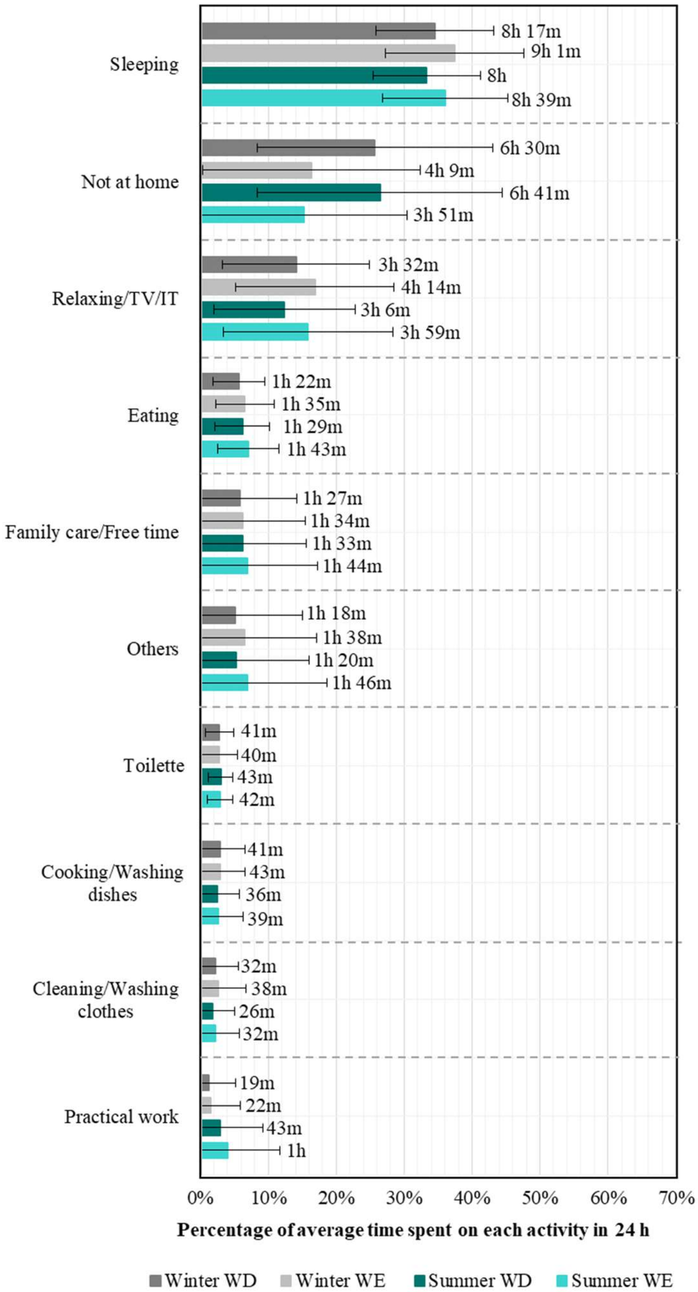


Figure 5.3-2. Daily time spent on the activities during summer and winter weekdays/weekends (±1 St. Dev.)

5.3.2 Time-related factors: Time durations and starting/ending times (ii)

Survival curves of activities' daily time durations

Figure 5.3-3 shows the probability that an activity survives for longer than a given period t once it has started. The longest time durations were linked to the sleeping activity. Around 90% of the respondents slept at least six hours in a row and 10% slept longer than 10 hours in a row. The second longest daily time durations were linked to activities away from home ("not at home"), this survival curve was less steep than the others, which reflected the large variety in duration of this activity throughout the day. The second longest activity performed at home, after sleeping, was relaxing and TV/IT usage. The activities with shortest durations were toilette, cooking/washing dishes, cleaning/washing clothes, and eating.

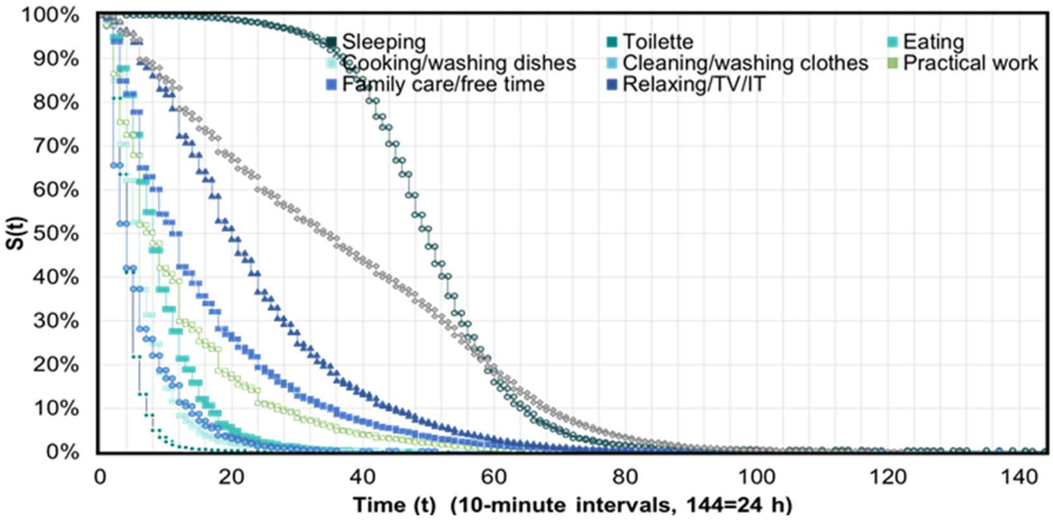


Figure 5.3-3. Survival functions for daily occupants' activities.

Starting/ending times of activities

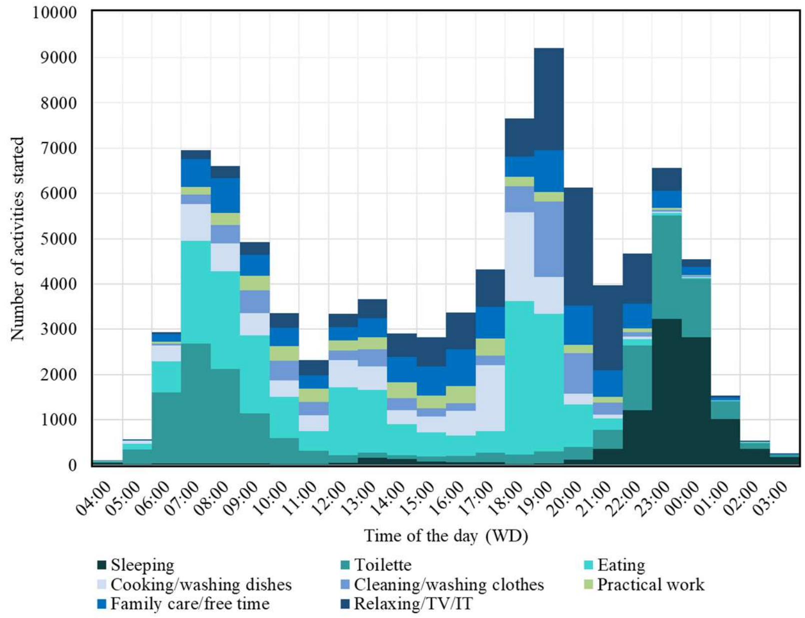
The number of activities started throughout the day is shown on an hourly basis in Figure 5.3-4 for a typical weekday (a) and weekend day (b), respectively. Figure 5.3-5 depicts when the same activities ended on a typical weekday (a) and weekend day (b). These graphs provided insights into the time dependency of the activities and highlighted the following key aspects:

- generally, there were three peak times for initiation of activities: morning hours (07:00-09:00), the late afternoon/early evening hours (18:00-20:00) and at bedtime (23:00);
- most survey respondents started their sleeping activity between 22:00 and 00:00 and ceased the activity between 06:00 and 10:00; moreover, both the onset and termination of sleeping activity was shifted later during weekend days;
- there were clear peak values for toilette use in the morning and evening hours in correspondence of the starting and ending time of the sleeping activity;

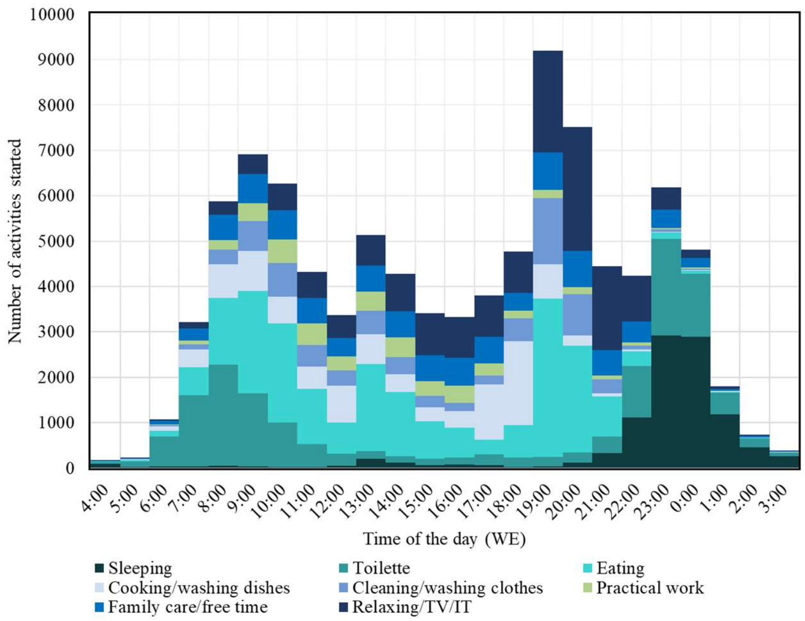
• as expected, the highest number of eating activities started and ended during breakfast (07:00-10:00), lunch (12:00-14:00) and dinnertime (18:00-20:00); cooking and washing dishes were also linked to these starting and ending times;

• activities related to relaxing and TV/IT usage began during the afternoon hours and reached the highest number of started activities in the evening hours (19:00-21:00); these activities mostly ended during the late evening hours (21:00-01:00);

• activities related to practical work and family care were not dependent on time of the day and starting/ending times were equally distributed throughout different hours of the day.



(a)



(b)

Figure 5.3-4. Number of activities started during (a) weekdays and (b) weekends.

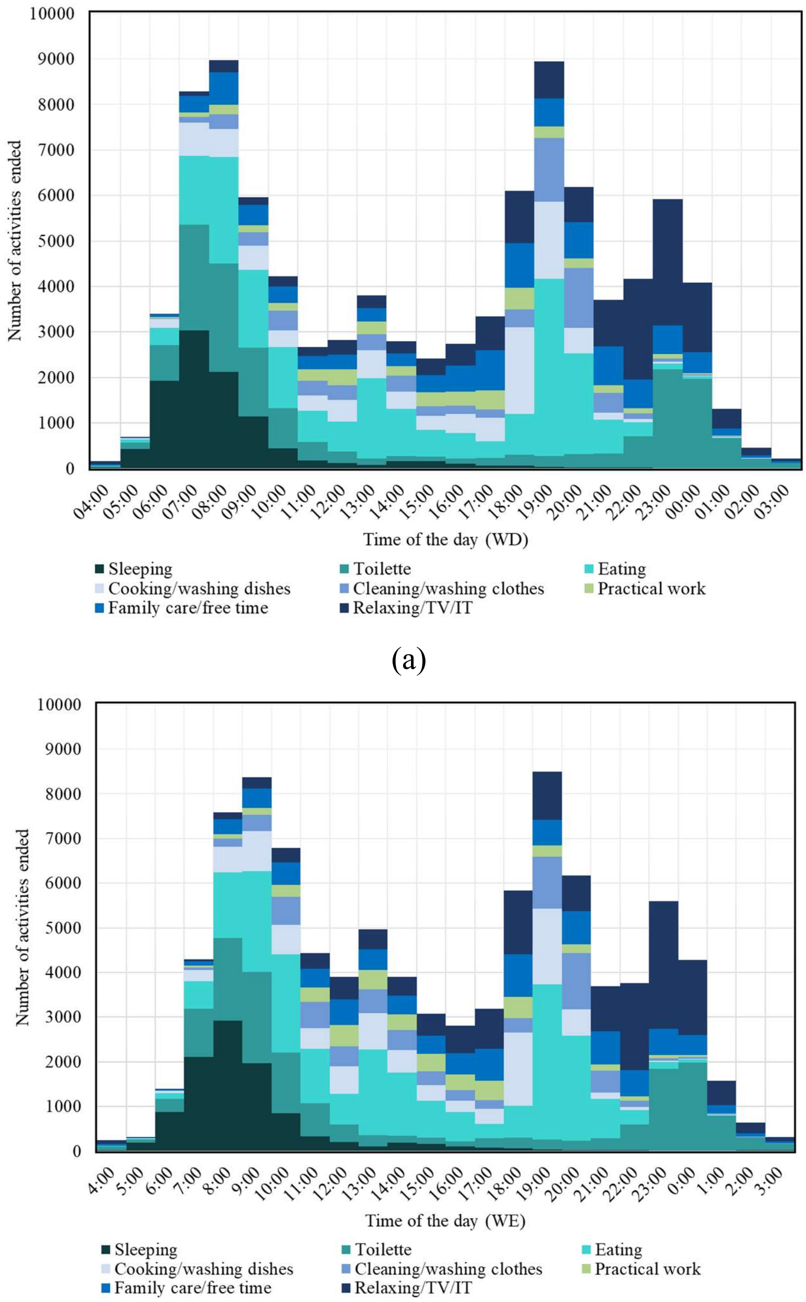


Figure 5.3-5. Number of activities ended during (a) weekdays and (b) weekends.

5.3.3 Occupancy profiling (iii)

The aim of this section is to gain a deeper knowledge on occupancy patterns in Danish households and to describe probabilities of occupancy related to state (probability of number of respondents at home) and transitions (probability of leaving/returning home). This information can be further elaborated for developing stochastic models aimed at capturing more accurately human presence in BEPS, and consequently contribute to reducing the gap between predicted and measured energy consumptions in the building sector. Figure 5.3-6 depicts the percentage of survey respondents at home throughout the day during weekends and weekdays. The highest percentage of respondents not at home occurred in the late morning hours, a small portion returned home at lunchtime, while most of the respondents came home during the late afternoon/evening hours. During the weekend, a larger fraction of the survey respondents were home compared to weekdays.

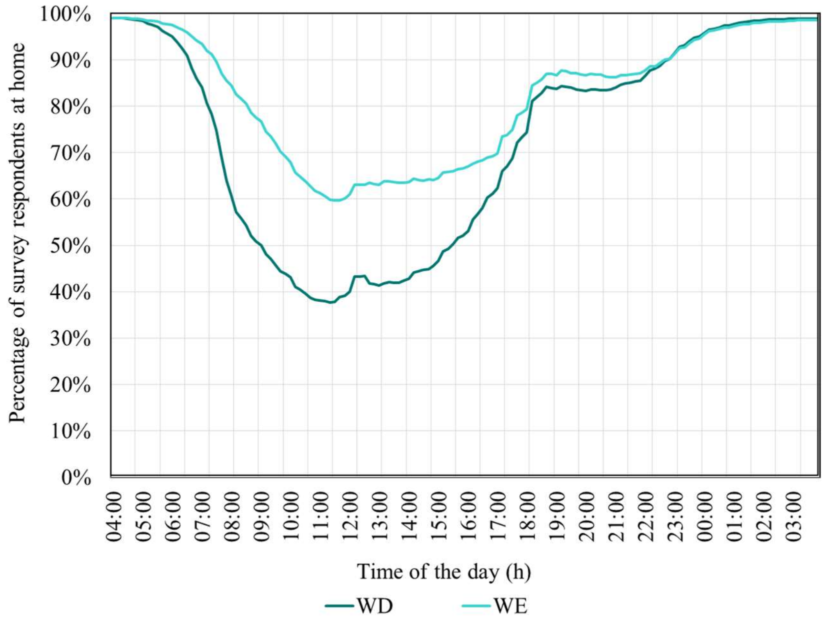
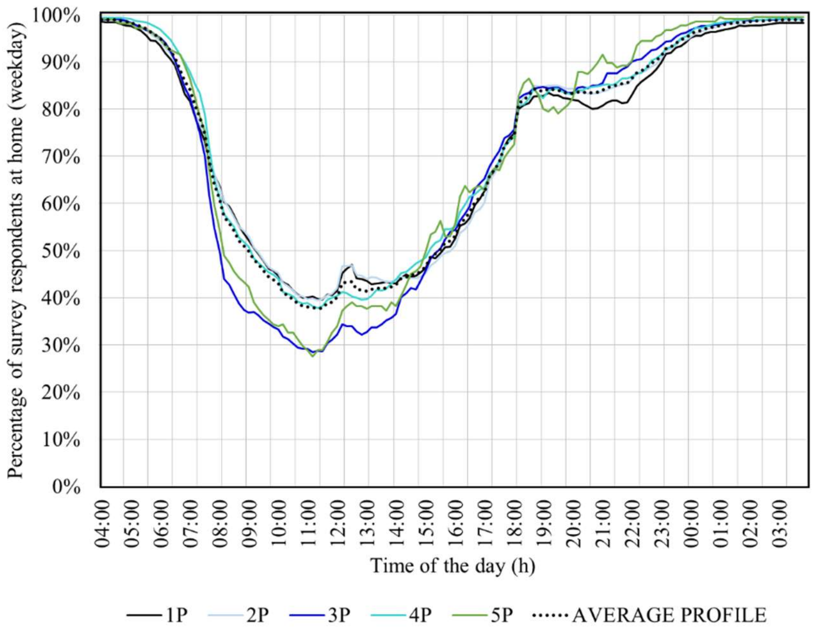


Figure 5.3-6. Occupancy patterns during weekdays (WD) and weekends (WE).

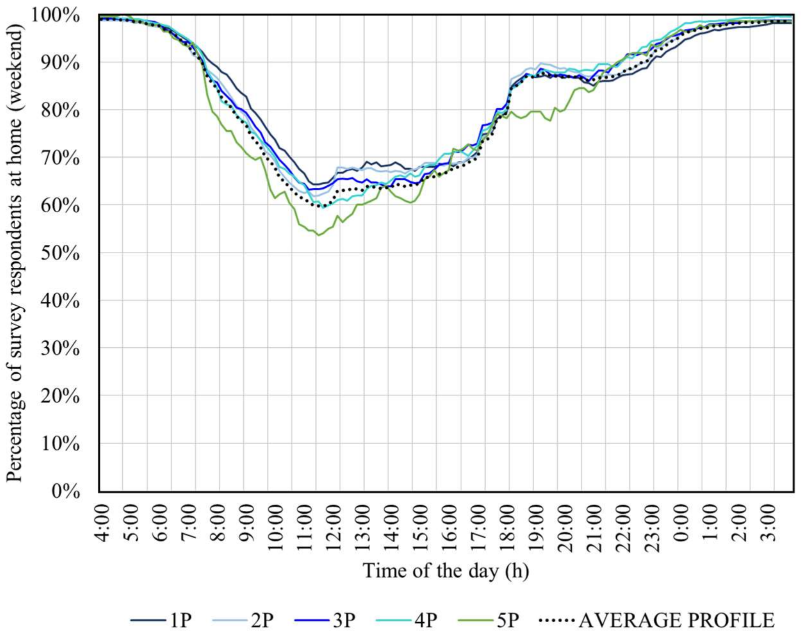
Figure 5.3-7 shows occupancy profiles during weekdays (a) and weekends (b) for different sized households. The percentage of survey respondents at home was referenced to the number of household members in each category. For example, in a 2P household 100% meant that 2 persons were at home and in a 3P household 100% meant that 3 persons were at home. Figure 5.3-8 depicts the probability of leaving (a) and returning to the home (b) within the next hour during weekdays and weekend days, respectively. The probability of leaving home was highest in the morning (06:00-08:00) and early afternoon hours (12:00-13:00). The probability of returning home was highest during lunchtime (11:00-13:00), dinnertime (16:00-18:00) and late evening (22:00-24:00). The probabilities of departure and arrival were calculated as the fraction of the total number of arrival or departure events at a time step and the number of respondents that were at home or away from home in the previous time step, respectively (Equation 2 and 3).

The probability of leaving home is characterised by less evident peak values during weekends than during weekdays (Figure 5.3-8a), while there were less difference in the peaks for the returning hours during weekdays and weekends (Figure 5.3-8b). Aggregated hourly data was used for this analysis to overcome inconsistencies in data trends at higher time resolutions (10-minute intervals) due to the tendency of survey respondents' to report the start or the end of activities at the full hour or half hour.

The levels of occupation were further analysed for different household types with different numbers of household members (from single-person households to 4-person households), and different types of day. To gain a better overview, a spectrum of occupancy profiles shows the level of occupation in 150 randomly-chosen households for each household type during weekdays (Figure 5.3-9a) and weekends (Figure 5.3-9b). This analysis clearly highlighted a higher occupant density and a more irregular spectrum during weekends with respect to weekdays. The tendency of respondents to leave home earlier during weekdays than on weekends is also clearly readable in the spectrums. A growing density of occupancy can be observed with an increasing number of household members. This analysis allowed for profiling individual occupancy patterns based on household type and day type, which can be directly implemented in BEPS by interested researchers or professionals. **To facilitate the applicability of the outcomes of this study in building energy simulation programs, individual occupancy profiles for different household compositions and types of day (weekday/weekend) have been made freely available online** (DTU Civil Engineering 2018)**.**

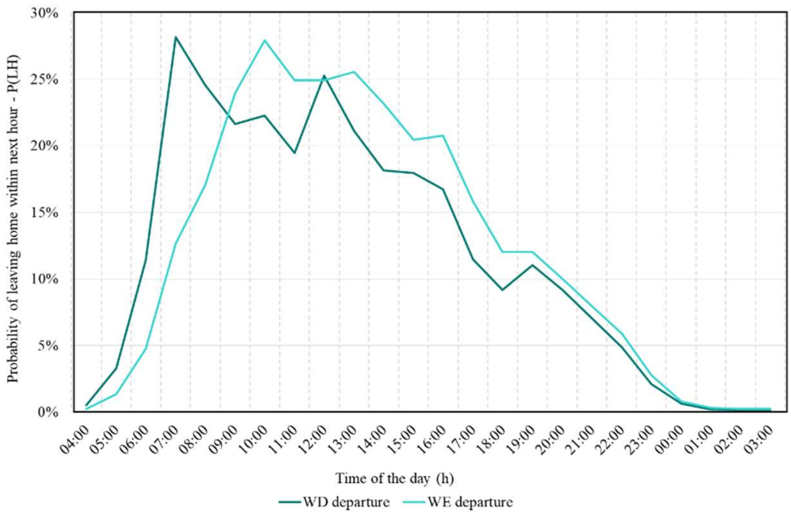


(a)

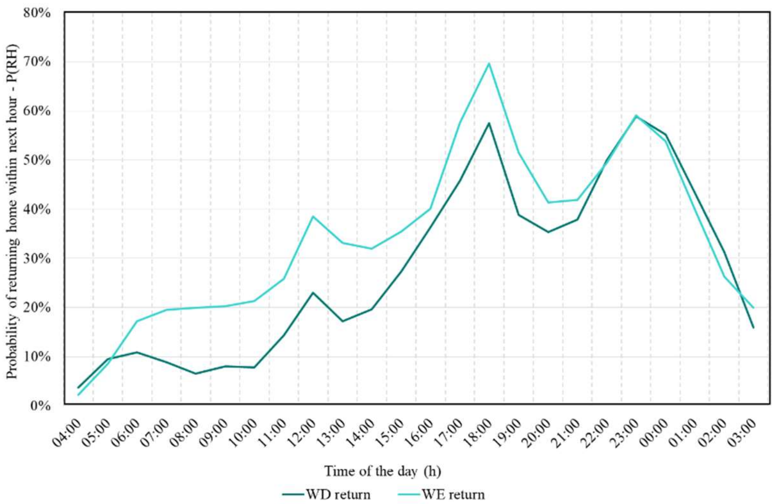


(b)

*Figure 5.3-7. Occupancy patterns for different household compositions (n*P=number of household members) during (a) weekdays and (b) weekends.*



(a)



(b)

Figure 5.3-8. Probability of (a) leaving home and (b) returning home during weekdays and weekends.

