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Window Use Habits as an Example of Habitual Occupant Behaviour in Residential Buildings

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" Climb mountains not so the world can see you, but so you can see the world"
– David McCullough Jr.

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Nomenclature

Acronyms

ABM	Agent-Based Model
AC	Air Conditioning
AIC	Akaike Information Criterion
BDI	Belief Desire Intention Theory
BES	Building Energy Simulation
BMS	Building Monitoring System
CO_2	Carbon dioxide
DHW	Domestic Hot Water
EBC	Energy in Buildings and Communities Programme
EBM	Event-Based Model
EPB	EnergiePrestatie en Binnenklimaat [Dutch] Energy Performance and indoor climate [English]
EPBD	Energy Performance of Buildings Directive
EPC	Energy Performance Coefficient
EROB	Event-based Residential Occupant Behaviour model
FPR	False Positive Rate
FTE	Full Time Employment
GLMM	Generalised Linear Mixed Models
HBS	Household Budget Survey
HH	Household
HVAC	Heating Ventilation Air Conditioning
IAQ	Indoor Air Quality
ID	Household Identification Number
IDEAS	Integrated District Energy Assessment Simulations, Modelica library
IEA	International Energy Agency
IEQ	Indoor Environmental Quality
LB	Logbook
NAM	Norm Activation Model
NZEB	Nearly Zero Energy Building
OB	Occupant behaviour
OP	Window Opening Percentage
OS	Online Survey
PTE	Part Time Employment
SPSS	Statistical Package for the Social Sciences
StROBe	Stochastic Residential Occupant Behaviour model

TIB	Theory of Interpersonal Behaviour
TPB	Theory of Planned Behaviour
TPR	True Positive Rate
TRA	Theory of Reasoned Action
TUS	Time Use Survey
US	United States
WOB	Window Opening Behaviour

Symbols

A	Surface area	m^2
B	Regression coefficient	-
F	Correction factor	-
g	Solar energy transmittance	-
h	Height	m
Il	Illuminance	lux
$J(\theta)$	Correction factor for the opening angle of a window	-
n50	Air permeability, leakage air change rate @50 Pa	1/h
p	Probability value	-
P_{close}	Probability that a window will be closed	-
P_{open}	Probability that a window will be opened	-
q_v	Air flow rate	m^3/s
$R^2{}_N$	Nagelkerke R^2	-
Rain	Precipitation	mm
RH	Relative humidity	%
SH	Solar hours	h
SR	Global horizontal solar radiation	W/m^2
T	Temperature	°C
U	Thermal conductance	$W/(m^2K)$
v	Wind speed	m/s
v50	Air permeability, leakage flow rate per m^2 transmission heat loss area @50 Pa	$m^3/h.m^2$

Greek symbols

Δ	Difference
τ	Kendall's tau b
χ^2	Chi-square statistic

Subscripts

abs	absence
arr	arrival
bed	bedroom
comf	comfort
corr	corrected
dep	departure
dm	daily mean
e	outdoor
gf	ground floor
i	indoor
int	intermediate
liv	living room
op	operative
pres	presence
prev	previous
r	rain
rm	running mean
s	summer
w	winter

Samenvatting

De laatste jaren groeide het besef van de impact van de klimaatverandering op deze planeet en daarbij de nood om energie te besparen. Het energiegebruik in residentiële gebouwen is afhankelijk van verschillende aspecten zoals de gebouwschil, de geïnstalleerde systemen, het klimaat, maar ook het gebruikersgedrag. De bewoner van een gebouw kan op verschillende manieren het energiegebruik beïnvloeden, variërend van eenvoudigweg aanwezig zijn tot meer dynamische acties zoals het openen van ramen of de keuze van de verwarmingstemperatuur. Uit literatuur blijkt dat deze invloed op het energiegebruik en het binnenklimaat niet te verwaarlozen is. Desondanks, wordt een 'typisch' gebruik van een woning beschouwd in de EPB-berekening, die de energieprestatie van een woning bepaalt. Het gebruik van dit typisch gebruikersprofiel is een van de oorzaken voor de voorspellingskloof ('performance gap') tussen het berekende, theoretische energiegebruik en het effectieve energiegebruik. Terwijl dit verschil op zich niet problematisch is voor het labelen van gebouwen, kan het wel problematisch worden wanneer renovatie- of investeringsstrategieën worden ontwikkeld op basis van deze theoretische gegevens. De voorspellingskloof beperkt ook de ontwikkeling en implementatie van adequate energie-efficiëntiemaatregelen in bestaande gebouwen.

Om het gebruikersgedrag en bijbehorende energiegebruik beter te voorspellen zijn er verschillende gebruikersgedragmodellen ontwikkeld. De huidige modelleeraanpak focust voornamelijk op de veronderstelling dat het gebruikersgedrag gebaseerd is op een zekere intentie om dat gedrag uit te voeren. Daarom linken talrijke modellen het gebruikersgedrag aan weer- en tijdsvariabelen. Echter geven gedragsstudies uit de sociologie en psychologie aan dat niet alle gedragingen beredeneerd zijn, maar dat gedragingen ook een gewoonte kunnen zijn, die uitgevoerd wordt zonder dat een persoon er bewust over na denkt. Deze gewoontes komen vooral voor in vertrouwde omgevingen, zoals bijvoorbeeld residentiële gebouwen. Hoewel er al een groot aantal studies omtrent gewoontegedrag zijn uitgevoerd in de sociologie en psychologie, is dit onderwerp nog niet specifiek toegepast in de ingenieurswetenschappen.

Het doel van deze doctoraatstudie is daarom om informatie te verzamelen over gewoontes in residentiële gebouwen die invloed hebben op het energiegebruik en binnenklimaat (Deel I). Verder wordt er ook een gebruikersgedragmodel ontwikkeld dat deze bevindingen in rekening brengt (Deel II) en wordt de invloed van het gebruik van dit model in gebouw-energiesimulaties geëvalueerd (Deel III). Aangezien gebruikersgedrag een ruim onderwerp is, werd er geopteerd

om in deze doctoraatstudie voornamelijk te focussen op raamopeningsgedrag.

Gebaseerd op gedragsstudies kunnen gewoontes gezien worden als het standaard gedrag. Dit gewoontegedrag wordt consequent herhaald zolang de context onveranderd blijft, enkel wanneer significante veranderingen optreden zal het gedrag niet meer gebaseerd zijn op deze gewoontes, maar zal het gedrag worden geleid door intenties.

De huidige modelleeraanpak voor gebruikersgedrag, en meer bepaald voor raamopeningsgedrag, is voornamelijk gefocust op deze intenties, door het gebruikersgedrag te linken aan weer- en tijdsvariabelen. Echter kan de validiteit van deze vaak gebruikte aanpak in twijfel getrokken worden door een aantal onzekerheden met betrekking tot de consistentie, diversiteit en seizoensgebondenheid van de relatie tussen het raamgebruik en deze verklarende variabelen. De modelleer methodes uit de literatuur zijn toegepast op meetdata van een bijna-energieneutrale woonwijk om deze relatie tussen raamgebruik en weer- en tijdsvariabelen te evalueren (Hoofdstuk 4). De resultaten tonen aan dat een groot deel van de geobserveerde variantie in raamgebruik verklaard kan worden door het seizoen en het identificatienummer van het huishouden. Dit betekent dat het raamgebruik varieert doorheen het jaar maar dat het binnen één seizoen stabiel is, en dat deze gedragingen significant variëren tussen de verschillende huishoudens. Deze observaties bevestigen de hypothese dat bewoners ramen gebruiken volgens specifieke seizoensgebonden gewoontes.

Daarom werd de aanwezigheid van raamopeningsgewoontes in residentiële gebouwen verder onderzocht in deze studie (Hoofdstuk 5). Gewoontes kunnen eenvoudig gedetecteerd worden door gebruik te maken van enquêtes of interviews. Door een beperkt aantal vragen te stellen kan er al veel informatie verzameld worden over raamopeningsgewoontes. De online enquête uitgevoerd bij Belgische huishoudens onthulde dat bijna alle bewoners een raamopeningsgewoonte hebben met ten minste één van hun ramen. De meeste gewoontes zijn gerelateerd aan specifieke activiteiten (vb. koken, kuisen, slapen) of de aanwezigheid van de bewoner in specifieke kamers van de woning. Een vergelijkende studie met raamopeningsgegevens uit de Verenigde Staten bevestigde dat ook daar gewoontes aanwezig zijn, maar dat het type en voorkomen van de gewoontes wel afhankelijk is van de specifieke context.

Bovendien tonen twee beperkte studies omtrent zonnewering en kledinggedrag aan dat gewoontes niet alleen voorkomen in raamopeningsgedrag maar ook in andere types van gebruikersgedrag (Hoofdstuk 6). Zo zullen bewoners zich comfortabel kleden in hun woning, wat resulteert in het dragen van ongeveer dezelfde kleding binnenshuis gedurende een seizoen. Er werden ook gewoontes gedetecteerd met betrekking tot het gebruik van de zonnewering, met een groot aantal bewoners die de zonnewering altijd open laten, altijd gesloten laten of enkel 's nachts sluiten.

Aangezien het gewoontegedrag een groot deel van de variantie in het raamopeningsgedrag kan verklaren, zal de inclusie van de gewoontes in gebruikersgedragmodellen leiden tot nauwkeurigere voorspellingen van het gebruikersgedrag. Bovendien vertegenwoordigen de gewoontes een grotere diversiteit in het gebruikersgedrag en relateren ze het gebruikersgedrag beter met het dagelijks leven van de bewoner. Daarom is in deel II een gebruikersgedragmodel ontwikkeld gebaseerd op gewoontes.

Allereerst is er onderzocht of het mogelijk is om te voorspellen welke gewoontes een huishouden heeft, gebaseerd op een beperkte set gebouw- en huishoudkarakteristieken (Hoofdstuk 8). Een aantal gewoontes waren beperkt gecorreleerd met deze karakteristieken, maar sterkere correlaties werden opgemerkt tussen de gewoonte in een bepaalde kamer en de gewoontes in de andere kamers, en tussen de gewoontes in winter en zomer. Dit betekent dat er een soort gewoonte-coherentie is tussen de verschillende kamers en in verschillende seizoenen. De voorspelling van de raamopeningsgewoontes gebeurt bijgevolg door eerst voor het huishouden een gewoonte over de verschillende kamers heen in de winter te bepalen, om dan een seizoens-coherentie toe te passen om de gewoontes in de zomer te bepalen. Deze gewoontes zijn vervolgens gelinkt met een aanwezigheid- en activiteitenmodel om raamopeningsprofielen te bepalen. De validatie van dit model gaf aan dat het model in staat is om de diversiteit in het raamopeningsgedrag op een nauwkeurige manier te voorspellen, en dat het model beter werkt dan een naïeve willekeurige toekenning van de gewoontes.

In de volgende stap is het raamopeningsgewoonte-model gecombineerd met modellen voor andere types gebruikersgedrag in een overkoepelend gebruikersgedragmodel (EROB) (Hoofdstuk 9). Aangezien de gewoontes sterk gerelateerd zijn aan de uitvoering van specifieke activiteiten en belangrijke momenten doorheen de dag van de gebruiker, is ervoor gekozen om een 'event-based' model te ontwikkelen. Dit gebruikersgedragmodel, gebaseerd op recente tijdsgebruiksdata, voorspelt de aanwezigheid- en activiteitenprofielen van het huishouden en het hieraan gerelateerde raamopeningsgedrag, verwarmingsgedrag, sanitair warm water gebruik, elektriciteitsgebruik, interne warmtewinsten en CO_2-productie. Het model is niet gerelateerd aan (gesimuleerde) binnenklimaat-variabelen en is daardoor in staat om zeer snel gebruikersprofielen te genereren. Verder is het model eenvoudig te koppelen met verschillende gebouwsimulatie-software.

In het derde en laatste deel, wordt de impact van het gebruik van het model op het voorspelde energiegebruik en binnenklimaat in gebouwsimulaties geëvalueerd. De simulatieresultaten tonen aan dat gebruikersgedrag een aanzienlijke invloed heeft op het energiegebruik voor verwarming, de binnenluchtkwaliteit (d.m.v. CO_2-concentratie) en de oververhitting (Hoofdstuk 11). De grootste impact is opgetekend voor de energiezuinige woningen en voor het raamopeningsgedrag. Het gemiddeld voorspelde energiegebruik is hoger bij de simulaties met het gebruikersgedragmodel dan een voorspelling met een basismodel (dat een typisch gebruik voorstelt) voor de bijna-energie neutrale gebouwen. Voor de overige gebouwen is een lager energiegebruik voorspeld. Een gelijkaardige trend was geobserveerd voor de voorspellingskloof, wat de veronderstelling ondersteunt dat de onnauwkeurige modellering van gebruikersgedrag mogelijks een deel van de voorspellingskloof kan verklaren. Hoewel bepaalde gebouwen en systemen goed presteren wanneer een typisch gedrag is verondersteld, variëren deze prestaties sterk wanneer ze de variatie in gebruikersgedrag in rekening nemen. Daarom is het belangrijk om tijdens het ontwerp en de inregeling van de systemen de verschillen in gebruikersgedrag in rekening te nemen.

Een gedetailleerdere studie van het raamopeningsmodel gebaseerd op gewoontes benadrukte het belang van de intrinsieke karakteristieken van het model, namelijk, dat het de diversiteit in het raamopeningsgedrag voorspelt, dat het onafhankelijk is van de binnenklimaat-variabelen en dat het raamopeningsacties op realistische momenten voorspelt (Hoofdstuk 12). Een vergelijkende studie met raamopeningsmodellen uit de literatuur geeft aan dat het gewoontemodel als één van de beste de diversiteit in het raamopeningsgedrag kan voorspellen. De modellen gebaseerd op de binnentemperatuur presteren minder goed, voornamelijk in woningen met lagere verwarmingssetpunten. Extra simulaties toonden aan dat het correct voorspellen van de raamopeningsacties doorheen de dag slechts een beperkte invloed heeft op de voorspelling van het energiegebruik voor verwarming, maar wel van belang is voor de evaluatie van de binnenluchtkwaliteit en oververhitting. Deze invloed is wel sterk afhankelijk van de raamopeningsgewoonten van het huishouden.

Een correcte voorspelling van het gebruikersgedrag rekening houdend met gewoontes leidt tot een realistische voorspelling van het energiegebruik en zal ook de mogelijkheid geven om correcte maatregelenpakketten te definiëren die effectief het energiegebruik zullen verlagen. Bovendien is een goed begrip van het gebruikersgedrag, en meer specifiek het raamopeningsgedrag, van essentieel belang voor de ontwikkeling, het ontwerp en de regeling van ventilatiesystemen en ramen, maar ook voor het voorkomen van oververhitting en de evaluatie van verschillende koelingssystemen.

Summary

In recent years, climate change awareness became more important and with that the need to conserve energy. In residential buildings the energy use is determined by numerous aspects such as the building envelope, installed systems, climate, but as well the occupant behaviour. The building user can perform a wide set of actions that can have an effect on the energy use such as opening or closing windows, doors, blinds, shades; using appliances; adjusting the heating set-points; using domestic hot water; or making wardrobe choices. Many studies from the literature highlighted the significant impact of occupant behaviour on the energy use and indoor climate in residential buildings. Nevertheless, in the EPB-calculations, the energy performance of a building is assessed according to a 'typical use' of the building. The application of this 'typical dwelling use' is indicated as one of the causes for the systematic gap between the calculated, theoretical energy use and the actual, measured energy use. While the performance gap by itself is not necessarily problematic for the purpose of labelling, it becomes a problem when it leads to suboptimal transformation of the building stock, as a result of policy or investment decisions that are based on the theoretical predictions. Additionally, the performance gap prevents the development and implementation of adequate energy efficiency measures in existing houses.

To predict the residential energy use more accurately, occupant behaviour models have been developed. The current approach towards occupant behaviour modelling is predominantly based on the assumption that occupant behaviour is deliberative, with many models relating the occupant behaviour to environmental and time-dependent variables. However, behavioural studies indicate that not all actions are deliberative, and that, especially in a stable context such as a residential building, the actions are often performed without conscious thought, out of habit. In contrary to the numerous social psychology studies on habits that have been conducted, the number of engineering studies regarding habitual behaviour with building controls are limited.

Therefore the objectives of the dissertation were to gather knowledge regarding building control habits in the residential setting (Part I), to develop an occupant behaviour model which includes these findings (Part II) and to assess the impact of this model on the energy use and indoor climate predictions (Part III). Since occupant behaviour encompasses a vast domain, this study will mainly focus on the window opening behaviour.

Based on the literature review on behavioural theories, habits can be seen as

the baseline response of occupant behaviour. Habits are consistently repeated day in and day out. The behaviour deviates from the known habits solely when the context changes, and is then guided by intentions rather than habits.

The commonly used approach towards occupant behaviour modelling, and more specifically window use modelling, focusses on the behavioural intentions, as it relates window use to physical environmental and time-dependent variables. However, based on uncertainties found in the literature, questions were raised regarding the consistency, seasonality, and diversity of the relationship between window use and these explanatory variables. The analysis of these relationships for nearly zero energy buildings in Belgium revealed that a large share of the observed variance in window opening behaviour can be attributed to the season and the household-ID, in contrast to the physical environmental variables (Chapter 4). This indicates that the window use varies across the year but is rather stable within one season, and that these behaviours differ significantly between households. These observations affirmed the hypothesis that occupants use windows according to specific seasonal habits.

Therefore, the presence of window use habits in residential buildings was investigated (Chapter 5). Habits can easily be detected by conducting surveys or interviews. By asking a few simple questions a lot of information can be gathered regarding the window use habits of the occupants. The online survey of Belgian households revealed that almost all occupants have one or more habits in relation to at least one window. Most habits are related to the performance of specific activities (e.g. cooking, cleaning, sleeping) and the presence of the occupant in a specific room. A comparative study of window opening behaviour in the US confirmed that habits are as well present in that context, and that the cultural aspect is influential on the type and distribution of the habits across the population.

Two limited studies have indicated that habitual behaviour is not constricted to window use alone, but is also present in clothing behaviour and solar shading use (Chapter 6). Occupants tend to dress comfortably at their homes, which results in a relatively consistent set of clothes despite fluctuations of the outdoor environmental conditions. Additionally, the habit regarding solar shades of the occupants is predominantly defined either by always opening the shades, always closing them or by only closing them at night.

By including habits in occupant behaviour models, the behavioural predictions, and correspondingly energy use and indoor environmental quality simulations, can be ameliorated. Since the habitual behaviour can explain a significant share of the variance in window use, the inclusion of habits will result in more accurate window use predictions. Additionally, habits encompass a greater variability between occupants and relate the window use more closely to the daily life of the occupants. Therefore, a habit-based occupant behaviour model was developed in part II of this study.

Firstly, the possibility to predict window use habits is evaluated (Chapter 8). The relationship between a limited number of household and building characteristics gathered from the online survey and the presence of specific habits is evaluated. While some rather small correlations were found with these characteristics, the window use habits per room per season were mostly related to the habits in the other rooms and to the habits in other seasons. This indicates a habit coherence across the different rooms and across seasons. Consequently, window use habits can be predicted based on an initial classification of the households according to the habit-coherence across the rooms in winter and the seasonality coherence. These predicted habits are coupled to an occupancy and activity model to predict window use profiles. The validation procedure of the model revealed that it is able to accurately predict the diversity in window use for a set of buildings, and predicts the presence of the different window use habits significantly better than a naïve random prediction.

Next, the window use habit model is combined with other types of occupant behaviours in an event-based occupant behaviour model (EROB) (Chapter 9). This model, based on recent time use data, allows to predict the occupancy and activity profiles of the households and linked to that the window use, heating set-points, domestic hot water use, electricity use, internal heat gains and CO_2-production. This habit-based occupant behaviour model allows for fast simulations as it is not related to any (simulated) indoor environmental variables, and it allows for effortless implementation of its output in building energy simulations (BES).

Finally, in Part III, simulations of the heating energy use, indoor air quality by means of the CO_2-concentration and overheating were used to evaluate the impact of including the occupant behaviour model in BES. The simulation results revealed a significant impact on the energy use and indoor climate predictions due to the inclusion of occupant behaviour, especially by the window use and especially in energy efficient buildings (Chapter 11). Compared to the base-model that represented a typical use, the inclusion of the occupant behaviour model in BES resulted in an average increase in predicted energy use in the energy efficient buildings, while the average predicted energy use decreased in the other buildings. This is a similar discrepancy as observed in the performance gap research and might indicate that the inaccurate modelling of the occupant behaviour is partly responsible for the performance gap. Even though certain systems or buildings perform well under the typical use, the performance differentiates highly due to the diversity in the households living in it. Therefore, it is important to include the different possible behaviours during the design and fitting of systems and buildings.

A more in depth analysis of the window use habit-model revealed the importance of the characteristics of the habit-model, more specifically, the prediction of the diversity in window use, the independence of indoor environmental variables and the prediction of realistic window action timings (Chapter 12). A comparative study with models from the literature revealed that the habit model is able to predict the diversity to a larger extent than the models based on indoor environmental variables, especially in buildings with low heating set-points. The impact of providing realistic timings of the window actions does not have a large effect on the heating energy predictions, but is more important for the evaluation of the IAQ and the overheating. However, the impact strongly depends on the type of window use habit performed by the household.

A correct assessment of occupant behaviour through inclusion of habits can lead to more realistic predictions of the energy use and therefore the possibility to define accurate measures to reduce the energy use further to comply with the climate targets. Additionally, a good understanding of the occupant behaviour, and more specifically window use, is as well of importance for the development, design and fitting of ventilation systems and windows, and for the analysis of natural cooling for the prevention of overheating.

1 Introduction

This introductory chapter positions the research in the broader context of energy use and the fight against climate change. The definition of occupant behaviour is explained, and how occupant behaviour impacts the energy use in residential buildings. Additionally, the knowledge gap related to the research on occupant behaviour and occupant behaviour modelling is clarified. The objective of the research is explained, and an outline of the dissertation is given.

1.1 Context

1.1.1 Climate change

In recent years concerns regarding the climate change have been growing. More and more attention is given to the effects of climate change on the planet. A report of the Intergovernmental Panel on Climate Change states that greenhouse gas emissions generated by humans have increased since the pre-industrial era, mainly due to economic and population growth [1]. This has led to a rise in the atmospheric concentrations of carbon dioxide, methane and nitrous oxide, to the highest concentrations in at least 800 000 years. The effects of these high concentrations of greenhouse gases are extremely likely the dominant cause of global warming, as expressed by rising global and ocean temperatures; decreasing ice sheets, glaciers and spring snow cover; rising sea level; increased acidification of the oceans; and more extreme events such as heatwaves and floods. The latest IPCC report [2] stated that "It is unequivocal that human influence has warmed the atmosphere, ocean and land." Affirming the responsibility of humans in the climate crisis. Some sources [3, 4] indicate that the increased emergence of infectious diseases, such as Covid-19, is a consequence of climate change as well, since it alters how we coexist with other species on the planet.

In 2007, the European Commission set out European energy targets [5], in which European member states engaged themselves to have a 20 % decrease in greenhouse gas emissions in 2020 compared to 1990, 20 % increase in energy efficiency and 20 % of end energy from renewables. In 2018 the greenhouse gas emissions in Belgium were reduced by 17.3 % since 1990 [6], however, the renewable energy consumption is only at 9.9 % [7]. The European commission already set out more ambitious EU 2030 targets [8], and strives to be climate neutral by 2050 [9].

In Europe, 26.1 % of the energy consumption could be attributed to households [10]. In Belgium, the residential sector accounts for approximately 24.5 % of the total energy consumption [11]. Therefore, improving the energy performance of residential buildings will be an important step to reach the climate goals.

1.1.2 EPBD-regulation

The European Union has established a legislative framework in 2002, the Energy Performance of Buildings Directive (EPBD), that promotes policies that will help achieve a highly energy efficient and decarbonised building stock [12]. Each European member country has to adopt this directive in national regulations. In the Flemish region of Belgium, the EPBD-regulations are described in the energy decree of the Flemish government [13]. In this decree the calculation method is described to determine the energy performance of a building (EPB). Additionally, some requirements are set out to which each building should comply. This includes requirements regarding energy performance of the building envelope, performance of the systems, on-site renewable energy production and indoor environmental quality. The energy performance level (E-level) that has to be reached for new buildings and for major renovations is made more stringent over time to be able to reach zero energy buildings in the future.

Additionally, some demands are set out for the current building stock in the Flemish long term renovation strategy [14]. The goal is to reduce the average EPC-level (Energy Performance Coefficient for existing buildings) of the entire building stock with 75% by 2050. Therefore, some regulations are set for new houseowners regarding the building envelope and systems, as well as demands for boilers that need to be met during the (bi-)annual check-up. Finally, incentives are provided to encourage homeowners to renovate their building.

In this context, the FWO SBO-project NEPBC "Next generation building energy assessment methods towards a carbon neutral building stock" [15] was initiated to evaluate the current energy assessment methods and to investigate possibilities to ameliorate it from different perspectives. In the project five doctoral students researched different aspects of the EPBD-assessment method, namely, the modelling of systems, the impact on the grid, the conceptualisation of the assessment method itself, the economical aspect and the impact of occupant behaviour. This dissertation is a result of the research of this latter objective.

1.1.3 Performance gap

Accurate energy performance predictions are crucial in this context. However, in many studies [16–23] it is found that the predicted energy use significantly deviates from the actual energy use in residential buildings, the so called "performance gap". A study on 345 Belgian dwellings with EPBD-certifications between 2012 and 2014, indicated similar results [24, 25] (Figure 1.1).

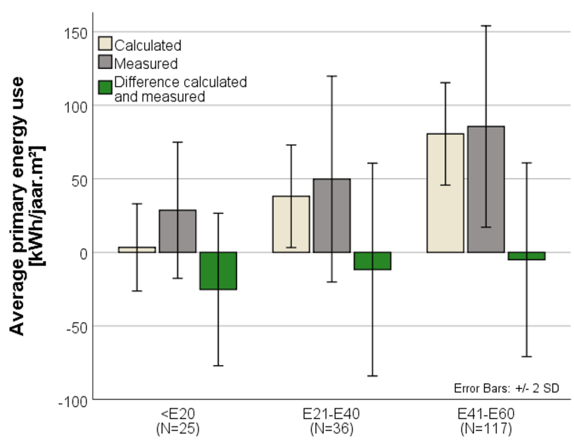


Figure 1.1: Calculated and measured average primary energy use [kWh/m^2/year] for different performance levels ranging from highly performant (<E20) to less performant (E41-E60). [24]

On average the primary energy use was underestimated with 8.7 kWh/m^2/year for all performance levels. The actual energy use deviated more from the predicted energy use for better performing dwellings [16, 17, 24, 25], with a significant underestimation of the total energy use in high performant buildings.

While the performance gap by itself is not problematic for the purpose of labelling buildings, it becomes a problem when it leads to the suboptimal transformation of the building stock, as a result of policy or investment decisions that are based on these theoretical predictions. Additionally, the performance gap prevents the development and implementation of adequate energy efficiency measures in existing houses.

The energy consumption in residential buildings is related to various factors such as:

- Climate
- Building envelope
- Installed systems
- Construction quality
- Occupant behaviour

Modelling improvements in these areas will lead to better energy use predictions, and with that a reduction in the performance gap. Nowadays, attention in the assessment methods is mostly directed towards the properties of the building, such as the building envelope and the systems, while occupant behaviour is often neglected.