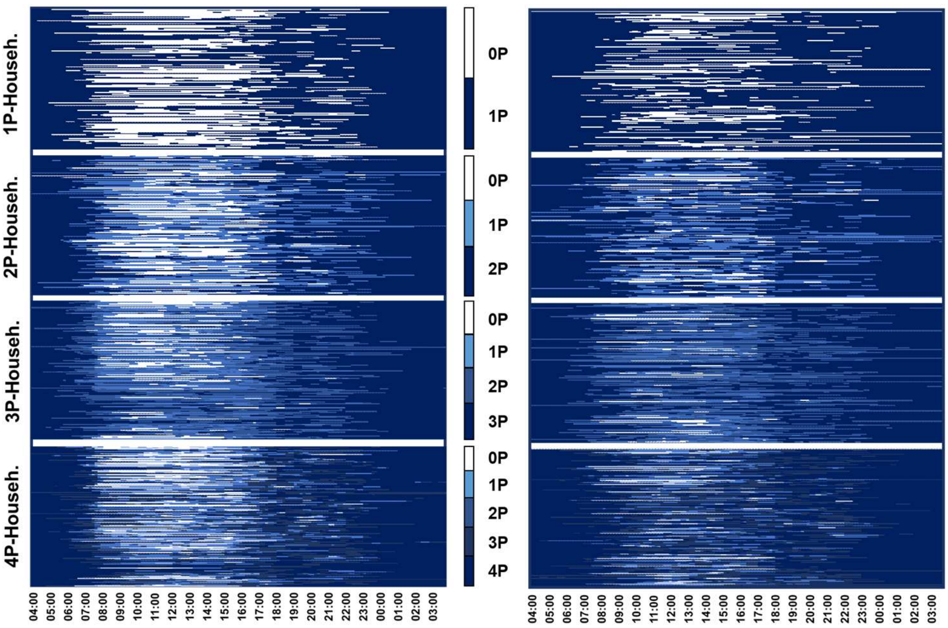


Figure 5.3-9. Spectrum of 150 randomly-chosen individual occupancy profiles of different household typologies during (a) weekdays and (b) weekends.

5.4 Discussion and further investigations

5.4.1 Applicability of the TUS data

Danish TUS-based daily activities vs. typical electric load profiles

The survey respondents and background information (with respect to, e.g., household composition, age range, yearly net income) of those who completed the DTUS 2008/2009 can be considered representative of the Danish population. To evaluate the applicability of TUS data for modelling occupant behaviour and related energy consumptions, it was necessary to determine whether the created activity profiles can be related to existing studies on electricity use trends in the residential sector. In line with this, the following supplementary analysis compared Activity 4 "cooking/washing dishes" (Figure 5.4-1), to typical hourly mean electric load profiles in Danish households during weekdays and weekends. The latter refers to the study of Marszal-Pomianowska et al. (2016) who developed a high-resolution model of household electricity use based upon a combination of measured and statistical data. Their study shows that typically there are two peaks during weekdays: a morning peak, which is caused by activities such as preparation of breakfast, morning toilette e.g. hair drying, and an evening peak, which reflects dinner preparation/cooking and evening entertainment, e.g. use of TV and/or PC. Furthermore, during weekends, the morning peak often moves to later morning hours due to longer sleep, and it is more flat. As depicted in Figure 5.4-1, similar trends was found from the analysis of the DTUS 2008/2009. These outcomes therefore confirmed that these activities could be related directly to the electricity loads in the households with an evident peak during dinnertime.

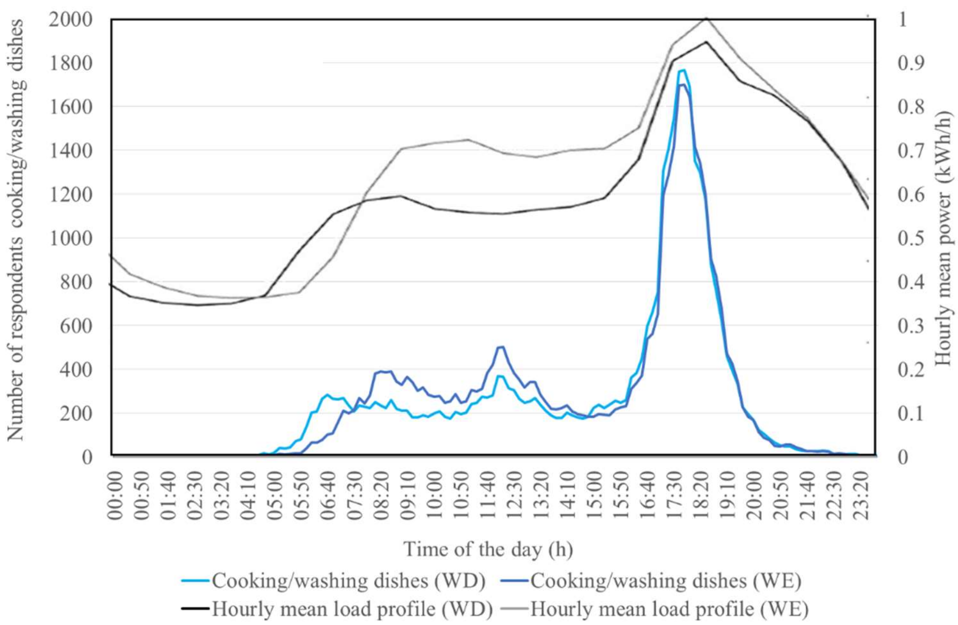


Figure 5.4-1. Number of survey respondents cooking/washing dishes during the day compared to hourly mean load profiles.

Danish TUS-based occupancy profiles vs. typical reference profiles

As mentioned previously, the definition of accurate occupancy profiles and their implementation in BEPS is crucial in order to predict building energy use more reliably. Developers of such tools tend to provide fixed predefined schedules that can be implemented when running simulations for other case studies. The U.S Department of Energy (DOE), for instance, developed reference buildings with predefined schedules for the EnergyPlus software (DOE 2017), such as schedules for occupancy, lighting use, electric equipment use, ventilation rates or heating and cooling set-points.

To the best knowledge of the authors, there are no existing studies presenting tailored approaches for modelling the presence of building occupants in Danish households. Therefore, the DTUS-based occupancy profile was compared with the occupancy profile provided by DOE. Figure 5.4-2 depicts their proposed occupancy profile for weekdays of a mid-rise apartment house (DOE 2018), which was compared with the occupancy profile obtained from this study. This graph indicates that there is a resemblance between the DOE occupancy profile and the Danish TUS-based occupancy profile. As a consequence, the DOE profile could be implemented in energy simulation software to establish an approximation of average occupancy in Danish households. In cases where closer representation is needed, the average occupancy profiles from Figure 5.3-6 and Figure 5.3-7 could be used. The occupancy profiles are freely available online and can be used in cases where average profiles are not adequate and where it is important to represent the diversity in occupancy profiles in Danish households (DTU Civil Engineering 2018).

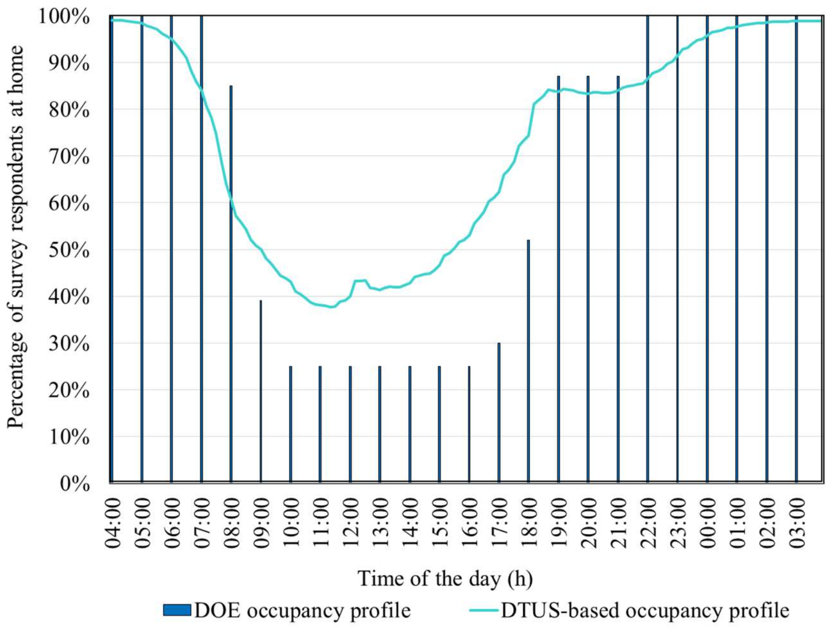


Figure 5.4-2. Comparison between the simplified DOE occupancy profile and the Danish TUS-based weekday occupancy profile.

Limitations of the TUS framework

However, it is necessary to acknowledge some limitations related to the application of the Danish TUS data to occupant behaviour profiling and modelling. These limitations are mainly attributable to the fact that most TUS frameworks are not specifically designed for energy-related research purposes. The TUS classification systems may not always reflect meaningful distinctions between specific activities of interest for the desired research task. To obtain a solid conceptual basis for the specific analytic endeavour, it is necessary to extract, transform and/or cluster useful information from the broad-ranging survey framework. The latter includes a large number of activities and sometimes does not allow for an unambiguous interpretation when it comes to the translation of general times use to specific energy-related activities. An important drawback of the Danish TUS framework is that it was not designed to capture simultaneous actions of the respondents (e.g. cooking and watching TV) since they could only report one activity at the time. It is also important to keep in mind that all the data collected in the diary was self-reported: occupants may have underreported or forgot to record some actions or they may have exaggerated the frequency of some of their actions. Respondents also tended to report new activities at the full or the half hour, which to some extent affected the reliability level of resolution of the data analysis when it comes to reporting starting and ending times of the activities. The Danish TUS data available to the authors were analysable only in aggregate form. It was thus not possible to explore other interesting predictors (e.g. job category, age) linked to individual diary entries.

5.4.2 Time Use in North Italian households: Investigation through ad-hoc surveys

In order to gain a better understanding on time use in the local context, the survey framework presented in Chapter 4 (see Annex A) was distributed to and answered by 453 respondents of households located in Northern Italy **(PAPER XIV)**. For shaping energy-related activities, the respondents were asked to report their activities performed at home during the last full day, choosing for every 15-minutes intervals among the proposed activities. This means that, while the responses of the Danish TUS had to be clustered into energy-related activities, here the latter could be directly investigated. This analysis therefore allows also for validating to some extent the effectiveness of the clustering procedure. However, unlike the Danish TUS data, it is necessary to highlight that the Italian sample cannot be considered representative for the wider Italian population, since the survey was compiled (online) mainly by respondents aged between 20 and 30 (60% of respondents). Indeed, further investigation is needed in order to extend the study to a more inclusive sample.

Similar to the results obtained based on the Danish TUS, in relation to weekdays activity profile (Figure 5.4-3a), sleeping was the dominant activity - 90% of the survey respondents were asleep between 2:30 and 6:00. During the weekdays the respondents have spent a significant portion of their time outside the home. Most of the respondents were not present at the home from 9:00 am to 18:30, however a part of respondents were back home during the lunch time (between 13:00 and 14:00). There are two evident peaks for „eating" activity during the lunch (around 13:30) and dinner time (around 20:30). It is possible to distinguish the peak for „TV/IT entertainment" activity in the evening hours- from 21:00 pm to 23:00 pm. The percentage of respondents who were doing „House cleaning/washing clothes" and „Practical work" activities were quite constant during all day.

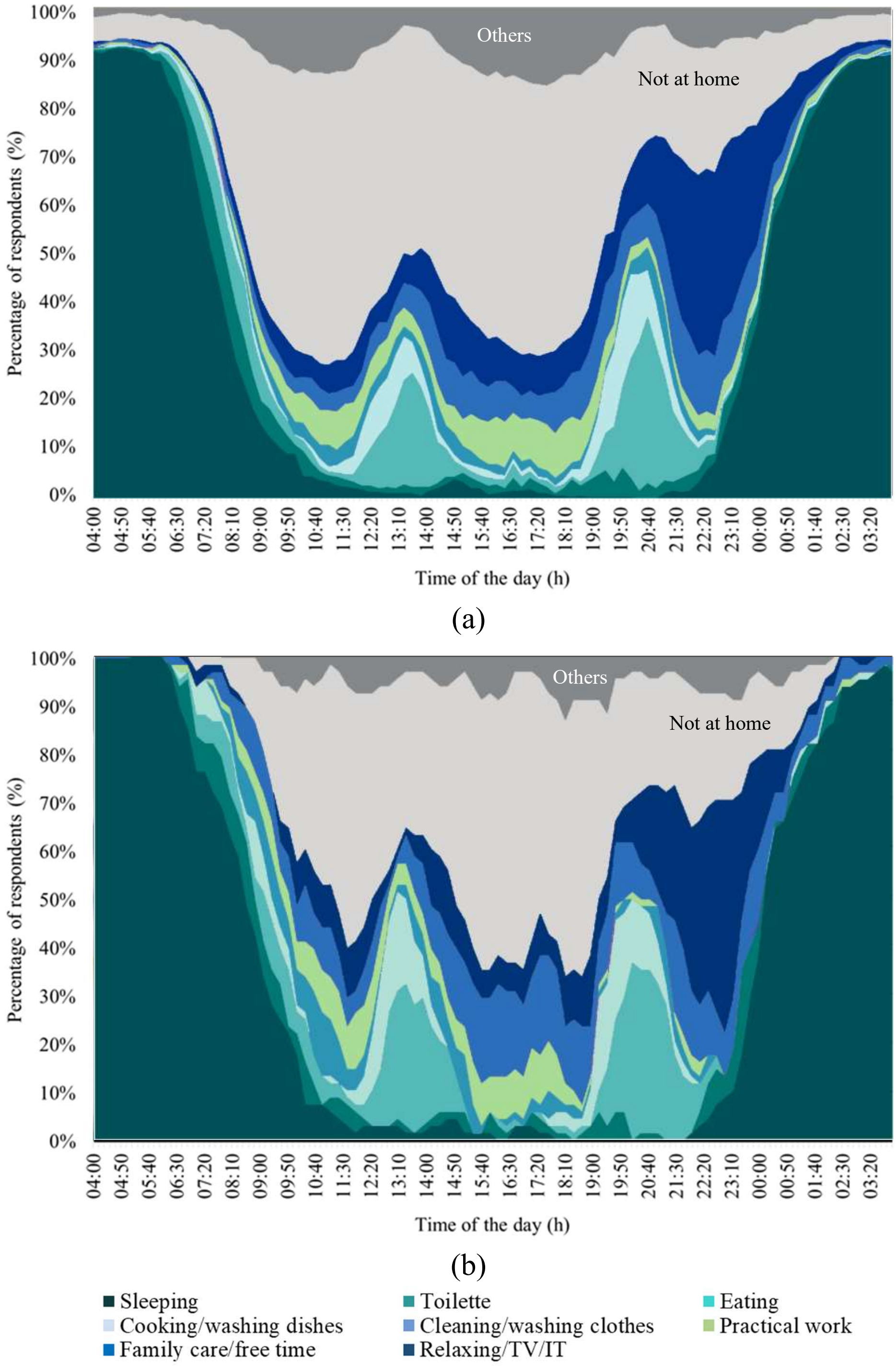


Figure 5.4-3. Daily activity profiles in investigated Italian households during (a) weekdays and (b) weekends (b).

In relation to weekend activity profile (Figure 5.4-3b), it is possible to notice that Danish and Italian respondents have spent much more time at home comparing to weekdays. The highest percentage of Italian respondents who were out of home (around 40 % of respondents) was at 11:30 and in the afternoon hours, from 15:30 to 19:00. The „sleeping" activity duration was slightly longer than during the weekdays - more than 90 % of respondents slept from 2:00 to 7:00. During the weekend the occupants spent much more time on „Free/family time" activity- with the highest peak in the afternoon, from 15:30 to 17:30. Similar to weekdays, there are two significant peaks for „Eating" activity- from 12:30 to 14:30 and from 19:30 to 21:30. During the weekend, the respondents spent slightly more time on „Cooking/washing dished activities" than during the weekends- there are two peaks in the lunch/dinner time- from 12:30 to 13:30 and from 19:30 to 20:30. For the „TV/IT entertainment" activity the respondents had similar preferences as during the weekdays- more than 30 % of occupants have spent their time watching TV or navigating internet from 21:30 to 23:00 pm. „House cleaning/washing clothes" and „Practical work" activities were distributed during the day and there are no significant peaks which could indicate the preferable time for those activities.

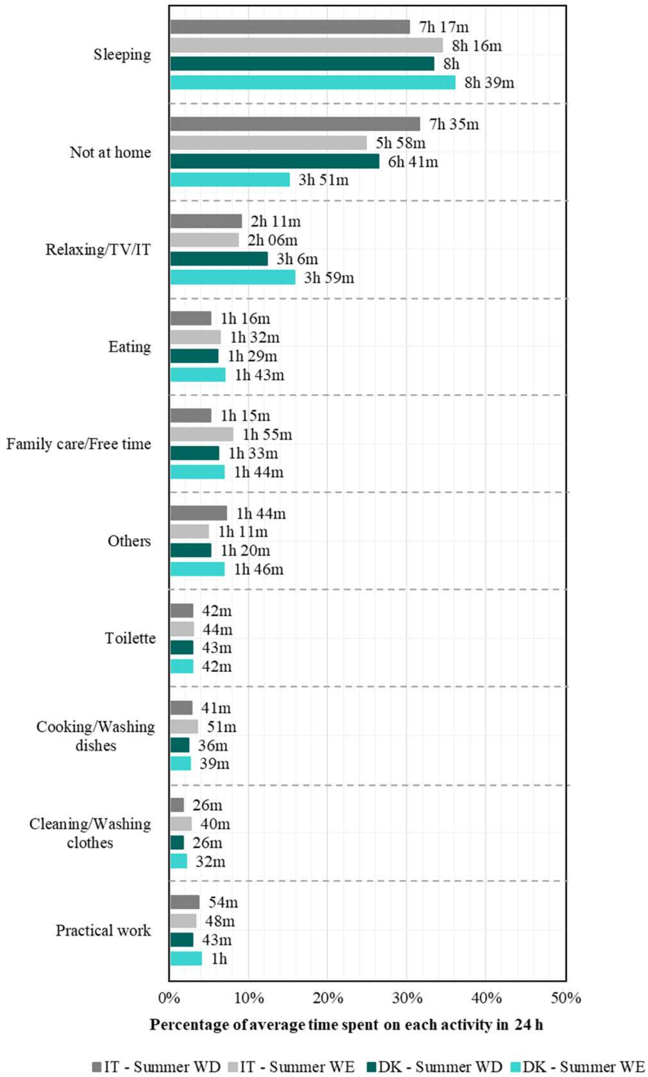


Figure 5.4-4. Comparison (Italian households vs Danish TUS) of daily time spent on the activities during summer.

Figure 5.4-4 represents the average time which the respondents have spent on the 10 energy-related activities in 24 hours during the weekdays and weekend compared to the Danish TUS-based investigation. The key results of these analysis were:

- longer sleeping times during weekends (8h 16m) with respect to weekdays (7h 17m) – Danish respondents reported to sleep longer with respects to the Italian respondents;
- longer occupant presence within the residence during weekends (18h 02m) with respect to weekdays (16h 25m) – Italian respondents reported to be out of home longer than Danish respondents;
- Italian respondents have longer free/family time during the weekends (1h 55m) than during the weekdays (1h 15m) and with respect to the Danish respondents;
- Danish respondents reported longer time spent for TV/IT entertainment activity during the weekends and weekends with respect to the Italian respondents;
- Italian respondents spent slightly longer time on cooking/washing dishes, while Danish respondents report slightly longer eating activities;
- no significant difference for time spent for personal care activity during the weekends and weekdays.

Finally, Figure 5.4-5 shows occupancy profiles based on the reported activities from the Danish and Italian respondents. This comparison highlights that Italian respondents in average reported to come home later with respect to the Danish respondents. The trend of higher percentages of respondents at home during weekends can be observed in both samples.

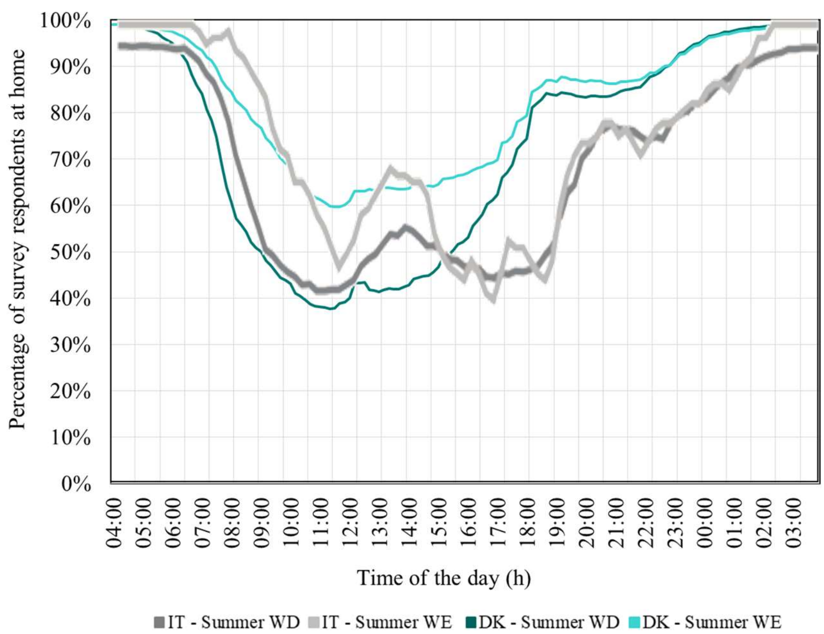


Figure 5.4-5. Occupancy profiles based on the Danish TUS and the Italian time use survey in North Italian households for a typical weekday and weekend day.