1.2 Occupant behaviour

We understand occupant behaviour (OB) as defined in IEA-EBC Annex 53 [26]:

"Observable actions or reactions of a building user in response to external or internal stimuli, or actions or reactions to adapt to ambient environmental conditions such as temperature, indoor air quality and sunlight"

There are different ways an occupant can influence the residential energy use by its behaviour (Figure 1.2). Already by just being present in the building the occupant affects the energy balance and indoor climate by dissipating heat, CO_2 and water vapour to the space. Additionally, the choice of activities of the occupants will determine which appliances and building controls are used (e.g. lighting, household appliances, tap points, ...). The most obvious way an occupant impacts the energy use is by controlling the heating and/or cooling systems (choice of setpoint-temperatures, conditioned rooms, ...). But the occupant can impact the energy use in many other ways as well. The occupant can regulate the solar gains by lowering the solar shades. Energy use related to lighting can be affected by the control of blinds. The occupant can

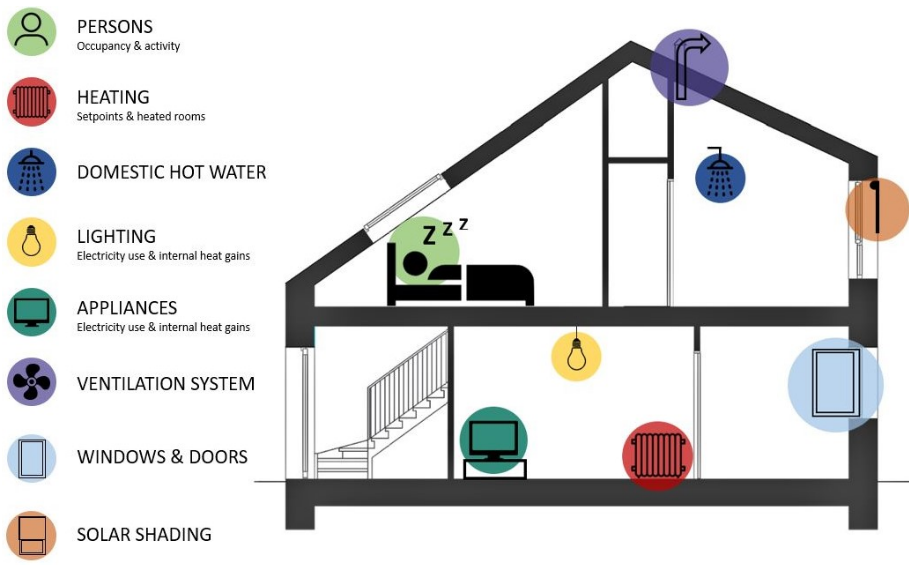


Figure 1.2: Illustration of the different types of occupant behaviour.

also have an influence on the ventilation in the dwelling, either by controlling the ventilation system, or by opening or closing windows and doors.

In the past, many studies have been carried out to assess the impact of OB on the total energy use [22, 27–31]. These studies compared either the real energy use between identical buildings, or simulated different types of OB for identical buildings to assess the impact of occupants. These studies revealed that the heating energy use can differ up to a factor 3 between minimum and maximum users, and the electricity use even up to a factor 5 [27, 29].

The simplified ways to model 'typical' OB in energy calculation methods are assumed to be one of the main causes of the performance gap for residential applications. The international review paper of Mahdavi et al. [32] revealed that 70% of the reviewed papers reported a form of occupant-related cause for the performance gap - either identified or presumed. The most recurrent occupant behaviour related cause of the performance gap (in 36% of the studies) is the frequency of window opening [17, 29, 33–48]. For instance, the actual heating demand was found to be higher than expected, as occupants opened windows more frequently or kept them open longer than assumed. Other studies [21, 29, 33] report that occupants turned off the installed mechanical ventilation system with heat recovery and used windows to ventilate instead, with significant energy implications. Heating behaviour is as well often indicated as a possible cause for the performance gap. A number of studies report higher actual indoor temperatures than assumed [17, 18, 29–31, 33, 34, 43–46, 49–56]. Cuerda et al. [35] noted that the actual heating periods were shorter than those suggested by standard schedules, leading to a lower energy consumption level than modelled. Similarly, there are studies documenting lower indoor temperatures or shorter heating durations than assumed [35, 57–60]. This is often associated with financial constraints and fuel poverty [16, 59]. The number of heated rooms was as well correlated with the performance gap [61]. Other possible OB-related causes for the performance gap are the use of solar shades, appliance use and internal heat gains, which are mostly related to inaccurate predictions of the occupancy of the households.

1.3 Occupant behaviour models

The previous paragraphs have highlighted the importance of OB and its impact on the residential energy use. OB-models are therefore necessary to predict realistic (representing things as they are in real life [62]) residential energy use in simulations. Over the years many OB-models have been developed ranging from simple static schedules, to probabilistic models and advanced artificial intelligence models. Many different factors are defined as occupant behaviour drivers in the literature [27, 63–67]. Occupant behaviour models designed for building energy simulations are often based on physical environmental variables. These physical environmental variables are used as quantitative predictors for building control actions. While in social and psychological sciences the emphasis is on the occupant itself as a necessity for building control actions. This occupant makes decisions based on different internal or external driving forces. Therefore, it is necessary to look at OB in residential buildings from a multi-disciplinary approach [68, 69].

Furthermore, the high inter-occupant diversity is a key issue for OB-models [70–72]. In most studies the goal is to develop an aggregated model that captures the main tendencies regarding occupant behaviour, sometimes allowing for some variability across households through stochastics or random factors. However, the problem is accurately defined by O'Brien et al. [71]: "This results in a statistically representative occupant rather than a true representation of a population of occupants." Aggregating distinct behaviours to an average behaviour is insufficient, especially when the model is applied to assess the robustness of a design or to predict extreme energy demands [70].

1.4 Habits

Research has shown that many occupant actions are related to the occupants' presence and performance of specific activities [73–75]. These daily routines lead to specific repeated building control actions, which can be defined as building control habits. In this dissertation habits are defined as follows:

"A habit is an automatic action carried out without conscious effort that is the consequence of frequently repeating this action in a stable context"
- Ouellette and Wood [76]

Consequently, a building control habit is an action with a building control such as a thermostat, window or solar shade, which is repeated frequently and performed without much consideration. Habits are elaborately researched in the field of sociology and psychology [76–80], however, little research [81,82] is carried out in the building sciences.

A specific distinction has to be made between deliberative actions and habits. All habits start out as a deliberative action. By repeatedly performing these actions, and repeatedly arriving at a satisfying outcome, these actions become routinely and will require less and less conscious thought. However, when the context changes this action will again require consciousness.

A small illustration: An occupant wakes up each weekday at approximately the same time, and opens the window when departing for work. The occupant repeats this everyday so the morning routine requires little thought. However, when a pandemic hits and everyone is obliged to work from home, the context changes, and the occupant may create another morning routine. This new morning routine now requires again conscious thought. It may not be comfortable to work from home with the window opened therefore the occupant might decide not to open the window in the morning.

OB is a result of both habits and conscious thoughts. Depending on the situation and context one of the two has the upper hand. Since a residential setting is a very stable context, this is a context with similar stimuli day in and day out, it is assumed that many actions are habitual, so not based on conscious thought.

1.5 Research objectives

Accurate energy predictions require models which capture the OB in a realistic manner and include the inter-occupant diversity. Therefore, it is necessary to consider the building control habits. The goal of this study can be summarised in three objectives:

1. Gather knowledge on building control habits.

This first objective aims to answer following research questions:

- How can habits be detected?
- Which building control habits are present? Are there any?
- How prevalent are building control habits?
- How context specific are building control habits?
- What is the relationship between certain building and/or occupant characteristics and the presence of specific habits? Is there one?

2. Development of an OB-model which takes the findings on building control habits into account.

The creation of an OB-model that includes the building control habits might lead to models that are closer connected with the daily-life of the occupants and which might be able to include the large inter-occupant diversity. For this second objective, it is first necessary to evaluate the current approach to OB-modelling and then to decide which approach lends well to the incorporation of habits. Next, a model needs to be developed and validated to be used in energy simulations.

3. Evaluate the impact of the habit-based OB-model on the building performance assessment.

The application of the habit-based OB-model can have important implications for the energy use and indoor climate predictions in residential buildings. Therefore, building energy simulations (BES) need to be conducted to evaluate the impact of each aspect of the habit-based OB-model.

1.6 Approach

It is assumed that building control habits can be present for all types of OB, but it is impossible to cover them all in one dissertation. Therefore, it was determined to focus this research on one type of OB, namely window opening behaviour (WOB). Previous research has shown that WOB has one of the highest impacts on the residential energy use and the performance gap (Section 1.2). Window use is one of the behaviours that has a direct effect on the indoor environment, influencing both the occupants' comfort and health. Additionally, the building control habits of two other OB types - solar shading and clothing - are discussed, to illustrate the difference in type, presence and strength of building control habits. The structure of the different dissertation chapters in relation with the research questions and the gathered data is given in Figure 1.3.

Chapter 2 discusses the case study used to analyse OB and building control habits. Information regarding the case study neighbourhood and its inhabitants is given, as well as information regarding the monitoring system by which OB-data is gathered. The remainder of the dissertation is structured in three parts each tackling one of the three research objectives.

In *Part 1*, the first objective of the study - gathering knowledge related to building control habits - is discussed. In *Chapter 3* the theoretical background regarding occupant behaviour and habits is set out. In *Chapter 4 & 5* the focus is narrowed to only window use. In *Chapter 4*, the currently used approach to WOB-modelling is analysed and the problems related to this approach are discussed, which hint to the presence of habits. In *Chapter 5*, the prevalent window use habits in Belgium are revealed based on monitoring data and an online survey. The dependency on the context of the window use habits is

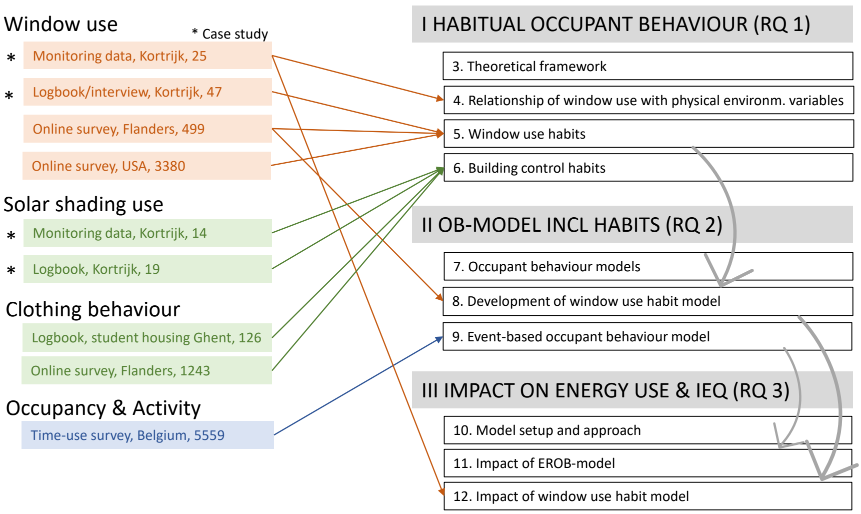


Figure 1.3: Structure of the dissertation. Connection between data (left) and the different chapters (right).

evaluated by comparing the Belgian window opening habits to window use data from the USA. Finally in *Chapter 6*, the focus is broadened again, by evaluating if habits are as well present for other types of occupant behaviour.

Part 2 is focussed on the second objective - the modelling of the OB based on habits. In *Chapter 7* some typical approaches to OB-modelling are discussed with their advantages and disadvantages. Additionaly, the current inclusion of OB in codes and standards is discussed, and how these are considered in the design practice. In *Chapter 8*, the development and validation of a window use model based on the habits is covered. The relation between different variables and the presence of certain habits is elaborated. The modelling is described in detail as well as the validation procedure. In *Chapter 9*, an Event-based Residential Occupant Behaviour model (EROB) is developed for use in building energy simulations.

Finally, *Part 3* focusses on the third objective - assessing the impact of this alternative approach towards occupant behaviour modelling on the energy use and indoor climate. First in *Chapter 10* the modelling approach is elaborated. The development of a model of one house from the case study for application in building energy simulations is explained. In *Chapter 11* the importance of including OB in energy simulations is demonstrated by performing BES with the newly developed habit-based EROB-model. While in *Chapter 12* the advantages of including habits in window use models are highlighted by comparing the results of the newly developed window use habit model with models from the literature. Additional simulations are carried out to emphasize the importance of predicting window use actions at the correct moment in the day.

The final chapter (*Chapter 13*) discusses the main conclusions of the dissertation, with a discussion of the advantages but as well the limitations of this alternative approach to OB-modelling, which in turn leads to some future perspectives.

2

Case study

Data collected from an NZEB social housing neighbourhood is used for the analyses in this dissertation. In this chapter, the case study buildings are discussed. Next to information regarding the buildings, some characteristics of the households are given as well. Additionally, it is described how OB-data is gathered in the case study with the focus on the use of windows and solar shades.

2.1 Overview

The research was based on data collected from an NZEB social housing neighbourhood in Belgium, which was part of the EU-Concerto ECO-Life project [83–85]. The neighbourhood consists of 106 apartments and 90 single family dwellings (Figure 2.1). The building design was based on the passive house standards, aiming at a net energy demand of 15 kWh/m^2/year for space heating, leading to building envelope U-values below 0.15 W/m^{2}K and an airtightness n50 of 0.6 h^{-1}. The apartments and 39 houses are fitted with a balanced mechanical ventilation system with heat recovery; the other dwellings have demand-controlled exhaust ventilation with trickle vents. All dwellings are heated by a district heating system coupled to radiators and regulated through a central heating system.

Figure 2.1: Overview of the NZEB social housing neighbourhood [86]

There are 40 two-story houses with two to five bedrooms, which consist of an open plan living area on the ground floor, and bedrooms and bathroom on the first floor (Figure 2.2). Furthermore, there are 50 three-story, three-bedroom houses that have a similar layout, with the addition of a third bedroom on the second floor. In the new-built houses, the living room is situated next to a garden facing south, with full-height windows (Figure 2.3). In these houses the windows on the ground floor are shaded by a static horizontal shading device and the upper windows are equipped with dynamic solar shades that are operated manually. Some renovated houses have a different orientation (Figure 2.4), with the street-side oriented South. In these houses all south-facing windows have dynamic solar shades. Smaller windows are situated in the bedrooms and the bathrooms. When the bedroom is situated on the top floor, the window can be a pivoting roof window instead of a turn and tilt window.

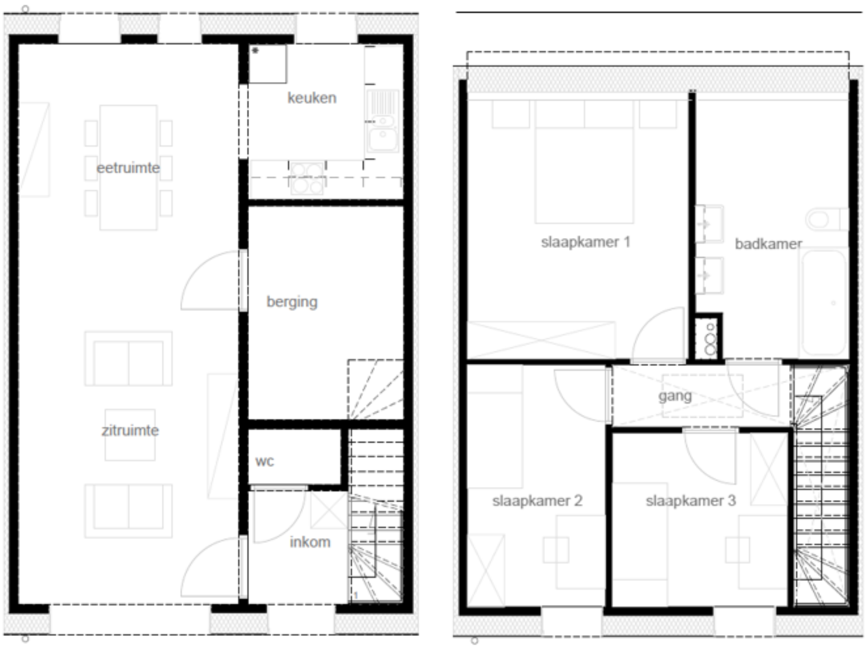


Figure 2.2: Plan of a typical two-storey house

Figure 2.3: South-facade garden-side of houses

Figure 2.4: South-facade street-side of houses

There are 47 one-bedroom apartments and 41 two-bedroom apartments, which have similar layouts (Figure 2.5). They are accessed by a gallery; consequently, the bedroom windows that are positioned at the entrance side are sheltered from wind, rain and direct sun. The apartments have full-height slide windows in the living room which give access to the balconies (Figure 2.6). These windows are south-oriented and are sheltered from the weather due to the balconies above. In the bathrooms, storage rooms and toilets of the apartments, there are no windows. The corner apartments have additional windows at the lateral facade of the building in the living room and bedroom(s). These are the only windows in the apartments that are equipped with dynamic shades. The other 18 apartments are duplex apartments, in which the bedrooms and bathroom are positioned on the second level. All windows, except for the slide windows, are of the tilt and turn type.

The dwellings were commissioned by a social housing association, who provided some socio-economic data on the occupants (age of head of household, occupation, age, income). The average income in the case study is approximately one third of the average income in Flanders [85]. Still the occupants need to pay their energy bills themselves (the heating bill was averagely 2.5% of the households income). The apartments were mostly rented out to elderly people, while most houses were occupied by families. In the houses, the average age of the head of the household was 53 years, with 14% of the occupants older than 65. The average age in the apartments was 60 years with 38% of the occupants older than 65; consequently, most of the occupants were retired. More occupants of the houses (31%) went to work during the day than occupants of the apartments (25%). Nevertheless, in most houses (80%) at least one person stayed at home.

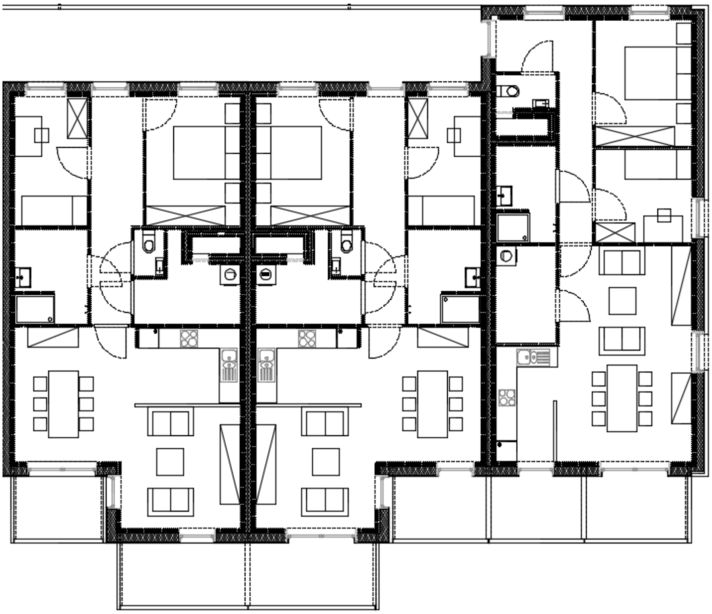


Figure 2.5: Plan of three typical apartments

Figure 2.6: South-facade of apartment block

2.2 Metering and monitoring

An extensive monitoring campaign was set-up in the neighbourhood, primarily to evaluate the actual operating conditions of the buildings and building systems during the first years of occupation starting in 2015 as part of the ECO-life project [83–85]. Continuous metering in all dwellings (heat use, electricity use, living room temperature) and the central production plant was used to assess the primary energy balance, while detailed metering and monitoring was present in a small sample of dwellings (N=25) for in-depth studies. Some characteristics of the in detail monitored dwellings and households are given in Table 2.1.

2.2.1 Climate and weather

A weather station was installed on the project site. The station measured the outdoor temperature [°C], wind speed [m/s], relative humidity [%], the global horizontal solar radiation [W/m^2] and precipitation [yes/no] every 5 minutes. The amount of precipitation per hour [mm] was gathered from a climate station situated less than 5 km from the project site. Indoor climate variables were measured as well, with an interval of 15 minutes. In all dwellings the indoor temperature [°C] and relative humidity [%] was measured in the living room, while the bedroom temperature was measured in a smaller set of dwellings (N=61). The descriptive statistics of the monitored variables are given in Table 2.2.

2.2.2 Windows

In 12 apartments and 13 houses, magnetic window sensors were installed which provided direct measurements on the window opening actions. The time and state of the windows were registered when a window was opened or closed. However, only one sensor was installed on each window; therefore, it was impossible to differentiate between turning and tilting actions and there was no indication of the opening width. In the apartments, the signals of the sensors were combined into one signal, representing the moment that a first window in the apartment was opened and the moment that the last open window was closed again. As a result, the actions with each individual window were not registered in the apartments. In the single-family dwellings the signals of the sensors were gathered at room-level. In total data is gathered in 31 bedrooms, 13 bathrooms, 12 living rooms, 3 kitchens and 3 hallways. Since the data-sample for the kitchens and hallways were very small, these data were not used in further analyses.

2.2.3 Solar shades

Solar shading sensors were installed in 14 houses. The sensors are situated in the electrical circuit of the manual switch in each room. It is only possible to fully open or close the solar shades, no intermediate position is possible

Table 2.1: Characteristics of the monitored dwellings and the occupants. The age and employment refer to the head of the household.

ID	Dwelling type	# bedr	Ventilation system	# pers	Age	Employment	monitored windows	monitored shades
H26	Terraced	2	Balanced	1	61	Employed	3	2
H27	Terraced	2	Balanced	1	57	Unemployed	4	2
H28	Terraced	3	Balanced	3	61	Unemployed	4	1
H29	Terraced	2	Balanced	2	68	Retired	4	2
H50	Terraced	2	Exhaust	1	59	-	4	2
H51	Terraced	3	Exhaust	2	-	Unemployed	5	1
H52	Terraced	2	Exhaust	1	77	Retired	4	2
H53	Terraced	2	Exhaust	1	61	Employed	4	2
H57	Terraced	2	Balanced	2	72	Retired	3	2
H79	Terraced	3	Balanced	3	57	Unemployed	3	3
H88	Terraced	3	Exhaust	3	46	Employed	7	2
H93	Terraced	3	Balanced	5	37	Employed	6	2
H101	Terraced	3	Exhaust	-	-	-	7	3
A1	Apartment	1	Balanced	2	75	Retired	comb.	1
A9	Apartment	2	Balanced	2	65	Retired	comb.	1
A18	Apartment	2	Balanced	1	66	Retired	comb.	0
A19	Apartment	2	Balanced	1	44	Employed	comb.	1
A21	Apartment	2	Balanced	1	64	Retired	comb.	0
A22	Apartment	2	Balanced	1	53	Employed	comb.	1
A39	Apartment	2	Balanced	3	35	Employed	comb.	0
A42	Apartment	2	Balanced	1	63	Retired	comb.	0
A46	Apartment	2	Balanced	1	85	Retired	comb.	0
A51	Apartment	1	Balanced	1	67	Retired	comb.	0
A55	Apartment	2	Balanced	2	89	Retired	comb.	0
A60	Apartment	1	Balanced	1	32	Unemployed	comb.	0

Table 2.2: Descriptive statistics of the monitored variables for the year 2016 (excl. 31/5 to 12/6 due to system malfunctioning)

	min	max	median	mean	SD
Outdoor temperature [°C]	-2.0	36.4	11.2	12.5	6.7
Wind speed [m/s]	0.2	16.7	1.7	2.1	1.7
Outdoor relative humidity [%]	28	96	77	75	13
Global horizontal solar radiation [W/m^2]	0	1325	0	125	217
Precipitation [mm/h]	0.0	26.4	0.0	0.1	0.5
Indoor temperature Living room [°C]	11.4	32.3	23.2	23.5	2.4
Indoor temperature Bedroom [°C]	10.6	30.9	21.5	21.9	3.0
Indoor relative humidity Living room [%]	24	80	48	48	8

in these houses. For each shading device two logs are made: status open and status closed. Status open gives ‘1’ when an opening action occurs and returns ‘0’ when the solar shading is lowered. Status closed returns exactly the opposite. Some problems were encountered with the logged data. All datasets contained several series of actions that followed very shortly after each other. These series go up to 161 registrations with only a couple of seconds between each registration. Such series appear in both datasets that are available for each solar shade (“status open” and “status closed”). The exact reason for this error remains unclear but may have something to do with the electronic contact in the switch. Furthermore, the “status open” dataset is not exactly the opposite of the “status closed” dataset. Some actions are registered in one dataset but not in the other one. It was uncertain if “status open” or “status closed” was the correct dataset. An arbitrary decision was made to use the “status open” data in the further analyses.

Part I

Habitual occupant behaviour

Part one of this dissertation will tackle the first research objective, which is gathering knowledge on building control habits. In first instance it is necessary to grasp the theoretical background of occupant behaviour and habitual behaviour. Therefore, a literature study was conducted both from the building science stance as from a socio-psychological perspective (Chapter 3). First, in Chapter 4, some insights are gathered in the currently applied methods for window opening behaviour modelling, and the importance of habitual behaviour in this context is evaluated. In Chapter 5, it is determined if habits are present in a residential setting, to what extent and what kind of habits. As an example these studies are conducted for the window use. However, in Chapter 6, it is investigated whether habits are as well present in other types of occupant behaviour.

3

Theoretical framework

In order to study occupant behaviour, and more specific habitual behaviour, it is necessary to understand which factors can predict behaviour. Therefore, a literature review is conducted on behavioural theories and occupant behaviour drivers, both from the building science perspective as from the socio-psychological perspective. Additionally, it is discussed in which way habits are included in this theoretical framework of occupant behaviour.

3.1 Occupant behaviour drivers

The first step in OB-studies is to investigate the drivers for the behaviour. Which factors lead to the execution of specific building control actions? While these drivers vary for the use of different building controls (windows, lights, blinds, solar shades, air conditioning, thermostats, fans and doors [67]), they can be generalised in a few categories [27,63–67]. Stazi and Naspi [87] divided the drivers in two main categories: the objective drivers and the subjective drivers. The objective drivers concern characteristics which are linked to general, context-specific or external aspects, while the subjective drivers are related to personal and individual features (Figure 3.1). Both categories can be further divided in some sub-categories, as explained below.

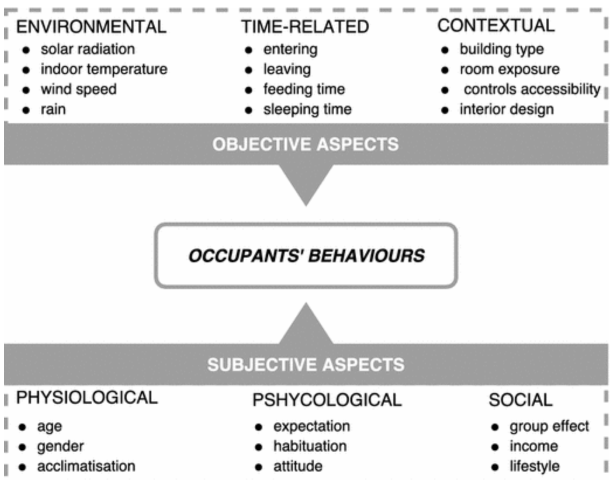


Figure 3.1: Visualisation of the factors that influence the occupant behaviour [87]. Exemplary list of OB-drivers, for a more complete overview see [88]

- **Physical environmental drivers.** Variables describing the environmental conditions, such as the indoor or outdoor temperature, the relative humidity, the solar radiation, the wind speed and the CO_2-concentration.

- **Time-dependent drivers.** The time of day, the day of the week or the season.

- **Contextual drivers.** Factors that have an indirect influence on the occupants. They determine the context in which the occupants behave. Some examples are the insulation of the building, the orientation, the installed systems, the function of the building and the specific room.

- **Biological or physiological drivers.** Drivers such as age, gender, health, activity level and intake of food and beverages. These factors determine the physiological condition of the occupant.

- **Psychological drivers.** Drivers related to feeling comfortable and the expectations occupants have about their environment (e.g. preference temperatures, expected indoor air quality, ...) But as well awareness (e.g. environmental concerns), knowledge, and habits.

- **Social drivers.** These factors focus on the occupant's social status and the interaction between occupants. Examples of social factors are the income and composition of the household.

Previously, the environmental and time-related variables were often the only ones included in building related OB-research. However, in recent years numerous studies highlighted the importance of analysing the underlying drivers of OB from a behavioural science perspective [64, 87], resulting in an increase in OB studies focussing on the subjective drivers.

3.2 Behavioural theories

The subjective drivers are often included in other fields of study such as sociology and psychology, but as well economy. A few behavioural theories from these fields are briefly discussed in this section. A more complete overview of behavioural theories linked to occupant behaviour in buildings can be found in the review paper of Heydarian et al. [89].

3.2.1 Rational Choice Theory

A basic theory of human behaviour can be found in the economic sciences, namely the Rational Choice Theory [90]. The theory stipulates that individuals always try to actively maximise their advantage in any situation, while minimising their losses. According to this theory all decisions are based on rational calculations. Additionally, it is assumed that complex social phenomena are driven by individual human actions and that individuals always act out of self-interest.