5.5 Perspectives and challenges

The analysis provided in this study demonstrated that TUS data provides valuable information for developing enhanced building simulation inputs for modelling occupant behaviour and its influence on energy consumption in the residential sector. Based on the Danish TUS data, daily profiles of ten energy- and occupancy-related activities were different depending on the season day of the week (weekdays and weekends). Survival curves of the daily time durations of the activities provided typical starting/ending times of each activity and representative occupancy profiles for different household typologies during weekdays and weekends. Furthermore, during weekdays occupants were most likely to leave their home at 08:00 or 13:00 and tended to return at noon or in the late afternoon/early evening hours (18:00). To enhance building simulation inputs for occupancy in the Danish residential sector, online access to a spectrum of individual occupancy profiles for different household typologies and different days of the week is provided.

The outcomes were in line with typical trends of hourly electricity profiles in Danish households. Indeed, similar peak values of hourly electric load profiles and some energy-related activities were observed during the same hours of the day. In detail, these peaks referred to the early morning hours, lunch time and dinner time, and could therefore be strictly correlated to cooking and eating activities. The Danish TUS data provided occupancy patterns similar to an existing simplified occupancy profile developed by the U.S DOE. The Danish TUS is an important source for developing more accurate energy-related occupant behaviour profiles in Danish households. However, future work is necessary to further explore the TUS data and **extracted occupancy patterns to create stochastic models that can be implemented in dynamic energy simulation programs** towards bridging the gap between predicted and real energy consumptions. Further work should also investigate the link between energy-related activities and respective electricity demands in order to define high resolution demand profiles in Danish and Italian households.

5.6 Publications

PAPER XI **Barthelmes, V.M.**, Li, R., Andersen, R.K., Bahnfleth, W., Corgnati, S.P., Rode, C. (2018). Profiling Occupant Behaviour in Danish Dwellings using Time Use Survey Data – Part I: Data Description and Activity Profiling. In: Proceedings of the 4th International Conference on Building Energy & Environment 2018, 5-9 February, Melbourne, Australia, pp. 97-102.

PAPER XII **Barthelmes, V.M.,** Li, R., Andersen, R.K., Bahnfleth, W., Corgnati, S.P., Rode, C. (2018). Profiling Occupant Behaviour in Danish Dwellings using Time Use Survey Data – Part II:

Time-related Factors and Occupancy. In: Proceedings of the 4th International Conference on Building Energy & Environment 2018, 5-9 February, Melbourne, Australia, pp. 103-108.

PAPER XIII **Barthelmes, V.M.,** Li, R., Andersen, R.K., Bahnfleth, W., Corgnati, S.P., Rode, C. (2018). Profiling occupant behaviour in Danish dwellings using time use survey data, *Energy and Buildings* 177, pp. 329-340.

PAPER XIV **Barthelmes, V.M.,** Becchio, C., Crespi, G., De Nicoli, M., Fabi, V., Corgnati, S.P. (2019). Profiling Occupant Behaviour in Italian Households for enhanced building simulation input: Insights Into A Survey-based Investigation. Paper accepted at the Building Simulation conference, 2-4 September, Rome, Italy.

Chapter 6

Development of Energy Engagement campaigns for behavioural change

6.1 Overview

The previous chapters were aimed at modelling and profiling occupant behaviour with focus on individuals (Chapter 4) and large-scale investigations (Chapter 5). Chapter 3 and 4 explored key drivers of the human-building interaction based on the assumption that different occupant behaviour lifestyles can significantly impact building energy use and thermal comfort conditions of the occupants. Indeed, Chapter 1 highlighted that energy efficiency goals can be only met if the occupants adopt an aware attitude concerning their energy-related actions and consequences on energy use. Indeed, raising awareness among building occupants on how their behaviour, comfort criteria settings, and lifestyles affect building energy use has become a central topic of innovative energy efficiency strategies. Reaching European energy efficiency goals does not only require the optimization of building design and features, but also necessitates the real energy consumers to be more aware of their energy-related inter-actions with the building. However, motivating occupants to change their behaviour can become a challenging task. It is essential to provide novel, stimulating, and easily understandable information that help triggering a more energy-friendly behaviour on a daily basis. Motivations of the occupants to change their behaviour can differ significantly from context to context (residences, offices, public buildings). In line with this, the chapter is aimed at presenting methodological frameworks of energy engagement campaign to which I contributed during my Ph.D studies. Although if these campaigns investigate different typologies of feedback and triggers and/or communication tools, it is possible to identify a general framework that is implemented in all the campaigns. Figure 6.1-1 shows the overview of Chapter 5 depicting the human in the loop and a schematic process that reflect the overall strategy of behavioural change investigations. In this Chapter, three different energy engagements are analysed and compared following the structure of the elements shown in the loop (sensor network and data collection, data analytics and feedback, and communication tools). This chapter is aimed at contributing to the following research questions:

- How to leverage efficiently behavioural change through innovative triggers (e.g. health, comfort, peer comparison)?
- How to assess and evaluate behavioural change and related campaigns?
- What analytical solutions can be developed for feedback provision?
- How much energy can be saved through behavioural change?

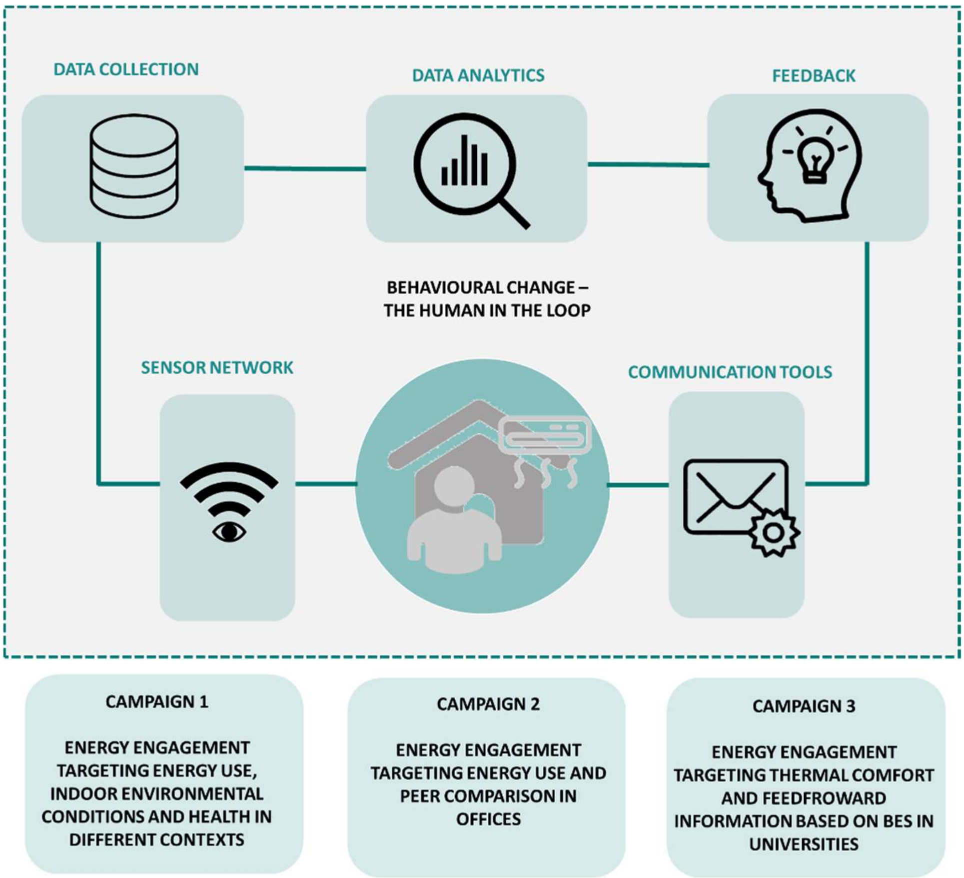


Figure 6.1-1.Overview Chapter 6.

6.2 Energy engagement targeting energy use, indoor environmental conditions and health

6.2.1 Project framework

The project presented in this first section originated from the Horizon 2020 framework "MOBISTYLE- MOtivating end-users Behavioral change by combined ICT based tools and modular Information services on energy use, indoor environment, health and lifestyle" (Grant Agreement no: 723032)(Op't Veld et al. 2016).

This project is still on-.going and deploys a multidisciplinary approach (including expertise on energy and indoor environmental quality, health and the human body, anthropology and the human mind, and ICT solutions) (Figure 6.2-1) to motivate behavioural change by raising user awareness through a provision of attractive personalized information on user's energy use, indoor environment and health, through information and communication technology (ICT) based services. Indeed, the most relevant motivational factors and Key Performance Indicators (KPIs) for encouraging a more energy conscious and healthy lifestyle were defined by means of a people-centered approach (Tisov et al. 2018). The novelty of the project consists in feedback provision that includes not only energy and environmental aspects, but that combines the latter with suggestions on how to improve health conditions and personal well-being of the participants.

The final objective and potential key outcome of this 42-months-long project is to achieve at least 16% of overall energy consumption and a subsequent reduction of CO_2 emission. The achievement of this objective is aimed at confirming the effectiveness of a multidisciplinary engagement approach and innovative ICT solutions and the importance to exploit such strategies to hit environmental EU targets.

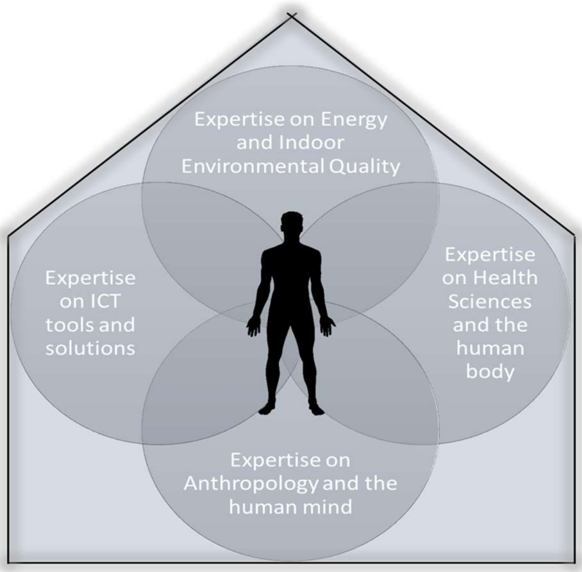


Figure 6.2-1. Multidisciplinary approach to raise energy awareness among building occupant (Fabi et al. 2017).

6.2.2 Real-life application: Project testbeds

The MOBISTYLE methodology is implemented in five selected testbeds across Europe, located in different geo-clusters and characterized by different types of buildings, end-users and scales (Table 6.2-1)(Skovgaard Møller et al. 2017).

Table 6.2-1. MOBISTYLE project testbeds.

Country	Type	Scale	Target users	Geo-cluster
Denmark	Residential	Building complex	Households	Northern
Slovenia	Higher education, offices	Faculty buildings	Faculty staff	Continental Central
Italy	Hotel	Building	Guests, staff	Mediterranean
Poland	Smart city	District	Households	Continental Central
The Netherlands	Offices	Building	Employees	Western Central

6.2.3 Methodological framework based on combined feedback targeting energy, IEQ, and health

The core idea behind this on-going project is to deploy an interdisciplinary approach addressed to develop an effective methodology that combines together three key triggers: energy, indoor environmental quality, and health; where the latter is the innovative component to stimulate behavioural change on a long term **(PAPER XVI)**. To drive users towards more conscious and energy-friendly actions, it was necessary to plan and undertake a series of steps that allowed for setting up an effective monitoring and engagement campaign: (i) data collection, (ii) parameter definition, (iii) data analysis and elaboration (iv) definition of Key Performance Indicators (KPIs), and finally (v) the awareness campaign. A framework of data collection, data analysis and elaboration, and tailored information was defined provided for each testbed (Table 6.2-1)(Fabi et al. 2017).

The data collection was aimed at investigating the operation of users on energy systems through behaviour-related data (objective monitoring campaign on building and subjective data collection regarding the occupants). Then, data analysis and elaboration is used to depict human behaviour (related to energy, comfort, health) through user data (both wearable sensors and surveys, for example monitoring human presence and practices thanks to anthropological studies) and to obtain human-related performance indicators. Finally, energy savings and improvement of indoor environmental conditions and humans' health and wellbeing is achieved by implementing behavioural communication strategies (awareness campaign).

Tailored information campaign should rely on simple and immediate information using different communication methods and effective ICT tools (Olivadese 2018) in order to be understood by the target users and to achieve an effective knowledge transfer. In the context of this Ph.D. dissertation, the implementation of the methodological framework will be presented in the Italian MOBISTYLE testbed – a hotel located in Turin (North Italy) **(PAPER XV)**.

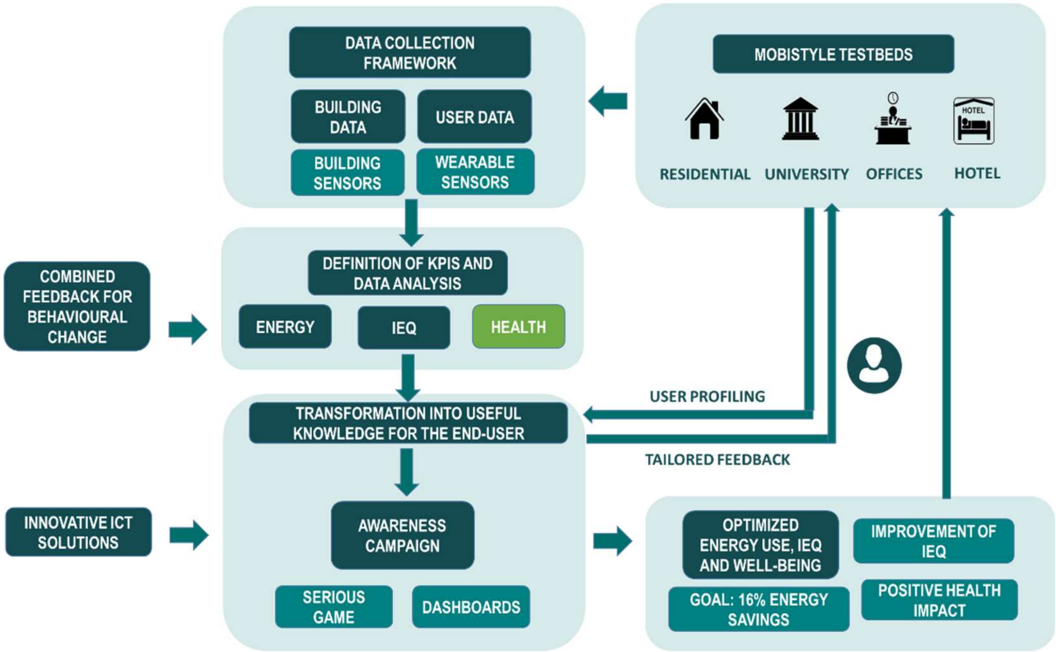


Figure 6.2-2. Methodological framework of the MOBISTYLE project.

Sensor network and data collection

A residence hotel, an urban hotel located in a central area of Turin, is the Italian demonstration case. This case study presents a very traditional structure since the building was built at the beginning of 20th century with load bearing masonry walls. The building is heated by two condensing boilers powered by natural gas, also used for Domestic Hot Water (DHW) production. A chiller (cooling capacity 97 kW) is installed for the cooling system. Two-pipes fan coil units, placed in the false ceiling, are the terminals of the heating and cooling system (except radiators inside bathrooms). At present, the building does not have mechanical ventilation system (except for exhaust air systems in bathrooms and kitchens) and it does not a use any on-site renewable energy source. A tailored monitoring and engagement campaign was set up in four residential hotel apartments and the reception area.

The monitoring campaign is based on continuous measurements of indoor environmental variables, electricity consumptions of domestic appliances (washing machine, dishwasher, microwave, TV), and behavioural patterns (e.g. window opening/closings, thermostat regulation, occupancy). Figure 6.2-3 depicts types and locations of the sensors installed in two apartment typologies. In all four apartments, measurements regarding energy consumption and indoor environmental quality (IAQ) will be taken. In particular, the following parameters are gathered:

- indoor air temperature (T) [°C]: every 15 minutes;
- indoor relative humidity (RH) [%]: every 15 minutes;
- indoor CO_2 level (CO_2) [ppm]: every 10 minutes;

- electricity consumption [kWh]: every 10 minutes;
- electricity power [W]: every 10 minutes.

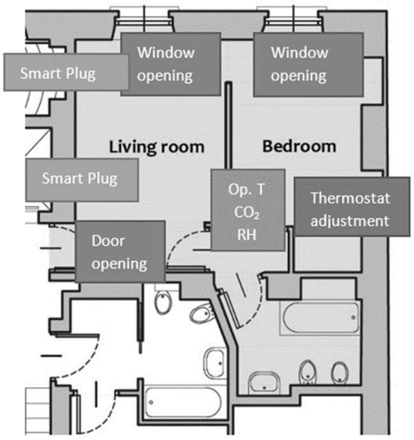
To understand the mechanisms of occupants' behaviours, it is necessary to monitor the behaviour itself but also to determine the cause and effect relationships that behaviours have with energy consumption, indoor and outdoor environment, and the occupants' health status.

The types of behaviour analysed in this case study can be listed as follows:

- Occupancy (room access);
- Thermostat adjustment;
- Window opening/closing;
- Whitegoods or other electrical devices;
- Door opening/closing.

Furthermore, the monitoring campaign at a future stage might also include measurements on Physical activity (PA) in order to see if the PA pattern are in correlation with the environment and how this relationship can be exploited to optimize well-being of the occupants (and productivity).

Outdoor conditions during the campaign are established by third-party out-door data logging. Indeed, outdoor environmental variables, such as temperature, solar radiation, relative humidity, wind speed/direction, are acquired through online sources.



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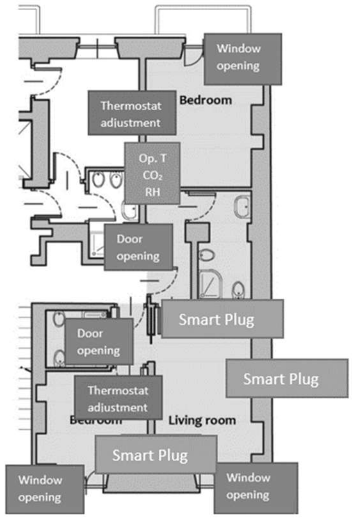


(b)

Figure 6.2-3. Apartment typologies A (a) and B (b) and sensors/measured variables (Barthelmes et al. 2019).

Data analytics and feedback

In this step, the raw data collected in the case study is transformed into Key Performance Indicators (KPIs) for (i) evaluation purposes (see section 6.2.4) and (ii) providing useful and easy-to-understand information for the target users, such as the hotel guests (Table 6.2-2). At this stage, some of the KPIs are translated in more intuitive units for the end users (e.g. energy costs or number of trees that it takes to absorb produced emissions) in order to optimize the knowledge transfer.

Similar KPIs were defined for the hotel staff (receptionists) that refer to IEQ variables, as well as electricity consumptions of electric devices, such as the personal computer and the printer. The hotel manager is provided with all the KPIs (apartments and reception) in order to allow for understanding and optimizing current building operation strategies.

Table 6.2-2. Examples of KPI definition for hotel guests.

KPI	Unit	Translation for the user	Unit (for guest)	Learning objectives
Air Temperature	°C	Indication of adequate temperature levels	°C	• Improve perception of comfort • Improve IEQ conditions for health • Save energy (heating/cooling) • Decrease environmental impact
Level of relative humidity	%	Indication of adequate relative humidity levels	%	• Improve perception of comfort • Improve IEQ conditions for health
Level of CO_2	ppm	Indication of adequate CO2 concentration levels	ppm	• Improve perception of comfort • Improve IEQ conditions for health
Electricity consumption (apartment)	kWh/day	Emission of $CO_{2,\ equivalent}$ translated into number of trees that it takes to absorb emissions Costs for electricity consumption	number of trees/year €/day	• Save energy (apartment level) • Decrease environmental impact
Elec. consumption (electric devices)	kWh/day	Indication of adequate consumption levels		• Save energy (electric devices) • Decrease environmental impact

To guide the users to change practices to achieve energy savings or to improve indoor environmental quality, it is necessary to provide tailored feedback based on the collected data and the elaborated KPIs. For this purpose the KPIs are (i) shown to the users in real-time as well as historical trends with an intuitive representation if suggested limits are exceeded (see next subsection) and (ii) used for providing real-time suggestions aimed at triggering specific actions towards energy savings and better environmental and health conditions.

Table 6.2-3 shows the key behavioural change objectives in the hotel environment for the different target users (guests, receptionists).

Table 6.2-3. Behavioural change objectives (Fabi et al. 2017).

	Behavioural Change Objective	Target	Action	Context	Measure	Sensor	Variable	Unit
H1	Energy Saving/IEQ - Heating Cooling	Hotel Guest	Adjusting setpoint temperature	Hotel Apartments	[°C]	T/RH/CO_2 sensor	Temperature	[°C]
H2	Energy Saving - Washing Machine		Switching off stand by power – Reduction and optimization of washing cycles	Hotel Bathroom	[kWh]	Smart Plug	Electricity Consumption	[kWh]
H3	Energy Saving - Dish Washer		Switching off stand by power - Reduction and optimization of washing cycles	Hotel Kitchen	[kWh]	Smart Plug	Electricity Consumption	[kWh]
H4	Energy Saving - TV		Switching off stand by power/ Reduction of viewing activity	Hotel Living	[kWh]	Smart Plug	Electricity Consumption	[kWh]
H5	Energy Saving - Microwave		Switching off stand by power	Hotel Kitchen	[kWh]	Smart Plug	Electricity Consumption	[kWh]
H6	Health - IAQ		Opening/closing windows	Hotel Bedroom	[kWh]	T/RH/CO_2 sensor	CO_2 concentration level	[ppm]

H7	Energy saving PC	Staff	Switching off stand by power	Reception	[kWh]	Smart Plug	Electricity Consumption	[kWh]
H8	Energy saving Printer		Switching off stand by power	Reception	[kWh]	Smart Plug	Electricity Consumption	[kWh]

For each behavioural change objective, conditional decision trees were developed in order to provide real-time feedback to the users and to make them aware how they could positively influence energy use and the indoor environment through specific actions. Furthermore, the target users are provided with additional information (e.g. eco pills) aimed at supporting the learning process and to achieve behavioural change objectives (van Marken Lichtenbelt et al. 2017). As an example, the awareness campaign promotes "temperature trainings" that should motivate end users to adopt a healthy lifestyle and healthy ageing strategy. This consists in explaining the users that lowering the thermostat for a certain time slot, will not just bring energy savings but can also contribute to their better well-being and metabolic health. Another example is that users are encouraged to take stairs instead of an elevator as this does not only saves building's electricity consumption but also is healthier for them. Furthermore, hints and tricks on a clever and conscious use of appliances (e.g. stand-by mode) can complement the feedback based on measured variables and support the attractiveness of the services.