3.2.2 Theory of Reasoned Action (TRA)

A theory closely related to the rational choice theory is found in the social psychology. Ajzen and Fishbein [91] developed in 1975 the Theory of Reasoned Action (TRA). Likewise, this theory assumes that all actions are intentional and rational. The TRA stipulates that behaviour is predicted by the intention to perform the behaviour, which in turn is predicted by attitudes and subjective norms.

- **Attitude**: Attitude towards a behaviour is determined by the evaluation of the outcomes associated to the behaviour and the strength of these associations

- **Subjective norm**: Subjective norm relates to the individual's belief that specific individuals or groups think he/she should (not) perform the behaviour

- **Intention**: Intention is an individual's subjective probability that he/she will perform a certain behaviour

3.2.3 Theory of Planned Behaviour (TPB)

In 1985 the TRA was adapted by adding a third factor predicting the behavioural intention, namely perceived behavioural control [92,93]. This is the individual's beliefs in personal control over the behaviour. These beliefs are related to the perceived possession of various personal attributes and characteristics needed to perform the behaviour. This extension of the TRA results in the commonly used Theory of Planned Behaviour (TPB), which is visually represented in Figure 3.2.

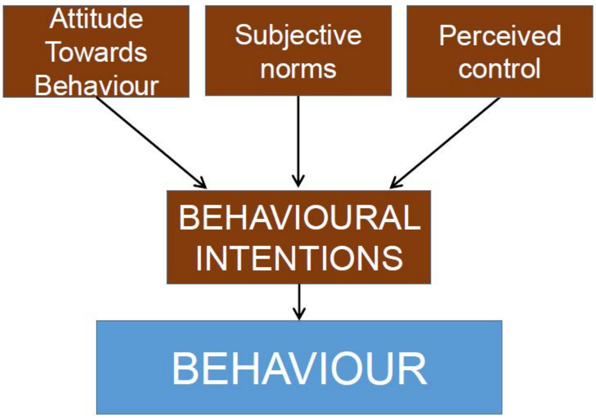


Figure 3.2: Schematic overview of the Theory of Planned Behaviour.

3.2.4 Belief Desire Intention Theory (BDI)

Another theory is the Belief Desire Intention theory (BDI) [94,95]. The essential assumption of the BDI theory is that actions are derived from practical reasoning, which is composed of two steps. In the first step, according to the current situation of the agent's beliefs, a set of desires is selected to be achieved. The second step is responsible for the determination of how these specific goals can be achieved by means of the available options for the individual [95]. This theory is often used as the base for agent-based models [96–98] (discussed later on in Section 7.1.4).

3.2.5 Norm Activation Model (NAM)

The Norm Activation Model (NAM) has been developed by Schwartz et al. [99] to predict altruism and helping behaviour. The basic assumption of the theory is that people help other people when they feel morally obliged to in a given situation, the so called personal norm. The NAM proposes three factors that affect whether personal norms are activated:

- **Awareness of need**: a person needs to be aware of the need
- **Ascription of responsibility**: a person needs to hold beliefs about personal responsibility, needs to reflect feelings of responsibility for the negative consequences of not acting, needs to belief that there are actions which could relieve the need
- **Perceived control**: a person has to perceive him- or herself as capable of performing the helping action

For energy-related behaviours specifically, this indicates that occupants tend to save energy if they are aware of the consequences of energy use on the environment [99]. That awareness leads to the consideration if energy-related actions can mitigate potential harm to the environment and if the occupant itself is capable of performing the pro-environmental behaviour. When one believes their energy-related actions can mitigate potential harm, a personal norm to save energy can be activated.

3.3 Habitual behaviour

The above discussed behavioural theories assume that actions are rational reasoned actions. However, this may not always be the case, as some actions may be executed out of habit.

3.3.1 Definition

Habits are defined by Ouellette and Wood [76] as: *"A habit is an automatic action carried out without conscious effort that is the consequence of frequently repeating this action in a stable context"*

When a habit is firstly initiated it is reasoned, but due to often repeating this action in a stable context (a context with similar stimuli day in and day out) the cognitive processes underlining the action become automatic and can be performed quickly in parallel with other activities and without conscious effort.

In social and environmental psychology copious research has been carried out regarding habits (e.g. travel mode choices [100], snacking [101], exercising [102], water consumption [103]). The existence of habits is important, as it contradicts the rational choice theory. This is of interest, especially in pro-environmental studies, for the justification of the reduced effectiveness of incentives to change behaviour [104].

3.3.2 Habits in behavioural theories

Already in 1979, Triandis [105] observed that not all behaviour could be explained equally well by intentions. He argued that for repetitive behaviours the influence of intentions is weaker, while at the same time the influence of habits grows. Ouellette and Wood [76] argued that not all actions are rational, reasoned actions, some actions are performed out of habit. They defined that when the context is stable, and people have had enough opportunity to perform a certain behaviour, past behaviour has direct influence on future behaviour by means of habits. Behaviour is mostly lead by conscious intentions when people have limited opportunity to perform the behaviour, or when the behaviour occurs in shifting or difficult contexts. In this theory, habits are seen as the baseline response. In a stable context, this is a context which is subject to constant stimuli, and with high opportunity, the habits are executed. When the context changes, the habit-strength diminishes and people act based on their behavioural intentions.

An example of this is taking your bike to work. The first time you go to a new workplace you consciously deliberate which transportation mode you will take. After a certain amount of days cycling to work you do not consciously think about your choice of transportation, you just take your bike. But when the context changes (e.g. you get a flat tire, it is snowing, you need to be at another location) the habit of taking your bike to work will not have the upper hand any more and deliberate thought is needed to decide how you will go to work.

Based on these observations, Verplanken and Aarts [106] adapted the TPB to include habitual behaviour. A schematic overview is given in Figure 3.3. This approach is similar as the Theory of Interpersonal Behaviour (TIB) as defined by Triandis [105], with the difference that intention is determined in the TIB by attitude, social factors and affect (emotional response to a decision).

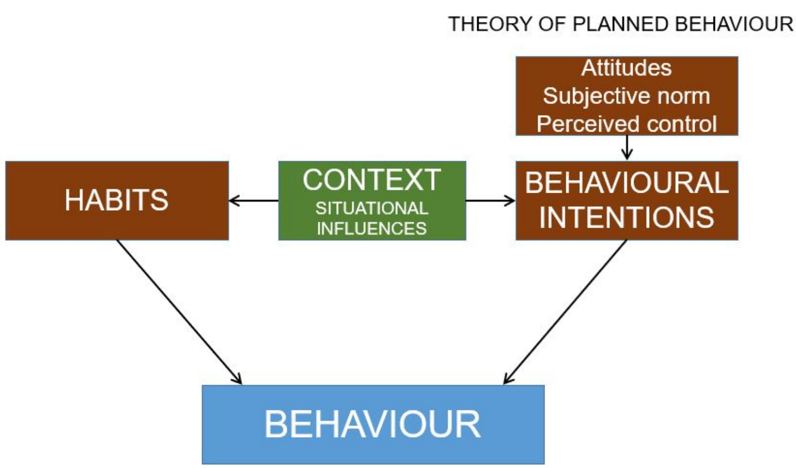


Figure 3.3: Schematic overview of the adaptation to the Theory of Planned Behaviour.

It should be noted that Ajzen [77,93] countered this adaptation. According to him, repeated behaviour is guided by automatically activated or spontaneous attitudes and intentions. He argued that when the same desires and beliefs are present, and therefore the same intentions, the behavioural outcome will be the same. However, this explanation does not account for the fact that some studies provided evidence of the relatively automatic processes guiding habits [107]. A study of Wood et al. [107] revealed that when people were engaged in habitual behaviour, they were likely to think about issues unrelated to their behaviour, proving that intentions are not involved, not even the automatically activated or spontaneous intentions.

3.4 Application of behavioural theories to interpret occupant-building interactions

In recent years there is an increasing interest in the use of behavioural theories in building related OB-studies. However, overall very few articles in the engineering field explicitly apply the behavioural theories in the design of the study or discuss it in the results [89]. The majority of OB-studies focus on very few, well-known behavioural theories such as the Theory of Planned Behaviour and Norm Activation Model, which all focus on intentional behaviour.

Only a few studies apply the TIB or the adapted TPB to predict OB with the inclusion of habits. The study of Lo et al. [81] revealed that for certain behaviours, such as turning off lights and monitors, habit was a stronger predictor in comparison to intentions. Mulville et al. [82] emphasised the importance of habits in a feedback study regarding energy saving efforts in offices. The surveys revealed that habit changes are the drivers of energy-saving efforts, rather than attitudes and social norms.

Some studies mention the presence of habits without referring explicitly to behavioural theories. Stazi et al. [67] state that not only environmental and contextual factors affect OB but also routine and habits. In numerous studies a relationship was found between the OB and the daily routines of the occupants. For example, lights and windows are usually adjusted when arriving or departing from the office [72,74,108–112] and in residential buildings window use can often be related to repetitive domestic activities [63, 73, 113–116]. It should be noted that most of the habit-indications discussed here refer to repetitive behaviour, and do not allow for evaluation of the consciousness of the behaviour. This problem together with other remarks on the use of the definition of habits as applied in this dissertation, are discussed in Section 5.1.4.

Very few information is at hand regarding building control habits in residential settings. Nevertheless, following the TIB/adapted TPB it is assumed that habits are frequently performed in the residential setting as it is a very stable context in which behaviour will be likely based on habits rather than intentions.

4

Relationship of window use with physical environmental variables

The literature study revealed that behaviour is not always guided by intentions but can as well be performed out of habit. While very few studies were conducted on building control habits (and more specifically window use habits), it can be hypothesised that these are often present in residential buildings due to the stability of this context.

Before knowledge is gathered regarding window use habits it is necessary to gain insights in the currently applied methods for window opening behaviour (WOB) modelling and to evaluate the importance of habitual behaviour in this context. The currently used approaches to WOB-modelling are discussed and the problems related to these approaches are revealed. This chapter is based on the article "Evaluation of the relationship between window use and physical environmental variables: consistency, seasonality and diversity" by Verbruggen et al. [117].

4.1 Introduction

Ventilation is an area of great interest in residential buildings. The ventilation rate should be sufficiently high to provide an adequate indoor air quality to prevent health problems, discomfort (e.g. odour) or moisture related damage to the building. On the other hand, in the heating season it should not be higher than that to avoid excessive energy use for heating. With the evolution towards nearly zero-energy buildings (NZEB), the relative influence of window airing on energy use has increased, since heat losses by transmission, infiltration and dedicated ventilation are reduced compared to less energy efficient buildings. For this reason, opening a window in an NZEB can have a substantial impact on its total energy demand [118]. In the Flemish EPB-calculation [119], it is assumed that the ventilation heat loss, as part of the energy use for space heating calculation, only depends on the building air-tightness and the characteristics of the installed ventilation system. However, occupants who live in dwellings with a mechanical ventilation system still open their windows, even to the same extent as occupants of naturally ventilated buildings, according to some studies [63, 120]. To make better estimates of the residential energy use and indoor environmental quality, adequate window use models are needed.

Window use models are most often created by applying (multiple) linear regression [114, 121–125] or (multiple) logistic regression [70, 108, 113, 115, 126–128]. The logistic models can predict the probability that a window is in a certain state (open/closed) or the probability that an action is undertaken (opening/closing). In recent years, the latter option has gained popularity as these probabilities can be used as transition probabilities for Markov Chain models [70, 108, 129]. Models focussing on the occupant itself as actor, the so-called agent-based models (ABM), are recently developed for occupant behaviour in buildings [130–133]. Finally, artificial intelligence techniques such as machine learning [134, 135] can be applied as well.

Depending on the goal of the study different model requirements need to be met. Mainly two distinct types of applications can be supposed. First, window use models can be used to assess the influence of window use on aggregate energy use predictions (e.g. monthly or yearly calculations). For this application, it is not necessary to have highly time resolved window use predictions. Consequently, for this application it is interesting to look at window use variables that represent the opening duration over a specific period, such as the number or proportion of open windows [63, 114, 122, 124, 136] or the opening percentages per day [116, 121, 137]. Second, window use models can be applied in more detailed simulations to assess the indoor air quality, performance of systems and energy use on a finer scale. For this application, window use data with a fine time-granularity need to be used, e.g. window state per hour/minute or the moment the action is taken. The latter is more often applied since the action-data may be more telling about the circumstances in which the occupant decided to perform an action [108]. Additionally, the use of the state of the window may lead to distorted relationships with indoor climate variables since the state of the window will affect the indoor environment [64, 126]. For this second application, it is necessary that the window use models predict realistic window actions. It is not sufficient that the total opening duration per day is correctly predicted. For example, the window may be opened half of the time but the impact on the indoor environment, energy use and occupants' comfort will be highly diverse when this is during the night or during the day. The focus is not necessarily on the exact time the action is performed, rather on the fact that the action should coincide with the daily life of the occupants. Furthermore, for both applications, it is necessary that the diversity between households is captured [70,71]. Occupant behaviour is highly variable therefore window use models need to allow for variation in the window use. Additionally, a causal relationship between the independent variables and the window use is preferred to allow for extrapolation to other contexts. Models based on variables that are correlated to the window use, but lack a causal relationship, will only be valid for that context. In other contexts, these models may not predict accurate window use due to changes in the real causes of the window opening behaviour.

Many studies have been carried out over the last decades to predict the window opening behaviour. In the majority of the models developed for building energy simulations, mainly physical environmental variables and time-dependent variables are included as window use predictors [67, 70, 72, 108, 113–116, 121–127, 129, 135, 138, 139]. Most models include thermal variables such as outdoor temperature [70, 108, 113–115, 121–127, 129, 135] and indoor temperature [70, 108, 113, 115, 122, 126, 127, 135]. Thermal comfort is as well the driving factor for action in some agent-based models [131, 132]. Other variables that are often included are wind speed [108, 115, 121, 123–127], solar radiation [123,125–127,135], indoor relative humidity [70,113,115,126,127,135], outdoor relative humidity [108, 113, 115, 124, 126, 127], precipitation [108, 127] and CO_2-concentration [70, 113, 115, 126, 135].

In addition to the physical environmental variables, the time of day is often included in window use models as well [113,114,124,125,129,140]. Conan [124], for example, found that for every hour that passed between 9 am and 6 pm, there was a drop of 0.5% to 1.3% in fraction of open windows to openable windows. In the model developed by Cali et al. [129] transition probability matrices are defined for every minute of the day. Multiple studies [72, 74, 141] found that window opening actions in offices usually happen around the same time when workers arrive in or depart from the office. Similar insights are included in the ABM's of Chapman et al. [130] and Langevin et al. [131]. Kalvelage et al. [133] developed a task-based model since they observed that different types of work in offices required different environmental conditions that resulted in different behaviour. These last types of models are based on the performance of actions or occupancy-changes rather than on the exact time of day, relating the window use closer to the daily life of the occupants.

Even though it is a common approach to include physical environmental and time-dependent variables in window use models, the validity of this approach can be questioned based on some observations in the literature:

4.1.1 Uncertainty regarding the consistency of the relationship with physical environmental variables

As discussed above, most window use models include one or more physical environmental variables. Often at least one thermal variable is included. In studies based on the state of the window the outdoor temperature has mostly been defined as the preferred driver [74, 114, 115, 142], while in studies based on action data the indoor temperature is favoured [72, 108, 126, 127, 141, 142]. Other variables are not consistently included. This can be either caused by the fact that not in every study the same variables are measured, or can indicate that some selected parameters are only indirectly correlated with the window use and do not represent a direct relationship. If there was a strong direct relationship, the same parameters would have more likely been selected in each model.

Surprisingly, variables that are associated with ventilation related discomfort such as odour or noise are not included, even though often mentioned as a reason for opening or closing windows [63, 74, 137, 143]. Odour for example is a variable that is easily detectable by humans and is a common trigger for ventilation related actions.

Many of the physical environmental variables are inter-correlated; therefore, the directionality of the relationship is highly dependent on the included variables. For example, the indoor and outdoor temperature were found to individually have a positive relationship with the opening of windows, but when jointly included the directionality of the regression coefficients can switch [114, 115, 126, 127, 141, 142]. Combining intercorrelated variables may induce erroneous trends. Due to the intercorrelation it is not clear whether there is a direct influence of the physical environmental variable on the window use or whether this is indirect. The presence of indirect relations may reduce the quality of the model due to a dampening of the contribution of the direct drivers.

Additionally, the explanatory power of physical environmental variables is rather limited in most studies. The Nagelkerke R^2-values of the logistic models for the window state are for example: .170 for the model of Rijal [128], .286 for the model of Yao and Zhao [115], .283 for the model of Haldi and Robinson [108], and .230 and .530 for the Tokyo and Neuchâtel models of Schweiker et al. [142]. The Nagelkerke R^2 for the opening probability are respectively, .040, .009 and .057 for opening actions during presence according to Haldi and Robinson [108] and Schweiker et al. [142] in Tokyo and Neuchâtel. The relatively low predictive power of the physical environmental variables indicates that these variables alone are insufficient to describe the set of circumstances under which window actions take place [141].

4.1.2 Seasonality

Window use models are often created to predict the window use year-round. However, Tahmasebi and Mahdavi [144] compared different window opening models developed for offices with measured data and found good correspondence in free floating situation but not in wintertime. Some studies include this seasonality by creating distinctive models for the seasons [126–128, 137]. Rijal [128], for example, defined a model based on physical environmental variables solely for the free running period. During the heating and cooling periods, it was assumed that the windows were always closed since very few actions were registered in these periods. It can be questioned if physical environmental variables are good window use predictors year-round, or only in specific seasons.

4.1.3 Inter-occupant diversity

Occupant behaviour is specifically characterized by large inter-occupant diversity [63, 70–72, 108, 113, 116, 122, 126, 136]. In most studies the goal was to determine an aggregated model that captures the main tendencies regarding window use, sometimes allowing for some variability across households through stochastics or random factors. However, the problem is accurately defined by O'Brien et al. [71]: "This results in a statistically representative occupant rather than a true representation of a population of occupants." Aggregating distinct behaviours to an average window opening behaviour is insufficient especially when the model is applied to assess the robustness of a design or to predict extreme energy demands [70].

Another way of including inter-occupant diversity is by categorizing occupants [72, 136, 145–147]. Rijal et al. [147], for example, categorized the occupants as active or passive based on their response regarding the frequency of window adjustments. This approach is a simple way to include diversity in window use models, however, difficulties arise when defining the thresholds for clustering. The distinction between the clusters is often not clear from observed data as it is often a continuous distribution, consequently defining a threshold is arbitrary [70, 71]. Therefore, Haldi et al. [70] created a mixed-model, by adding a random variable that affects the effect of each of the environmental variables on the window use. Most models try to include the diversity by randomized factors. However, to be able to improve the models it is necessary to understand the causes for the high diversity between occupants.

4.2 Approach

To assess the extent of the uncertainties discussed above, the modelling methods found in the literature are applied to monitoring data collected in the case study (Chapter 2) to evaluate the consistency, seasonality and diversity of the relationship between window use and explanatory variables. In this chapter, we try to answer three questions:

1. Is the relationship between window use and the explanatory variables consistent?

Are the same variables included in the models in different contexts? Is the relationship consistently positive/negative? Can the physical environmental and time-dependent variables explain enough of variance in the window use?

2. Is the relationship between window use and the explanatory variables sensitive to seasonal changes?

Are window use models developed for a year valid in all seasons? Can the same variables predict the window use in summer and winter? Is the predictive power of these variables equally strong across seasons?

3. Is the relationship between window use and the explanatory variables comparable for individual households?

Are the same variables identified as drivers for all households? Is the directional relationship with each variable similar across households? Are the differences between households captured sufficiently by the model?

First, general observations regarding the window use in the case study are discussed. Next, for each research question the relationship between window use and the explanatory variables is assessed and compared to findings from the literature.

4.3 Methods

The analyses are performed both for the state of the window defined as opening percentage per day and the opening actions based on the window sensor data gathered in the case study (Section 2.2.2). These two types of data can be used to illustrate the approaches found in the literature. Closing actions were not discussed in this study, as the approach is similar as for opening actions.

4.3.1 Data processing

When a window is opened, the exact timestamp is registered by the window sensors (see Section 2.2.2). In addition, the duration of these openings can easily be derived since the closing actions are registered as well. In this way, the action-data consist of a time-series indicating the opening actions (1=opening action, 0=no action), with additionally the corresponding durations of these openings. Since the living room window was often used as door, the openings with a duration shorter than 3 minutes were excluded from the analysis. Next to the action data, window state data are analysed as well. The window state is quantified by the opening percentage per day, this is the fraction of the day that a window was opened. This value is comparable to variables as 'hours per day' or 'fraction of the day' [114, 121, 124, 137]. The opening percentages per window were directly obtained by calculating the mean value per day. The window sensors did not allow to differentiate between turn and tilt actions, and no information is present on the opening angle. Consequently, a binary state was used of closed (0) and open (1), without differentiating in opening angle.

4.3.2 Statistics

The relationship between the different variables and window use was statistically tested with IBM SPSS Statistics [148]. The opening percentages and action-data did not fulfil the assumptions for parametric tests, so instead of Pearson's correlation analysis and t-test, respectively Kendall's tau-b correlation analysis and Mann-Whitney U tests were used. Additionally, bias-corrected and accelerated bootstrapping were performed to generate a confidence interval for the statistics. Backwards and forwards variable selection was performed based on the Akaike information criterion (AIC), with lower AIC-values representing better models [126, 127, 142]. Additionally, Nagelkerke R^2 is reported as an indication of the predictive power of the model.

In the boxplot, the horizontal line represents the median, the cross represents the mean and the box represents the 25 to 75-percentile. The difference between the 75 and 25-percentile is the length of the box and can be defined as the interquartile range (IQR). The circles in the boxplot represent the outliers which are values between 1.5 IQR's and 3 IQR's from the end of a box. Finally, the stars represent the extremes which are values more than 3 IQR's from the end of a box.

4.3.3 Limitations of the dataset

In this study, little data is available regarding the occupancy of the residents. The survey responses regarding employment status revealed that many occupants are unemployed or retired. This could indicate a high presence level in the households; however, this is highly speculative. Due to the uncertainty of the occupancy in the buildings the window use models in this study are created based on data from the full observation period. A few studies from the literature [113, 127, 135] followed the same approach by not correcting for the occupancy. The lack of occupancy data will not have implications for the analysis of the opening percentage per day, however, it might have implications on the analysis of the window opening actions.

4.4 Initial observations

First, the window opening variables of the case study were analysed. Both yearly data and data for the astronomical winter and summer were assessed. In the houses, the windows in the bedrooms stayed open the most during the year (average opening percentage 26%), followed by the bathroom (24%) and the living/dining room (21%) (Figure 4.1). The rank order for the rooms is similar as in the literature [63, 121], where the windows in the master bedroom stayed open the most and the windows in the living area the least. In summertime, the windows stayed opened the most in the living room (48%) followed by the bathroom (42%) and bedroom (41%). In winter, on the other hand, the living room windows were opened the least with an average opening percentage of only 3%. In the bedroom, the average opening percentage dropped to only 9%. The bathroom was the room with the highest average opening percentage in winter (16%). It should be noted that in winter many outliers were observed, the median opening percentages were only 0.6%, 0.7% and 0.5% respectively for the bedroom, bathroom and living room. A large variation was observed between the opening percentages of the individual houses. In the bedroom, the opening percentages ranged from 0% to 66% when an entire year was considered, while in summer the opening percentage ranged from 0% to 100%.

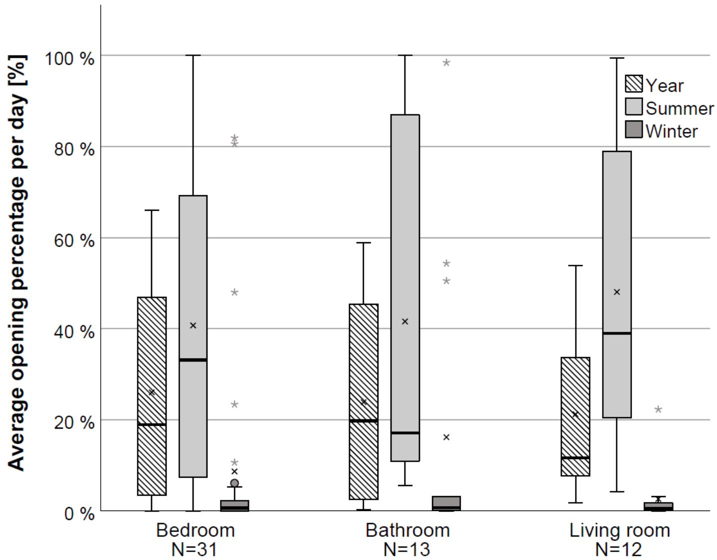


Figure 4.1: Opening percentages per room, results of 13 houses. The box represents the 25 to 75-percentile, the circles represent the outliers, the stars represent the extremes, the horizontal line represents the median, and the cross represents the mean.

The opening percentages in the bedroom compare well with a Belgian study from 1986 [137] (winter: 15.8%, summer: 47.9%). In the other rooms the measured opening percentages were higher for the case study especially in summertime, indicating that in these NZEB dwellings the windows stayed open longer compared to the older, less energy-efficient buildings of the previous study (living room: 2.1% - 25.0%, bathroom: 5.8% - 29.1%). Another more recent survey by Delghust [61] regarding window use in the heating period in a social housing neighbourhood in Belgium compared well with the opening percentages in the living room and bathroom but not in the bedroom, with much higher opening percentages (25%) in the old neighbourhood.

The yearly average duration of the window openings was analysed as well. In the houses, the bathroom had the highest average opening duration of 48 hours, followed by the bedrooms (35h), and the living room (3h) (Figure 4.2). These average opening times are relatively long, mostly due to some very long openings. In the living room, the windows were most often opened (yearly average 6.0/day), but for the shortest time. The bathroom windows (0.2/day) and the master bedroom windows (0.6/day) were less often opened, but for a longer time. This difference could be attributed to the use of the space. There tends to be a higher occupation during daytime in the living room compared to bedrooms, consequently the occupants can interact more with the windows to adapt faster to their comfort needs. In the bedrooms, windows are opened longer since during the day there is no need to change the state of the windows when nobody is present and during the night the occupants are asleep.

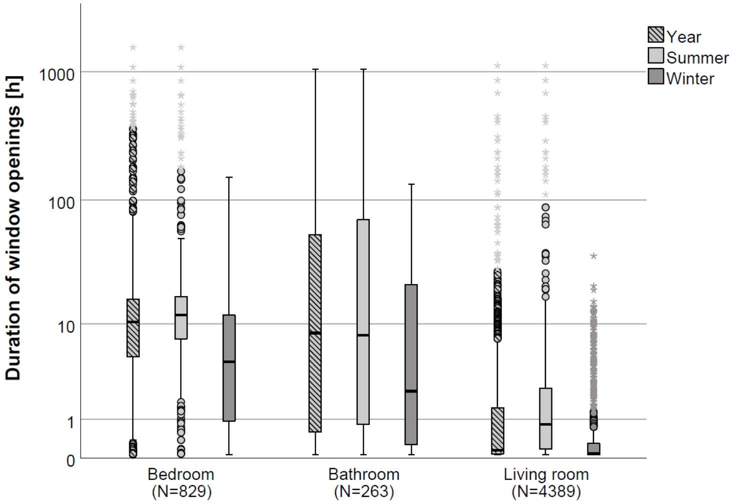


Figure 4.2: Duration of window openings in hours, results of 13 houses. The box represents the 25 to 75-percentile, the circles represent the outliers, the stars represent the extremes, and the horizontal line represents the median.

4.5 Consistency and seasonality

The introduction discussed the lack of consensus about which environmental variables to include in window use models. Additionally, the predictive power of the models was rather low, and some studies revealed that the models developed based on yearly data may not predict the window use accurately in separate seasons. To evaluate the consistency and seasonality, the relationship between the window use and the physical environmental variables is assessed for this case study. The analysis was performed for both the opening percentage per day and the opening actions. The physical environmental variables that were measured in this case study and that were influential in one or more studies in the literature were included in the analysis.

4.5.1 Opening percentage

Most environmental variables were correlated to the opening percentage per day when considering an entire year's worth of data (Table 4.1). Across all rooms the outdoor temperature was the strongest correlated to the opening

Table 4.1: Correlations (Kendall's tau-b) of the opening percentages per day with the daily mean environmental variables. Winter and summer refer to the astronomical seasons. Correlation is significant at the **.01/*.05-level (2-tailed). Non-significant values are indicated in grey. The underlined values indicate inconsistencies.