Table 6.2-4 shows representative examples of feedback provided to the target users related to the temperature settings (H1), the use of an electric device (H2), and the indoor air quality (H6). Threshold values that trigger the feedback provision are shown in Table 6.2-5. The theoretical framework for the creation of the decision trees included the definition of two levels of alarms/suggestions (yellow and red) based on different threshold values and the urgency to intervene through a specific action; in reality, due to challenges in the practical implementation in the ICT services, the users will directly receive feedback when they exceed the first limit (yellow). The proposed examples serve a demonstration of the proposed methodology, but could still change throughout the project.

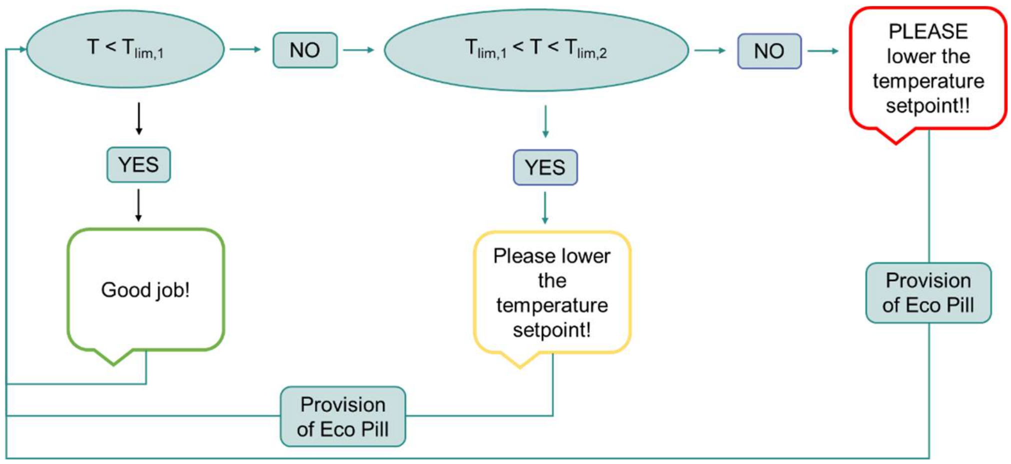
Table 6.2-4. Examples (H1, H2, and H6) of feedback provision (message to users, criteria for decision trees, and complementary eco pills).

H1	Energy Saving/Indoor environment – Heating/Cooling
Message	DURING DAY – Please lower/raise the set-point temperature to "xxx". DURING NIGHT - Please lower/raise the set-point temperature to "xxx".
Criteria for decision tree	DURING DAY - If set-point temperature is higher/lower (winter/summer) than "xxx", DURING NIGHT - If set-point temperature is higher/lower (winter/summer) than "xxx",
Headlines of eco pills	▪ Lowering the heating/cooling temperature by 1°C can reduce the overall energy by 7% ▪ lower temperatures are beneficial for heat loss during activities ▪ Reducing the environmental temperature might increase your alertness ▪ Do the temperature training to increase resilience! ▪ Lower temperatures help to have healthy metabolism! ▪ Reduce the temperature and boost your brains! ▪ Want to lose some weight due to increased metabolism rate? Reduce the heating set-point in your office! ▪ High temperature might kill your productivity. Switch off heating for a while! ▪ If you feel cool, put on some clothes! ▪ Variable indoor environmental temperature are likely to increase your alertness and well-being ▪ When outdoor conditions are suitable, opening the window will freshen your room and provide energy savings.

	▪ Fresh air is beneficial for health. However, leaving the window open too long does not benefit much your wallet! Instead you will lose money for heating. ▪ Open the window now and for just one minute. You will provide fresh air, without losing money for heating/cooling.

H2	**Energy Saving– Washing machine**
Message	Please turn the washing machine completely off when you don’t use it.
Criteria for decision tree	If stand-by consumption of washing machine is detected
Headlines of eco pills	▪ People use significant part of electricity for small electric appliances ▪ Devices draw energy all the time, even when in standby mode ▪ If you aren't frequently using a device, unplug it ▪ Schedule automatic power off ▪ Try to reduce electricity wastes and vampire loads. Do you really need all the devices plugged in? ▪ Filled the washing machine to the nominal load? ▪ Try the eco-cycles to reduce your environmental footprint

H6	**Indoor Air Quality – Window control**
Message	Please open the windows for improving the indoor air quality!
Criteria for decision tree	If the indoor CO_2 concentration is higher than “xxx”
Headlines of eco pills	▪ Fresh air to stay in health ▪ Boost your alertness with fresh air



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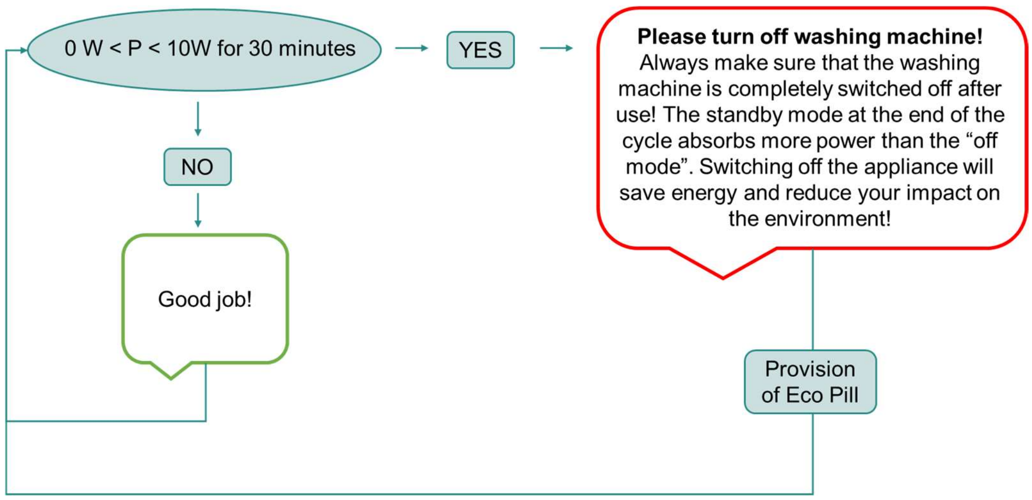

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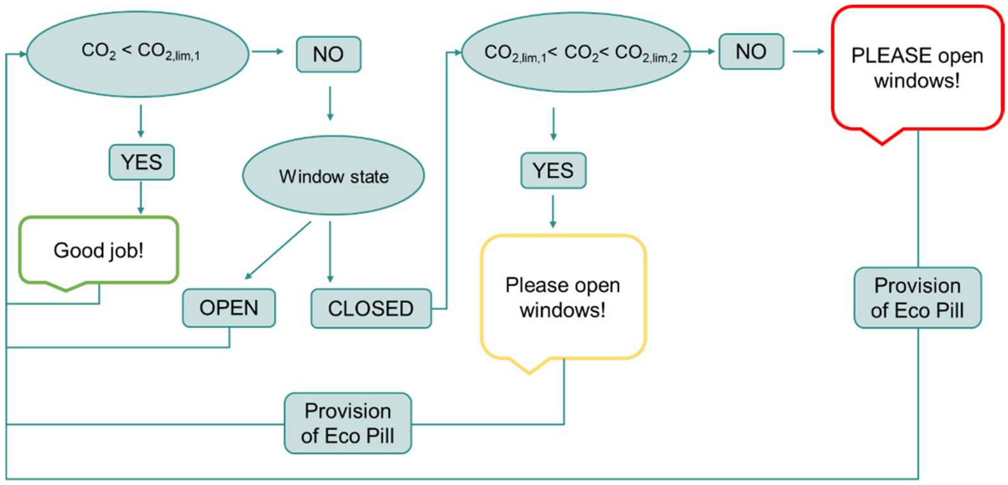


(c)

Figure 6.2-4. Example of decision trees related to temperature settings (H1) (winter season - during day), stand-by detection of the washing machine (H2), and window openings based on the indoor air quality (H3).

Table 6.2-5.Threshold values for examples of decision trees.

Label	H1 Threshold values	H1 - Temperature (winter day) (^oC)	H6 Threshold values	H6 - CO_2 concentration (ppm)
GREEN		< 22		< 800
YELLOW	$T_{lim,1}$	22-23	$CO_{2,lim,1}$	800 – 1000
RED	$T_{lim,1}$	> 23	$CO_{2,lim,2}$	> 1000

Communication tools

The feedback will be provided to the participants through two different (but related) ICT services: a dashboard for the visualization of the KPIs and a mobile application for KPI visualization and prompts/alerts that encourage specific actions given certain conditions (indoor environmental conditions and energy use)(Figure 6.2-5).

Information regarding energy use is based on the overall electricity use in the apartment and on the usage of single electrical appliances (depending on which appliances are used in the specific apartments). The KPIs will be displayed to the end user in a graphical with an indication of three colour levels: green (the conditions are fine), yellow (the threshold of suggested limit values is exceeded to some extent), and red (the threshold of suggested limit values is exceeded significantly). The relationship between colour levels and energy consumption is based on a generic profile defined during benchmarking and energy saving targets for the case study (energy saving of 16%). Users also have the possibility to read real-time consumption and historic records in order to gain a better understanding of their actions over time.

Similarly to the representation of energy usage, the IEQ conditions are translated to the user mainly through a graphical form that involves also in this case the use of three levels of colour, depending on their trend with respect to threshold values defined by European standards (Cen 2007). In other MOBISTYLE testbeds, the communication strategy is based on serious gaming, or rather interactive games based on a story-telling-approach with an educational scope.

Figure 6.2-5. Prototype of the mobile application (still in development).

Furthermore, in order to keep participants and stakeholders up to date on the development of the project, regular newsletters with latest updates are distributed in each MOBISTYLE testbed.

6.2.4 Key findings/Evaluation method

Since the MOBISTYLE project is still on-going, at the time-being it is not possible to provide final results on energy savings and improved indoor environmental and health conditions. However, a tailored methodological framework for the evaluation of the project was developed **(PAPER XVII)**. Indeed, extended literature in the field of project management has highlighted that the evaluation process should not be an afterthought (Dahlbom et al. 2009; Patton 2001). Planning for an evaluation and developing ad-hoc evaluation methodologies before-hand can help to overcome unexpected evaluation challenges by mitigating risks in advance (e.g. definition of parameters that have to be evaluated to answer certain research questions or to verify if the project goals were achieved, timing of the project), lead to more useful results, and improve the optimization process of the project (Wade and Eyre 2015). Indeed, planning the evaluation helps articulating research goals and identifying areas for improvement. Evaluation can also be a beneficial tool for communicating project results and demonstrating the effectiveness of deployed strategies. An evaluation should be driven by a specific set of questions, which are the foundation of all evaluation efforts, and that can focus on any stage of a project and generally fall into one of the following categories: Outcome evaluation, impact evaluation, and process evaluation. The outcome evaluation determines how well the desired outcomes and associated objectives for a project are met. In the MOBISTYLE project, this refers to achieving pre-set goals in terms of energy savings, improved indoor environmental quality and well-being of the occupants (Figure 6.2-6). These goals are meant to be achieved by a pro-active change of the occupants' behaviour, which therefore has to be tackled as a key parameter during the evaluation process. The impact evaluation assesses longer-term changes in social, economic, and environmental conditions, as well as long-term maintenance of desired behaviours (Duignan 2011). This type of evaluation addresses if the occupants adopt the new behaviour in their daily routines in a long-term perspective and if pre-set goals can be maintained during time. The process evaluation analyses the development and implementation of a project in different stages by assessing whether strategies were implemented as planned, and whether expected outputs were produced (Linnell 2015). This type of evaluation allows for identifying possible optimization and improvements of the implemented MOBISTYLE strategies.

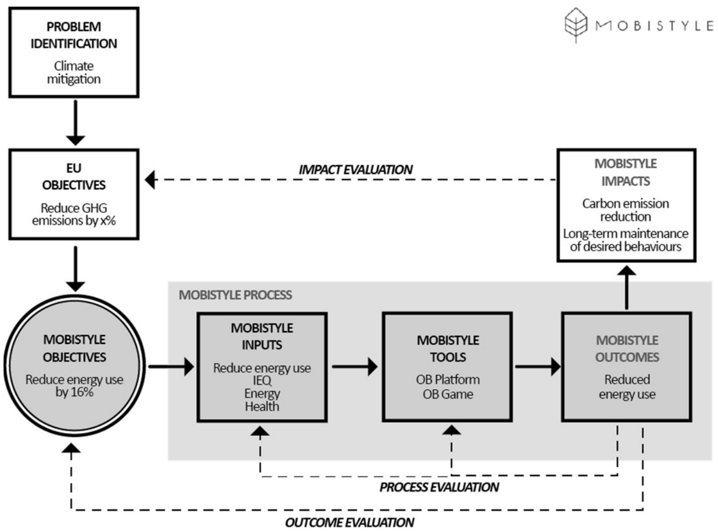


Figure 6.2-6. Overall evaluation strategy (Barthelmes et al. 2018).

To set up an effective evaluation process during the entire project, the proposed MOBISTYLE evaluation strategy consists of three monitoring periods (M0, M1, M2) alternated with follow-up evaluation steps (E1, E2, E3)(Figure 6.2-7). Over time, monitoring periods and evaluation steps were planned to be implemented in 6 steps scheduled as follows:

- Initial monitoring (M0)
- Benchmark definition (E1)
- Feedback provision (M1)
- Intermediate evaluation (E2)
- Optimized feedback provision (M2)
- Final evaluation (E3)

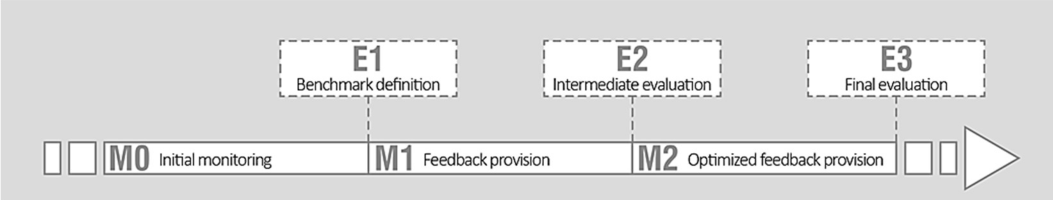


Figure 6.2-7. Monitoring and evaluation steps throughout time (Barthelmes et al. 2018).

The aim of the initial monitoring period (M0) is to gather data for measuring and assessing the baseline performance in the project testbeds (Skovgaard Møller et al. 2017). In each testbed, selected parameters are measured and, if necessary, transformed into meaningful KPIs that describe the trends of energy consumption, indoor environmental quality, and health aspects, before the implementation of the MOBISTYLE services. The data collected in this initial phase hence serve as a comparative etalon in the evaluation process and will underlie the calculations required for the benchmark definition (E1). During the initial monitoring period, no service or feedback will be provided, for capturing the "usual" daily routines and habits of the occupants and the impact of the latter on the energy consumptions and indoor environmental conditions. During this phase, the only influence on the occupants might be an effect described by Hawthorne (Adair 2000; Seligman et al. 1977) in which 'subjects may behave differently, because they are aware that they are being studied.' However, this effect might slowly fade away if the users are observed for a sufficient amount of time.

The first evaluation step, or rather the benchmark definition (E1), is aimed at analysing the collected data in M0 to provide a structured assessment of the baseline performance in the testbeds. The benchmark definition is used to measure performance using specific indicators resulting in a metric of performance that is then comparable to the same indicators in future evaluation steps (E2, E3).

The second monitoring period (M1) includes the provision of MOBISTYLE services and feedback through ICT tools (dashboard, mobile application) to the end users and represents the core of the project. The data collected in this second monitoring period allows for assessing a comparative analysis to evaluate the changes in behaviour and related impacts on energy consumption, indoor environmental quality, and well-being of the occupants.

The intermediate evaluation (E2) is aimed at gaining a first insight on the achievements of the MOBISTYLE strategy and implemented ICT solutions. This step allows for overseeing the current outcomes of the implemented strategies and the verification of a successful process. At this stage, it is possible to exploit first results for improving and optimizing feedback and other factors that might to some extent act as obstacle to the effectiveness of the proposed solutions (e.g. problems related to the usability of the ICT solutions, ineffectiveness of the provided feedback, difficulties in achieving energy saving goals).

Based on the results and recommendations of the intermediate evaluation (E2), in monitoring period (M3) data based on optimized feedback provision is collected.

The gathered data will underlie the final evaluation of the MOBISTYLE project for evaluating if the project's goals were achieved.
In the final evaluation (E3) the same assessments of E2 should be performed. Particularly, the final evaluation is a comparative analysis between monitoring phase M2 (provision of optimized feedback) and monitoring phase M1 (feedback provision) and M0 (initial monitoring).
Moreover, this final evaluation step is aimed at verifying if MOBISTYLE goals were achieved (16% of energy savings).

Outcome evaluation

An outcome evaluation assesses the effectiveness of the awareness campaign at an overall level of the project as well as in individual MOBISTYLE testbeds. The outcome evaluation is aimed at analysing the energy savings obtained in the MOBISTYLE testbeds and quantifies their environmental impact. A comparative analysis of specific KPIs defined in benchmark (E1) is necessary to establish changes in energy consumption, IEQ, health, and behavioural patterns of the occupants:

- **Energy savings:** The amount of energy used before (M0) and after the feedback provision (M1, M2) is evaluated. It is necessary to consider external constraints (e.g. vacation period, long absence period, seasonal variations). In this case, it is suggested to remove as much as possible data related to these irregular patterns; and consequently calculate the resulting energy savings. This result can be obtained by direct measurements or dynamic energy simulations.
- **Greenhouse Gas (GHG) emissions:** Once the amount of energy used is calculated, it is possible to link the results to the impact on the environment of each MOBISTYLE testbed. It is measured applying the conversion factors for primary energy (calculated for the used electricity or thermal energy typologies).
- **Indoor Environmental Quality (IEQ) and comfort:** Variations of IEQ throughout the different monitoring periods need to be analysed. The analysis should include time profiles of thermo-hygrometric parameters and indoor air quality indicators, as well as statistical values that are essential to describe and evaluate the indoor environmental quality (mean hourly values, standard deviation, minimum and maximum values during the investigation period, frequency distribution and cumulated frequency). For evaluating the conditions of comfort (or discomfort) during the three monitoring periods, it is required to calculate the amount of time, in which the occupants might perceive discomfort (Cen 2007).
- **Health:** Questionnaires during the static and during the dynamic indoor environment will be delivered to the involved users. Moreover, body temperature, heart rate and physical activity will be recorded in a subset of participants. A comparison between the two different indoor environmental conditions will be compared in two different seasons and linked to comfort, sensation, sleepiness, alertness and well-being.

- **Behavioural change:** Questionnaires before (M0) and after the feedback provision (M1, M2) will be delivered to the involved users. The investigations for assessing the behavioural change include: knowledge on MOBISTYLE project and its progress, change on comfort preferences and satisfaction and health-related aspects. Behavioural patterns should be compared before (M0) and after the (optimized) feedback provision (M1, M2) to assess the change of users' interactions with technical building systems, building components and home appliances. These interactions patterns involve: number of window/door openings, temperature control, blinds control, lighting control, usage of home appliances (e.g. analysis of instant power data related to individual devices). These trends should be correlated with IEQ conditions and (human) body parameters, if available.

Process evaluation

The process evaluation is aimed at a potential optimization and improvement of the implemented process. Separate evaluation for each category of provided feedback (for example, advices related to temperature control or stand by usage of home appliances) should be performed. In this case, a comparative analysis of specific KPIs defined in the benchmark (E1) is needed for evaluating the results.

Questionnaire assessing the usefulness of feedback from the user's point of view are developed and addressed to the MOBISTYLE end users. The questionnaires address different aspects of the feedback provision:

- **Typology:** Different feedback category will be analysed and compared in terms of achieved results. For example, it is possible to compare feedback related to heating, lighting, home appliances with the final energy used for heating, artificial lighting, home appliances to calculate where the major savings are obtained.
- **Time-frequency:** Efficacy of feedback frequency (hourly, daily, or continuous) leading to increased user awareness and the best results in terms of behavioural change shall be assessed.
- **Communication content:** The efficacy of the following characteristics should be verified for the provided feedback
  - Type (numerical, graphical),
  - Communication strategy (prompts, pop-up message, educative advices, serious game, newsletters),
  - Length (concise/long),
  - Wording and design (efficacy of the chosen terms in the message),
  - Content (antecedent, i.e. announcing the availability of positive or negative consequences; consequent, i.e. providing advices about the action carried out at that specific moment),
  - Credibility (coherency of provided feedback),
  - The level of detail of the provided information.

- **Tools:** The efficacy of paper-based (poster, brochure) or ICT-based (mobile phone, website, email, room displays) communication media should be evaluated in terms of
  - Usability;
  - User-friendliness, ease of use, barriers;
  - Reliability;
  - User satisfaction/experience;
  - Adaptability for meeting research goals and expected energy savings.

The efficacy of the tools can be further evaluated by acquiring directly information from the ICT tools that allow for assessing:

- How frequently the users interact with the tools (analytics for sub-tools e.g. number of asked questions through the 'help' sub-tool) and the relation with the time of sending a notification;
- Length of use (number of hours, analytics for sub-tools);
- How many people downloaded the MOBISTYLE application.

Impact evaluation

Concerning the impact evaluation of the implemented MOBISTYLE strategy, the main objective is to understand to which extent the occupants adopt the new and more conscious behaviour in their daily routine once the MOBISTYLE project is over. The aim is hence to test the behavioural persistence of the engaged occupants, or rather to verify if there is a long-term change in users' habits and the internalization of new behaviour as part of daily living and routines, also without active input from the MOBISTYLE team. The evaluation process should specifically depict the tendency of the occupants to continue performing the new behaviour, saving energy and maintaining good IEQ and health conditions, while changing their lifestyle in a long-lasting manner. At this stage, the outcomes of the behavioural persistence analysis could contribute to investigating specific research questions on project outcomes on the long term, such as gaining a deeper knowledge on:

- The types of feedback that lead to the most effective behavioural change;
- Time thresholds necessary to induct behavioural persistence in the users after which tailored feedback is no longer needed;
- How communication design, tools, and feedback developed within the MOBISTYLE project shape perspectives for a long-lasting internalization of the new behaviour.