	Houses									Apartments		
	Bedroom			Bathroom			Living room					
	Year N=2362	Winter N=586	Summer N=579	Year N=3012	Winter N=784	Summer N=729	Year N=2832	Winter N=774	Summer N=650	Year N=6894	Winter N=1795	Summer N=1631
Outdoor temperature	.366**	.068*	.024	.320**	-.003	.028	.372**	.027	.035	.242**	.088**	.107**
Solar Radiation	.301**	-.001	-.043	.230**	-.077**	.005	.313**	.054*	.008	.171**	.038**	.024
Wind speed	-.025	.011	-.022	-.047**	.003	-.035	-.028*	-.010	-.015	-.020**	.034*	-.054**
Outdoor relative humidity	-.231**	-.027	-.003	-.170**	.071*	-.015	-.237**	-.064**	-.008	-.134**	-.059**	-.036*
Precipitation	-.121**	.002	-.006	-.116**	-.025	.006	-.112**	-.029	-.023	-.044**	.005	-.046**

	Bedroom			Bathroom			Living room			Bedroom			Living room		
	Year	Winter	Summer	Year	Winter	Summer	Year	Winter	Summer	Year	Winter	Summer	Year	Winter	Summer
Indoor temperature	.225**	.097**	-.254**				.098**	.091*	-.496**	.195**	.003	-.001	.301**	.241**	.075**
Indoor relative humidity							.223**	-.213**	.195**				.099**	-.065**	.036*

percentage, followed by the solar radiation and outdoor relative humidity. It should be noted that these variables were as well the ones that are the strongest intercorrelated, so it is uncertain if all variables have a direct effect on the window use. In this case, the correlation with the outdoor temperature is stronger than with the indoor temperature, affirming several studies based on window state data from the literature [74, 114, 115, 142]. The directionality of the correlations is as expected with positive correlations for the outdoor temperature, solar radiation and indoor temperature, and negative correlations with the outdoor relative humidity, wind speed, precipitation and indoor relative humidity.

Of equal interest is the amount of variance explained by these variables. The logistic models were fitted using multiple linear regression with the logit of the opening percentage as dependent variable and the physical environmental variables as independent variables (Equation 4.1).

$$log(\frac{OP}{1-OP}) = b_0 + b_1 * x_1 + b_2 * x_2 + ... \tag{4.1}$$

With OP the opening percentage per day, and x_1, x_2, ... the different explanatory variables.

A summary of the evaluated models is given in Table 4.2 and the parameter estimates of these models can be found in Appendix 14.1.1. The table includes results of the models based on physical environmental variables, season, and ID of the households; the latter two will be discussed later in this chapter. The best fitted model including environmental variables was selected based on the AIC. In the models based on yearly data up to four variables are included in the different rooms, namely the outdoor temperature, solar radiation, wind speed and indoor temperature. While both for the indoor temperature and outdoor temperature a positive correlation was present, when jointly added in a regression model they have opposing signs. This affirms the observations of several studies in the literature [114, 115, 126, 127, 141, 142] and indicates that the resulting models should be cautiously evaluated.

The predictive power of the yearly models was of similar magnitude as results from the literature [108,115,128,142]. The outdoor temperature was the most important window opening driver, followed by the indoor temperature and solar radiation. In most window use models based on the state of the window, the outdoor temperature was indeed defined as most important window use driver.

In the apartments, the developed models were less significant compared to the houses. This can probably be attributed to the fact that the data in the apartments are collected on housing-level instead of room level, neglecting the distinct window use in different rooms. But might also be attributed to the difference in sample size.

Even though on yearly basis the opening percentage was closely correlated to the environmental variables, both in wintertime and in summertime most correlations lost significance (Table 4.1). Similarly, the logistic regression models trained and fitted for the individual seasons had little to no predictive

Table 4.2: Goodness-of-fit estimators (Nagelkerke R^2 and AIC) for logistic models including one or more variables for the opening percentage per day trained and tested on respectively, year, winter, and summer. The underlined values are the best models including physical environmental variables. Significant at the **.01/*.05-level. Non-significant values are indicated in grey.

		YEAR		WINTER		SUMMER	
		R_N^2	AIC	R_N^2	AIC	R_N^2	AIC
Bedroom	T_e	.218**	17275.645	.002	3205.569	.001	4767.404
	T_e, T_i	.239**	17207.877	.008	3204.069	.075**	4718.651
	T_e, T_i, SR	.248**	17178.008	.009	3205.806	.089**	4710.882
	T_e, T_i, SR, v	.251**	17171.919	.009	3207.622	.089**	4712.857
	ID	.211**	17313.393	.114**	3149.615	.570**	4229.431
	Season	.180**	17399.085				
	ID & Season	.360**	16787.665				
Bathroom	Te	.189**	20607.963	.002	3949.601	.002	5423.226
	T_e, v	.195**	20586.111	.002	3951.599	.003	5433.558
	RH_e, Precip.	.047	21097.140	.018*	3939.046	.001	5434.970
	ID	.245**	20412.269	.078**	3905.455	.617**	4752.152
	Season	.210**	20531.761				
	ID & Season	.437**	19533.959				
Living room	T_e	.190**	17045.853	.001	4183.345	.001	4316.019
	T_e, T_i	.264**	16777.153	.046	4150.195	.447**	3933.800
	T_e, T_i, SR	.271**	16755.513	.053	4146.002	.451*	3931.793
	T_e, T_i, RH_i	.267**	16772.025	.162**	4051.797	.450	3932.334
	T_e, T_i, RH_e	.267**	16770.962	.053	4145.923	.453**	3929.100
	ID	.399**	16223.549	.540**	3605.091	.724**	3496.866
	Season	.203**	17007.868				
	ID & Season	.615**	14973.869				
Apartments	$T_{i,liv}$	.037**	25795.041	.029**	8704.662	.006*	3885.454
	$T_{i,bed}$	.026**	25848.835	.006**	8740.995	.012**	3880.988
	$T_{i,liv}$, SR	.041**	25776.344	.033*	8700.882	.008	3886.417
	$T_{i,liv}$, SR, RH_i	.042**	25772.495	.034	8701.714	.010	3886.632
	ID	.213**	24871.298	.238**	8351.189	.412**	3500.907
	Season	.017**	25892.507				
	ID & Season	.240**	24715.467				

power (Table 4.2). Only the model of the living room was significant with a predictive power of .162 in winter and .453 in summer. The lack of significance and the low correlation coefficients indicate that within the individual seasons the opening actions undertaken by the occupants were less likely or not influenced by the climate variation, except for the living room. These results are in correspondence to the findings of Tahmasebi and Mahdavi [144], namely that the window use models are good predictors during free-floating situation but not in wintertime.

This problem of seasonality can be illustrated by examining the relationship between the opening percentage and the outdoor temperature (Figure 4.3). A significant difference was observed between the window use on cold days and on warm days in both the living rooms and bedrooms. Over the entire year a strongly positive correlation was observed. However, in wintertime only the data-cloud at low temperatures and low opening percentages was considered in which the correlations were not significant. Similarly, in summer the correlation was less strong compared to the total year. The 'jump' between cold and warm days is more gradual in the living room in comparison to the bedroom. This could explain why the model of the living room with environmental variables shows a better fit than the models of the other rooms.

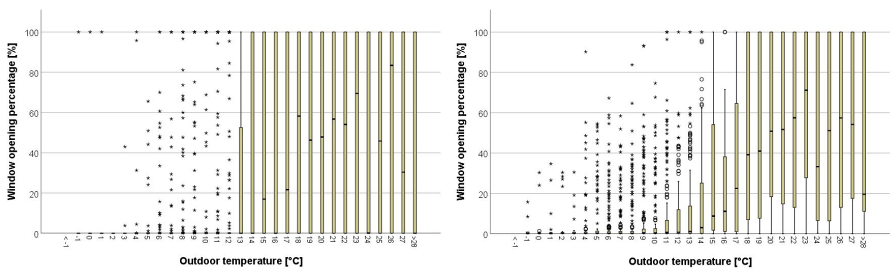


Figure 4.3: Relationship between the daily average outdoor temperature (binned per 1°C) and the opening percentage per day in the master bedrooms (N=14) (left) and the living rooms (N=12) (right). The box represents the 25 to 75-percentile, the circles represent the outliers, and the stars represent the extremes.

Based on these observations, it can be hypothesized that the variability in window use may be explained by the seasonal change instead of the environmental variables, especially for the bedroom and bathroom. It might be that the window use is distinct over the separate seasons, but within the season relatively constant. To test this assumption a model was created with the season (four categories) as explanatory variable. This model has an R^2 of respectively .180, .210 and .203 in the bedroom, bathroom and living room, which is comparable to the best models based on environmental variables (Table 4.2). The fact that the models based on environmental variables have a low predictive power in the separate seasons and the predictive power of the season itself is of equal magnitude, leads us to affirm the assumption that the window use is distinct across seasons, but rather stable within the season itself. A comparable observation was made in the study of Herkel et al. [74] in offices.

They revealed that the window use was rather related to the seasons than to the temperature itself, as they found distinct window use on warm winter days and cold summer days with similar temperatures.

4.5.2 Opening actions

The analysis is repeated for the opening actions. The instantaneous values of the environmental variables were used. Since the probability of performing a window opening action was evaluated, data-points when the window was already in an open state were discarded in the analysis. The performance of actions was recorded with 1 minute time intervals (no actions during time interval = 0, action(s) = 1). Consequently, many data points were available for each window. This large sample size had an important influence on the significance of the different statistical tests, therefore special attention was given to the evaluation of these tests. Additionally, it should be noted that the window use data is not corrected for the occupancy. This might have implications for the relationship between window use and the time of day and with environmental variables that follow a daily cycle (e.g. outdoor temperature, solar radiation). It is assumed that the correlations with the time of day might be stronger than when occupancy would be considered since the most actions will occur at times occupants are present. Correspondingly, the correlations with the environmental variables might be smaller since the range of observed values for these environmental variables is larger than when occupancy would be considered. Nevertheless, the lack of occupancy data may as well lead to stronger correlations with some environmental variables. For example, the indoor temperature will increase with occupancy, which could lead to stronger correlations when considering all data instead of only the occupied data.

In general, the results of the Mann-Whitney U-tests for the opening actions led to the same conclusions as the correlation analysis with the daily opening percentage. The results are given in Table 4.3, both the Mann-Whitney U statistics and the mean differences between the two groups (opening action/no action) are reported. Opening actions were performed with higher outdoor temperatures, higher solar radiation and lower outdoor relative humidity, as shown by the sign of the mean differences. It should be noted that the mean differences were small. The relationship with the indoor temperature is less clear. In the bedroom more actions are performed when the indoor temperature is higher, which could be expected. In the living room, on the other hand, more actions are taken with lower indoor temperatures and higher relative humidity. Instantaneous values of the environmental variables are used so this will not be caused by the effect of opening actions on the indoor environment. We will further elaborate on this observation in Section 4.6.

In many studies, the time of day was found to be a window opening driver as well [113, 114, 124–126, 129, 135]. From the visualization of the number of opening actions per hour in Figure 4.4, it is clear that there were more interactions with the windows during daytime, when occupants were more likely awake. Most opening actions occurred in the morning, and in the living room in the evening as well.

Table 4.3: Results of Mann-Whitney U test for the evaluation of the relationship between opening actions and the instantaneous values of the physical environmental variables. The mean difference between two groups (action/no action) is given as well. Correlation is significant at the **.01/*.05-level.

	Bedroom			**Bathroom**			**Living room**		
	Year *N=3742135* *Nact=452*	Winter *N=847033* *Nact=87*	Summer *N=505197* *Nact=195*	Year *N=4430862* *Nact=434*	Winter *N=1098064* *Nact=92*	Summer *N=542229* *Nact=142*	Year *N=4407333* *Nact=23964*	Winter *N=1063531* *Nact=5897*	Summer *N=496139* *Nact=2879*
Outdoor temperature	3.796E+8** 4.33	2.606E+7** 1.46	4.59E+07 -0.52	5.490E+8** 3.17	4.76E+07 0.07	3.52E+07 0.41	3.826E+10** 0.48	2.666E+9** 0.54	6.40E+08 0.81
Solar radiation	3.924E+8** 108	2.849E+7* 66	4.045E+7** 14	4.878E+8** 103	3.655E+7** 23	3.143E+7** 62	3.225E+10** 37	2.321E+9** 38	5.551E+8** 59
Wind speed	5.99E+08 0.16	2.800E+7** 0.81	4.66E+07 -0.04	7.14E+08 0.16	4.57E+07 -0.17	3.84E+07 0.13	4.00E+10 0.04	2.849E+9** 0.14	6.389E+8** 0.3
Outdoor relative humidity	5.137E+8** -4.1	2.749E+7** -4.4	4.500E+7* 2	6.155E+8** -4.3	4.43E+07 0.9	3.61E+07 -1.4	3.821E+10** -1.3	2.820E+9** -1.6	6.254E+8** -2.8
Indoor temperature	3.842E+8** 1.91	1.648E+7** 2.17	4.058E+7** -0.6				4.058E+10** -0.14	2.823E+9** 0.32	6.431E+8** -0.32
Indoor relative humidity							2.713E+10** 1.6	2.213E+9** 0.4	4.241E+8** 1.4

Logistic models were created for the action-data using stepwise binary logistic regression (Equation 4.2). A summary of the evaluated models is given in Table 4.4 and the parameter estimates of these models can be found in Appendix 14.1.2.

$$log(\frac{P_{open}}{1-P_{open}}) = b_0 + b_1 * x_1 + b_2 * x_2 + ... \quad (4.2)$$

With P the probability that a window will be opened per minute, and x_1, x_2, ... the different explanatory variables.

Goodness-of-fit improves when indoor environmental variables and solar radiation are included in the model. The observation that the indoor variables have the highest predictive power in the window opening action models is in correspondence with findings in the literature [108, 126, 127]. These studies indicate that the indoor variables are most important for the opening probability as they describe the environment the closest to the occupant, while for the closing probability the outdoor temperature is more important [108].

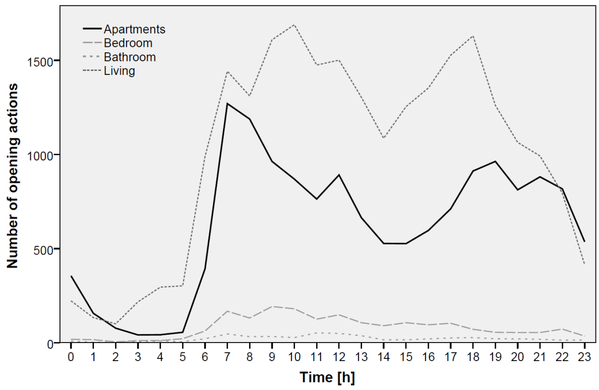


Figure 4.4: Number of opening actions per hour for the bedroom, bathroom and living room of the houses and the apartments, summed over all buildings.

When only the winter or summer period was considered, the models based on environmental variables were less strong and not significant in the bedroom and bathroom. Therefore, separate models were created including the season as explanatory variable, similarly as with the opening percentages. As Table 4.4 shows, the season itself could explain some variance in these rooms (bedroom:.026, bathroom:.011, living room:.011). In the living room however, the environmental variables still have a significant influence in the separate seasons, indicating that in the living room the window use is closer related to the environmental conditions compared to the other rooms. It is hypothesised that this is linked the use of the room. In the living room occupants are more actively present and therefore more susceptible to adaptive behaviour, in contrast to the other rooms in which the presence is rather short or the occupants are asleep.

Table 4.4: Goodness-of-fit estimators (Nagelkerke R^2 and AIC) for logistic models including one or more variables for the opening probability per minute trained and tested on respectively, year, winter, and summer. The underlined values are the best models including physical environmental variables. Significant at the **.01/*.05-level. Non-significant values are indicated in grey.

		Year		Winter		Summer	
		R_N^2	AIC	R_N^2	AIC	R_N^2	AIC
Bedroom	T_e	.021**	8194.147	.010**	1626.768	.001	3327.465
	T_i	.021**	8191.929	.087**	1501.350	.006*	3310.508
	T_e, T_i, SR, RH_e	.029**	8136.561	.100	1479.330	.008	3309.310
	T_i, SR, v	.027	8149.037	.111**	1465.924	.007	3312.171
	Time	.028**	8182.329	.045**	1613.821	.044**	3229.283
	ID	.026**	8172.136	.087**	1514.053	.074**	3099.954
	Season	.026**	8159.012				
	ID & Season	.056**	7921.665				
Bathroom	Te	.012**	8203.829	.000	1747.536	.000	2549.825
	SR	.010**	8215.459	.001	1745.118	.003**	2543.819
	T_e, SR	.015**	8180.704	.001	1747.090	.003	2545.469
	Time	.034**	8061.799	.070**	1669.631	.037**	2500.859
	ID	.051**	7893.181	.122**	1553.357	.064**	2404.649
	Season	.011**	8208.772				
	ID & Season	.057**	7851.109				
Living room	T_i	.002**	220968.894	.002**	53487.025	.013**	27119.739
	RH_i	.004**	220570.247	.001**	53599.250	.006**	27297.175
	SR, T_i, RH_i	.018**	217716.062	.015**	52835.064	.028**	26734.947
	T_e, T_i, v, RH_e, RH_i	.017*	217835.641	.007	53241.945	.042**	26351.623
	T_e, T_i, SR, v, RH_e, RH_i	.020**	217186.264	.015	52836.127	.042	26351.447
	Time	.042**	212441.610	.053**	50884.210	.034**	26602.639
	ID	.109**	198206.107	.080**	49468.901	.078**	25399.765
	Season	.011**	219020.919				
	ID & Season	.109**	198085.051				

Additionally, the time of day was included in the analysis as well. Since the time of day is periodic, the use of a continuous variable (e.g. hour of the day) may lead to unrealistic results, therefore, the time of day is included as a categorical variable, defined as bins per hour. The yearly regression models based solely on the time of day had R^2-values of respectively .028, .034 and .042 for the bedroom, bathroom and living room, which is slightly higher than the values obtained for the models based solely on environmental variables, especially in the bathroom and living room (Table 4.4). Consequently, it can be assumed that the window use in this case study is related to the daily routines of the occupants, even to the same extent as environmental variables. Since the environmental variables are strongly correlated with the time of day it is uncertain which of these are most influential. However, when evaluating the models in the separate seasons, the models including the time of day were still significant in the separate seasons, with a predictive power similar as for the entire year. This leads to the assumption that the window use is more closely related to the performance of daily activities than to the environmental conditions.

The results revealed that the environmental variables can predict some of the variance in window use across a year, however in separate seasons the models are less strong. It can be concluded that the window use in this case study is distinct across seasons, however, within seasons the window use is relatively stable, and only slightly influenced by the momentaneous environmental conditions, especially in the bedroom and bathroom. Additionally, the models including the time of day have a higher predictive power than the models based on environmental variables, especially in the separate seasons, indicating that the window use in this case study is strongly influenced by the daily routines of the occupants, and less by the physical environmental variables.

4.6 Inter-occupant diversity

The initial observations showed that the behaviour in different households is highly diverse (Figure 4.1, Figure 4.2). In most studies in the literature aggregated models are created to predict the window use over the general population, which neglects this inter-occupant diversity. The validity of the aggregated approach is tested by repeating the analysis for each individual household. Figure 4.5 gives for example the correlation coefficients for the opening percentage and the environmental variables for the individual dwellings. Most correlation coefficients for the individual households are either non-significant or vary substantially between the households. The correlation coefficient for a specific environmental variable can differ up to .600 in value. Nevertheless, the correlations based on yearly data were unidirectional across all houses, but in the separate seasons this was not always the case.

A large variation in time dependency was observed as well. In Figure 4.6, the mean opening percentages for each hour for different dwellings during wintertime are illustrated. In some dwellings the relation between opening percentage and time of day was very pronounced. Consequently, on individual level the hour of the day was a stronger driver than on aggregated level.

The lack of consistent relationships can in some cases even lead to questionable aggregated results. For example, we observed in Section 4.5.2 a negative relationship between the opening probability and the indoor living room temperature. When analysing this relationship in more depth, it was revealed that this negative relationship resulted from one household which had relatively low indoor temperatures (21.5°C in comparison to the average of 23.5 °C) and performed a lot of opening actions. The many actions at low indoor temperatures resulted in an overall negative relationship, even though in most houses it was positive. This affirms that the between-household variations should not be neglected.

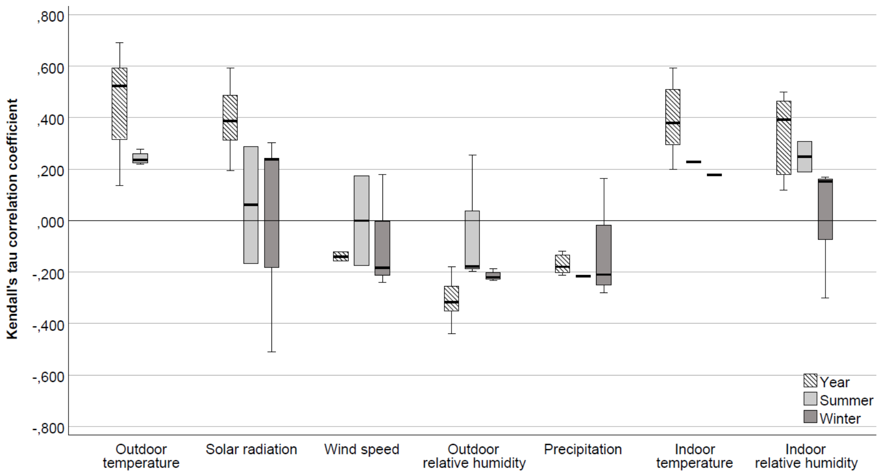


Figure 4.5: Variation in the correlation coefficients (Kendall's tau) of the opening percentages per day with the daily mean environmental variables across the living rooms (N=12). Only the significant correlation coefficients ($p < .05$) are included.

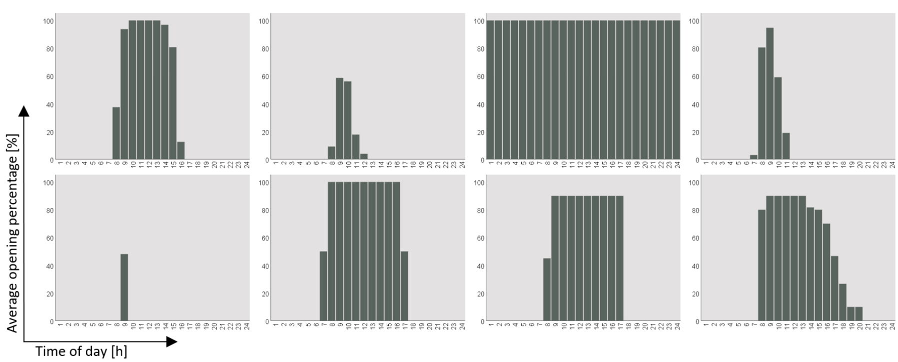


Figure 4.6: Average opening percentage for each hour of the day in wintertime for different rooms in different dwellings

Consequently, we can not assume that the measured window use is independent of the dwelling it was obtained from, which is a prerequisite for the application of logistic regression. Andersen et al. [126] tackled this problem by testing variable independency through the analysis of the interaction terms between the explanatory variables and the dwelling index. If the interaction term was retained in the model, it was taken as an indication of dependence and the explanatory variable was removed from the model. However, they indicated already that this might not be an accurate way to handle this, since possible important variables may be excluded from the model. Applying this approach to the case study would result in none of the environmental variables being included in the model since all interaction terms proved to be significant.

Haldi et al. [70] suggested the mixed-model approach, in which random factors are added to the regression coefficient to capture this diversity. Generalized Linear Mixed Models (GLMM) can be used as they account for the non-independence of the measurements by adding random effects. This results in an equation similar as for standard logistic regression but with the addition of extra randomized terms (Equation 4.3). For a more detailed explanation of the use of GLMM for window use data we refer to the article of Haldi et al. [70].

$$log(\frac{P_{open}}{1-P_{open}}) = b_0 + a_0 + \sum_{k=1}^{n}(b_k * x_k + a_k * x_k) \tag{4.3}$$

With P the probability that a window will be opened or the opening percentage, x_k *the different predictors,* b_k *the regression coefficients of the fixed effects and* a_k *the random variable representing the deviation from the mean distributed as a normal distribution* $N(0,\sigma^2)$.

In this method, it is assumed that the regression coefficients of the random effects (a_k) are normally distributed. However, in this case study these were often found non-significant, especially in the separate seasons. This indicates that the variability in window use of the different households in this study is difficult to grasp by adding a normally distributed random effect.

The distinct window use can be illustrated as well by examining the relationship between the window use and the household-ID (Table 4.2 and Table 4.4). The predictive power in the bedroom, bathroom and living room increased significantly just by adding the ID as explanatory variable. The ID can predict the same amount of variance as the other explanatory variables and is in the living room even a significantly better predictor.

The inter-occupant diversity in window use is difficult to capture with aggregated models. The predictive power of the ID of the household reveals that the variance in window use is larger between households than over the days in individual households, especially in the living room. It is important to conduct more research on the causes for this diversity between households.

4.7 Discussion

It can be concluded that the window use in this case study is distinct across seasons, however, within seasons the window use is relatively stable, and only slightly influenced by the momentaneous environmental conditions, especially in the bedroom and bathroom. Additionally, the between-household diversity is significant. It seems that within individual households the window use is relatively consistent in each season, but that these behaviours differ significantly between households.

While the window use models based on environmental variables had Nagelkerke R^2 values of respectively .251, .195 and .267 for the opening percentage in the bedroom, bathroom and living room, the ID and season alone had R^2-values of .360, .437 and .615 (Table 4.2). Similar results were obtained regarding the probability to open a window with R^2 of .029, .015 and .020 for environmental variables and .056, .057 and .109 for the ID and season together (Table 4.4). In general the ID and the season together could predict two to five times more variance in window use compared to the environmental variables. This indicates that even though environmental variables may have an influence on the window opening behaviour, a large part of the variance can already be explained by the distinct repetitive behaviour of different households in different seasons. The fact that window opening behaviour is repetitive was already described in the study of Lyberg in 1983 [122]."It was found that the variation between households in terms of their total daily window opening was greater than that within households. There were indications that occupants adopt consistent airing patterns."

From the results of the time of day it was revealed that many occupants interact with the windows repetitively around the same time. The predictive power of the time of day is significant but not always very strong. It is assumed that window use in residential buildings is related to the repetitive performance of domestic activities [63, 67, 73, 113–116], rather than at an exact time. For example, many occupants open the windows when they wake up, however, other occupants may wake up later or earlier (e.g. Figure 4.6). The primary driver for opening the window would then be the waking-up event, so not the hour of the day which is obviously closely related to the waking-up event. A similar approach is taken in the model of Haldi and Robinson [108], relating the window use to arriving in, working, and leaving the office. Schweiker et al. [142] proved that this model works well for living rooms. However, they indicated that this model may not capture the often habitual behaviours which are specific to the residential setting, such as opening the window while cooking or opening the window when waking up. Research should therefore focus more on the repetitive behaviour and only in a second step on the physical environmental variables which possibly still explain some of the variance in window use.

The residual correlations of the environmental variables are rather small in this case study which might be attributed to the lack of data on occupancy. The lack of occupancy-data may induce an important bias in the obtained results. Nevertheless, the lack of occupancy-data may even lead to stronger correlations with some environmental variables. Further research is necessary to assess the impact of neglecting the occupancy on the conclusions drawn from this study.

Finally, it should be noted that some habits may be indirectly included in existing models without being identified as the cause for window use. In data-driven modelling methods the habits may be disguised as an external influence, such as different indoor environmental variables or the time of day.

4.8 Conclusion

Even though it is a common approach to include environmental and time-dependent variables in window use models, the validity of this approach can be questioned based on uncertainties discussed in the literature. To assess the implications of these uncertainties, the modelling methods found in the literature were applied to monitoring data of NZEB residential buildings to evaluate the consistency, seasonality and diversity of the relationship between window use and explanatory variables. The results revealed that a large share of the observed variance in window opening behaviour can be attributed to the season and the household-ID. This indicates that the window use varies across the year but is rather stable within one season, and that these behaviours differ significantly between households. These observations indicate that occupants open or close windows according to specific seasonal habits, which are often related to daily activities. Since the ID and season could explain significantly more of the variance in window use compared to environmental variables, window use studies should focus more on analysing the repetitive behaviour of the occupants. This may improve the models to better represent realistic window actions and include the inter-occupant diversity.

5

Window use habits

The previous chapter indicated that window use in residential buildings might be habitual. The focus in this chapter is therefore on evaluating the extent and type of window use habits in residential buildings.

First, it is explained how window use habits can be detected. The different techniques that were used in this study to assess the presence of habits are discussed, along with their advantages and disadvantages. Based on the discussed techniques, the prevalent window use habits in Belgium are determined and discussed. This section is partially based on the article "Habitual window opening behaviour in residential buildings" by Verbruggen et al. [149]. Finally, the context dependency of the window use habits is evaluated by comparing the self-reported habits in the Belgian survey to window use data gathered in the USA.

5.1 Methods for determining habits

To investigate the extent to which habits are present and to assess the importance, it is necessary to find a way to determine the presence of habits. In this section some techniques that were used to detect habits in Belgian households are discussed.

5.1.1 Direct window use monitoring

In the introduction following definition was given for habits:

A habit can be defined as an automatic action carried out without conscious effort that is the consequence of frequently repeating this action in a stable context [76]

Therefore, a first way to assess if window use habits are present is to analyse the window use data on repeated actions. This can be done by examining the opening percentage per hour. When the opening percentage reaches 100%, it indicates that the window is always opened at that time; consequently, the possibility of an opening habit is very high.

Monitored data was available for the case study (Chapter 2) through the BMS, however only for 12 apartments and 13 houses. To broaden the window opening data, a logbook study was carried out between 20 January and 27 February 2017. The occupants were asked to write down when the windows were opened and closed, and to mention whether those were opened completely or tilted. A total of 47 occupants filled in a logbook. However, the motivation of occupants to participate dropped off considerably after a few weeks. The validity of the logbooks was checked in two different ways.

The first way to check the validity of the logbooks was by doing observations. This meant passing by the dwellings and writing down the windows that were open at that time. If a window was observed as open and it was not registered as open on the logbook, the logbook was viewed as inaccurate. The observations were carried out on 17, 19, 20 and 23 January and 20 and 21 February 2017. Although it is a useful method for checking the logbooks, not all logbooks could be checked in this way. The observations were only made at a certain moment, on certain days, consequently they could give an indication of the correctness but could not determine that the logbooks were filled in correctly for the entire measuring period. A second method for evaluating the validity of the logbooks was by comparing them with the data of the window sensors. This method was only possible for the households living in dwellings equipped with window sensors that participated in the logbook study (N=10). It was checked if the window actions reported on the logbook were present in the monitoring data, with an allowance of 1 hour time difference to compensate for inaccurate clock-settings and the delayed filling in of the logbooks. In total 62% (20 apartments, 9 houses) of the logbooks were evaluated as correct based on the two validity checks.

Figure 5.1 illustrates the average opening percentages for every hour of the day of some of the dwellings of Venning (logbook study and sensor data). When a clear peak in opening percentages is observed, but the 100%-mark is not reached, an opening habit may still be present. This can indicate an opening habit that occurs a limited number of times in the week (e.g. only on weekdays), a habit that is slightly shifted in time over the days or a habit with a duration shorter than one hour.

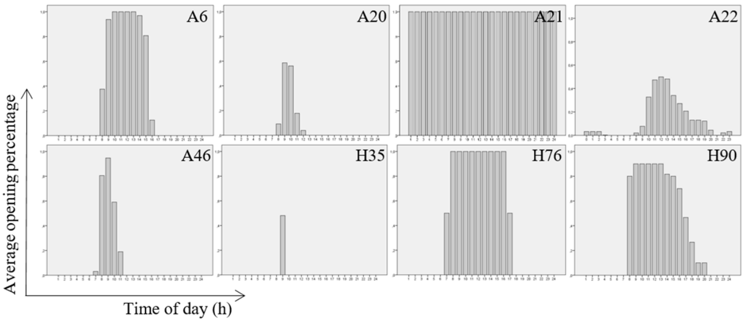


Figure 5.1: Average opening percentage for each hour of the day in wintertime for different rooms in different dwellings

Solely basing the analysis of habits on monitored data has some limitations:

- Difficulties in detecting habits that are not daily executed (e.g. opening window when cleaning once a week)
- Difficulties in detecting short habits (e.g opening the window 15 minutes after cooking)
- Difficulties in detecting habits that are not consistently repeated at exactly the same time (e.g. opening the windows when waking up in week versus weekend)
- The detected habits represent repetitive behaviour, but may not necessarily be a habit. Based on monitoring data alone it can not be ascertained that the behaviour is executed without conscious thought.

5.1.2 Interviews

More information was gathered by conducting informal interviews with the residents of the neighbourhood who participated in the logbook survey (N=47). The interviewer talked unscripted with the occupants about their window use. During these talks many occupants could exactly say when they opened or closed windows. Furthermore, they revealed some of the shorter or non-daily habits. Conducting interviews is a good method to capture habitual behaviour, however, interviews are time-consuming, especially when data on a large population is required.

5.1.3 Online survey

To reach a larger more diverse population, an online survey was carried out between March 19 and May 6, 2019. The survey was deployed using social media and mailing lists. In total 499 occupants of Belgian households filled in the survey. Since the survey was only conducted in Dutch, the study represents primarily the window opening behaviour of households in Flanders.

The sample represents the Flemish population relatively well. The distribution of the different building types and household characteristics in the sample is closely related to the distribution across Flanders (Table 5.1). It is difficult to reach the older population with an online survey, consequently, the age category above 55 years is less represented in the sample (16%) compared to the complete population (42%). Due to that the family type 'single' is as well less represented with only 10% in the survey compared to 32% in the population. In Table 5.2 some additional household and building descriptives are given.

Table 5.1: Building and household characteristics of the participants in the survey in comparison with the population of Flanders [150].

		Survey	**Flanders**
Dwelling	Terraced	29%	23%
	Semi-detached	21%	20%
	Detached	30%	30%
	Apartment	20%	27%
Family type	Single	10%	32%
	Couple	33%	29%
	Couple with children	44%	29%
	Single parent	3%	8%
	Other	10%	2%
Age of head of household	18-25	3%	10%
	25-35	38%	15%
	35-55	43%	33%
	55-75	15%	30%
	>75	1%	12%

Table 5.2: Descriptives of building and household characteristics of the participants in the online survey

	mean	std. dev.	N
Year of built	1970	43.87	406
# Bedrooms	2.95	1.10	499
# Persons	2.96	1.26	499
# Children	0.82	1.04	499

The online survey was designed based on the previously performed interviews in the case study. The survey consisted of questions asking to indicate how they interact with each window in each room. The different response options were based on the responses from the interviews and optimised for a wider public by performing a test survey with university members. An example of such a question is:

Do you have any specific window use habits in the bedroom in wintertime? Think about last winter period (temperature below 10°C). In which way did you interact with the windows in that period? Do not consider days with extreme temperatures (<-5°C). If you only interacted irregularly with the windows, please indicate "I do not have a habit". When your specific habit is not in the list please indicate "other" and specify your habit.

- *The windows are always closed*
- *The windows are opened in the morning for a short period (< 2 hours)*
- *The windows are opened in the morning for a long period (> 2 hours)*
- *The windows are opened for a short period before going to bed*
- *The windows are opened during the night and closed during the day*
- *The windows are always open*
- *I do not have a habit*
- *Other: ...*

The full questionnaire [Dutch] is included in the Appendix (Section 14.2). The questions in the survey were posed for both winter and summer. These seasons represent respectively the heating and free-running period, since in Belgium very few household (4%) have a fixed cooling system in their home [151]. When households replied with 'Other', the answers were evaluated, and accordingly categorised with a pre-defined category or a new category. Very small categories ($N < 5$) were marked as missing values. Additionally, questions were asked regarding the behaviour when performing specific activities and some general information was collected about building properties (building type, year of built, ventilation system, type of windows in each room, number of bedrooms) and household characteristics (number of people, number of children, age, employment type, tele-workdays, education level, pets).

Self-reported habits in interviews and surveys are often used in habit-studies [81, 152]. However, this approach assumes that all occupants can correctly report habits which is based on the supposition that all occupants are (fully) conscious of their habits. Ideally a combination of both detection techniques (monitoring and survey/interview) is used, but this is very resource and time consuming.

5.1.4 Remarks on the habit identification

The identification of window use habits, as discussed above, has some limitations.

Repetitive behaviour vs habitual behaviour

Detecting habits based on monitoring and online survey data purely focusses on the repetitiveness of the behaviour, while another key-aspect of habits is that habits are performed without conscious thought. It is very difficult to assess if a repetitive behaviour is consciously performed or carried out without conscious thought. Wood et al. [107] investigated this problem by conducting diary studies. The participants were asked to complete each hour a diary/small survey on the behaviour they were performing, the thoughts they had during the performance and their emotions. It was as well queried if this was a behaviour that they frequently performed (each day, once a week,...) and if this activity was usually performed in the current location. The answers to the two latter questions were used to determine if the behaviour was habitual or non-habitual. Results showed that the participants were less likely to think about their behaviour when performing habits (e.g. thinking about math test when driving home). In about 60% of the reported habitual behaviour the thoughts wandered from the performed activity. This is one way to prove the consciousness of the activity.

In this study no such evaluation is performed. Therefore, it can not be defined if an action is a habit or just a repetitive behaviour. The wrongful classification of a repetitive action as a habit will not generate much problems for predicting the behaviour. Even tough the behaviour is influenced by conscious thought, the repetitiveness can still be predicted correctly, leading to realistic OB-models. On the other hand, the uncertainty regarding the presence of conscious thought might be more problematic when trying to influence behaviour. When behaviour is deliberative, choices are made to perform that activity and targeted campaign trying to alter those choices might lead to changes in behaviour. However, changing behaviour is more complex when habitual behaviour is considered. As no deliberation is involved. Other more intrusive campaigns are needed to get people to change the behaviour.

Origin of the habit

Additionally, very few insights in the formation of these habits are obtained. A habit is formed over time with many highly diverse reasons at the base of it such as upbringing or past experiences. For example, the reason for opening windows in the morning may be because your mother always told you to open the windows in the morning because fresh air was important for a healthy environment. Since you are so used to this behaviour of opening the windows in the morning, you might still perform it even if the house you live in now has a correctly functioning ventilation system. This sociological narrative is an important base for the explanation of habits. Furthermore, these sociological narratives might not only explain the window opening behaviour but as well other building control habits. Going further on the example above. As you are always told that fresh air is necessary for a healthy environment, it might led you to spend much more time outdoors (often eating outside, preference for outdoor activities,...) with a reduced occupancy as a consequence or you might got acclimatised to colder temperatures leading to reduced heating set-points and a shorter heating period.

Based on the informal interviews some individual sociological narratives could be deduced. However, the focus of the interviews was not on this aspect, consequently no systematic evaluation was conducted. A more elaborate multi-disciplinary study on the underlying origins of the habits would be a very interesting future perspective.

Seasonality

Finally, according to the definition, habits are seen as the baseline response, and only when the stable context is disrupted conscious thought is used to determine the action. The online survey queries the window use habits in summer and winter respectively, with disregard of the extremely hot and cold periods. These queried habits are presumed to be performed during the entire astronomical season in this study, and switch only to another habit when the season changes. However, there is no indication that the habits are shifted exactly at the time the astronomical seasons change, it is even very unlikely that this is the case. The heating period itself might be a better switching point, however, this is different for each household and no questions were asked regarding the heating behaviour in the online survey. Further research is required to determine this switching point between winter and summer habits, and if there is such a thing as a autumn/spring habit or free-floating habit. The insights regarding the social narrative behind the habit might lead to a more accurate estimation of the switching point. For example if the underlying driver for the window use is IAQ, as in the example above, the switching point to the winter habit may occur much later in the season than when the main driver is thermal comfort.

Based on these remarks habits are evaluated in this dissertation as repetitive behaviour performed in the stable residential setting.

5.2 Window use habits in Belgian households

The responses to the online-survey revealed that almost all occupants (99,4%) habitually interact with at least one of their windows. In this section, the habits in the different rooms will be discussed as well as the habits related to the performance of specific activities.

5.2.1 Window-use habits in the different rooms

The survey queried the window use habits in the different rooms and in the different seasons. A summary of these responses is given in Figure 5.2. The most habits are present in the bedroom (97%), still at least 81% of the occupants reported having a habit in the other rooms. It could as well be observed that slightly more occupants reported having a habit in a specific room in winter compared to summer.

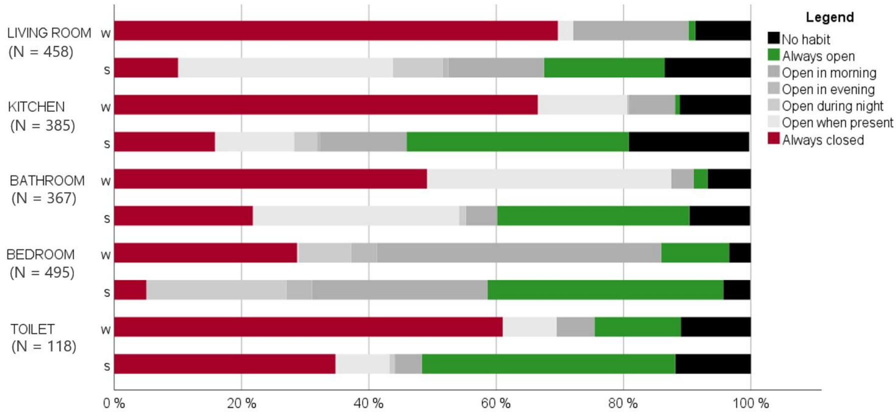


Figure 5.2: Summary of the self-reported window use habits in different rooms in winter (w) and summer (s). Open when present in the bathroom and in the kitchen respectively refers to during a bath/shower and during cooking.

The majority of the occupants (70%) leaves the living room windows always closed in wintertime. While one fifth regularly opens the windows in the morning or when present. A few people leave the living room windows always open (1%). The window opening behaviour in summer in the living room is significantly different from winter time. Only 10% keeps the windows always closed, while 19% leaves the windows always open. Many occupants (57%) open the windows regularly for a shorter period of time in the morning, in the evening, during the night and when present.

The kitchen window remains always closed in 66% of the households in wintertime. In summertime this decreases to only 16%. Almost 35% of the households leaves the kitchen window always open in summertime. This is a larger proportion compared to the living room, which is often combined with the kitchen in one zone. It may be that occupants want to ventilate the living area but want to prevent discomfort by for example draught and therefore choose to open the kitchen window. In the kitchen there are as well habits observed regarding the activity of cooking. Approximately 9% opens the window while they are cooking and 3% after they have cooked.

In the bedroom the windows are open most often, and the most window habits are present. Only 29% of the occupants leave the windows always closed in winter, this drops even further to a mere 5% in summer. More than 10% leaves the bedroom windows always open in wintertime, this increases to 37% in summer. The windows may be open more often in the bedroom as the people are rarely actively present there, so do not feel discomfort as the consequence of opening a window in winter.

An increase in occupants keeping their bedroom window always closed could be observed in households with mechanical ventilation systems (Figure 5.3). The difference between window habits in dwellings with different types of ventilation systems is significant in both winter ($\chi^2(12)=68.118$, p=.000) and summer ($\chi^2(12)=70.518$, p=.000). However, still 40% of occupants with balanced ventilation systems open windows frequently in wintertime and over 75% in summertime.

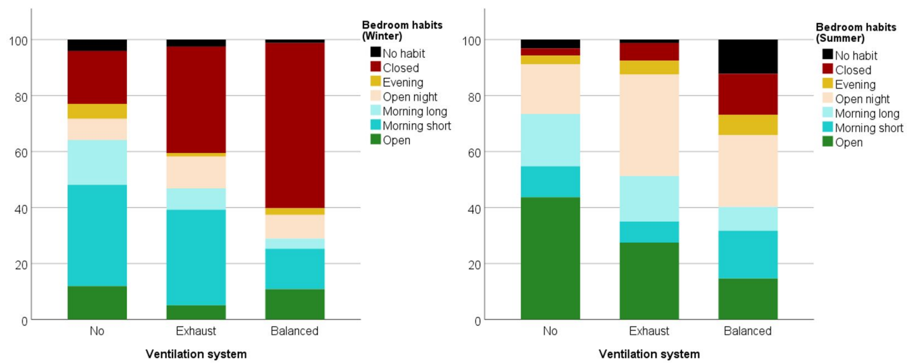


Figure 5.3: Self-reported habits in the bedroom in wintertime (left) and summertime (right) according to the type of ventilation system.

The windows in the bathroom are most often closed in the winter (49%). Other window actions are related to the use of the room, with 33% of the occupants opening the windows after a shower or bath. In summertime, the bathroom windows are less often kept closed (22%) and less often opened after a shower or bath (22%) in favour of leaving the windows always open (30%).

Only 118 households have a separate toilet with openable window. In winter these windows remain always closed in 61% of the households. Nevertheless, in 14% of the households the window is always open in wintertime. In summer this percentage rises to 40%.

5.2.2 Window-use habits related to activities

Next to the specific room habits, occupants sometimes open the window related to daily activities. In the survey, the window actions when the occupants go to bed and when they leave the dwelling were queried. Additionally, it was asked if occupants usually open the windows when they are performing specific activities such as drying clothes, cleaning the house or smoking.

More than 80% of the occupants closes one or more windows when going to bed in wintertime (Figure 5.4). Most of them (56%) close all windows, 20% closes all but the bedroom window, and 5% closes all accessible windows (windows accessible from the outside). Only 18% does not change anything to the state of the window. This means that when the windows are open before going to bed they remain open during the night, or when they are closed they remain closed. In summertime, 75% closes one or more windows, this is similar as in winter. However, the number of occupants that leave the bedroom window open increases significantly to 41%. Approximately the same amount of occupants (15%) do not change anything to the state of the windows when going to bed. A few more people (6%) have the tendency to open windows when going to bed in summer.

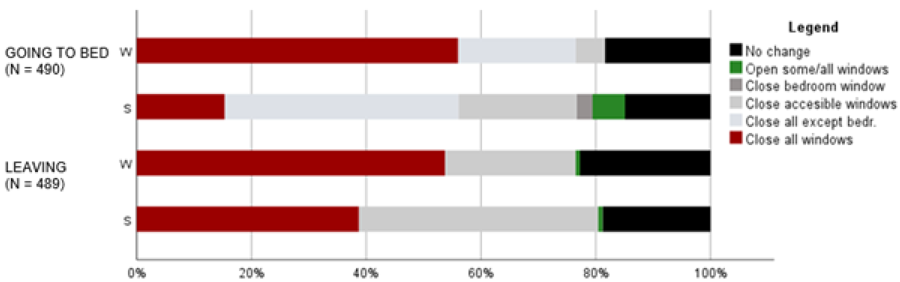


Figure 5.4: Summary of the self-reported window use habits when going to bed or leaving in winter (w) and summer (s)

Only 54% of the occupants closes all windows when leaving the dwelling in winter. With an additional 22% that closes only the accessible windows. The number of occupants who close windows when leaving is similar as when going to bed. In summertime, the percentage of occupants who close all windows is reduced to 39%. More occupants close only the accessible windows in summertime (41%).

It was assumed that the performance of some specific household activities may lead to opening actions as well. Results from the survey indicate that only a few occupants have such a habit (Table 5.3). 6% opens a window when vacuuming, 10% for ironing, 17% for drying clothes and 21% for cleaning. Indirectly a positive observation was done regarding smoking in the house. From the participants of the survey almost nobody (2.8%) smoked inside or let anyone else smoke inside their home.

Table 5.3: Windows opened when performing specific activities.

Open window when...	Yes	Sometimes	No	Not applicable
Ironing	9.8%	21.6%	56.1%	12.4%
Drying of clothes	16.6%	28.5%	46.3%	8.6%
Vacuuming	5.8%	13.8%	77.6%	2.8%
Cleaning	20.6%	32.3%	45.9%	1.2%
Smoking (indoors)	1.0%	0.0%	1.8%	97.2%

5.3 Context dependency

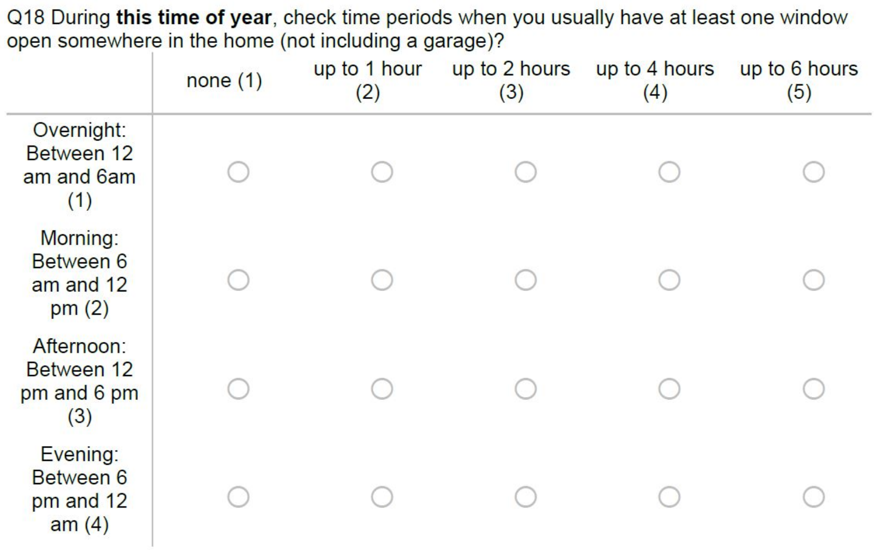
In the previous sections it was revealed that most occupants in Belgium report having some kind of window use habit. It can be questioned to what extent these habits are present in other contexts. Are the same number and type of window use habits present in other cultures?

To evaluate the context dependency of window use habits, the self-reported habits in the Belgian survey are compared to window use data gathered in the US.

5.3.1 Overview study US

A window use study was conducted in the US by Morrison and Date [153]. The study consisted of an online survey which was deployed 12 times between April 2016 and June 2018 through Amazon Mechanical Turk. In total they gathered 3380 responses from across the US. The goal of the survey was to collect information regarding personal operation of windows and doors, accounting for timing, frequency, extent of opening and motivation. This study was not specifically designed to detect habits. The study mainly questioned the window use in the different rooms on the day prior to the survey. The window use is indicated in 4 time-bins (0-6h, 6-12h, 12-18h, 18-24h) and for each time-bin an opening duration needs to be defined (none, up to 1 hour, up to 2 hours, up to 4 hours, up to 6 hours). Nevertheless, there is as well a question included regarding the 'usual behaviour' during this time of the year (Figure 5.5).

Even though this question is less detailed (building-level instead of room-level) compared to the question regarding the window use on the previous day, we can assume that when the building-level result is in correspondence to the response for the individual rooms, the window use observed on the previous day represents the 'usual behaviour'. For 65% of the respondents the window use of the previous day was similar as the typical behaviour, so for these households it is assumed that the window use is habitual.


Q18 During **this time of year**, check time periods when you usually have at least one window open somewhere in the home (not including a garage)?

	none (1)	up to 1 hour (2)	up to 2 hours (3)	up to 4 hours (4)	up to 6 hours (5)
Overnight: Between 12 am and 6am (1)	○	○	○	○	○
Morning: Between 6 am and 12 pm (2)	○	○	○	○	○
Afternoon: Between 12 pm and 6 pm (3)	○	○	○	○	○
Evening: Between 6 pm and 12 am (4)	○	○	○	○	○

Figure 5.5: Question regarding 'usual' window opening behaviour in the survey of Morrison and Date [153].

5.3.2 Sample comparison

For the comparison between the Belgian study and the American study it is necessary to know the similarities and differences between the samples.

Climate

Belgium has for the majority a temperate oceanic climate, with only in a few areas a warm-summer humid continental climate (e.g. Bastogne, Bütgenbach, Waimes, Saint-Hubert). The temperate oceanic climate is rare in the US (Southern appalachians, Seattle), however, the humid continental climate is quite common in the North-eastern part of the US. The climate zones are indicated on the maps in Figures 5.6 and 5.7. For the further analysis, the comparison will be made with the data from the North-eastern US only (N=1733), since this represents the climate closest to that of Belgium.

Building properties

A large difference is observed between the building types of the two studies. In the US a lot more detached homes are present, and a lot less attached homes (Figure 5.8-left). Apartments are similarly represented. The dwellings in Belgium have slightly more bedrooms (Figure 5.8-right).

In Belgium only 4% of the homes is equipped with cooling [151]. In the study of the US 93.5% of the homes have some type of AC (3% Split AC, 31% Window AC, 65% Central Air System). The presence of an AC-system will have an important influence on the window use.

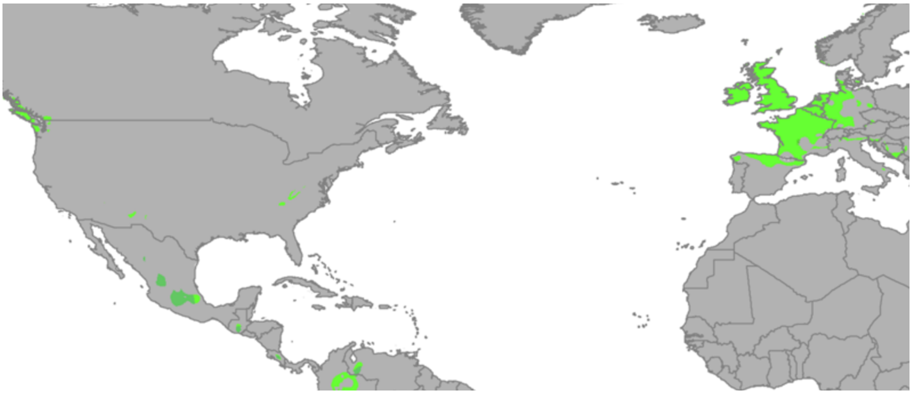


Figure 5.6: Map for temperate oceanic climate

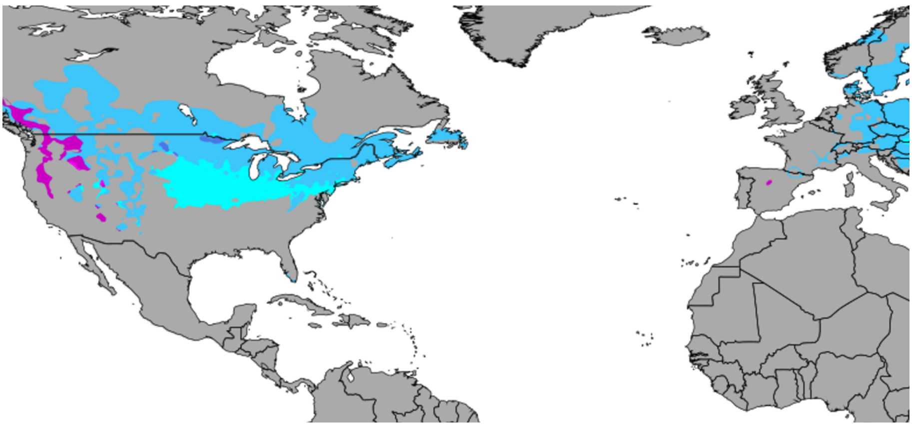


Figure 5.7: Map for humid continental climate

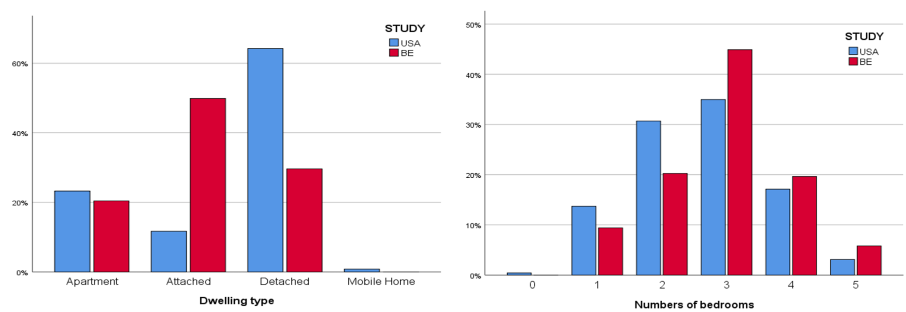


Figure 5.8: Histogram of dwelling types (left) and number of bedrooms (right) for the Belgian study and the American study (only data from NE)

In Belgium most often hydraulic central heating systems are present, while in the US building are more often heated with air systems. No additional data was available on the presence of ventilation systems in the US-study.