Finally, in case of behavioural changes induction though ICT-solutions provision and awareness campaign, benefits for the occupants in terms of energy saved, emissions avoided, but also IEQ and health improvement are expected. All these aspects need to be considered in the assessment, as well as their effect at macroeconomic level (e.g. sanitary costs reduction). Moreover, monetization of those benefits could give support in communicate the exploitation potential of the activities envisaged within the project, namely ICT-solutions and awareness campaign provision, and, more in general, in investigating the potential market for ICT solutions pushing behavioural changes. Furthermore, monetizing benefits related to behavioural changes contribute in making them tangible, then it is a valuable tool to motivate occupants towards new persistent behavioural patterns.

In this context, the introduction of a Cost-Benefit Analysis in the evaluation strategy has the potential to be innovative from a research point of view and, more interestingly, it could help in addressing the necessity for macro-economic perspective adoption in the evaluation process and the relevance of co-benefits monetization activities on a long term.

6.3 Energy engagement targeting energy use and peer comparison in offices

6.3.1 Project framework

The aim of the second experimental study **(PAPER XXI)** was to provide employees with adequate tools, which encourage the conscious and rational use of energy and environmental resources thanks to smart monitoring and persuasive communication systems that help to understand the influence of occupant behaviour on electricity uses and to manage efficiently energy consumption in workplaces, especially in offices. The installation of monitoring tools like power meters and THL sensors (air temperature, relative humidity and lighting) allowed for assessing real-time data and to send automatically alerts to the occupants via mobile application on Tablet or cell phone (data visualization tool). In this experimental study, employees were provided with real-time feedback that consisted in suggestions for specific actions that the employees should perform in order to reduce energy consumptions and to improve indoor comfort conditions at the same time. Suggested actions regarded opening/closing of windows and doors, adjustments of window blinds, regulation of fan coil units, usage of electric office appliances, as well as the regulation of artificial lighting. In particular, an IT company was involved in the project to develop a smartphone application as a persuasive communication tool. In this way, it was possible to supply educational and feedforward information based on detailed algorithms that take into account the environmental conditions inside the offices (considering thermal comfort, visual comfort and air quality) and the energy consumption of plant systems and desktop appliances.

6.3.2 Real-life application: Project testbeds

The testbeds of this experimental investigation were four offices (pilot offices 1, 2, 3 and 4) located in a city in the climatic zone D (HDD = 2259) in Italy. Figure 6.3-1 illustrates the orientation of the four analysed offices. Two of them were situated on the first floor facing east (office 1 and 2) while the other two were located on the second floor facing north (office 3 and 4). Each office was occupied by four employees with a working time from 7 a.m. to 20 p.m. Every office was equipped with two fan coils units for heating and cooling, 6 ceiling lighting appliances and plugs for several electric devices (fax, PC, printer).

Figure 6.3-1. Location and layout of the pilot offices.

6.3.3 Methodological framework: Real-time suggestions and peer comparison

The intervention strategy consisted in four monitoring periods with different levels of feedback provision (Table 6.3-1) and experimentation efficacy. Indeed, it was crucial to understand if the monitoring of either environmental variables or the energy use of electric office appliances had a greater influence on the potential energy reduction and to evaluate how many sensors devices are actually needed in order to apply an efficient monitoring system and assess behavioural change. For this reason, the intervention program was structured in sequential stages in order to verify efficacy of the feedback generated based on environmental sensors first, energy sensors secondly and peer comparison finally. Each stage (with the exception of the first monitoring period, which covered a 6-month period) lasted 1 month per season (wintertime and summertime).

Similar to the framework presented in section 6.2.3, the first period, nominated Stage 0, consisted in monitoring the offices during a 6-month period in summertime and wintertime without any kind of interaction with the building occupants. The aim of this stage was to establish basic values used as reference state (benchmark) in the successive experimentation steps. During this phase, the only influence on the occupants might be an effect described by Hawthorne (Seligman and Darley, 1977) in which 'subjects may behave differently, because they are aware that they are being studied.'

The second period, nominated Stage 1, consisted in sending educational and feedforward information to the employees notifying them about the environmental conditions (related to thermal and visual comfort and IAQ) of their offices during winter and summer time.

The third period, called Stage 2, included feedback regarding the energy consumption of electric appliances in every office (e.g. PC, monitors). The main goal of this step was to warn the employees if they did not turn off the electric office equipment during the not-working hours (night time or weekends).

The last period, Stage 3, consisted in comparing the energy used in the four offices and the whole building and in encouraging employee's energy saving attitude through peer comparison (using social norms as a key trigger).

Table 6.3-1. Program stages.

Stage	Feedback typology	Description
0	Reference state (no feedback)	Without users' interaction to establish basic values as reference state (benchmark). The only influence on the occupants might be an effect described by Hawthorne (Seligman et al. 1977) in which "subjects may behave differently, because they are aware that they are being studied."
1	Feedback on environmental comfort ▪ Thermal comfort ▪ Visual comfort	Users' interaction through feedbacks to the employees about the environmental conditions (thermal and visual comfort) and their relationship with energy usage.
2	Feedback on environmental comfort <u>and</u> energy consumptions (electric devices)	Users' interaction through feedback regarding the energy consumption of electric devices (e.g. PC, fax) to warn the employees if they do not turn off the appliances during night or weekends.
3	Competition	Peer comparison encouraging employee's energy saving attitude with compensations (energy competition).

Sensor network and data collection

The installation of monitoring tools like power meters and THL sensors (air temperature, relative humidity and lighting) allowed to assess real-time data and to send automatically information to the occupants via mobile application on tablet or cell phone (data visualization tool). Air temperature, relative humidity, lighting levels, and CO_2 concentration in the office room were measured for both inside and outside (Table 6.3-2). Final use of electric energy for artificial lighting, electric appliances and fan coil units (kWh/m^{2}y) were measured in real-time. In order to outline the influence of occupant behaviour on energy consumption at work, occupancy sensors revealed employee's presence in office and their opening and closing actions on windows and doors.

Since this application allowed to monitor and control electric energy consumption of the office at any time during working period and to send feedforward information in real time, each employee was reached via mobile application for smartphone or PC. These tools displayed the advices and tips of a virtual 'energy coach'.

Table 6.3-2. Measured variables.

Environmental variables (indoor)	Environmental variables (outdoor)
• Air temperature (°C) • Relative Humidity (%) • Lighting level (lux) • CO_2 concentration (ppm)	• Air temperature (°C) • Relative Humidity (%) • Solar radiation (W/m^2) • CO_2 concentration (ppm) • Wind speed and direction (m/s)
Final energy use	**Occupant behaviour**
Electricity • Artificial lighting • Electric appliances • Fan coil units	• Presence of the employees • Opening/closing doors • Opening/closing windows

Data analytics and feedback

Similar to the framework described in Section 6.2.3, feedback provision in Stage 1 and 2 was based on decision trees that allowed for sending suggestions on specific action to perform based on environmental conditions (Stage 1) and energy usage (Stage 2). In addition, in Stage 3, feedback was based on peer comparison aimed at stimulating changes in thought and behaviour that result in short and long-term reductions in energy use. First, it was used to catch attention and to involve the employees in an interest-arousing manner. Energy competition among peers was also useful to educate them by communicating information on what, why and how behaviour should change to win the race. In this way, motivating and enhancing users to desire to change behaviour increased the perception and reality of self-efficacy and suggested employees concrete and actionable behaviour. A competition called "Energy Marathon" in this engagement program compared participants on energy use, energy reductions and/or progress completing educational tasks or other goals (Figure 6.3-2).

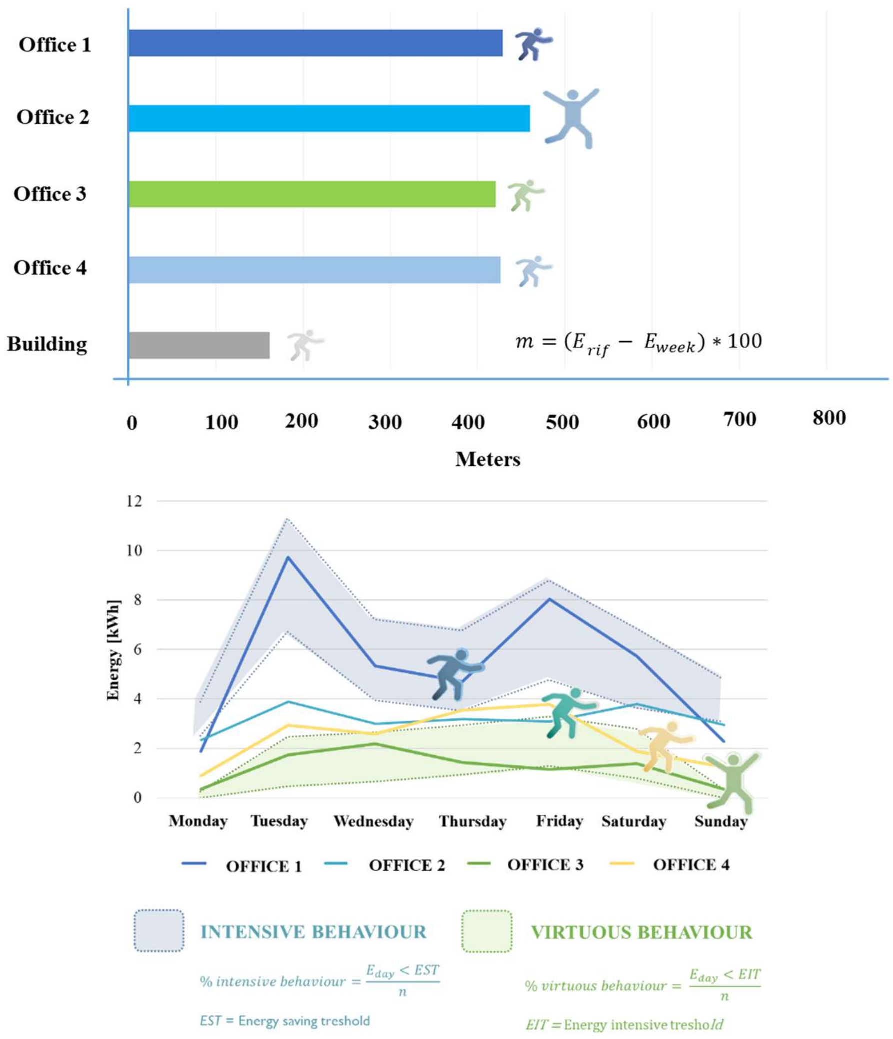


Figure 6.3-2. Examples for the peer comparison communication: "energy races" (Fabi, Barthelmes, and Corgnati 2016).

Communication tools

Figure 6.3-3. User interface on mobile device.

The model used for comparing employees' energy use included energy reports sent to them as electronic reports (Figure 2) which aimed at educating them about their energy use and encouraging them to save electricity and not waste it. Tables and graphs showed employees the rank of individual participants and teams regularly every week. Based on the actual indoor environmental conditions, direct suggestions for actions to perform were provided through a mobile device interface shown in Figure 6.3-3.

6.3.4 Key findings

The outcomes of this study confirm the high energy saving potential that can be reached through behavioural change. The highest effectiveness was achieved by providing combined feedback on the environment and electric devices (plug-load usage related to electric appliances) (Figure 6.3-4). Savings were achieved also through peer comparison, but it was not as effective a real-time feedback that required to perform certain actions as soon as the analysis of indoor environmental parameters suggested so. The outcomes of Stage 2 demonstrate energy saving potentials up to ca. 40%.

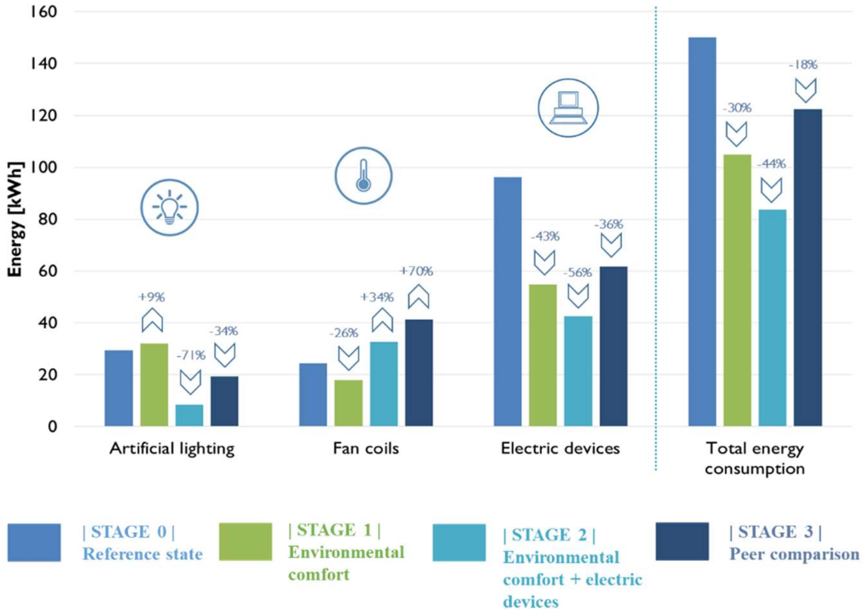


Figure 6.3-4. Energy savings achieved throughout different stages of the energy engagement campaign (Fabi, Barthelmes, and Corgnati 2016).

6.4 Energy engagement targeting thermal comfort and feedforward information based on BES in university buildings

6.4.1 Project framework

The investigations of this section are part of the ComfortSense project (Università degli Studi di Torino 2018) funded by the ”Bando regionale a sostegno di 25 progetti di ricerca industriale e/o sviluppo sperimentale di applicazioni integrate e innovative in ambito Internet of Data - IoD - POR-FESR 2007 - 2013” **(PAPERS XIX and XX)**. The goal of this project was to enhance the human-building interaction through a crowd-sensing approach that allowed for real-time visualization of thermal comfort conditions, as well as feedforward information based on dynamic energy simulations (Figure 6.4-1). Parameters collection and data analysis were established for the realization of a Direct Virtual Sensor (DVS) allowing to match systematically objective and subjective measures of comfort and to provide final feedback on comfort conditions to the room end-users and useful indicators to the energy manager. Furthermore, collected data allowed to calibrate dynamic energy simulations of the case study and to exploit alternative scenarios related to user behaviour.

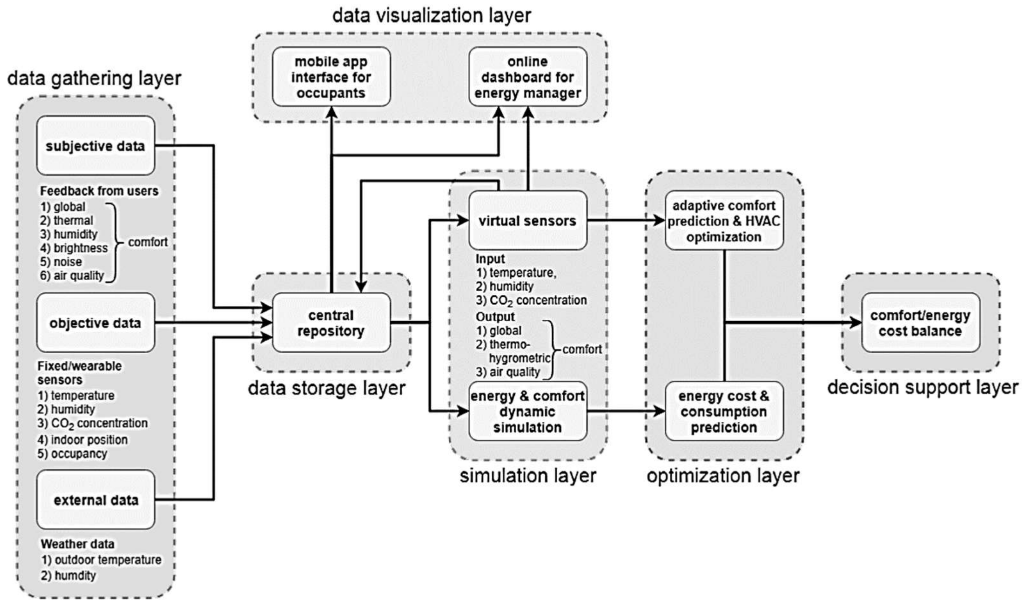


Figure 6.4-1. Methodological framework of the ComfortSense project, figure from Cottafava et al. (2019).

6.4.2 Real-life application: Project testbed

An Italian University campus located in Northern Italy was one of the principal ComfortSense case studies and represents the testbed for this analysis. The University campus consists in several buildings scattered throughout the city, which differ significantly in terms of building typology, dimension and construction year. The university comprises many student houses in the proximity of the main building that, however, were not taken into account during the analysis. In Figure 6.4-2, a floor map of the main building taken as case study for the project is reported.

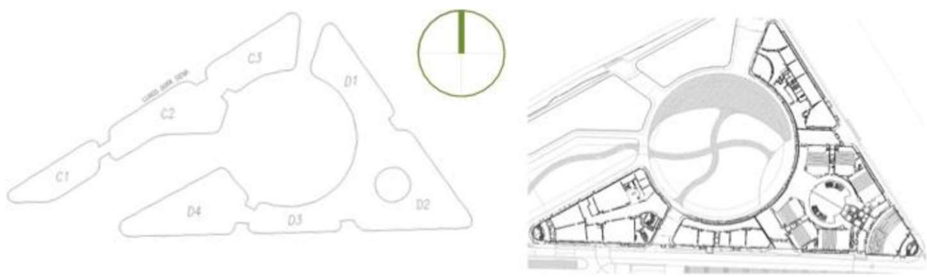


Figure 6.4-2. One of the ComfortSense project testbeds.

6.4.3 Methodological framework: building energy simulation for behavioural change

Sensor network and data collection

In particular, a network of sensors allowed for measuring a representative set of indoor environmental parameters useful for the evaluation of comfort: air temperature, relative humidity, CO_2 concentrations and people density were gathered every 10 minutes. Moreover, wearable sensors were adopted in the project for collecting data on air temperature, air relative humidity and illuminance level to be matched with the data gathered by fixed building sensors.

The second source of information was the smartphone application on which the participants at the Living Lab were able to express the perception of their comfort condition. Since the variability in energy consumption was described by an increase (or decrease) in terms of comfort conditions, the ultimate goal was to match the customized feedback related to the energy consumption with users' perceptions of comfort. In this way, building (or zone) occupants, could provide their feedback on perceived comfort conditions, and at the same time understand the relationship between the comfort and the amount of energy use.

Data analytics and feedback

Different evaluation methods have allowed to analyse information with specific purposes. First, data processing has allowed to obtain both statistics on participation to the Living Lab and real-time measurements. These elaborations were represented by infographics and reported in a project dedicated website, in social media main pages and in a specific application for the energy manager.

Then, the data collection allowed the estimation of a Direct Virtual Sensor, which provided the average comfort level as a function of the measured objective and subjective data. DVS was useful to give the users information on comfort conditions in all the zones, even if not equipped with sensors. DVS comfort outcomes were directly displayed on the smartphone app that was realized during the first months of the experimentation.

A dynamic building energy simulation software (IDA ICE, v.4.6) was used to model the monitored rooms and perform predictions energy dynamic simulations. The simulation outcomes were scaled up to the building level to have a benchmark for comparing different user behaviour scenarios. In particular, the simulation inputs were calibrated by taking into account in-field measurements and real consumption data in order to obtain a model close to reality. Since the purpose of the simulation scenarios was to define different occupant behaviours, three different types of users were simulated: “Standard” User, “Aware” User and “Unaware” user. In particular, “Standard” user was modelled as defined in the EU standard and policies (i.e. EN 15251); "Aware" and "Unaware" users are broken down into further sub-categories, each of them characterized by variations in indoor environmental parameters requests having an impact on comfort assessment. User behaviour effect was then modelled by running sequential simulations varying specific physical environmental parameters. The set of performed simulations allowed to verify the effect of each variable separately (From Scenario 1.1 up to 1.5 and from Scenario 2.1 up to 2.5), and the combined effect (Scenario 1 and Scenario 2) with respect to the Standard User (Scenario 0). Table 6.4-1 outlines the different values considered for the definition of the simulation scenarios. Obtained outcomes were then used to define customized feedback for the engaged users.

The following variables were identified for the definition of the simulation scenarios:

- Winter and summer temperature set-point (°C);
- Relative humidity (%);
- Indoor illuminance level (lux);
- CO_2 concentration (ppm).

The results obtained from the energy dynamic simulations were useful for other stakeholders, i.e. the energy managers, who could link energy forecast scenarios to optimize the operation of the building plant systems.

Table 6.4-1. Assumed user scenarios based on indoor environmental variables.

	Set-point Winter	Set-point Summer	Relative Humidity	Illuminance level	CO2 Concentration
			Standard User		
Scenario 0	**21°C**	**25°C**	**40%-70%**	**500-700 lux**	**700-1000 ppm**
			Informed User		
Scenario 1.1	**19°C**	25°C	40%-70%	500-700 lux	700-1000 ppm
Scenario 1.2	21°C	**27°C**	40%-70%	500-700 lux	700-1000 ppm
Scenario 1.3	21°C	25°C	**50%-80%**	500-700 lux	700-1000 ppm
Scenario 1.4	21°C	25°C	40%-70%	**500-550 lux**	700-1000 ppm
Scenario 1.5	21°C	25°C	40%-70%	500-700 lux	**800-1300 ppm**
Scenario 1	**19°C**	**27°C**	**50%-80%**	**500-550 lux**	**800-1300 ppm**
			Uninformed User		
Scenario 2.1	**23°C**	25°C	40%-70%	500-700 lux	700-1000 ppm
Scenario 2.2	21°C	**24°C**	40%-70%	500-700 lux	700-1000 ppm
Scenario 2.3	21°C	25°C	**40%-50%**	500-700 lux	700-1000 ppm
Scenario 2.4	21°C	25°C	40%-70%	**300-1000 lux**	700-1000 ppm
Scenario 2.5	21°C	25°C	40%-70%	500-700 lux	**500-700 ppm**
Scenario 2	**23°C**	**24°C**	**40%-50%**	**300-1000 lux**	**500-700 ppm**

Communication tools

Three different data visualization types have been developed, based on JavaScript, on the main website of the project, in the form of a real-time dashboard:

- display the historical power consumption;
- display of all the data collected during the project;
- display of average values of collected data, referred to a selected time interval and a specific zone in the campus map (Figure 6.4-3).

Finally, an estimate of the energy consumption variations and related costs arising from changes in the physical environmental parameters such as temperature, relative humidity and CO_2 were calculated by running energy dynamic simulations of the case study.