Household characteristics

The average number of occupants in each household is similar in both studies with 2.68 in the NE-US and 2.93 in the Belgian study (Figure 5.9-left). The slightly higher value in Belgium may be attributed to the fact that 1-person households are under-represented in the survey. The age distribution is comparable in both surveys, with for both surveys little data for occupants above 55 years (Figure 5.9-right).

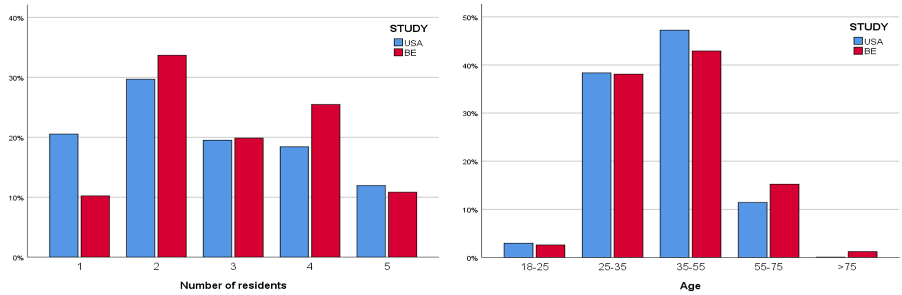


Figure 5.9: Histogram of number of occupants (left) and the occupant's age (right) for the Belgian study and the American study (only data from NE)

5.3.3 Window opening durations

In the US the average opening percentage in the bedroom in winter was 5% and in summer 35%. This is slightly lower than observed in the case study in Belgium (monitoring data: winter 9%, summer 41%)(see Section 4.4). In the living room the opening percentage per day was 1% in winter and 20% in summer, which is lower than in the case study (winter 3%, summer 48%). Overall windows were opened for less time in the US compared to Belgium.

5.3.4 Window use habits

Translation of time-bins to habits

In the US-study window use is indicated in 4 time-bins (0-6h, 6-12h, 12-18h, 18-24h) and for each time-bin a duration of opening windows is given (none, up to 1 hour, up to 2 hours, up to 4 hours, up to 6 hours). These time-bins can be translated to window use habits. Some examples are given below.

- up to 1 hour opening in time-bin 6-12h = Shortly opened in the morning
- up to 6 hour opening in time-bin 0-6h = Opened during the night
- during all time-bins no windows opened = Always closed

Habits in wintertime

In the US 82% of the respondents keep the bedroom windows always closed in wintertime (N=608) (Figure 5.10). While only 2% keep the bedroom windows always opened. In Belgium far less occupants keep the bedroom windows always closed (29%), in favour of other short window use habits (e.g. opening shortly in the morning, opening in the evening, opening during the night). In the living room the windows are opened for less time per day compared to the bedroom in both studies, with only 1% of the occupants keeping the windows always open (Figure 5.11). In the US 85% of the respondents have the windows always closed, which is slightly higher than in Belgium (72%).

The results of the US-study indicate mostly 'always closed' or 'always open' habits and very few other habits such as opening in the morning or evening. The window use in the specific time-bins is indeed stable across the day and, in contrast to the Belgian data, does not reveal more actions in the morning or evening (Figure 5.12).

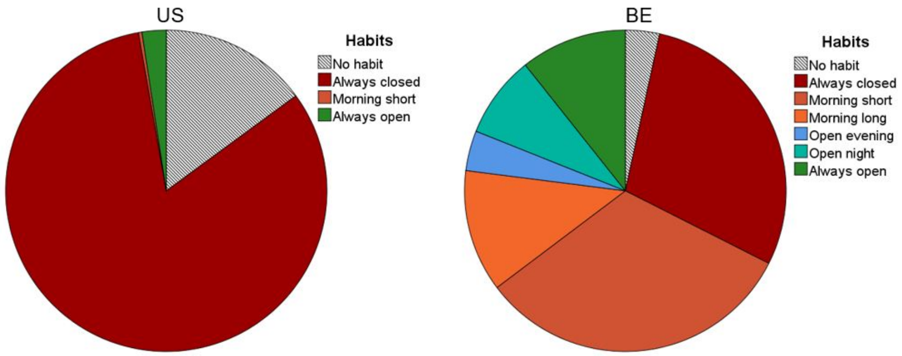


Figure 5.10: Window use habits in the bedroom in wintertime for the American study and Belgian study (N=608)

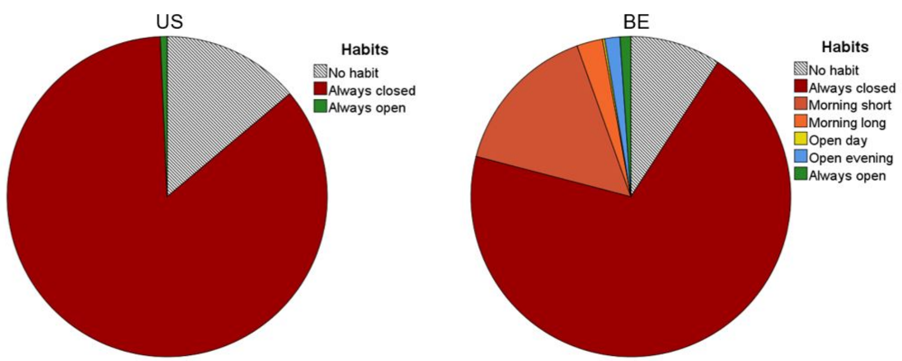


Figure 5.11: Window use habits in the living room in wintertime for the American study and Belgian study (N=608)

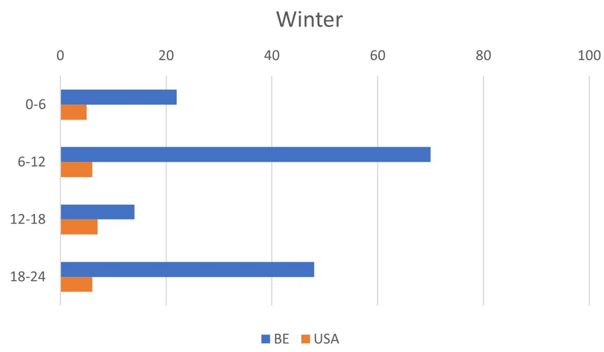


Figure 5.12: Percentage of occupants that opened a window per time-bin in wintertime for the Belgian study and American study (N=608)

Habits in summertime

22% of the occupants in the US (N=623) keep the windows always open in summertime and 36% in Belgium (Figure 5.13). However, the percentage that keeps the windows always closed is significantly higher in the American study (35% vs 6%).

In the living room, 45% of the occupants kept the windows always closed in the US, while this was only 18% in Belgium (Figure 5.14). The proportion of always open was comparable in both studies (US 12%, BE 17%). In summertime a lot of occupants did not have a habit in the US (40%). Similarly, in the Belgian study, less habits in summer were observed compared to winter. It may be that the window use in summertime is less habitual and more related to the prevailing weather conditions.

Context sensitivity?

The comparative study revealed that in the US there are as well window use habits present, but these mainly represent uniform behaviour across the day (always open/always closed). It should be noted that the results are not based on a survey focussing on habits, therefore the results should be interpreted cautiously. For this study it was assumed that when the answers to the typical behaviour on building-level did not correspond to the answers of the previous day, that these occupants did not have a habit. This assumption has some implications. When there would be only a habit present in the bedroom and not in the other rooms the response of that household for all rooms would be defined as ‘no habit’. This will lead to a higher percentage of occupants without a habit. Additionally, shorter habits related to specific activities are less likely to be captured by questions regarding window use at a specific time with time-steps of 1 hour.

Consequently, we can not draw definitive conclusions from this comparative study. The window use seems to be comparable in the living room in wintertime but not in the bedroom and not in summertime. The high proportion of windows always closed in the US in summer may be attributed to the presence of AC-units, which are rarely present in Belgian residences. Based on the received data it can not be defined if the AC-units supply fresh air or recirculate air. We observed some indications that the window use habits are indeed context dependent, however, more studies in a variety of contexts specifically focussed on habits need to be conducted to affirm this.

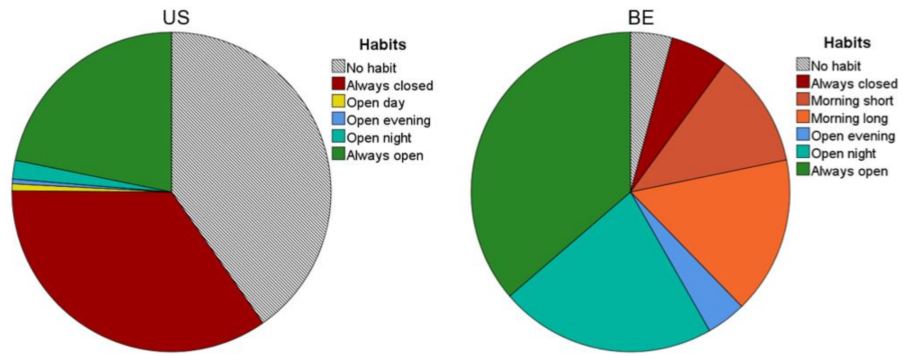


Figure 5.13: Window use habits in the bedroom in summertime for the American study and Belgian study (N=623)

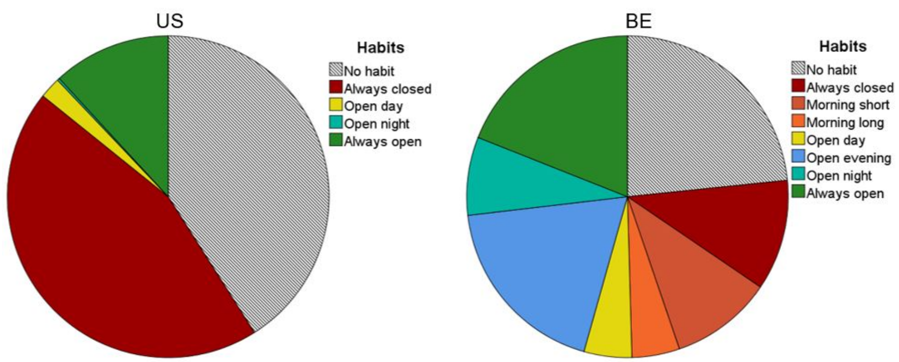


Figure 5.14: Window use habits in the living room in summertime for the American study and Belgian study (N=623)

5.4 Conclusion

It can be concluded that habitual behaviour is widely present in window opening behaviour in residential buildings. The online study revealed that almost all occupants perform some kind of habit with at least one window.

Habits can be easily detected by surveys or interviews. By asking a limited number of simple questions many information can be gathered regarding the window use habits of the occupants. The online survey revealed that most habits are related to the presence in a specific room and the performance of specific activities (cooking, cleaning, showering, sleeping). Slightly more habits are performed in the winter compared to the summer, which leads to the assumption that in summertime the window use is more deliberative, and probably closer related to the environmental conditions.

Preliminary results of the comparative study reveal that window use habits are present in a different context as well. The cultural aspect is influential on the type of habit and distribution of the habits across the population. Wider research is necessary in other contexts with studies focussing specifically on habits.

6

Building control habits

The results of the previous chapters emphasise the importance of habitual window use. It can be questioned whether other types of behaviours in residential settings are equally influenced by habits. Therefore, two other types of occupant behaviour are analysed for the presence of habits: clothing behaviour and solar shading use. These two additional types of occupant behaviour were chosen as they also have a direct influence on the comfort of the occupant, in a similar way as the window use. Additionally, direct measurements are available in the case study for the solar shading use.

6.1 Clothing Behaviour

6.1.1 Introduction

Clothing can be looked at from a variety of perspectives. It can be used as a safety layer in dangerous or unhealthy working spaces. But clothing is also a part of a culture, a society or a religion. Clothing can be used to express one's personality or to outwardly display a sign of togetherness as a group or organisation. Above all, clothing is used as a thermal resistance and insulation layer, formed between a human's body and its immediate environment. People wear clothes to be thermally comfortable. Changing clothes is an opportunity for people to play an active part in maintaining their own comfort. Especially in offices, where it is not always possible to change indoor temperatures or to operate a window, clothing adjustments are perhaps one of the most important opportunities to alter thermal comfort. But at work, there are limitations to changing clothes due to ethics, dress code, clothing availability, etc... At people's homes however, all the clothing segments are available, and people can wear whatever they want. Since clothing has an impact on thermal comfort, it therefore indirectly has an impact on the energy use in buildings. By putting on more clothes the heating set-points could be lowered and energy could be saved. This is a way of energy saving that is often overlooked but can have an important impact.

Furthermore, the ability of occupants to change clothes to directly adapt their thermal comfort is sometimes overlooked in the design of buildings. The responsibility of thermoregulation seems to lie exclusively with HVAC-systems and not with the individual occupant. The occupants can wear whatever they want indoors, providing that they are prepared to pay the financial and environmental costs of the energy use [154]. This attitude is diametrically opposed to the goal of using less energy.

Getting insight in the clothing behaviour of occupants can lead to a better assessment of thermal comfort and a better design of HVAC-installations. However, literary sources point out a lack of data about clothing behaviour in residential buildings [155–158]. Yan et al. [155] declared that several stochastic models have been developed to describe window operations, blinds and lighting, but that other behaviours such as operation of air-conditioning and clothing adjustment have been studied less. Especially, information regarding small clothing adjustments and clothing-levels in homes is lacking [158]. Newsham [156] pointed out that seasonal changes in clothing have been frequently observed and seem effective in thermal comfort moderation, but that there are few data on short-term (within a day) clothing adjustments.

There are many determinants that can potentially influence occupants' clothing behaviour, however, little consensus is found in the literature. The age of the occupant was not found to influence the clothing-levels by Karjalainen [158], but was found significant by Liu et al. [159], with higher clothing-levels for older people. Even though some literary sources point out that there is a difference in thermal preferences between women and men

[158, 160, 161], no significant differences in clothing insulations were noted [158,162,163].

Since few studies were reported from residential settings, the dress code in offices may be the cause of the limited differences in clothing levels between the different occupants. A dress code may affect the ability of occupants to adapt their clothing insulation. Morgan and de Dear [164] found, for example, that clothing insulation worn by the office workers on 'casual' days showed a significant correlation with outdoor temperatures, but not when the dress code was in place. Even though in residential settings mostly no dress code is present, the choice of clothing may be limited when there are visitors. When people are home alone or with their direct family, they feel free to wear whatever they want. However, if they have visitors, occupant's clothing behaviour might change due to psychological and social factors.

Besides occupant characteristics, the thermal environmental conditions have been found to influence the clothing behaviour as well. Even though the indoor conditions are closely related to the occupants' thermal comfort, the indoor temperature has a small to negligible influence on the clothing behaviour [157, 163, 164]. Probably due to the rather stable indoor conditions over the year. The daily mean outdoor temperature [157, 164], the outdoor temperature at 6am in the morning [162, 163] and the running mean outdoor temperature of the past week [159, 164] were much stronger clothing behaviour predictors. It was revealed that occupants choose what they wear in the morning and perform little to no adaptive actions during the day [157,165]. Clothing is not typically used to improve comfort on an hourly basis, but was more strongly based on people's expectations in the morning about what the external thermal conditions might be that day, hence the strong relationship with the daily mean outdoor temperature and not with the indoor temperature. The choice of clothing in the morning is influenced both by the weather memory of the previous day(s) and the forecast for the present day [164].

In this section the clothing behaviour of occupants of residential buildings is assessed, with a specific focus on short term clothing adjustments and clothing levels in the home. In first instance the relationship between clothing levels and occupant characteristics and environmental variables is researched, which is the commonly applied approach. Additionally, it is evaluated if the clothing behaviour is as well a habitual behaviour.

6.1.2 Methods

Two kinds of surveys were used to collect data: logbook surveys and online questionnaires. Both surveys, executed between March 11 and April 5, 2019, query after the clothing behaviour of the participant, but each in a different way.

The logbook survey (LB) is a survey on paper in which the participant notes his/her clothing behaviour every 15 minutes during one or two days. From this survey, information about clothing adjustments, sleepwear, activities, ... throughout a whole day can be derived (Figure 6.1). The logbook surveys were conducted in a student home in Ghent, Belgium. The apartments are all

Hour	Activity: Which activity are you performing? Indicate your main activity of the last 15 minutes. Only one activity can be filled in per line.	Clothes Which clothes are you wearing? Indicate with a cross which clothes you wear for every 15 minutes. When you can't find your clothing item in the list, write it in the column 'other'.															Sit/lay on If you are not standing: On which furniture are you sitting/laying?						Space In which space are you?				Visitors Are you alone or in company?		
		Underpants	Socks	Bra	Long trousers	Shorts	Skirt	Dress	T-shirt	T-shirt without sleeves	T-shirt with long sleeves	Thin sweater	Warm sweater	Slippers	Shoes	Other	Bed	Sofa	Extra blanket	Chair	Office chair	Other	Living area/ kitchen	Bedroom	Bathroom	Hallway	Alone	Partner	Other
05.30 – 05.45	sleep	x															x							x				x	
05.45 – 06.00	"	x															x							x				x	
06.00 – 06.15	"	x															x							x				x	
06.15 – 06.30	Wake up & get dressed	x		x	x				x															x				x	
06.30 – 06.45	washing	x		x	x				x																x		x		
06.45 – 07.00	eating	x		x	x				x											x			x				x		
07.00 – 07.15	Clean up	x		x	x				x														x				x		
07.15 – 07.30	washing	x		x	x				x																x		x		
07.30 – 07.45	Preparing to leave	x		x	x				x				x		x	scarf										x	x		
07.45 – 08.00	away																												
08.00 – 08.15																													
08.15 – 08.30																													
08.30 – 08.45																													
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09.15 – 09.30																													
09.30 – 09.45																													
09.45 – 10.00																													
10.00 – 10.15																													

Figure 6.1: Logbook paper with columns for time, activity, clothing, furniture, room and people that are present.

equipped identically and have the same lay-out and orientation. All the 126 participants are from the same age group (age 18-28), making it relatively easy to compare results, e.g. for examining the influence of gender on occupant's clothing behaviour. Additionally, each participant received an indoor temperature sensor that they had to put in the room in which they were present. Outdoor temperatures were available from a climate station in Melle, near Ghent.

The online survey (OS) is a short questionnaire that inquiries about the participants' clothing behaviour at the time of participation (see Appendix 14.3 for the full questionnaire). Which clothes are being worn? How comfortable is the participant? In which room is the participant at that moment? In total, 1243 answers were collected. It should be noted that people could participate more than one time. The respondents were aged between 7 and 85 years, with a majority of the occupants in the category 18 to 25 years (Figure 6.2). The respondents were mostly female (72%).

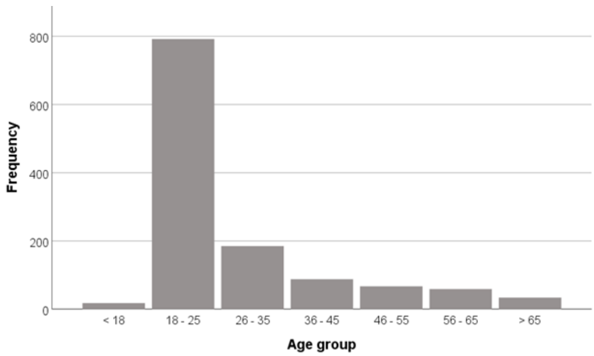


Figure 6.2: Histogram of the age groups.

To be able to analyse the clothing behaviour of the occupants, the set of clothing garments a person is wearing are converted to a total clo-value. For this values from ASHRAE Standard 55 - 2010 [166] and ISO 7730 – 2005 [167] are used. The metabolic rate will influence the clothing behaviour of the occupants as well. However, because it is assumed that people will not be very active while filling in the online survey, no adjustments for clothing insulation values were needed. The metabolic rate of the participants of the logbook survey may increase during the day. However, the available data is too limited so this will not be taken into consideration in this study.

6.1.3 Initial observations

The mean clothing insulation is respectively 0.51 clo and 0.58 clo for the logbook study and online questionnaire. This corresponds with a clothing outfit consisting of shoes, socks, underwear, long trousers and a long-sleeve thin sweater. These values were obtained in early spring in Belgium. People can reach thermal comfort not only by adjusting clothes, but also by making a change in seating furniture. In this study the mean insulation value given by furniture (without accounting for bedding and blankets) is respectively 0.16 clo and 0.09 clo, for the logbook study and online questionnaire, which can be compared to the insulation provided by a standard office chair.

For the logbook study there is also data available on the clothes being worn during the night. The mean clothing insulation is 0.14 clo at night (underwear and t-shirt), with an added 4.07 clo due to bedding and blankets.

The mean clothing values in this study are close to the clothing value defined for summer months (0.50 clo) by Fanger [160]. However, this study is performed in early spring, with outdoor temperatures between 4 and 12°C, which are not representative for a Belgian summer.

6.1.4 Relationship with environmental variables

Indoor temperature

Both indoor temperatures and clothing behaviour can make a direct impact on the thermal comfort. The average indoor temperatures of the room in which the participants stayed, were stagnant (Figure 6.3). It should be noted that the research period is rather short (less than a month), so it is logical that little variation is present. However, Schiavon and Lee [162], who performed a comparable research over an entire year, reported that the indoor air temperature does not change significantly throughout the year in residential buildings. In the study of Janssens and Vandepitte [168] a relatively constant indoor temperature was observed as well when the outdoor temperature was below 15°C. With higher outdoor temperatures, the indoor temperature was more variable. In the logbook study the average indoor temperature was 22.0°C (min = 20.2 °C, max = 27.2 °C). In the online survey participants were asked to report the temperature that was on their thermostat, however, only 46% of the participants provided this data. For these participants the average indoor temperature during the research period was 20.5°C (min = 13°C, max = 26°C). The mean difference between the indoor temperatures in the online survey and logbook study is 1.5°C, which is an important difference. The higher indoor temperatures with the young group of students is unexpected. One of the possible causes is that the price for energy use in the student housing is fixed, unrelated to the energy use, so the students can use as much energy as they want without having to worry about the price. Other possible explanations can be found in the use of different temperature sensors, and the diversity in participants and building characteristics.

The indoor temperature of the room in which the participant stays at the time of participation (OS) is negatively correlated with the insulation value of the clothing he/she wears at that time (τ= -.103, p= .001) (Figure 6.4). This relation is as one may expect, the higher the indoor temperature, the lower the clothing insulation value. However, from these results we can not conclude that occupants adapt their clothing when the indoor temperature changes. Data is needed on a longer period to make such conclusions. For most occupants only data for one or two days is available which is not sufficient to be able to conclude something on changes of clothing related to the environment. One thing that can be deducted is that each participant clothes him/herself to be comfortable

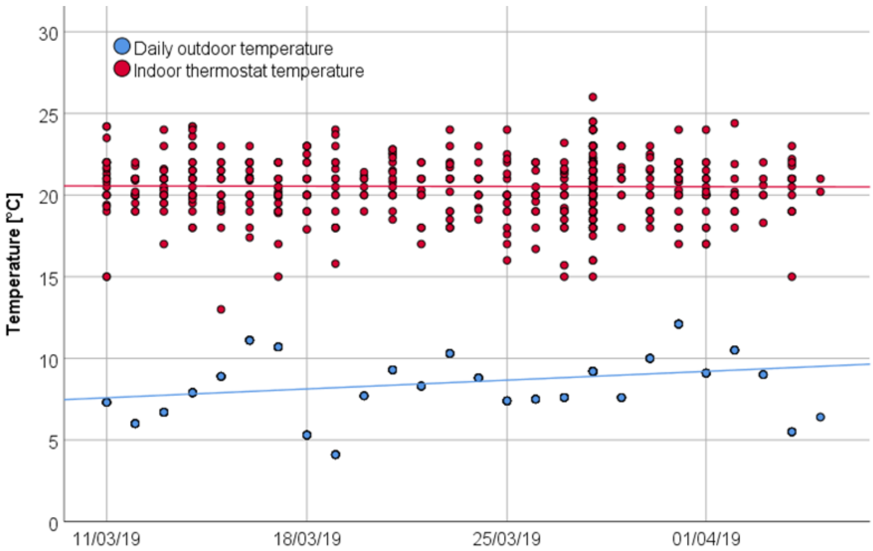


Figure 6.3: Indoor temperature (red) and outdoor temperature (blue) during the research period (OS).

in the temperature of their own environment, which varies between the different participants. Some occupants may be accustomed to a lower room temperature than others. This may be out of necessity (e.g. due to economic problems), because the resident explicitly chooses to (e.g. to bear a smaller ecological footprint) [169] or for other personal reasons. This acclimatization can be shown by the relationship between the indoor temperature and the thermal comfort rating of the occupants (Figure 6.5). More extreme temperatures do not necessarily indicate less comfort. There is no significant difference in indoor temperatures for the different comfort categories ($F(3,569) = 1.360$, $p=.254$).

Outdoor temperature

The outdoor temperatures fluctuated between 4.1°C and 12.1°C, with a continuous rise in temperature over time (Figure 6.3). The relation between the outdoor temperature and clothing at the time of participation is analysed. No significant relationship (τ=.008, p=.684) could be found when analysing the temperature at the moment of participation and the clothing the occupant is wearing. However, a significant negative correlation between the outdoor temperature and the total clothing insulation (insulation value for clothing garments and furniture) at the time of participation is present (τ=-.072, p=.001) (Figure 6.6). This could mean that people make small adjustments in their direct environment to be comfortable, not by changing clothes, but more so by changes in seating furniture and blankets.

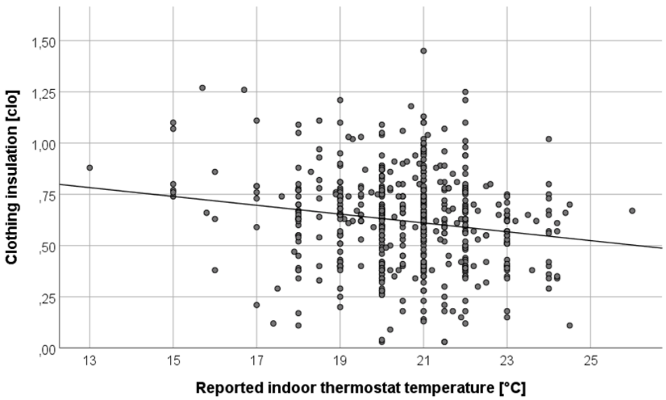


Figure 6.4: Relationship between indoor temperature and clothing insulation (OS).

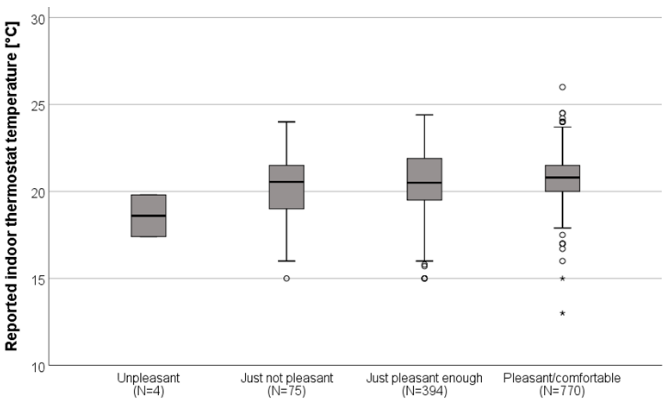


Figure 6.5: Indoor temperature for each comfort level (OS).

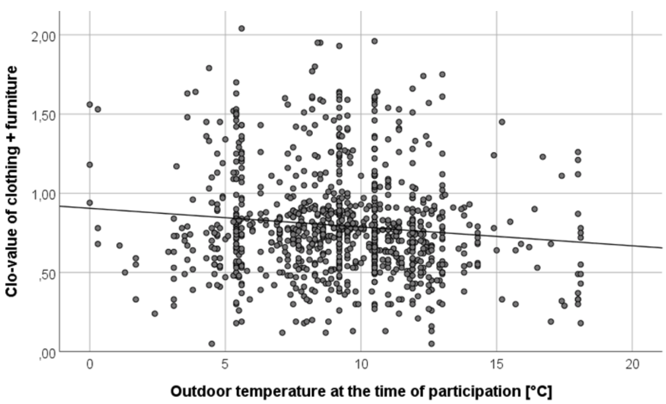


Figure 6.6: Relationship between daily mean outdoor temperature and clothing insulation (OS).

The negative relationship between the clothing worn by the occupants and the outdoor temperature is significant when instead of the outdoor temperature of that moment, the daily mean temperature is considered (τ=-.059 , p=.001). This indicates that clothes are adapted not based on short time temperature changes but on longer periods of time. Occupants often choose a set of clothes in the morning and do not change this during the day. This is in accordance with the literature. Morgan and de Dear [164] suggested that the timing of when clothing decisions are made is a key factor in explaining the relationship between clothing and outdoor temperature. Also, Schiavon and Lee [162] found a strong correlation between outdoor temperatures at the time when people get up and the clothes they wear during the day.

Furthermore, an important factor in clothing choices according to the literature is the weather history memory. People make clothing decisions partly by memory of the thermal outdoor environments of the day before, and on the weather forecast of that day [157, 164, 165]. In this study the influence of both the weighted outdoor temperature of the past 4 days [163], and the mean outdoor temperature of the last 30 days is researched. In the online survey, a slight negative significant relationship (τ=-.057, p=.001) exists between the weighted outdoor temperature of the past four days and the clothing insulation worn at the moment of participation. Similarly, a slight negative significant relation is found between the mean outdoor temperature of the last thirty days and the clothing insulation worn at the time of participation (τ=-.085, p=.001). The correlation is stronger for the past 30 days compared to the past 4 days, which could indicate that people take the temperatures from a wider period into account when making clothing decisions.

6.1.5 Relationship with occupant characteristics

Gender

The participants in the online survey are mostly women (72%). In 5 cases the respondent could not identify him/herself as man or woman and indicated ‘other’. In the logbook surveys, the number of participants was more proportionally divided into 45% men and 55% women. In the online survey, the average difference in clothing insulation between genders is 0.04 clo (Figure 6.7). An insulation value of 0.04 clo (corresponding with underwear) is relatively small and can be neglected. This is in correspondence with the literature [158, 160, 162, 163]. However, the logbook surveys, filled out by students, show a much larger difference in clothing insulation value between men and women (Δ clo = 0.12 clo) (Figure 6.8). This clothing difference corresponds with a t-shirt or blouse and cannot simply be ignored. It is found that this higher difference between genders is due to a lower clothing insulation worn by the male students. Women wear the same amount of clothing in both surveys. The fact that male bodies heat up more than female bodies [158], in combination with higher mean indoor temperature, can be a possible explanation as to why male students, compared to the female students and the participants of the online survey, wore less clothes during the period of the investigation.

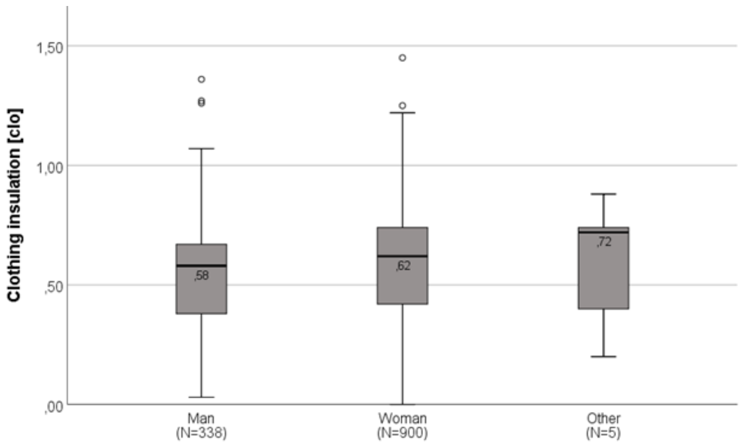


Figure 6.7: Clothing insulation according to gender (OS).

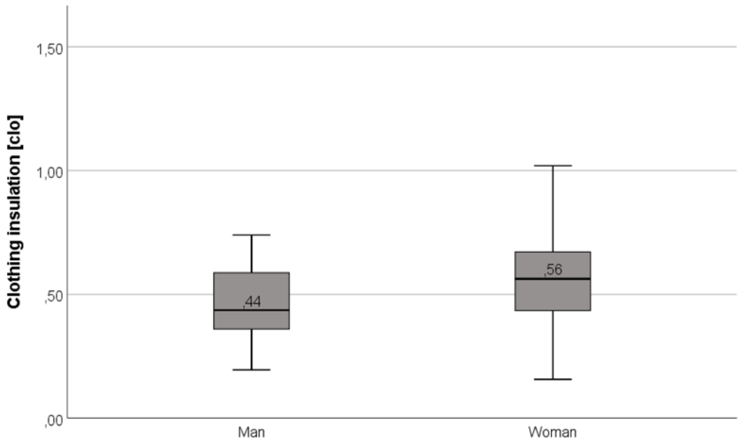


Figure 6.8: Clothing insulation according to gender (LB).

In the analysis of the clothing behaviour and the outdoor temperature, men seem to wear similar clothes every day, independent of the outdoor temperatures, while the clothing insulation of women varies over the different outdoor temperatures (Figure 6.9). This may be attributed to a higher weather sensitivity of women. Another possible explanation can be found in the high variance in options for women's clothing compared to the clothing options for men. With more options, the variation in clothing worn can be larger.

Age

The age of the 1243 participants in the online survey ranges from 7 to 85 years. The age-group 18 – 25 is represented the most with 64%. Figure 6.10 shows the significant positive relation between the clothing that the participants wear on the moment of the survey and the age of the participant (τ=.099, p=.001). The older the occupant, the more clothes he/she wears at home. A significant positive relationship also exists between age and indoor temperature (τ=.097, p=.001), the older the participant, the higher the indoor temperature. Older people maintain their comfort therefore both by adapting the environment and their clothing. It should be noted that the age-distribution of the data sample is not representative for the Flemish population as only a smaller group of older people participated in the survey.

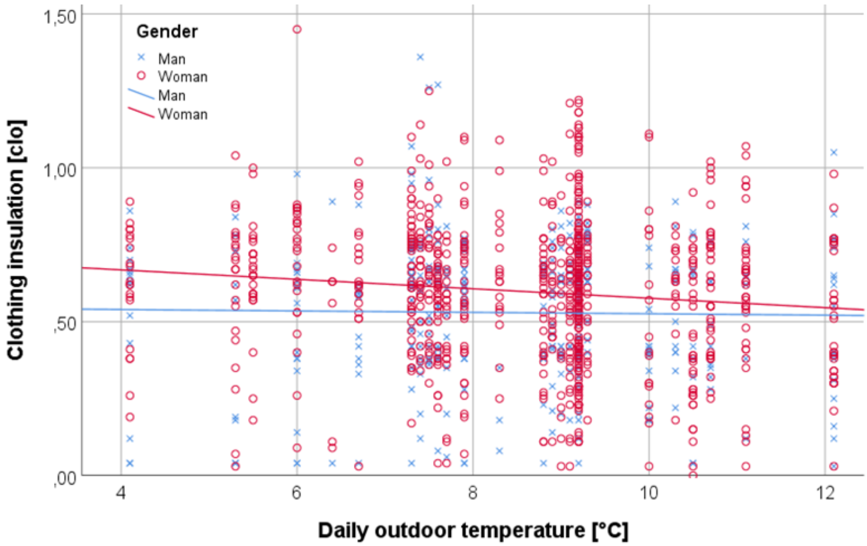


Figure 6.9: Relationship between outdoor temperature and clothing insulation according to gender (OS).

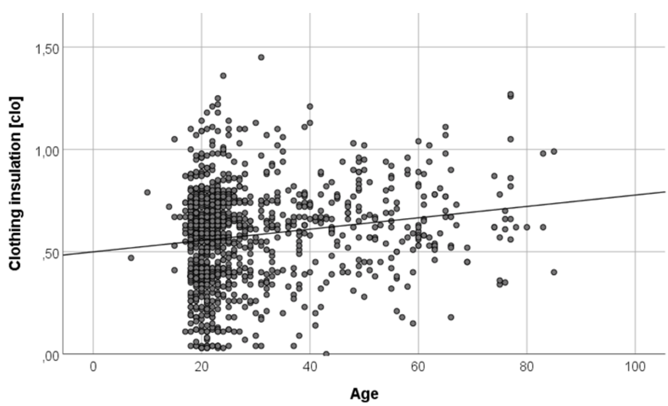


Figure 6.10: Relationship clothing insulation and age (OS).

6.1.6 Habitual behaviour?

The strongest correlation with clothing behaviour is observed for the indoor temperature, with higher clo-values for lower indoor temperatures. Outdoor temperatures and weather history memory had an influence on the occupant's clothing behaviour as well. The temperature at the moment of querying did not have a direct influence on the clothing insulation, but the daily mean temperature, the weighted outdoor temperature of the past 4 days, and the mean outdoor temperature of the last 30 days did have an influence. Nevertheless, the temperature at the moment of participation was correlated with the total insulation value, including insulation due to furniture and blankets. This indicates that occupants cloth themselves based on their weather history memory, but that hourly variations in temperatures might be compensated with a change in seating furniture or blankets.

It should be remarked that the correlation coefficients found in this study are relatively low. This could be the result of the rather short research period. A longer research period would allow more solid conclusions. Another possible explanation could be that people do not significantly change their clothing, even when outdoor or indoor temperatures slightly change. As discussed previously, the correlation between indoor temperature and clo-value is probably not the result of the adaptation of clothing to a changing indoor temperature, but more likely due to personal preferences. People living in lower indoor temperature wear, on average, more clothes than people living in higher indoor temperatures. This suggests that occupants have specific habits in their homes. Occupants do not only want to be thermally comfortable; they also want to wear clothes that they like and in which they feel comfortable in their homes. Many occupants commonly wear a comfortable outfit at home, independent of any (small) changes in indoor or outdoor temperatures. It is hypothesised that this basic outfit is only adjusted when confronted by extreme outdoor and/or indoor temperature change, like during a hot summer - or a cold winter day.

The results of this study indicate that habits are as well present in the clothing behaviour in the residential setting.

6.2 Solar shading use

6.2.1 Introduction

The use of solar shading can have a significant influence on the thermal comfort of occupants in a building. Closing the solar shades is a passive way to decrease overheating and will reduce the cooling demand. The correct use of solar shading can contribute to considerable energy savings, especially in zero-energy buildings in which the cooling load is critical. Furthermore, the use of solar shading can as well attribute to the visual comfort in a building. By lowering shades, the overall brightness in the room can be reduced as well as glare (e.g. on computer screens). It can also provide more privacy. Raising the shades on the other hand increases the daylight levels, the visual room spaciousness and the views to the outside [170].

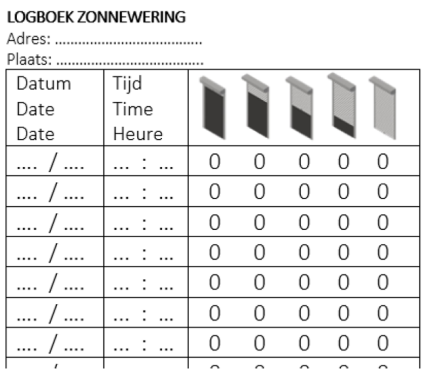
Many studies have been carried out on the solar shading behaviour in offices, however, information regarding residential dwellings is lacking. For offices different models have been developed to predict solar shading behaviour. A lot of these models are based on maintaining visual comfort [108, 109, 141, 171–176], by using parameters such as illuminance and solar radiation. In a study of Haldi [174], which included both visual comfort and thermal comfort parameters, it was found that only visual comfort parameters had a significant impact on the solar shading behaviour. The occupancy in the offices influences the solar shading behaviour as well. More shading actions occur when occupants enter their office than during intermediate times [108, 171, 172, 174, 177]. There is no agreement about the frequency of actions upon departure. The orientation of the shades is as well of importance. South- and west-oriented shades will be most often closed in winter, while east-oriented shades will most often be closed in summer [175]. Higher closing values during winter can be explained by the fact that the solar altitude is low, allowing the sun to penetrate deeper into the room, which causes more glare problems. The solar altitude or orientation of the windows are therefore often included in solar shading models [173, 175].

It can be concluded that in offices the main reasons for using the solar shades are to provide visual comfort rather than to avoid overheating [174, 178]. Since the research in the literature is almost uniquely focused on offices, information on the use of solar shading in residential dwellings is lacking. In offices visual comfort is of utmost importance to be able to work. It can be assumed that visual comfort will be less of a driving force in residential buildings, where maintaining thermal comfort will be essential.

6.2.2 Methods

For the solar shading study data is gathered from the case study (Chapter 2), both by the monitoring system (BMS) and by additional logbooks (LB).

The logbook study was carried out in the case study project during the summer of 2018 (6 August to 4 September) to supplement the data gathered through monitoring. The occupants of the neighbourhood were asked to write down every action they performed with the solar shades during the period of the study. For each window equipped with solar shades, they were given a paper (Figure 6.11) on which they could fill out the date and time of performing an action, and mark the position they changed the solar shades to. In some houses it was possible to put the shades in an intermediate position, therefore five options were given to mark the changed position: fully open, quarter closed, half closed, three quarters closed and fully closed. It needs to be noted that the social housing company asked the tenants not to put the solar shades at intermediate positions since this could cause damage to the windows. All occupants of the houses were asked to participate in the study, however, only 19 occupants did so. To check whether the participants filled out the logbooks correctly, different observations were performed during the study period. In the end only 10 of the 19 logbooks were assumed to be correct, as there was no conflict between the observations and the logbooks allowing for deviations of up to an hour due to incorrect clock settings and delayed filling in of the logbook.



LOGBOEK ZONNEWERING
Adres: ....
Plaats: ....

Datum Date Date	Tijd Time Heure					
.... /	... : ...	0	0	0	0	0
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.... /	... : ...	0	0	0	0	0
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.... /	... : ...	0	0	0	0	0
.... /	... : ...	0	0	0	0	0

Figure 6.11: Logbook for solar shading use.

6.2.3 Initial observations

The first aspect that is considered is the frequency of shading adjustments. The average number of shading interactions per month is 4.97 (Figure 6.12), as logged by the solar shading sensors. The solar shades in the living room and in the main bedroom are used most frequently. The number of actions includes both opening and closing actions. The low frequency of actions with the shades is in correspondence with the literature on offices. Stazi et al. [67], and Foster and Oreszczyn [179], for example, noted that shades often remain in the same state for weeks or even months.

The logbook study was carried out for less than one month, so monthly averages are not available. The logbooks do confirm that in general little actions are taken on the solar shades. Seven out of the ten participating occupants never changed the position of one or more of the solar shades during the period that the study was carried out.

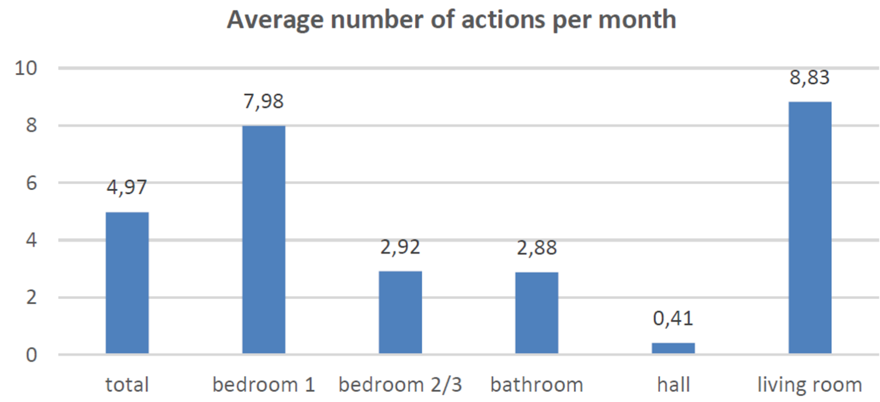


Figure 6.12: Frequency of shading adjustments per month per room (BMS).

It was observed that most actions are performed in the morning, and in the evening (Figure 6.13). This is in correspondence to findings in offices related to the occupancy [108, 171, 172, 174, 177]. When each case is assessed separately, different patterns could be distinguished. There are occupants that perform more closing actions in the morning and more opening actions in the evening (e.g. H1 Bedroom, Figure 6.14). These occupants probably use their solar shades to limit overheating during the day. However, other occupants (e.g. H3 Bedroom, Figure 6.15) perform more opening actions in the morning and closing actions in the evening. This indicates that they close the shades during the night probably to provide privacy or to make the room darker. In this study almost a quarter of the occupants (23%) used the shades as blinds (Figure 6.16).

The total average closing percentage is 62% for the sensor data. In the living room (77%), the main bedroom (71%) and the bathroom (68%) the solar shades are closed most often. For the bathrooms and the bedrooms, the difference in closing percentage varies a lot between the different houses; the values range from 2% to 100%. As discussed previously a lot of the solar shades stay either always open or always closed. 38% of the observed solar shades remained closed for more than 90% of the time, of which 15% always stayed closed (Figure 6.16). And 15% of the observed solar shades remained open for more than 90% of the time, of which 8% always remained open. Especially in the bathrooms a lot of the solar shades remain always closed. This can be attributed to the use of solar shades to provide privacy.

When solar shades are installed in both the bedroom and the bathroom, the closing percentage is similar for both rooms in most cases. The closing percentage thus seems to be defined more by occupant preferences in general than by function of the room. Even though the logbook study was carried out during summer, the total average closing percentage of the logbook study (57%) (Figure 6.17) is slightly lower than the average closing percentage obtained from the monitoring data. This difference can be attributed to the sample size. Since there are only a few responses, extreme values will have a larger impact on the mean value.

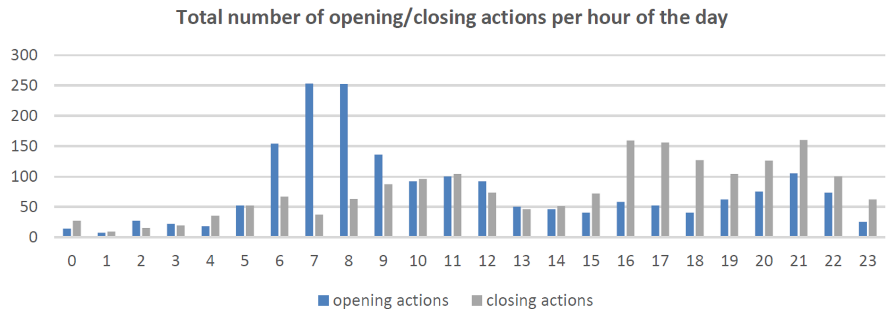


Figure 6.13: Number of actions per hour of the day (BMS).

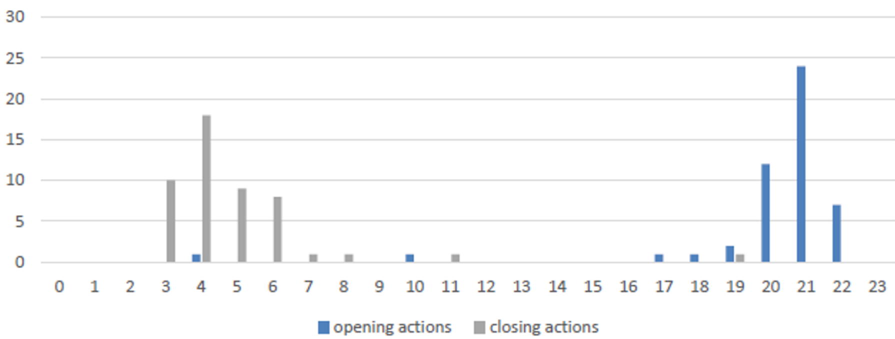


Figure 6.14: H1 Bedroom - Number of shading adjustments per hour of the day (BMS).

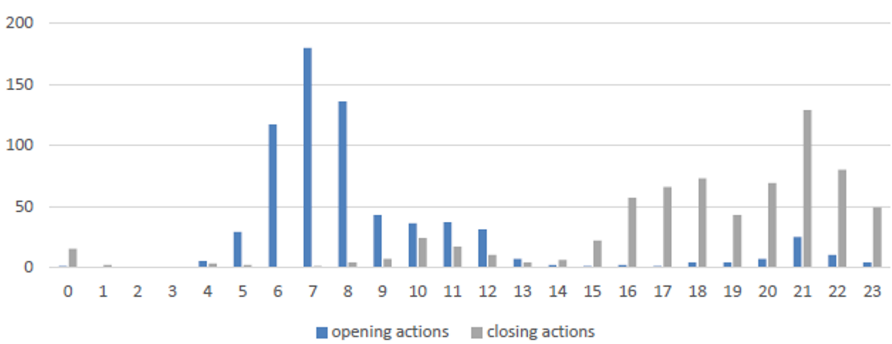


Figure 6.15: H3 Bedroom - Number of shading adjustments per hour of the day (BMS).

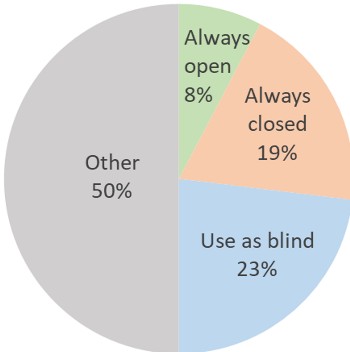


Figure 6.16: Observed patterns of solar shading use based on sensor data (BMS).

6.2.4 Relationship with environmental variables

Outdoor temperature

The outdoor temperature, as measured in the climate station with 5 min intervals, was found to have a small positive correlation with the closing percentage per day (τ= .095, p= .000) (Figure 6.18). More solar shades are closed when the temperature increases. However, the increase is small with approximately 5% more closed shades between 0 ˚C and 30 ˚C.

When the outdoor temperatures at the moment of opening is compared to the mean temperature of closing the solar shades, we notice that for all cases both actions happen averagely at the same temperature. The average outdoor temperature when opening a solar shade is 13.1˚C while the average outdoor temperature when closing a solar shade is 13.6 ˚C. This can be attributed to the fact that many solar shades are not often used, and that most actions happen either in the morning or the evening, when lower temperatures are present.

Indoor temperature

One of the reasons for adjusting the solar shades is to preserve thermal comfort. Therefore, it seems plausible that the indoor temperature has an important influence on the shading behaviour. According to a study of Haldi and Robinson [108], the indoor temperature is a better parameter to predict shading behaviour than the outdoor temperature. Sutter et al. [176] found that for the same illuminance levels, the percentage of closed solar shades increased up to 30% for indoor temperatures higher than 26 ˚C compared to indoor temperatures below 26 ˚C.

A small positive relationship is present between the measured indoor temperature per 15 min and the closing percentage per day (τ= .039, p= .000) (Figure 6.19). Indicating that solar shades are closed slightly more when the indoor temperature is higher. When the different rooms are analysed separately, only in the bedroom a significant positive relationship is present (τ= .060, p= .000).

CLOSING PERCENTAGE

House	Bedroom	Bedroom 2	Bedroom 3	Bathroom	Living	Hall
H1	49,32 %			98,12 %		
H2	90,46 %*			90,46 %*		
H3	63,92 %					
H4	99,29 %			99,60 %		
H5				2,17 %	63,08 %	10,85 %
H6		74,83 %	69,44 %			
H7				80,15 %	90,50 %	46,18 %
H8			27,42 %			
H9	99,59 %			74,79 %		
H10		2,26 %*	2,26 %*			
H11	7,65 %			8,60 %		
H12	60,92%			65,52 %		
H13		100,00 %	31,72 %			
H14	96,10 %			96,29 %		

Figure 6.17: Closing percentage of each solar shade (LB).

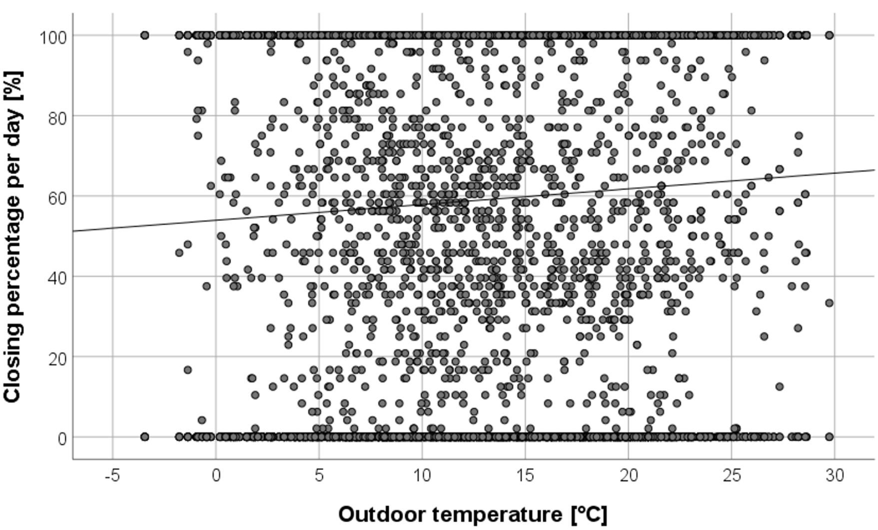


Figure 6.18: Relationship outdoor temperature and closing percentage per day (BMS).

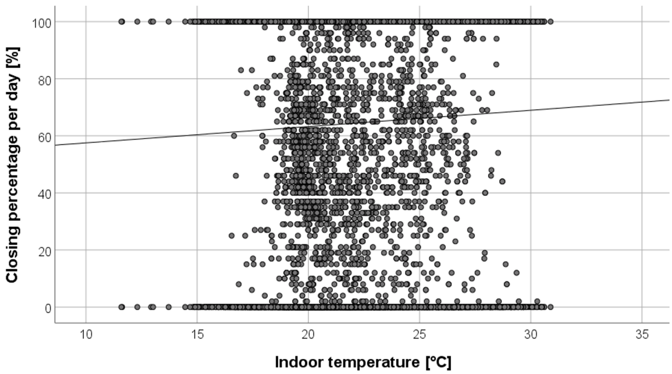


Figure 6.19: Relationship closing percentage per day and indoor temperature (BMS).

The opening and closing actions happen at approximately the same indoor temperature. The average indoor temperature when opening a solar shade is 22.0 ˚C, while it is 22.1 ˚C when closing a solar shade.

Solar radiation

Solar radiation is the parameter that was often defined in the literature as most influential on the shading behaviour in offices. Visual comfort was found to be the biggest reason to adjust the solar shades in offices, rather than thermal comfort. In these dwellings however, the solar shades are mostly installed in rooms where people are usually not present during the day (i.e. the bedroom, bathroom and hall). Therefore, it seems unlikely that a strong correlation would be present between the shading behaviour and the solar radiation. A positive correlation between the closing percentage per day and the measured solar radiation is observed (τ= .038, p= .000)(Figure 6.20), with slightly more solar shades closed with higher solar radiation. However, the correlation is rather small.

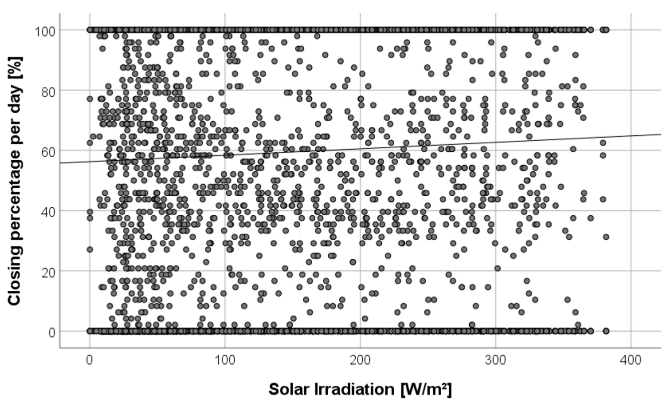


Figure 6.20: Relationship solar radiation and closing percentage per day (BMS).

6.2.5 Habitual behaviour?

The studied weather variables, in the considered format, only showed very small to negligible correlations with the solar shading behaviour in this case study. The solar shades are rarely adjusted and are thus in the same position for a long time, independent of the temperature or solar radiation. The position of the solar shades seems to be influenced more by the personal preference of the occupant than by the external factors. A lot of occupants leave their solar shades open or closed for almost all the time. Furthermore, many occupants use the shades as blinds. The variation in solar shading use differs largely with the extremes being the most common.

These observations are a strong indicator that the solar shading use is as well habitual.

6.3 Conclusion

Both in clothing behaviour and solar shading use some indications are present regarding habitual behaviour in residential settings. Occupants tend to wear a relatively stable set of clothes despite fluctuations in the outdoor environmental conditions. Additionally, the use of solar shades seems to be for most occupants a habit with either leaving the shades always open, always closed or closing them at night.

The limited studies on solar shading and clothing behaviour, provide with some indications that habitual behaviour might not be constricted to window use alone in residential settings. However, the samples are too small to make general conclusions.