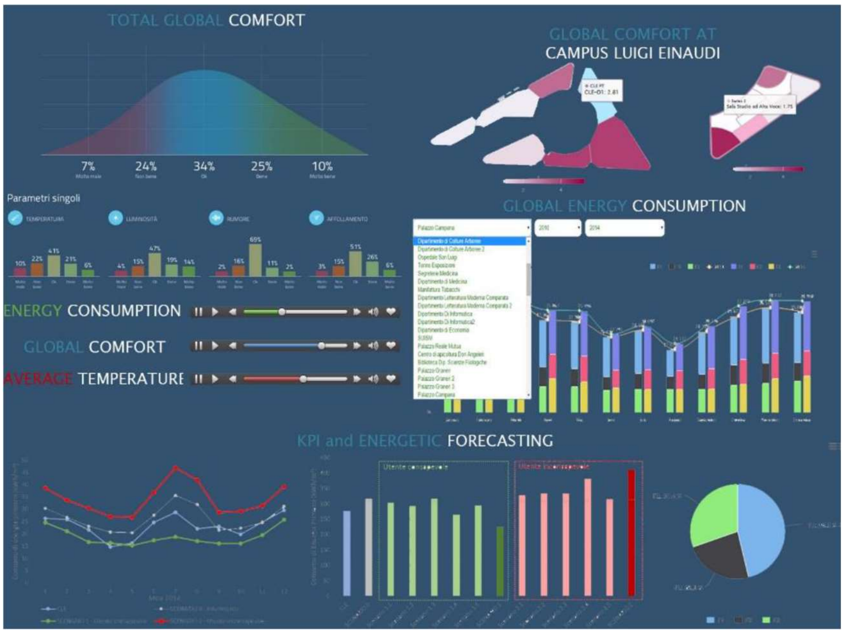


Figure 6.4-3. Real time visualization on dashboard (Cottafava et al. 2019).

6.4.4 Key findings

Each simulation scenario depicted in Table 6.4-1 is represented in Figure 5 and was compared to the measured energy consumption of the building ("Real Building"). The results of these scenarios were used to create "what if" scenarios implemented as direct feedback for the users in the mobile application. Indeed, the feedback related to different potential scenarios aimed at raising user awareness by showing them how their behaviour might influence building energy performances, also in terms of thermal comfort and costs. The synergy between ICT tools and energy simulations was therefore a crucial aspect for this research: On one hand, energy simulations were calibrated with collected data from the ICT tools; on the other hand, the results of the energy simulations were implemented to give feedback via mobile application and obtain behavioural change. Results showed that a generic "Unaware User" corresponds to significant energy savings and to a decrease of the classic peak of energy consumption for cooling during the summer months.

In particular, the "Aware" User defined in Scenario 1 leads to a decrease in terms of annual primary energy consumptions by -29%. As regards the single effect of each variable setting, the highest energy savings are related to Scenario 1.4, in which the illuminance level range was set to 500-550 lux with respect to the "Standard" User (500-700 lux). Scenario 1.3, which regarded the variation of the indoor relative humidity settings, instead, did not lead to any significant changes of the annual primary energy uses of the building.

On the other hand, the "Uninformed" User represented as Scenario 2 increased the annual primary energy use of the building up to +30% with respect to the "Standard" User. Similar to Scenario 1, the highest impact is given by Scenario 1.4, in which the range of the illuminance level was assumed to be 300-1000 lux.

Among the “Unaware” User scenarios settings, the variation of the CO_2 concentration ranges (Scenario 2.5) did not alter significantly the outcomes of the simulation results. In Figure 6.4-5, the final annual energy consumption of the main simulated user types (“Standard”, “Aware”, “Unaware”) are plotted against the real measured primary energy use (blue line) The graph highlights that the modelled “Standard” User (Scenario 0) is similar to the real building energy consumption profile. Indeed, Scenario 0 (grey line) was calibrated according to the current comfort settings in the case study. The simulated consumption profiles of the “Aware” and “Unaware” users are presented by the green and the red line, respectively. The latter profiles show a significant variation in terms of primary energy consumptions throughout the whole year, and especially during the summer peak.

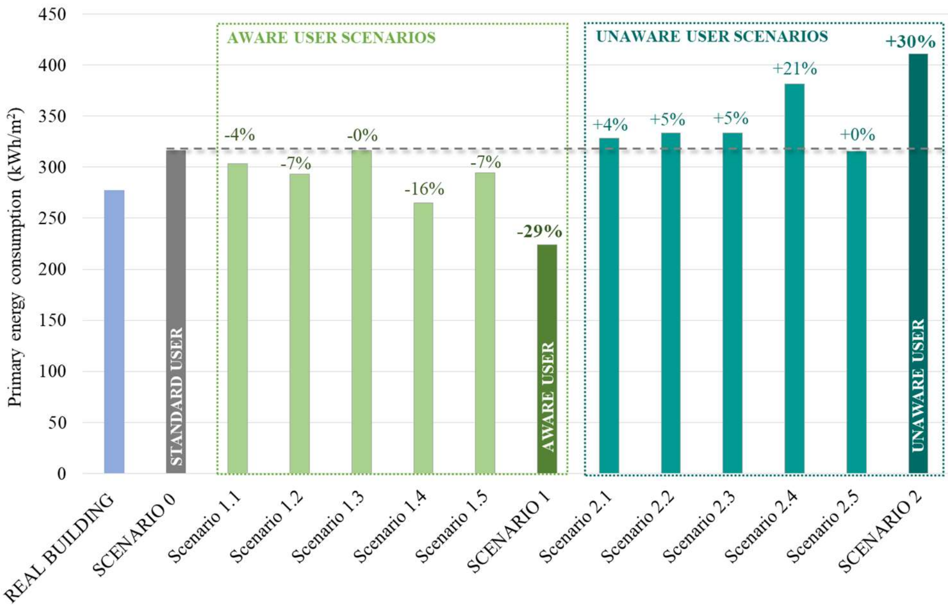


Figure 6.4-4. Primary energy consumptions of the analysed energy scenarios.

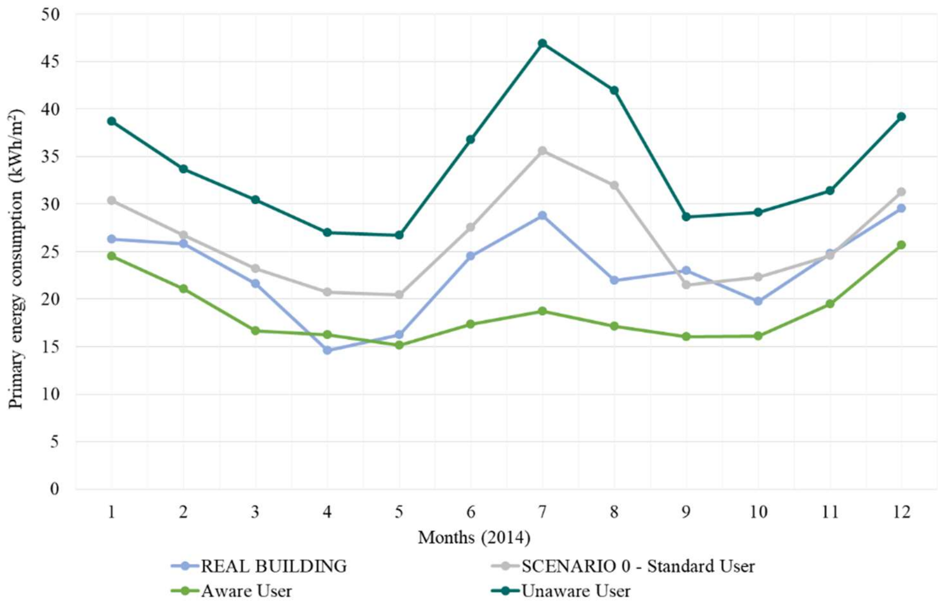


Figure 6.4-5. Annual primary energy consumption of the analysed scenarios.

Finally, Table 6.4-2 summarises the main simulation results in terms of thermal comfort conditions and energy consumptions (electric, thermal and primary). As regards the simulated thermal comfort conditions, the authors referred to the European Standard EN 15251 (CEN 2008) and to the Predicted Mean Vote (PMV) Index (EN 7730; 2005) evaluation during winter and summer, respectively.

In particular, the table highlights that in Scenario 1 ("Aware User"), the PMV indexes both in winter and summer period are close to 0, corresponding to a neutral thermal condition and at the same time to a decrease of annual primary energy consumption of -29%.

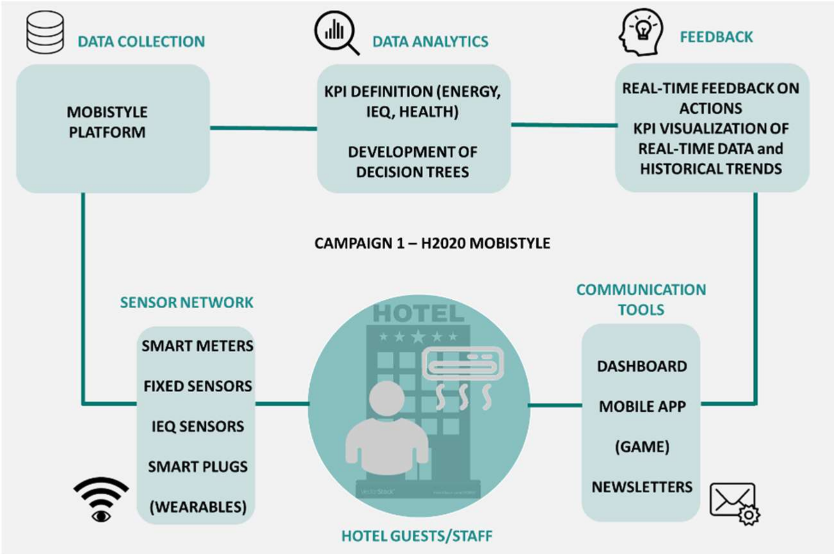
Table 6.4-2. Simulation results of the analysed scenarios.

			Scenario 0 Standard User	**Scenario 1 Aware User**	**Scenario 2 Unaware User**
Comfort	EN 15251	Category I	23%	16%	31%
		Category II	34%	23%	34%
		Category III	43%	50%	35%
		Category IV	0%	10%	0%
	EN 7730	PMV winter	-0.16	-0.24	-0.11
		PMV summer	0.02	0.08	0
Energy Consumption	Electric	($kWhel/m^2$)	117.5	86.6 (-26%)	152.1 (+29%)
	Thermal	($kWht/m^2$)	61.1	36.1 (-41%)	80.7 (+32%)
	Primary	($kWhEP/m^2$)	316.1	224.1 (-29%)	410.7 (+30%)

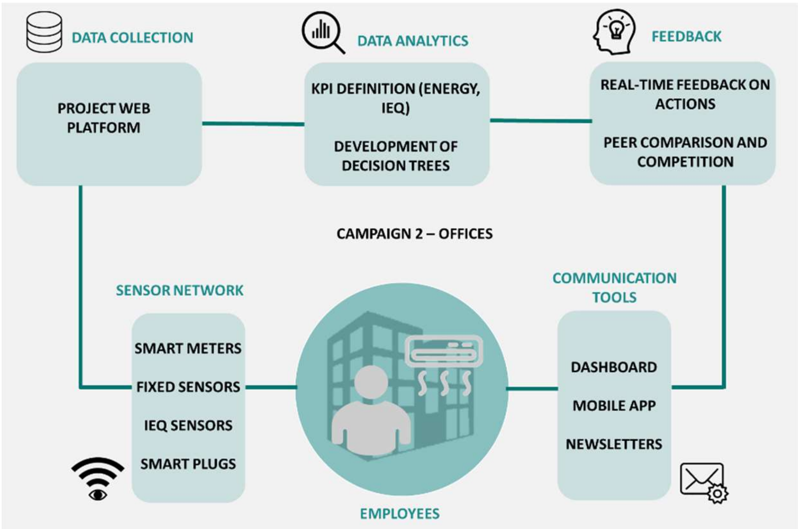
6.5 Discussions and further investigations

6.5.1 Comparison of the three analysed engagement campaigns

Figure 6.5-1 shows the behavioural change strategy for each of the presented projects. This comparison is aimed at highlighting that behavioural change can be leveraged through different triggers and that different typologies of feedback can be provided towards reaching energy efficiency goals and well-being of the occupants at the same time. The effectiveness of Campaign 1 still needs to be fully explored, however it represents the most interdisciplinary approach that tackles not only energy and comfort-related aspects, but also anthropological and biological (health) factors of the engaged users. A holistic approach and the combination of different areas of expertise seem to be essential to fully understand and leverage the behaviour of users in different building contexts. Campaign 2 exploits the stimulus of the employees to "be better than others" through peer comparison at work. The development of decision trees that allow for providing the users real-time feedback permit to interact with the users instantly when an action to improve their indoor environment was required. Campaign 3 exploited dynamic energy simulations to provide university staff and students information on how their behaviour can impact building energy consumption. The common objective of these campaigns is to move towards a **new human-building ecosystem**, in which occupants become living sensors and exercise smart control over their indoor environment. This can only happen if the occupants are engaged to adopt a **long-term behavioural change**.



(a)



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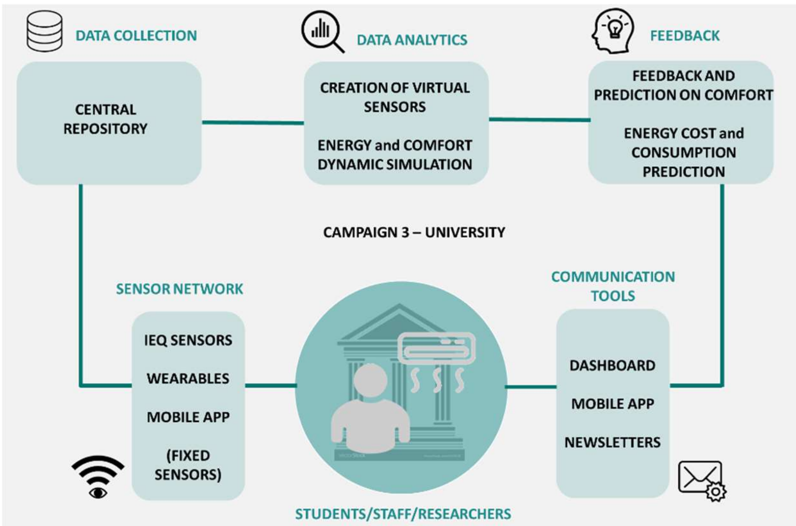

(c)

Figure 6.5-1. The human in the loop - comparison of the 3 behavioural change campaigns.

6.5.2 Towards a new human-building ecosystem

As shown in Figure 6.5-2, the user becomes an active player in the human-building ecosystem and interacts with the building and systems causing changes in indoor environmental quality and energy consumption (Fabi et al. 2017). The user node is activated by technology to be part of the sensing system (i.e. sensors and devices), receiving feedbacks on indoor environmental quality and health levels and the outcomes on energy savings. As a result, people will interact with the building and systems in a more "informed" and aware manner.

Technology is then used to design buildings that help people work, live, perform and feel their best.

Technology is a fundamental tool to let buildings be flexible and dynamic.

The "DYNAMIC BUILDING" node refers then to buildings becoming active, flexible and adapting themselves according to the preferences of the users. A set of indoor, outdoor, fixed and wearable sensors gain and provide data through an app. Tailored information from and to users let the system learn and adapt itself to the user needs.

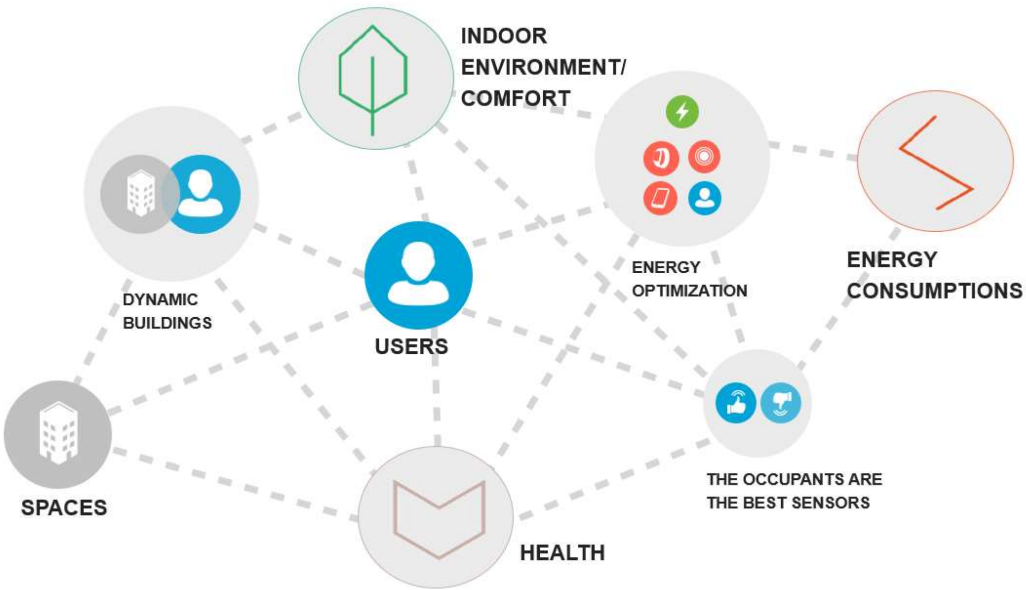

Figure 6.5-2. The human-building ecosystem (Fabi et al. 2017).

6.5.3 Long-term behavioural change objective

According to the behavioural automatization process presented by Fabi et al. (2017), the long-term behavioural change can be described as follows (Figure 6.5-3):

• **Unawareness**: The occupants might not be aware if and/or how their behaviour might impact energy consumption, their indoor environment quality and their own well-being ("I don't know that I don't know");

• **Learning:** With the help of the MOBISTYLE awareness campaign, the occupants learn about how their behaviour affects building energy use, the indoor environmental quality and their well-being ("I know that I don't know");

• **Habit formation:** The occupants start putting into practice the information they learnt and may develop a change in routine habits ("I know that I know");

• **Internalization of behaviour:** The occupants adopt and internalize the new and more conscious behaviour and now act automatically ("I don't know that I know").

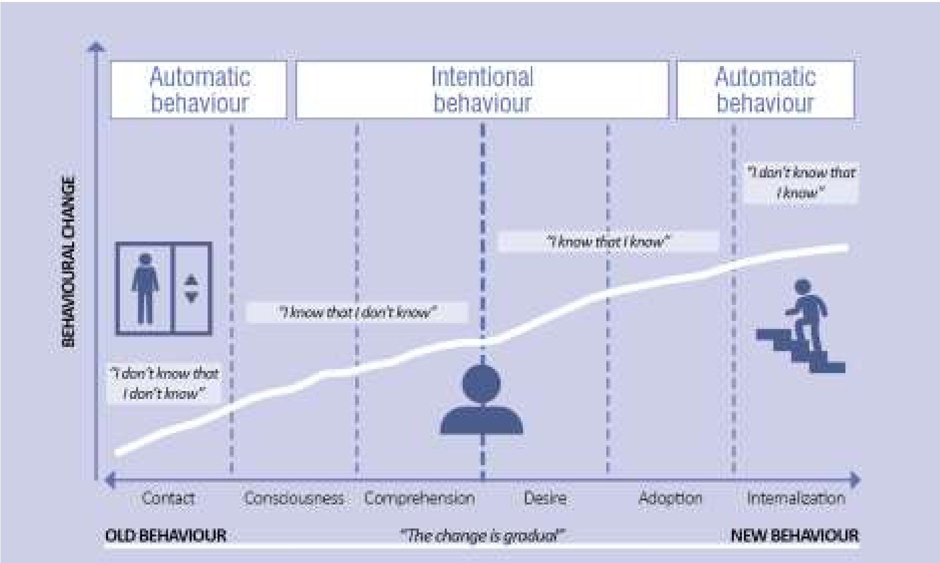

Figure 6.5-3. Long-term behavioural change objective (Fabi et al. 2017).

6.5 Perspectives and future challenges

The presented energy engagement campaigns highlight that energy efficiency goals can be only met if the occupants adopt an energy-aware aware lifestyle. For this reason they should be informed about the consequences of their energy-related actions and how they can become "smart" users in smart buildings. Only in that way the impact of the human factor on building energy demand can be optimized and it is truly possible to reach the nearly zero energy target (Chapter 1). In order to optimize the behavioural change process, further work is needed to address the capability of innovative triggers in different building typologies and on a large scale. The effectiveness of different feedback strategies (e.g. feedback or feedforward information) and related analytics are crucial aspects that need further attention. Also the effectiveness of different feedback typologies compared to each other should be carefully investigated. This includes characteristics such as type (numerical, graphical), communication strategy (prompts, pop-up message, educative advices, serious gaming, newsletters), length (concise, long), wording and design (efficacy of the chosen language), credibility (coherency of provided feedback. Oftentimes, behavioural change programs are designed to follow one particular approach, but do not evaluate the effectiveness of a wider range of feedback and communication strategies. Furthermore, a key challenge is to explore the required duration of energy engagement campaigns that allows for obtaining behavioural change on a long term, since otherwise the engaged users might fall back into their old (and not energy-friendly) habits. To this aim, further work is needed to perform post-project evaluations in order to assure energy savings not only on a short term, but rather to achieve and guarantee a reliable energy conservation measure through leveraging long-term behavioural awareness.

6.6 Publications

PAPER XV **Barthelmes, V.M.**, Fabi, V., Corgnati, S.P., Serra, V. (2019). Human Factor and Energy Efficiency in Buildings: Motivating End-Users Behavioural Change, *Advances in Intelligent Systems and Computing* 825, pp. 514-525.

PAPER XVI Fabi, V., **Barthelmes, V.M.**, Kingma, B., van Marken Lichtenbelt, W., Heiselberg, P., Corgnati, S.P. (2017). Combining energy, comfort and health data for behavioural change. In: Proceedings of the 10th International Symposium on Heating, Ventilation and Air Conditioning, 19-22 October, Jinan, China.

PAPER XVII **Barthelmes, V.M.**, Becchio, C., D'Oca, S., Litiu, A.V., Tisov, A., Vergerio, G., Corgnati, S. (2019). A methodological framework to motivate and assess behavioural change: Insights into an interdisciplinary user awareness campaign. Paper accepted at the 51th International AICARR conference, 20-22 February, Venice, Italy.

PAPER XVIII Corgnati, S.P., Buso, T., **Barthelmes, V.M**. (2017), Energy management strategies for University Campuses. Chapter in: News from the Front of Sustainable University Campuses, edited by P. Lombardi and G. Sonetti, Edizioni Nuova Cultura, Rome, Italy, pp. 23-44.

PAPER XIX Fabi, V., **Barthelmes, V.M.**, Heo, Y., Corgnati, S.P. (2017). Monitoring and stimulating energy behavioural change in university buildings towards post carbon cities. In: Proceedings of the 15th IBPSA Conference 2017, 7-9 August, San Francisco, USA, pp. 423-429.

PAPER XX Cottafava, D., Magariello, S., Ariano, R., Arrobbio, O., **Barthelmes, V.M.,** Baruzzo, G., Bonansone, M., Console, L., Contin, L., Corgnati, S.P., Fabi, V., Gambino, P., Gerlero, I., Grillo, P., Guaschino, G., Landolfo, P., Malano, M., Mana, D., Matassa, A., Monterzino, L., Mosca, S., Nuciari, M., Olivetta, E., Padovan. D., Rapp, A., Sanseverino, M., Sciullo, A., Simeoni, R., Vernero, F. (2019). Crowdsensing for a sustainable comfort: behavioural change for energy saving, Energy and Buildings 186, pp. 208-220.

PAPER XXI Fabi, V., **Barthelmes, V.M.,** Corgnati, S.P. (2016). Impact of an engagement campaign on user behaviour in office environment. In: Proceedings of the 14th International Conference of Indoor Air Quality and Climate (Indoor Air 2016), Ghent, Belgium, pp. 1-8.

Chapter 7

Conclusions

7.1 Conclusive summary

This Ph.D dissertation tackled different challenges in the field of energy-related behavioural research. Table 7.1-1 summarises research gaps, research questions and respective efforts made in this dissertation to contribute addressing shortcomings in the current research body.

Table 7.1-1. Conclusive summary of this Ph.D dissertation.

Research gaps	Research questions	Contributions
Lack of understanding to which extent OB can impact building energy use and thermal comfort in high performing buildings	How significant is the impact that OB can have on building energy use and thermal comfort conditions of the occupants, especially in the context of high performing and technologically optimized buildings?	Estimation of the impact of OB on building energy use and thermal comfort in low energy buildings **(Chapter 2)**
Gap between real and predicted building energy use due to an oversimplification (e.g. fixed schedules) of the human factor in simulation programs	Is there an innovative approach to model the stochastic nature of the human-building interaction influenced by key environmental and time-related drivers towards bridging the gap between real and predicted building energy use?	Exploration of the Bayesian Network framework for developing advanced stochastic OB models **(Chapter 3)**
Absence of qualitative data and individual characteristics and preferences of building occupants in existing models	Which role do qualitative data and individual characteristics of the occupants play (e.g. thermal comfort attitudes) and how can they be introduced in the modelling process?	Introduction of qualitative data and individual characteristics of the occupants in these models through tailored OB surveys **(Chapter 4);**
Lack of reliable and affordable ways to collect large-scale occupant behaviour data	Is there a reliable way for profiling OB on a large scale to provide enhanced building simulation input?	Profiling OB (daily activities and occupancy) on a large scale based on Time Use Survey data **(Chapter 5)**
Lack of innovative solutions for motivating and assessing behavioural change towards energy efficiency goals	How to engage and assess behavioural change to optimise building operation and well-being of the occupants?	Development and evaluation of energy engagement campaigns in different environments to improve OB and raise user awareness **(Chapter 6)**

7.1.1 Estimation of the impact of OB on building energy use and thermal comfort in low energy buildings

The key findings of this chapter highlight that the energy-related occupant behaviour lifestyles significantly influence the energy performance and thermal comfort conditions, especially in high performing buildings, in which technological features have been optimized. Furthermore, results highlight that energy performance is also heavily dependent on the type of post-occupancy household arrangements. Hence, a building can only be considered an nZEB **if zero-capital actions related to the behavioral change of the occupants become as important as technological high-performing solutions** for the building features. Indeed, if the behavior of the inhabitants is energy wasting, it might be unmanageable to reach the nZE target, even if the building itself is defined "high performing;" the occupants need to be proactive in saving energy as well. Understanding the potential impact of technology-based and occupant behavior-based strategies—and the combination of the two—is, therefore, a key to learning how to make high-performing buildings commonplace and how to reduce spread in energy consumption. This chapter also confirms the **urgent need of developing reliable models that can capture the stochastic nature of the human factor** in modelling environment to bridge the gap between real and simulated building energy use. Table 7.1-2 summarises tailored research questions and key outcomes of Chapter 2.

Table 7.1-2. Conclusive summary Chapter 2.

Contribution	Tailored research questions	Outcomes
Estimation of the impact of OB on building energy use and thermal comfort in low energy buildings	What impacts can different occupant behaviour lifestyles and household arrangements have on the energy performance of a nearly zero energy building?	With respect to the basic standard consumer scenario (REF-SC), the energy consumptions vary from –83% for the low consumer scenario up to +76% for the high consumer. with respect to the basic scenario (REF, people per floor area: 0.04 pers/m2), two-person household compositions might imply significant reductions in energy consumptions (–102%). Indeed, the variation of different types of households additionally increases the discrepancy of the final energy consumptions in the several scenarios (~240%). This percentage is in line with the literature values regarding the variation of the energy uses due to occupant-driven interactions with the building envelope and systems (~300%; Andersen 2007; Mahdavi 2011).
	What impacts can different occupant behaviour lifestyles and household arrangements have on the thermal comfort conditions of a nearly zero energy building?	During winter, the best thermal comfort conditions are linked to the high consumer profiles for all types of household compositions On the contrary, the low consumer profiles are generally responsible for the poorest comfort conditions. However, energy savings and adequate comfort conditions can be achieved at the same time through adaptive actions (clothing adjustment). Results suggest that the thermal comfort conditions, especially associated to two-person households, during the cooling period do not vary significantly according to the different consumer lifestyles (Class I varies from 31 to 36% for the old and young couples scenarios, respectively). Low consumer profiles might, therefore, be accepted also for their indoor thermal comfort conditions.
	Which are the key behavioural patterns that should be addressed by decision-makers of behavioural change programs in high performing buildings?	The most influencing occupant-driven variables on final energy consumptions are related to the electric equipment use in first place (from –28% up to +25%), and second, to the lighting use (from –26% up to +18%). Indeed, the unpredictable loads related to these variables gain greater influence than in buildings whose envelope-driven loads dominate the consumptions profile.

	Do these key behavioural patterns differ in high and low performing buildings?	As shown above, in the (i) nZEB scenario, the most influencing occupant-driven variables on final energy consumptions are related to the electric equipment use in first place (from –28% up to +25%), and second, to the lighting use (from –26% up to +18%). Indeed, the unpredictable loads related to these variables gain greater influence than in buildings whose envelope-driven loads dominate the consumptions profile. In the latter, or rather the scenario related to (ii) RB, results show that the most influencing key variable on energy consumption is given by the variation of the behavioural patterns related to the space heating/cooling set-points.

7.1.2 Exploration of the Bayesian Network framework for developing advanced stochastic OB models

This chapter proposed Bayesian Network modelling as a methodology to model window opening behaviour of occupants in residential buildings. The case study on the basis of measured data in a residential apartment located in Copenhagen, Denmark demonstrated the potential benefits of using the Bayesian Network framework for modelling the stochastic processes of energy-related behaviour with consideration of various factors that drive final control actions. The key research questions related to modelling stochastic window control behaviour were addressed through the case study and key findings are summarised in Table 7.1-3.

Table 7.1-3. Conclusive summary Chapter 3.

Contribution	Tailored research questions	Outcomes
Exploration of the Bayesian Network framework for developing advanced stochastic OB models	Which variables are key drivers that determine window control behaviour?	The Kolmogorov-Smirnov (K-S) two sample test allows for identifying key variables that impact window control actions regardless the data type (i.e., continuous, categorical) and underlying trend between variables. The K-S two sample test ranked the following variables with respect to their influence on triggering window opening actions: time of the day, CO_2 concentration, indoor and outdoor temperature, and indoor relative humidity. However, it is important to highlight that this analysis was based on data from one apartment, eventually drivers might change in other apartments.
	What is the most suitable target variable of window control behaviour?	Correlation analysis was performed to identify strong correlations between dominant variables that impact window opening behaviour. Adding correlations between the variables in the BN model by linking them with arcs did not increase the BIC score (criteria for best model selection) as it increases the model complexity but does not substantially increase the predictive power of the BN model.
	What level of correlations resides between variables and should they be captured in the BN model?	This study showed that the window opening action is more suitable as a target variable to model window control behaviour than the window open/close state. Indoor environment variables such as indoor CO_2 concentration level and indoor temperature were identified as key variables that change the window state, but at the same time, the indoor environment conditions are directly influenced immediately after a window control action takes place. Hence, when the window state was used as a target variable, the statistical model with using indoor environment variables as predictors did not correctly represent relationships between the indoor variables and window control behaviour.
	How to handle mixed data in the BN framework?	The study demonstrated that most BN models used for only discrete or continuous datasets are not suited to fully exploiting information embedded in the mixed dataset. A reversed BN model was proposed to appropriately handle mixed data in the bnlearn environment. The proposed model was structured to predict the probability of a window opening action given the identified key environmental and time variables. In line with existing studies and the K-S two sample test results, arc strengths in the BN model also

		indicated that, in this case study, the time of the day, CO_2 concentration and indoor/outdoor temperature are the most important variables.
	How to validate stochastic BN models and does the BN model have a high predictive power?	The BN model was validated in terms of the expected loss value and the confusion matrix through the classical cross-validation procedure. As the data points with WOAs (Window Opening Actions) are much smaller than those with NOAs (No Opening Actions), a tailored validation approach was applied to select the same number of data points for each case and compute the confusion matrix. The validation measures confirmed the high predictive power of the model and its successful application for modelling window control behaviour. In summary, Bayesian network modelling well represents the stochastic nature of window control behaviour in relation to a variety of explanatory variables and consequently provides predictions with high confidence. However, steps involved in the modelling process, specifically variable selection and validation, need to be carefully set up to correctly reflect the stochastic nature in the analysis process.

7.1.3 Introduction of qualitative data and individual characteristics of the occupants in the modelling environment through tailored OB surveys

The objective of this chapter was to gain a deeper knowledge on human interactions with the building, and in particular window control behaviour. Field measurements with survey-based information of individual household members collected in 14 Danish town houses. Based on the collected dataset, the Bayesian Network (BN) framework was applied to capture underlying relationships between these factors and window control actions. The study showed that the Bayesian Network framework presents a promising environment for hierarchically and flexibly structuring a large number of explanatory variables that drive the occupant to perform a certain action. Table 7.1-4 summarises tailored research questions and key outcomes of Chapter 4.

Table 7.1-4. Conclusive summary Chapter 4.

Contribution	Tailored research questions	Outcomes
Introduction of qualitative data and individual characteristics of the occupants in these models through tailored OB surveys	How and which background information and individual characteristics/preferences of the occupants relevant to OB, and in particular window control behaviour, should be collected?	To introduce individual characteristics of the occupants or households in the modelling process, a tailored survey framework was developed (see Annex A). The survey-based information was collected once during the heating period and was aimed at investigating a more extensive set of potential drivers: • individual comfort attitudes and preferences; • physiological factors and individual characteristics (e.g. gender, age, height, weight, smoking habits); • social and economic factors (e.g. education, household composition, household income); • perceived control and psychological factors (e.g. satisfaction of control options, knowledge of control options, interaction frequency with controls, safety); • motivations and habits related to window control behaviour; • adaptive opportunities (e.g. sequence of actions that occupants perform when they feel hot/cold).
	How can these factors be introduced in the modelling process and does the latter confirm that are they relevant?	This study proposed a BN-based modelling procedure for window control behaviour that included not only environmental and time-related factors, but also a preliminary set of individual characteristics of the

		respondents, such as thermal comfort attitude and preferences. The study was based on a combination of field measurement and survey-based investigations in 14 Danish town houses. In this case study, the outcomes revealed significant probabilistic dependencies between individual thermal comfort attitudes, preferences, and window control behaviour.

7.1.4 Profiling OB (daily activities and occupancy) on a large scale based on Time Use Survey data

In order to explore reliable ways to profile occupant behaviour on a large scale, in Chapter 5 data gathered in the diary-based Danish Time Use Survey (TUS) 2008/09 of 9640 individuals from 4679 households was analysed. Individuals' daily activities were logged in 10-min time increments for 24 h, starting and ending at 04:00, during both weekdays and weekends. The aims of this study were to (i) profile energy-related daily activities of occupants during different seasons and weekdays/weekends (ii) investigate time-related characteristics of activities such as starting and ending times and durations, and (iii) profile occupancy patterns for weekdays/weekends for different household types. The outcomes highlight that TUS is a valuable data source for large-scale-analysis and can provide a solid base for valuable input for building energy simulation for bridging the gap between simulated and real energy consumption in the Danish residential sector; typical occupancy profiles for different household types for different days of the week are freely available online. Tailored research questions and key outcomes of Chapter 5 are summarised in Table 7.1-5.

Table 7.1-5. Conclusive summary Chapter 5.

Contribution	Tailored research questions	Outcomes
Profiling OB (daily activities and occupancy) on a large scale based on Time Use Survey data	Is TUS data a useful source for profiling OB on a large (national) scale?	The analysis provided in this study demonstrated that Danish TUS data provides valuable information for developing enhanced building simulation inputs for modelling occupant behaviour and its influence on energy consumption in the Danish residential sector.
	How can TUS questions be clustered into useful knowledge on OB (energy-related activities and occupancy)?	In this study, the activities in the original survey framework were consolidated into a set of 10 energy- and occupancy-related activity clusters valuable for occupant behaviour analysis in the residential sector. Since the focus of the study was to model occupant behaviour in dwellings, activities taking place outside the domestic environment were all placed in category: no. 9 "not at home". Moreover, the definition of a category "not at home"allowed for development of detailed occupancy profiles.
	How can this information be translated into enhanced input for building energy simulation?	The aims of this study were to (i) profile energy-related daily activities of occupants during different seasons and weekdays/weekends (ii) investigate time-related characteristics of activities such as starting and ending times and durations, and (iii) profile occupancy patterns for weekdays/weekends for different household types. The outcomes provide valuable input for building energy simulation for bridging the gap between simulated and real energy consumption in the Danish residential sector. To enhance building simulation inputs for occupancy in the Danish residential sector, online access to a spectrum of individual occupancy pro- files for different household typologies and different days of the week is provided.
	What are the outcomes (activity and occupancy profiling) in the Danish context?	Daily profiles of ten energy- and occupancy-related activities were different depending on the season day of the week (week- days and weekends). Survival curves of the daily time durations of the activities provided typical starting/ending

	times of each activity and representative occupancy profiles for different household typologies during weekdays and weekends. Furthermore, during weekdays occupants were most likely to leave their home at 08:00 or 13:00 and tended to return at noon or in the late after- noon/early evening hours (18:00).
Do occupancy profiles based on the Danish TUS data differ from conventional profiles?	The outcomes were in line with typical trends of hourly electricity profiles in Danish households. Indeed, similar peak values of hourly electric load profiles and some energy-related activities were observed during the same hours of the day. The Danish TUS data provided occupancy patterns similar to an existing simplified occupancy profile developed by the U.S DOE.

7.1.5 Development and evaluation of energy engagement campaigns in different environments to improve OB and raise user awareness

Energy efficiency goals can be only met if the occupants adopt an energy-aware aware lifestyle. For this reason they should be informed about the consequences of their energy-related actions and how they can become "smart" users in smart buildings. Chapter 6 presented three energy engagement campaigns, which were analysed and compared following the structure of the elements in a behavioural change loop (sensor network and data collection, data analytics and feedback, and communication tools). The three engagement campaigns focused on three different key triggers for leveraging behavioural change, such as health aspects, comfort and peer comparison. Research questions and key findings of this chapter are summarised in Table 7.1-6.

Table 7.1-6. Conclusive summary Chapter 6.

Contribution	Tailored research questions	Outcomes
Development of Energy Engagement campaigns for behavioural change	How to leverage efficiently behavioural change through innovative triggers (e.g. health, comfort, peer comparison)?	Section 6.2 highlighted that behavioural change might be leveraged through the introduction of health-related aspects in the motivation process. The willingness of the users to improve their own well-being (e.g. higher productivity in an adequate indoor environment, improvement of the cardiovascular system) represents a key trigger for raising user awareness and should be further explored. This goes in line with the improvement of comfort conditions highlighted in section 6.3. Also the comparison to other peers leverages behavioural change based on concepts of social norms and the motivation to "do better than this".
	How to assess and evaluate behavioural change and related campaigns?	The development of a methodology for assessing and evaluating behavioural change has been presented in section 6.2.4. It is highlighted that the planning of the behavioural change strategy is a key to obtain solid results and to obtain a long term impact.
	What analytical solutions can be developed for feedback provision?	Chapter 6 showed that there can be different analytical solutions for developing user feedback. The definition of Key Performance indicators based on real-time (or historic) in-field measurements allows for providing useful feedback; however, the indicators need to be translated in useful and understandable information to the users. Also feedforward information developed through simulation tools can make the user aware of the consequences of his action and his impact e.g. on the environment.
	How much energy can be saved through behavioural change?	Section 6.3.4 confirms that significant energy savings (up to 44%) can be achieved through behavioural change interventions. These type of low-cost interventions should therefore become a key strategy when implementing energy efficiency measures.

7.2 Achievements and publications

The framework of this Ph.D dissertation allowed for contributing to the current knowledge in literature through a series of international conference papers and journal articles, and in particular:

- 8 published peer-reviewed journal papers;
- 10 international conference papers;
- 1 book chapter.

Paper XI was awarded with a Best Paper Award at the 4th International Conference on Building Energy & Environment 2018, 5-9 February, Melbourne, Australia, pp. 97-102.

Further contributions were given in the context of the development of reports and deliverables of the presented projects (Chapter 6).

Chapter 8

Perspectives and future challenges

"The incredible thing about the human mind is that it didn't come with and instruction book" (Terry Riley)

This quote might be representative for the fact that the human mind and triggers for interacting with the building is a challenging task for the building energy research community. While the physical world and performances of the building services can be "measured and modelled" in a reliable way, the analysis of the human factor will always represent a key factor of uncertainty. However, the main objective of energy–related behavioural research is to reduce the factor of uncertainty and a lot of work has been done in this context in order to capture to some extent the stochastic nature of the human-building interaction. Further work is necessary to gain a more comprehensive picture of the way the users interact with the buildings, as well as targeting these behaviours to reach energy efficiency goals and reduce the environmental impact due to unaware actions. Table 7.2-1 summarises key challenges for each line of research that require further work and perspectives that should be addressed based on the lines of research of this Ph.D dissertation.

Table 7.2-1. Challenges, future work and perspectives.

Line of research	Challenges	Future work and perspectives
Estimation of the impact of OB on building energy use and thermal comfort in low energy buildings	Extension of impact estimations on a large scale	Upcoming studies should include further investigations on different building types, as well as exploration on a larger scale.
	Consideration of occupant diversity	Future work is needed to estimate the impact on building energy use and thermal comfort based on a larger variety of user types.
	Monitoring the impact on site	Next to the simulation of occupant behaviour lifestyle scenarios, future work is necessary to define impacts in low energy buildings through in-field studies.
	Impact reduction through building automation	Further work should be developed to gain a better understanding about the relationship between impacts of occupant behaviour and building automation solutions.

Exploration of the Bayesian Network framework for developing advanced stochastic OB models	Model comparison	Future work should address the comparison of different modelling approaches (e.g. Bayesian networks, logistic regression, Markov chains) in terms of their predictive power and ability to capture the human factor.
	Integration in building energy simulation programs	Further investigations should address solutions for integrating the model outcomes into building simulation software (e.g. EnergyPlus, IDA ICE).
	Overcome current model limitations	Future explorations should address current model limitations, such as the treatment of mixed data in a complex model.
	Integration of multiple target variables	Further work is needed to integrate multiple control actions in the same model such as window control, window blinds control, thermostat control, light switching and occupancy.
Introduction of qualitative data and individual characteristics of the occupants in these models through tailored OB surveys	Investigation of a more comprehensive set of drivers	Further exploration is needed on the relationship between occupant perception, satisfaction and behaviour related to social, psychological and cognitive factors.
	Behaviour and global comfort	Further work is necessary to the relationship between occupant perception, satisfaction and behaviour and factors related to global comfort (thermal comfort, visual comfort, acoustic comfort, and indoor environmental quality).
	Investigation of more complex hierarchical models	Future work should address how a comprehensive set of factors can be modelled statistically in a hierarchical Bayesian Network model (or with other modelling approaches).
	Integration in building energy simulation programs	Further studies are needed to understand how a model based on a set of comprehensive explanatory variables can be introduced in simulation environments and if occupants can be clustered according to e.g. social or cognitive characteristics.
Profiling OB on a large scale based on Time Use Survey data	Analysis of Italian TUS data	Further work is needed to explore and compare TUS data for modelling occupant behaviour in specific geographical areas, such as Italy.
	TUS data for energy-related modelling purposes	Time Use Surveys re not specifically designed to investigate energy-related behaviour, tailored surveys could improve the reliability of the obtained responses and the modelling outcomes.
	Link between TUS data and electricity demands	Further work should investigate the link between energy-related activities and respective electricity demands in order to define high resolution demand profiles in households.
	Development of TUS-based stochastic models and validation	Further investigations should regard the development of TUS-based stochastic models validating them against real energy consumption data.
Development of Energy Engagement campaigns for behavioural change	Innovative triggers for behavioural change	Further work should address the capability of innovative triggers to leverage behavioural change in different building/district typologies, and which of them is the more effective in which context.
	Innovative ICT solutions behavioural change	The development of innovative ICT solutions and their usability, as well as their capability to leverage behaviour to the maximum) is a topic that remains interesting to explore.
	Effectiveness of feedback typologies	Further work is needed to fully explore which feedback/feedforward typologies are the most effective.
	Optimization of the learning process	Further studies are needed in order to understand project time durations and assessments to reach a long-term behavioural change.

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Appendix A

SURVEY TEMPLATE developed for PAPER VIII and IX

1. INDIVIDUAL COMFORT ATTITUDES and PREFERENCES

1.1 Please indicate the **date and the exact starting time** in which you are compiling this survey.

Date ____________________ **Time** ____________________

1.1.1 In **which room** are you compiling this survey?

☐ Living room ☐ Bedroom ☐ Kitchen ☐ Bathroom ☐ Other____________

1.1.2 What **kind of activity** were you doing **shortly before starting** to compile the survey?

☐ Sleeping
☐ Relax/reading/watching TV
☐ Writing, desk work, typing
☐ Slow walking
☐ Light housework (cooking, dishes, ironing, making beds)
☐ Heavy housework (painting, washing floors/windows)
☐ Running, sports
☐ Other____

Please answer the following questions by indicating your answer on the scale as shown in the figure below (left). Otherwise please tick the selected option as shown on the right.

1.2 Please indicate **how you currently feel.**

Cold | Cool | Slightly cool | Neutral | Slightly warm | Warm | Hot

☐ Prefer not to answer

1.3 Do you currently feel **air movement** around you?

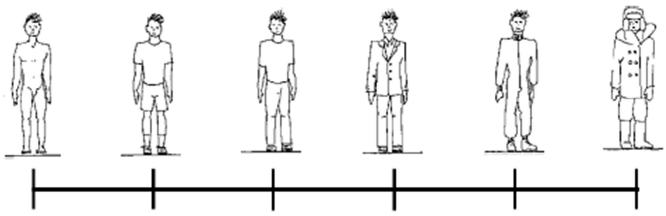
☐ No ☐ Yes

1.3.1 **If yes,** how acceptable is it?

Very unacceptable | Unacceptable | Slightly Unacceptable | Neutral | Slightly acceptable | Acceptable | Very acceptable

☐ Prefer not to answer

1.4 Please indicate how you are currently **dressed.**



☐ Prefer not to answer

1.5 Please describe the **lighting level** around you.

Very dim	Dim	Slightly dim	Neutral	Slightly bright	Bright	Very bright	☐ I don't know

1.6 How **satisfied** are you with the **amount of light** around you?

Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know

1.7 Please **describe** the **air** around you.

Very stuffy	Stuffy	Slightly stuffy	Neutral	Slightly fresh	Fresh	Very fresh	☐ I don't know
Very humid	Humid	Slightly humid	Neutral	Slightly dry	Dry	Very dry	☐ I don't know

1.8 How **satisfied** are you with the **air quality** around you?

Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know

1.9 Please **describe** the **noise level** around you.

Very silent	Silent	Slightly silent	Neutral	Slightly noisy	Noisy	Very noisy	☐ I don't know

1.9.1 If it is noisy, **where** does the noise **come from**?

☐ Indoors ☐ Outdoor ☐ Neighbours ☐ I don't know

1.10 How **satisfied** are you with the **noise level** around you?

Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know

1.11 Finally, please indicate your current **overall satisfaction** with the indoor environment.

Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know

1.12 How important are the following to you?

1.12.1 Not being **too cold** or **too warm.**

Very unimportant	Unimportant	Slightly unimportant	Neutral	Slightly important	Important	Very important	☐ I don't know

1.12.2 To have **fresh air.**

Very unimportant	Unimportant	Slightly unimportant	Neutral	Slightly important	Important	Very important	☐ I don't know

1.12.3 To have **good lighting** conditions.

Very unimportant	Unimportant	Slightly unimportant	Neutral	Slightly important	Important	Very important	☐ I don't know

1.12.4 Absence of noise.

Very unimportant	Unimportant	Slightly unimportant	Neutral	Slightly important	Important	Very important	☐ I don't know

1.12.5 Absence of drafts.

Very unimportant	Unimportant	Slightly unimportant	Neutral	Slightly important	Important	Very important	☐ I don't know

1.13 Please indicate how much you **agree or disagree with the following statements.**

	I strongly disagree	I disagree	Neutral	I agree	I strongly agree	
"I rather feel a little bit too cold in order to have a fresh air"						☐ I don't know
"I rather accept some noise from outdoors to have some fresh air"						☐ I don't know
"I rather feel a little bit too cold in order to save some energy costs"						☐ I don't know
"When I open windows I think about higher energy costs for heating"						☐ I don't know
"I rather accept a slightly bad indoor air quality in order to save some energy costs"						☐ I don't know
"My first priority is being comfortable with the temperature and air quality, I don't worry about energy costs"						☐ I don't know

"When I interact with windows and the thermostat, I think about my environmental impact" ☐ I don't know

"When I open the windows, I usually turn off the heating or lower the thermostat settings" ☐ I don't know

2. PHYSIOLOGICAL FACTORS and INDIVIDUAL CHARACTERISTICS

2.1 Please indicate your **gender**.

☐ Male ☐ Female ☐ Prefer not to answer

2.2 Please indicate your **age.**

_________ years ☐ Prefer not to answer

2.3 Please indicate your **height.**

_________ cm ☐ Prefer not to answer

2.4 Please indicate your **body weight.**

_________ kg ☐ Prefer not to answer

2.5 Do you **smoke**?

☐ No ☐ Sometimes ☐ Daily ☐ Prefer not to answer

2.5.1 Do you **smoke inside** the apartment?

☐ Never ☐ Sometimes ☐ Yes, always ☐ Prefer not to answer

2.5.1.1 Do you **open windows** to get rid of tobacco pollution?

☐ Never ☐ Sometimes ☐ Yes, always ☐ Prefer not to answer

2.6 Do you have **pets**?

☐ No ☐ Yes, I have____ ☐ Prefer not to answer

2.6.1 Do you **keep the pets inside** the apartment?

☐ Never ☐ Sometimes ☐ Yes, always ☐ Prefer not to answer

2.6.1.1 Do you **open windows/doors** to get rid of odors related to your pets or to let them in/out?

☐ Never ☐ Sometimes ☐ Yes, always ☐ Prefer not to answer

3. SOCIAL FACTORS

3.1 In a typical month, for **how long do you live** in the household this survey was sent to?

- ☐ Always
- ☐ More than half of the time
- ☐ Ca. half of the time
- ☐ Less than half of the time

☐ Prefer not to answer

3.2 Please indicate the **total number of adults** (including yourself) that in a typical month live in your household

Always ____
More than half of the time ____
Ca. half of the time ____
Less than half of the time ____

☐ Prefer not to answer

3.3 Please indicate the **number of children (under 18)** that in a typical month live in your household

Always ____
More than half of the time ____
Ca. half of the time ____
Less than half of the time ____

☐ Prefer not to answer

3.4 Please describe your **education**.

- ☐ Basic school
- ☐ Upper secondary school
- ☐ Vocational education
- ☐ Bachelor
- ☐ Master
- ☐ Other ________________

☐ Prefer not to answer

3.5 Please indicate your **job category.**

- ☐ Self-employed
- ☐ Skilled worker
- ☐ Unskilled worker
- ☐ Public/civil servant
- ☐ Trainee
- ☐ Assisting spouse/husband
- ☐ Parental leave
- ☐ Involuntarily unemployed
- ☐ In search for job
- ☐ Retired
- ☐ Housewife/househusband
- ☐ Student
- ☐ School pupil
- ☐ Pre-school child
- ☐ Other ____________

☐ Prefer not to answer

3.6 Please indicate the **monthly household net income.**

- ☐ less than 15.000 DKK
- ☐ 15.000-25.000 DKK
- ☐ 25.000-35.000 DKK
- ☐ 35.000-45.000 DKK
- ☐ 45.000-55.000 DKK
- ☐ 55.000-65.000 DKK
- ☐ more than 65.000 DKK
- ☐ Other ______

☐ Prefer not to answer

3.7 **Who** usually controls the **temperature settings** in your home?

- ☐ One specific person, please specify (father, mother, husband, wife): ___________
- ☐ Whoever feels uncomfortable changes the settings
- ☐ We have different ideas and usually discuss about this
- ☐ We decide together
- ☐ We usually don't change the settings
- ☐ Other______________

☐ Prefer not to answer

3.8 **Who** usually opens the **windows** in your home?

- ☐ One specific person, please specify (father, mother, husband, wife):______________
- ☐ Whoever feels uncomfortable operates the windows
- ☐ We have different ideas and usually discuss about this
- ☐ We decide together
- ☐ We usually don't open the windows
- ☐ Other ______________

☐ Prefer not to answer

3.9 **Who** usually closes the **windows** in your home?

- ☐ One specific person, please specify (father, mother, husband, wife): ______________
- ☐ Whoever feels uncomfortable changes the settings
- ☐ We have different ideas and usually discuss about this
- ☐ We decide together
- ☐ We usually don't open the windows
- ☐ Other ______________

☐ Prefer not to answer

3.10 **Which** and **how many** of the following **domestic appliances** are used in your home?

- ☐ TV ___
- ☐ Dishwasher ___
- ☐ Washing machine ___
- ☐ Dryer ___
- ☐ Personal Computer___
- ☐ Fridge___
- ☐ Other _________________________ ___
- ☐ Other _________________________ ___

☐ Prefer not to answer

4. PERCEIVED CONTROL and PSYCHOLOGICAL FACTORS

4.1 How **difficult or unhandy** is it for you to use

Thermostat	Very difficult	Difficult	Slightly Difficult	Neutral	Slightly easy	Easy	Very easy	☐ I don't know how to use it
Windows	Very difficult	Difficult	Slightly Difficult	Neutral	Slightly easy	Easy	Very easy	☐ I don't know how to use them
Shading devices	Very difficult	Difficult	Slightly Difficult	Neutral	Slightly easy	Easy	Very easy	☐ I don't know how to use them

4.2 Are you generally **satisfied** with the **following control options** in your home?

Thermostat	Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know
Windows	Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know
Shading devices	Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know

4.3 Overall, are you generally **satisfied** with the **control options** in your home?

Very unsatisfied	Unatisfied	Slightly unsatisfied	Neutral	Slightly satisfied	Satisfied	Very satisfied	☐ I don't know

4.4 In the last **14 days, how often** did you **interact with the**…(please check only one box per row)

	More than 3 times/day	3 times/day	2 times/day	1 time/day	3 times/week	2 times/week	1 time/week	Less than 1 time/week	Never
Thermostat	☐	☐	☐	☐	☐	☐	☐	☐	☐
Windows	☐	☐	☐	☐	☐	☐	☐	☐	☐
Shading devices	☐	☐	☐	☐	☐	☐	☐	☐	☐

5. MOTIVATIONS and HABITS

5.1 **Why and where** do you usually **open windows?** Please indicate all that apply.

- ☐ To let fresh air in **- if yes, where?** ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To let bad air out ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To let more natural light in ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To change the indoor temperature ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To enjoy the outdoor environment ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To get rid of tobacco smoke ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To prevent growth of molds on surfaces ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ I have specific **habits** related to window opening, in particular I open windows
  - ☐ at a certain time of the day, I tend to open windows
    - ☐ when I come back home ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ when I leave home ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ when I wake up ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ Other______________ ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
  - ☐ during certain activities
    - ☐ when I cook ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ when I sleep ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ after a shower ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ Other______________ ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
  - ☐ Other ________________

5.2 Do you usually **open windows** when…

You are in an especially **good mood** ☐ Never ☐ Sometimes ☐ Yes, always ☐ Not sure

You are in an especially **bad mood or stressed** ☐ Never ☐ Sometimes ☐ Yes, always ☐ Not sure

5.3 **Why and where** do you usually **close windows**? Please indicate all that apply.

- ☐ It is getting too cold/hot **- if yes, where?** ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ It is too windy ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To save energy ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ To reduce the noise level from outdoors ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
- ☐ I have specific habits related to window closing, in particular I close windows
  - ☐ at a certain time of the day, I tend to close windows
    - ☐ when I come back home ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ when I leave home ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ when I wake up ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ Other______________ ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
  - ☐ during certain activities
    - ☐ when I cook ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ when I sleep ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
    - ☐ Other______________ ◻ Living room ◻ Bedroom ◻ Bathroom ◻ Kitchen
  - ☐ Other ________________

5.4 Do you **close** your windows for **safety/security reasons**?

☐ Never ☐ Sometimes ☐ Yes, always

5.4.1 Do you generally use the **theft protection** when you open the windows? Please indicate all that apply.

☐ Yes, in the living room ☐ Yes, in the bedroom ☐ I don't use theft protection

☐ Yes, in other rooms:______________________

6. ADAPTIVE OPPORTUNITIES

6.1 Think of a situation in your home, in which you **felt hot** and **the outdoor temperature was lower than the indoor temperature** (e.g. **winter**), which action did you perform first? Please number the actions you performed in sequence **(only the ones that apply)** (e.g. _1_First action, _2_second action).

- ☐ ___Turn down the heating
- ☐ ___Take some layers of clothing off
- ☐ ___Open a window
- ☐ ___Regulate the window blind devices
- ☐ ___Move to a cooler space
- ☐ ___Other ____________

☐ I don't know

6.2 Think of a situation in your home, in which you **felt cold**, and **the outdoor temperature was lower than the indoor temperature** (e.g. **winter**), which action did you perform first? Please number the actions you performed in sequence.

- ☐ ___Turn up the heating
- ☐ ___Put some layers of clothing on
- ☐ ___Close a window
- ☐ ___Regulate the window blind devices
- ☐ ___Take a hot shower
- ☐ ___Eat something warm/have a warm drink
- ☐ ___Cook
- ☐ ___Increase the activity level (movement, sports)
- ☐ ___Put on a blanket
- ☐ ___Other ____________

☐ I don't know

6.3 Think of a situation in your home, in which you **felt hot** and **the outdoor temperature was higher than the indoor temperature** (e.g. **summer**), which action did you perform first? Please number the actions you performed in sequence.

- ☐ ___Use a fan
- ☐ ___Take some layers of clothing off
- ☐ ___Open a window
- ☐ ___Close a window
- ☐ ___Regulate the window blind devices
- ☐ ___Move to a cooler space
- ☐ ___Take a nap/relax
- ☐ ___Drink something cold
- ☐ ___Other ____________

☐ I don't know

6.4 Think of a situation in your home, in which you **felt cold** and **the outdoor temperature was higher than the indoor temperature** (e.g. **summer**), which action did you perform first? Please number the actions you performed in sequence.

- ☐ ___Put some layers of clothing on
- ☐ ___Open a window
- ☐ ___Regulate the window blind devices
- ☐ ___Take a hot shower
- ☐ ___Eat something warm/have a warm drink
- ☐ ___Cook
- ☐ ___Sit in the sun to get warm
- ☐ ___Other ____________

☐ I don't know

7. ACTIVITY and OCCUPANCY REPORTING

Please report your **activities** of your **last full day (24 hours - from 4am yesterday to 4am today)** in 10-minute intervals. Please put a **circle** on the activity you were performing at every time step.

This is an example that shows you how to fill in the diary indicating that you slept from 04:00 to 05:00, then went to the toilet for half an hour and then started to eat your breakfast.

21/10

Date

Time	SLEEP	BATH	EATING	...	...	...	...	...	...	...
04:00	1	2	3	4	5	6	7	8	9	10
04:10	1	2	3	4	5	6	7	8	9	10
04:20	1	2	3	4	5	6	7	8	9	10
04:20	1	2	3	4	5	6	7	8	9	10
04:40	1	2	3	4	5	6	7	8	9	10
04:50	1	2	3	4	5	6	7	8	9	10
05:00	1	2	3	4	5	6	7	8	9	10
05:10	1	2	3	4	5	6	7	8	9	10
05:20	1	2	3	4	5	6	7	8	9	10
05:30	1	2	3	4	5	6	7	8	9	10
05:40	1	2	3	4	5	6	7	8	9	10
05:50	1	2	3	4	5	6	7	8	9	10
06:00	1	2	3	4	5	6	7	8	9	10

Please now fill in your own diary based on the following **10 activities**:

Date

Time	1	2	3	4	5	6	7	8	9	10
	Sleeping	Toilette	Eating	Cooking/washing dishes	Cleaning/washing clothes	Practical work	Family care/free time	Relaxing/TV/IT	NOT AT HOME	Others
04:00	1	2	3	4	5	6	7	8	9	10
04:10	1	2	3	4	5	6	7	8	9	10
04:20	1	2	3	4	5	6	7	8	9	10
04:30	1	2	3	4	5	6	7	8	9	10
04:40	1	2	3	4	5	6	7	8	9	10
04:50	1	2	3	4	5	6	7	8	9	10
05:00	1	2	3	4	5	6	7	8	9	10
05:10	1	2	3	4	5	6	7	8	9	10
05:20	1	2	3	4	5	6	7	8	9	10
05:30	1	2	3	4	5	6	7	8	9	10
05:40	1	2	3	4	5	6	7	8	9	10
05:50	1	2	3	4	5	6	7	8	9	10
06:00	1	2	3	4	5	6	7	8	9	10
06:10	1	2	3	4	5	6	7	8	9	10
06:20	1	2	3	4	5	6	7	8	9	10
06:30	1	2	3	4	5	6	7	8	9	10
06:40	1	2	3	4	5	6	7	8	9	10
06:50	1	2	3	4	5	6	7	8	9	10
07:00	1	2	3	4	5	6	7	8	9	10
07:10	1	2	3	4	5	6	7	8	9	10
07:20	1	2	3	4	5	6	7	8	9	10
07:30	1	2	3	4	5	6	7	8	9	10
07:40	1	2	3	4	5	6	7	8	9	10
07:50	1	2	3	4	5	6	7	8	9	10
08:00	1	2	3	4	5	6	7	8	9	10
08:10	1	2	3	4	5	6	7	8	9	10
08:20	1	2	3	4	5	6	7	8	9	10
08:30	1	2	3	4	5	6	7	8	9	10
08:40	1	2	3	4	5	6	7	8	9	10
08:50	1	2	3	4	5	6	7	8	9	10
09:00	1	2	3	4	5	6	7	8	9	10
09:10	1	2	3	4	5	6	7	8	9	10

Time	1	2	3	4	5	6	7	8	9	10
	Sleeping	Toilette	Eating	Cooking/washing dishes	Cleaning/washing clothes	Practical work	Family care/free time	Relaxing/TV/IT	NOT AT HOME	Others
09:20	1	2	3	4	5	6	7	8	9	10
09:30	1	2	3	4	5	6	7	8	9	10
09:40	1	2	3	4	5	6	7	8	9	10
09:50	1	2	3	4	5	6	7	8	9	10
10:00	1	2	3	4	5	6	7	8	9	10
10:10	1	2	3	4	5	6	7	8	9	10
10:20	1	2	3	4	5	6	7	8	9	10
10:30	1	2	3	4	5	6	7	8	9	10
10:40	1	2	3	4	5	6	7	8	9	10
10:50	1	2	3	4	5	6	7	8	9	10
11:00	1	2	3	4	5	6	7	8	9	10
11:10	1	2	3	4	5	6	7	8	9	10
11:20	1	2	3	4	5	6	7	8	9	10
11:30	1	2	3	4	5	6	7	8	9	10
11:40	1	2	3	4	5	6	7	8	9	10
11:50	1	2	3	4	5	6	7	8	9	10
12:00	1	2	3	4	5	6	7	8	9	10
12:10	1	2	3	4	5	6	7	8	9	10
12:20	1	2	3	4	5	6	7	8	9	10
12:30	1	2	3	4	5	6	7	8	9	10
12:40	1	2	3	4	5	6	7	8	9	10
12:50	1	2	3	4	5	6	7	8	9	10
13:00	1	2	3	4	5	6	7	8	9	10
13:10	1	2	3	4	5	6	7	8	9	10
13:20	1	2	3	4	5	6	7	8	9	10
13:30	1	2	3	4	5	6	7	8	9	10
13:40	1	2	3	4	5	6	7	8	9	10
13:50	1	2	3	4	5	6	7	8	9	10
14:00	1	2	3	4	5	6	7	8	9	10
14:10	1	2	3	4	5	6	7	8	9	10
14:20	1	2	3	4	5	6	7	8	9	10
14:30	1	2	3	4	5	6	7	8	9	10
14:40	1	2	3	4	5	6	7	8	9	10
14:50	1	2	3	4	5	6	7	8	9	10
15:00	1	2	3	4	5	6	7	8	9	10
15:10	1	2	3	4	5	6	7	8	9	10
15:20	1	2	3	4	5	6	7	8	9	10
15:30	1	2	3	4	5	6	7	8	9	10
15:40	1	2	3	4	5	6	7	8	9	10
15:50	1	2	3	4	5	6	7	8	9	10
16:00	1	2	3	4	5	6	7	8	9	10
16:10	1	2	3	4	5	6	7	8	9	10
16:20	1	2	3	4	5	6	7	8	9	10
16:30	1	2	3	4	5	6	7	8	9	10
16:40	1	2	3	4	5	6	7	8	9	10
16:50	1	2	3	4	5	6	7	8	9	10
17:00	1	2	3	4	5	6	7	8	9	10
17:10	1	2	3	4	5	6	7	8	9	10
17:20	1	2	3	4	5	6	7	8	9	10
17:30	1	2	3	4	5	6	7	8	9	10
17:40	1	2	3	4	5	6	7	8	9	10
17:50	1	2	3	4	5	6	7	8	9	10
18:00	1	2	3	4	5	6	7	8	9	10
18:10	1	2	3	4	5	6	7	8	9	10
18:20	1	2	3	4	5	6	7	8	9	10
18:30	1	2	3	4	5	6	7	8	9	10
18:40	1	2	3	4	5	6	7	8	9	10
18:50	1	2	3	4	5	6	7	8	9	10
19:00	1	2	3	4	5	6	7	8	9	10
19:10	1	2	3	4	5	6	7	8	9	10

Time	1	2	3	4	5	6	7	8	9	10
	Sleeping	Toilette	Eating	Cooking/washing dishes	Cleaning/washing clothes	Practical work	Family care/free time	Relaxing/TV/IT	NOT AT HOME	Others
19:20	1	2	3	4	5	6	7	8	9	10
19:30	1	2	3	4	5	6	7	8	9	10
19:40	1	2	3	4	5	6	7	8	9	10
19:50	1	2	3	4	5	6	7	8	9	10
20:00	1	2	3	4	5	6	7	8	9	10
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21:00	1	2	3	4	5	6	7	8	9	10
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21:40	1	2	3	4	5	6	7	8	9	10
21:50	1	2	3	4	5	6	7	8	9	10
22:00	1	2	3	4	5	6	7	8	9	10
22:10	1	2	3	4	5	6	7	8	9	10
22:20	1	2	3	4	5	6	7	8	9	10
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23:30	1	2	3	4	5	6	7	8	9	10
23:40	1	2	3	4	5	6	7	8	9	10
23:50	1	2	3	4	5	6	7	8	9	10
00:00	1	2	3	4	5	6	7	8	9	10
00:10	1	2	3	4	5	6	7	8	9	10
00:20	1	2	3	4	5	6	7	8	9	10
00:30	1	2	3	4	5	6	7	8	9	10
00:40	1	2	3	4	5	6	7	8	9	10
00:50	1	2	3	4	5	6	7	8	9	10
01:00	1	2	3	4	5	6	7	8	9	10
01:10	1	2	3	4	5	6	7	8	9	10
01:20	1	2	3	4	5	6	7	8	9	10
01:30	1	2	3	4	5	6	7	8	9	10
01:40	1	2	3	4	5	6	7	8	9	10
01:50	1	2	3	4	5	6	7	8	9	10
02:00	1	2	3	4	5	6	7	8	9	10
02:10	1	2	3	4	5	6	7	8	9	10
02:20	1	2	3	4	5	6	7	8	9	10
02:30	1	2	3	4	5	6	7	8	9	10
02:40	1	2	3	4	5	6	7	8	9	10
02:50	1	2	3	4	5	6	7	8	9	10
03:00	1	2	3	4	5	6	7	8	9	10
03:10	1	2	3	4	5	6	7	8	9	10
03:20	1	2	3	4	5	6	7	8	9	10
03:30	1	2	3	4	5	6	7	8	9	10
03:40	1	2	3	4	5	6	7	8	9	10
03:50	1	2	3	4	5	6	7	8	9	10

Date

THANK YOU FOR YOUR TIME !! ☺