Part II

Occupant behaviour model including habits

The previous chapters have shown that habits are prevalent in residential occupant behaviour, therefore it is important to consider them in the development of occupant behaviour models. Which leads us to the second objective of this study: the development of an occupant behaviour model which takes the findings on building control habits into account.

Shifting the focus to habits will lead to models that can be easily implemented in building energy simulations, since the behaviour is not dependent on any other simulated variables such as indoor temperature or CO_2-concentration. Additionally, this will lead to realistic actions that fit in the day-to-day life of the occupants and it will better capture the diversity between households.

In order to develop such a model some background is necessary on the different types of occupant behaviour models and their applications. This will be discussed in Chapter 7. Following a similar approach as in part I, the focus is first on the development and validation of a window use model that includes habits (Chapter 8) and later on a more comprehensive occupant behaviour model (Chapter 9).

7

Occupant behaviour models

Over the years many OB-models have been developed ranging from simple static schedules, to probabilistic models and advanced artificial intelligence models. Different types of models can be used for different applications, so there is not one 'good' model.

In this chapter, different approaches to occupant behaviour modelling are discussed with the corresponding application possibilities [71, 155, 180–183].

7.1 Type of models

7.1.1 Average value models and fixed schedules

In average value models, the behavioural variables have a fixed value based on the average of a data set. Heap [184] for example defined an average ventilation rate, an average temperature and average internal heat gains based on a large set of data collected during different studies in the UK in the seventies. Schedules define a fixed value for each behaviour in time for each occupant. Schedules are often applied in occupancy modelling for offices in which a fixed working regime is assumed.

These type of models assume that all occupants behave like one specific occupant. However it is uncertain which occupant will be seen as this average user. It can be a synthetic user with the average values for the different behaviours, however, the application of averages for different types of behaviour may not necessary lead to a viable representation of real behaviour. Consequently, the use of average value models can lead to optimization of buildings for a standardised scenario rather than for actual operation [180]. Along with the neglect of the diversity in OB, the variability in OB is neglected as well since there is no variation in time and space of the OB. These models predict exactly the same behaviour each day. Simple schedules are however often applied in practice [180, 181](see Section 7.2) as they are very easy to implement in energy simulation tools.

7.1.2 Rule-based models

To include some variability in the OB, rule-based models can be applied. These models define the OB by numerical relationships between the behavioural variable and other variables. Most often regression analysis is used for the creation of these models. Conan [124,136] for example made a simple regression model including the number of occupants present and the number of hours the heating is on to directly derive the energy use of a household. Brundrett [123] made a model to determine the number of rooms with open windows based on different climatological factors, namely wind speed, outdoor temperature and solar radiation.

Rule-based models indicate some variability due to the dependence on predictor variables. Nevertheless, the models keep representing an average building user with fully predictable and repeatable behaviour. To assume that every occupant behaves in the same way when identical stimuli are present, neglects the large inter-occupant diversity due to the complexities of human behaviour [71]. What's positive about these models is that the data gathering can be simple and that no advanced computational techniques are needed to incorporate the models in energy simulation tools.

7.1.3 Stochastic models

Because building occupants naturally behave in a random way, stochastic modelling is an effective way to model and estimate occupant behaviour.

Stochastic models make use of probability distributions of the potential outcomes by allowing for random variation in one or more inputs. Every run of the model will therefore give a different outcome. Different types of stochastic models are applied to OB [108, 142, 155, 181–183]:

- **Bernoulli processes**: These models determine the probability of the state of the building control (e.g. the window being open, the thermostat turned off, the blinds closed) at each time step independently of the previous time step [108, 141, 142]. These models are simple, can be easily applied and are computationally efficient [155, 182]. Nevertheless, they fail to capture individual behaviour and comfort and do not predict the timing of individual actions [108, 155, 182].

- **Discrete-time Markov chains**: These models determine the probability of an action based on the state of the previous time-step [108, 126, 142]. Haldi and Robinson [108], for example, defined the probability of a transition from closed to open windows, and vice-versa for each time-step based on a number of explanatory variables. Discrete-time Markov chains are able to predict individual actions. However, these models require to simulate with a fixed time-step [181] and they ignore the specific OB caused by events, like arrivals or departures [108].

- **Discrete-event Markov chains**: These models determine the probability of an action occurring when the previous event is finished [108, 138, 185]. Most models applied in building simulations are based on occupancy events such as arrival and departure. The advantage of this approach is that the model is only triggered when significant changes occur to the inputs, so not with every time-step, which makes it less computational intense than discrete-time models [155, 182].

7.1.4 Agent-based models

An agent-based model (ABM) is explained by Bonabeau [186] as: *"A system is modelled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules"*. An agent represents a building occupant with personal attributes (behaviour rules, memory, resources, decision-making), interacting with other agents or with building systems [155, 181, 182]. Most Markovian models, as discussed above, can be characterised as rudimentary agent-based models.

ABM's allow for the modelling of adaptive behaviour and occupant interactions and for the inclusion of inter-occupant diversity. These models are often based on a larger set of explanatory variables, often including multi-disciplinary drivers. The disadvantage of ABM's is that they are computational intensive, especially when modelling larger populations. Additionally, they fail to represent cooperation and collaboration.

7.1.5 Event and Narrative-based models

In contrast to agent-based models, event-based models (EBM) are based on representation and simulation of the events, rather than on autonomous behaviour of individual agents. An EBM is a top-down model, where it is not necessary to model all the properties of the individual actors only those that are relevant for the event to take place. An event is determined by three key factors: the actors, spaces and activities. Or as Simeone et al. [187] define it for the built environment: *"Events are representations of the phenomenon of buildings-in-use, in terms of discrete activities, involving a number of users, and performed in specific spaces and time."* Event-based Markov chain and survival analysis models can be categorised as EBM as well. EBM's are frequently used in video game modelling, but have recently found their way in occupant behaviour modelling as well [133, 187, 188].

The advantage of EBM is the simplicity in creating the model, it is not necessary to know all detailed drivers of the occupant, only the ones relevant for the occurrence of the event. This results in faster computational time in comparison to ABM's. On the other hand this requires a good understanding of the events and the reactions to the events for a valid simulation.

By combining events into larger compositions, occupant behaviour narratives can be created [189]. Narratives provide a logical plot structure that unfolds during the simulation process according to event preconditions, as well as to stochastic processes [189]. In this way EBM's can be extended to include interaction between events as well [190].

7.2 Application in practice

As discussed above, different models can be used in different applications. Since the goal is to develop a model that could preferably be applied in practice, it is necessary to investigate which models are currently applied, what are their advantages and disadvantages and what are the requirements that need to be met for the OB-model to be applied in practice. Both the OB-models as applied in codes and standards are discussed, as the OB-models used in the design practice.

7.2.1 Occupant behaviour in codes and standards

An international study on occupant-related aspects in building codes and standards, involving codes from 23 regions, revealed that there is minimal explicit mention of occupants in building energy codes [191]. In building energy codes occupants are treated in very simplistic ways. Five predominant methods for including OB in building codes were observed.

Assume the building control is not used at all

In some building energy codes, it is assumed that specific building controls are not used. This is most common for operable windows, shades and blinds.

A likely reason for this is that the behaviour is too uncertain and variable, or because the building energy code aims at a conservative assumption of the energy performance (e.g. assuming that solar shades are not used will lead to the highest risk for overheating).

In the Flemish standard [119] this method is applied for operable windows in the heating energy calculation. It is assumed that in all (new) dwellings a mechanical ventilation system is installed that provides a sufficient hygienic ventilation rate, consequently, the windows are assumed to be always closed. Window use is, however, considered when assessing the risk of overheating.

Assume the building control is partially used

Another commonly used approach is to define a fixed factor denoting the time that the building control is used. In the Flemish standard [119], this method is applied for the blind use. A correction is applied to the U-values of the windows, this based on a fixed period when the blinds are assumed to be in use, which is 8h/day in the Belgian standard.

Provide credit depending on the level of automation of systems

Numerous codes [119, 192–196] give credit for automation. In the Flemish standard [197], credit is given in offices when a lighting control system is present. This credit varies depending on the type of control (e.g. 0.4 for automatic control). Other countries [192, 194] allow for a reduction in lighting power density when motion detectors are present.

Schedules, densities and setpoints

The most common approach to include occupants is by schedules, densities and setpoints. In the Flemish standard [119], default setpoints are used for heating (18°C) and cooling (23°C). Additionally, the energy use for domestic hot water in residential buildings is based on a fixed flow rate, which is calculated based on the volume of the building and the number of tap points (considering only bath, shower and kitchen tap points). In offices, fixed occupancy, lighting and equipment power density values are applied. Schedules are not used in Belgium (monthly method), however, are commonly used in other codes.

The international review showed considerable variations across the codes for offices with regard to the occupancy, lighting and equipment power density values (Figure 7.1), as well as for heating and cooling set-points.

Rule-based operation

Few codes apply rule-based models, in which the OB depends on environmental variables. The French code [198] is exemplary for this method. In the French code, the window opening is assumed to be affected by noise. France also relates the use of shades to the incident light, the type of shade, the indoor temperature and in some cases to the wind speed. Additionally, lighting use is dependent on the daylight levels.

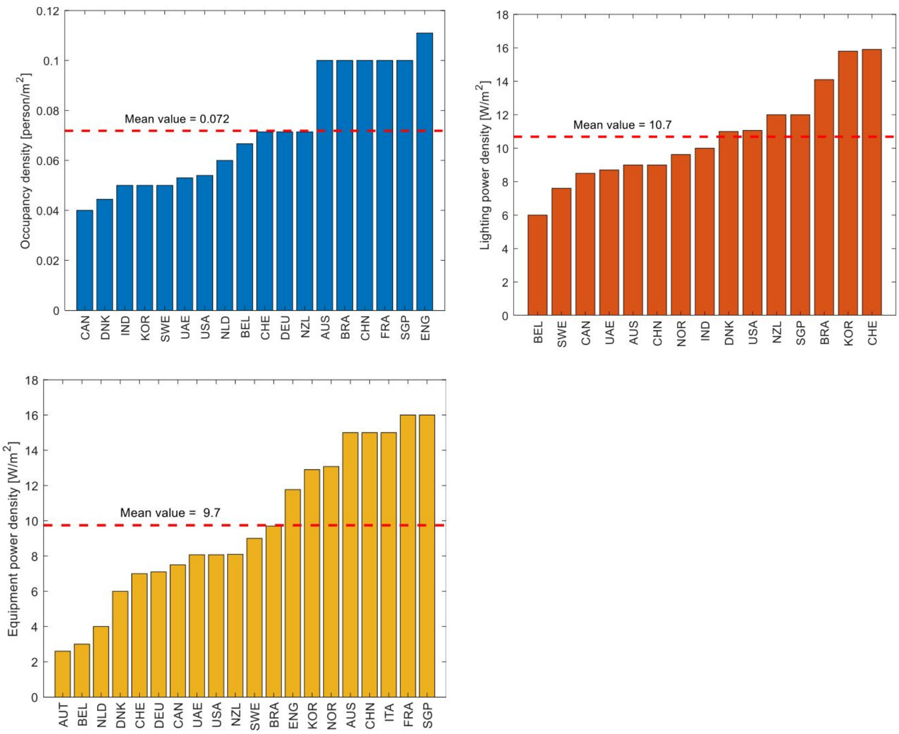


Figure 7.1: The values of occupancy, lighting power and equipment power density for offices given in national building energy codes. [191]

7.2.2 Occupant behaviour models in practice

During the design phase most practitioners focus solely on complying with the codes and standards, and do not include more advanced OB models [69, 199]. A major reason for this is that the more advanced models are difficult to implement in ready available tools and that these models require more advanced knowledge. Therefore, it is necessary to provide guidance to designers and building managers on how to apply occupant behaviour models in practice [69, 181].

7.2.3 Conclusion

While recent literature is focused on advanced occupant modelling, this scientific knowledge is rarely translated in building energy codes and in practice. One of the main reasons for this is that the more advanced models are generally not easy to implement in building performance simulations and require advanced knowledge [65]. Another reason is that the building energy codes should provide consistency [200]. Stochastic occupant models yield a different result every time a simulation is run, which causes issues when relying on single simulations. Nevertheless, codes and standards should predict realistic energy use to be able to result in optimal energy use predictions.

Therefore, a possible option is to provide a range of energy use for specific buildings, to allow for the bigger picture and to optimise the building for a variety of users. Including occupant behaviour in the codes and standards will yield improvements in practice as well, since most practitioners focus on the codes and standards during the different phases of the design process.

Based on this literature review, we can define a list of requirements for OB-models to allow for application in the building practice.

- The OB-models should be easy to implement in standard BES-software.
- The OB-model should not require advanced knowledge of the practitioner.
- The computational time should be limited.

In Section 11.6, the possible options of the inclusion in practice of the in the following chapters developed OB-model are discussed.

7.3 Choice of model

As defined before, the goal of this study is to develop a realistic OB model which includes possible habits and thus relates the OB to the daily life of the occupants. This means that the OB should be related to key moments in the day (events/tasks), rather than to specific times. Therefore, the use of an event-based model is preferred over an agent-based model, as we are not interested in what the occupant is doing exactly at each moment but rather which event takes place that is related to a habit. E.g. habitual behaviour might be opening windows when cooking, therefore we need to know when someone is cooking but we are not interested in exactly which member of the household is cooking. This has as well the advantage that it is less computational intensive than an agent-based model. Since the timing is of specific importance, the model should be developed with a fine time granularity (minute/10 minutes/hour).

An interesting model for this application is the StROBe-model (Stochastic Residential Occupant Behaviour Model) [201]. The StROBe-model starts by generating occupancy profiles for each household member. Based on these occupancy profiles and the activity probability functions, other OB are determined (e.g. appliance use, DHW-use). The approach is schematically represented in Figure 7.2. The model, which was developed in Python, generates output-files per minute for the electricity use by appliances and lighting, domestic hot water flow, internal heat gains and temperature set-points. These outputs can be used as input for building energy simulations in Modelica, by using the StROBe-component of the IDEAS-library [202]. The model was originally created for district-simulations and therefore as well validated based on district data. For more detailed information regarding the StROBe-model, we refer to the article by Baetens et al. [201].

This model was chosen as the starting point because it is an agent-based model that links certain behavioural actions to specific activities or moments in an occupant's day. Which lends it perfectly for incorporation of habits

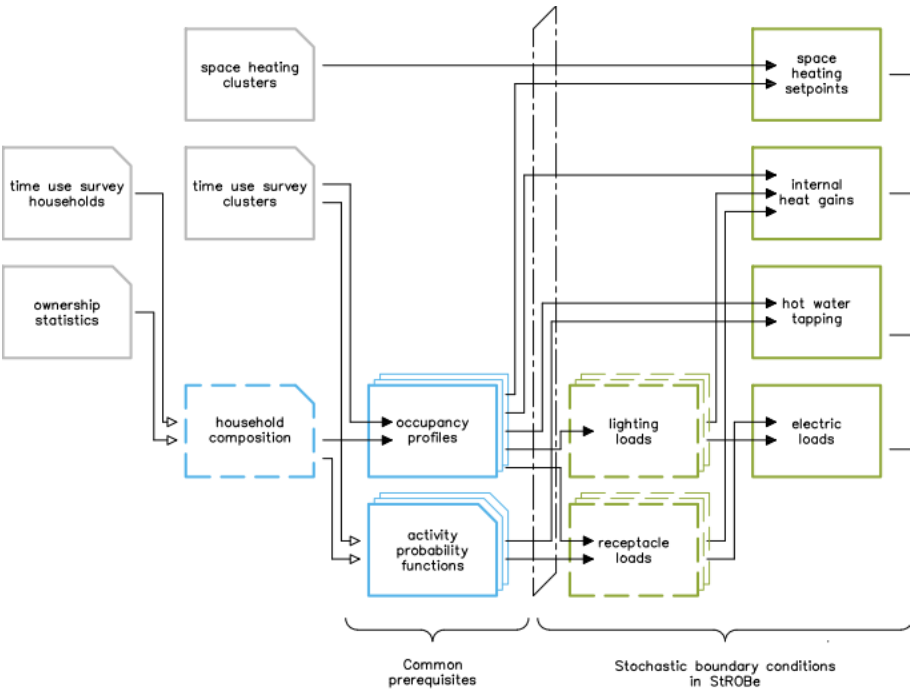


Figure 7.2: General overview of the implemented algorithms in StROBe

and is easily adaptable to an event-based model. Furthermore, the model is freely available on GitHub (github.com/open-ideas/StROBe). However, not all types of occupant behaviour are included. The use of windows or shades are neglected. Furthermore, the model only predicts the presence in the building as a whole, without differentiation between the different rooms. This has an important impact on the dispersion of the internal heat gains and the energy use by lighting.

Additionally, it was observed that the predicted electricity use is relatively high when compared to measured data of the case-study. This can be attributed to the individualistic approach towards appliance use modelling. The approach entails that for each individual occupant it is checked which appliances are used and those loads are simply added. It allows that one occupant can use different appliances at the same time, however, some activities can not be done simultaneously (e.g. cooking and vacuuming). There are no rules included in the StROBe-model that define these limitations. Furthermore, the StROBe-model did not correct for the shared use of appliances. Consequently, the load for shared appliances such as a television or fridge is included for each person that is using it. These issues result in an overestimation of the electricity use in the StROBe-model.

The domestic hot water use is as well overestimated, which can be attributed to the assigned properties (e.g. flow rate, tapping duration) of the tap points which are unrealistically high.

The StROBe-model is an interesting starting point for the development of a habit-based occupant behaviour model. Even though the original model is agent-based, the underlying modelling principles can be used for the development of an event-based model. In Chapter 9 the complete model development is set-out, and the corrections made to overcome the issues as discussed above are explained. Nevertheless, currently there is no model available to predict the habitual window use, therefore, first a window use habit model is developed in Chapter 8.

8

Development of a window use habit model

In Chapter 4 some currently applied approaches to window use modelling were evaluated. The main problems with the current models are that they are not able to grasp the large inter-occupant diversity, that they do not connect the window use to the day-to-day life of the occupants and that the included explanatory variables may not be the primary drivers for the window use. The development of a window use model that includes the habits as detected in Section 5.2, may resolve these issues.

In this chapter, the development and validation of a window use model based on habits is discussed. In first instance it is necessary to investigate whether it is possible to predict the presence of specific window use habits. The relationship between different variables, such as household characteristics and building properties, and the presence of certain habits is investigated. Based on these findings a window use model is created. The development of the model is described in detail as well as the validation procedure.

8.1 Prediction of habits

In this first section, it is questioned whether it is possible to predict the presence of specific window use habits. Habits are very personal and develop over time so it is uncertain if these can be predicted. As defined by Verplanken [106], habits used to be deliberative actions but by repeating the action over time it resulted in habitual behaviour. The underlying reasons for the development of the habit in the first place can be very diverse ranging from upbringing, ecological beliefs, to the presence of pets and building properties, but may allow for the prediction of some window use habits. As discussed in Section 5.1.4, no studies regarding the sociological narratives behind the habits were conducted, however, a limited number of building and household characteristics were gathered from the online survey that might explain some of the habits. Therefore, the relationship between a limited number of variables gathered from the online survey (section 5.1.3) and the presence of specific habits is evaluated.

8.1.1 Building properties

Ventilation system

As discussed in section 5.2.1, the presence of a balanced ventilation system with heat recovery leads to more always closed and less always open habits in the bedroom. Similar observations were done for the other rooms (e.g. living room in Figure 8.1). While the difference between no ventilation system and a balanced ventilation system is significant in both winter ($\chi^2(3)$=18.194, p=.000) and summer ($\chi^2(5)$=20.228, p=.001), the difference between no ventilation system and exhaust ventilation is not (winter:$\chi^2(3)$=1.973, p=.578; summer:$\chi^2(5)$=6.205, p=.287).

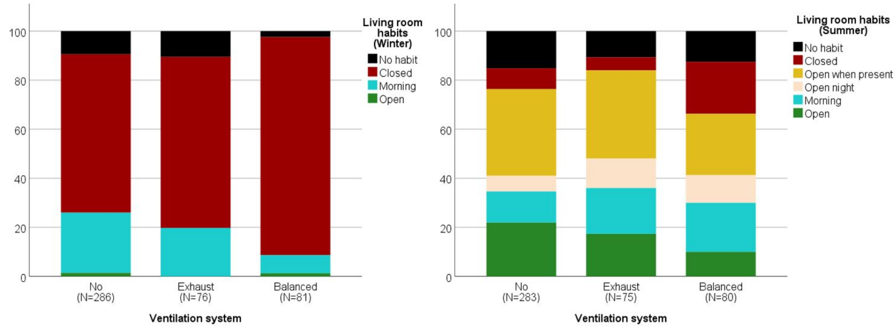


Figure 8.1: Habits in the living room in wintertime (left) and summertime (right) according to the type of ventilation system.

Type of windows

The type of windows are correlated to specific habits as well. In this study turn and tilt windows are most frequently present in the different rooms, with in the living areas often slide windows as well (Figure 8.2). In dwellings with slide windows the habit of opening windows when present in the room is more common in summer (39.2%) compared to dwellings without slide windows (27.4%) in which the windows are more often left open for a longer time. Sliding windows will less likely be left open when nobody is present in the room, which may be attributed to security issues. Overall there is a significant difference in habit-presence between dwellings with and without slide windows in the living room (summer: $\chi^2(5)=22.210$, p=.000). Slightly less 'always closed' habits in winter were registered in the kitchen when there were turn and tilt windows present ($\chi^2(1)=10.310$, p=.001). For the other window types there were no significant differences in room-habits.

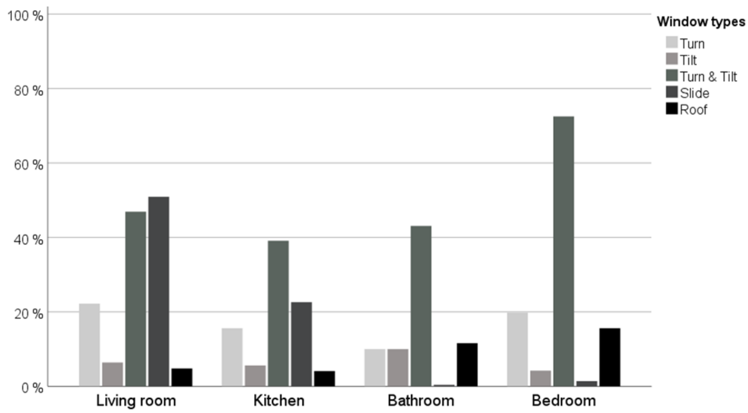


Figure 8.2: Histogram of the window types present in the different rooms (N=499). The percentage indicates in how much of the dwellings at least one window of a specific type is present.

Size, type and age of the dwelling

No distinction in habits was observed for different dwelling types (apartments, terraced, semi-detached and detached). Only in the kitchen a significant difference was observed between apartments and houses (winter: $\chi^2(4)=14.870$, p=.005; summer:$\chi^2(5)=13.219$, p=.021). It was observed that occupants of apartments have more often the habit of opening windows during or after cooking (Figure 8.3), which may be related to the fact that apartments are often smaller and therefore cooking odours may be more intrusive than in larger spaces. Significant differences in window use habits were observed between dwellings from different era's of built in the bedroom, but not in the living room in summertime (living room - winter: $\chi^2(8)=16.209$, p=.039; summer:$\chi^2(20)=13.506$, p=.855, bedroom - winter: $\chi^2(24)=55.864$, p=.000;

summer:$\chi^2(24)=52.659$, p=.001). In general, households that live in older dwellings (< 1975) have more often a morning habit or no habit at all.

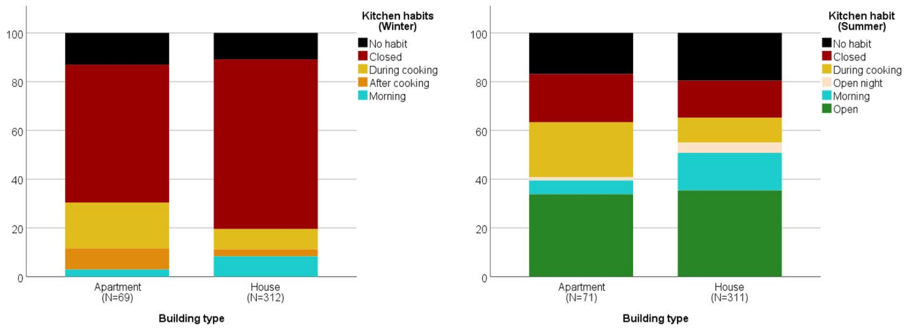


Figure 8.3: Habits in the kitchen in wintertime (left) and summertime (right) according to the type of building.

8.1.2 Household characteristics

Age

The age of the occupants is as well correlated with the presence of certain habits. Figure 8.4 shows an example for the bedroom, but similar observations were done in the other rooms as well. The households with the youngest head of the household (18-25) open the windows the most, however, that sub-sample is too small to draw conclusions. For the age between 25 and 75 a gentle rise was observed in the presence of always open and morning openings. The age-category above 75 years is again too small to draw conclusions. The difference in habits between the different age-categories (when neglecting the oldest and youngest category) is however not significant (winter:$\chi^2(12)=16.257$, p=.180, summer: $\chi^2(12)=14.811$, p=.252).

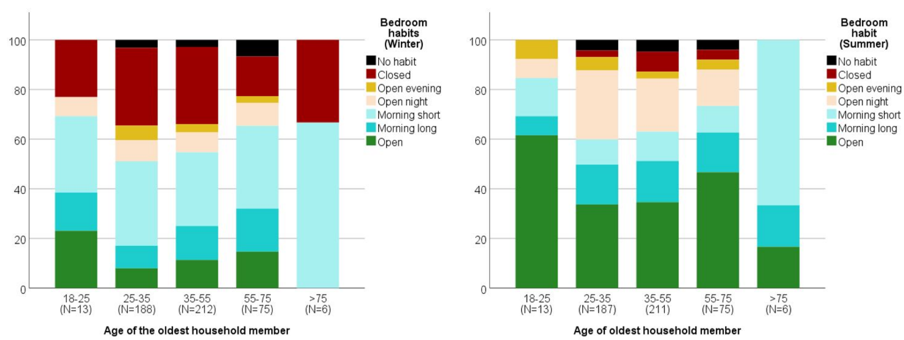


Figure 8.4: Habits in the bedroom in wintertime (left) and summertime (right) according to the age of the oldest household-member.

Type and size of the family

When there are two or more children present in the household the bedroom habit is more often ‘always closed’ and less often ‘always open’ compared to households with less children (Figure 8.5). The difference is significant in winter ($\chi^2(12)=25.907$, $p=.011$), but not in summer ($\chi^2(12)=10.782$, $p=.548$). So larger families tend to keep bedroom windows more often closed, which is possibly linked to preventing draught for small children or security reasons. However, since the size of the family is correlated with the age, it is uncertain which one is effectively correlated to the presence of habits. From Figure 8.6 it seems that the observed correlation between age and window use habits is still present in the different groups based on the number of children. The differences in window use habits between the age categories are only significant for the group without children ($\chi^2(12)=22.132$, $p=.036$), with more closed windows for occupants under 35 years. However, the samples are too small to draw conclusions.

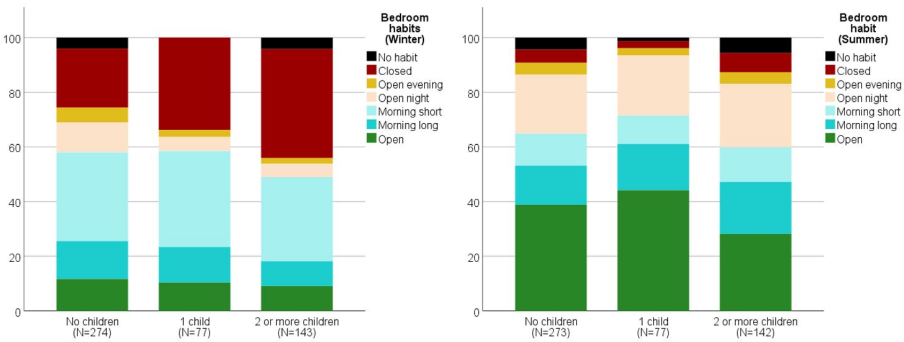


Figure 8.5: Habits in the bedroom in wintertime (left) and summertime (right) according to number of children.

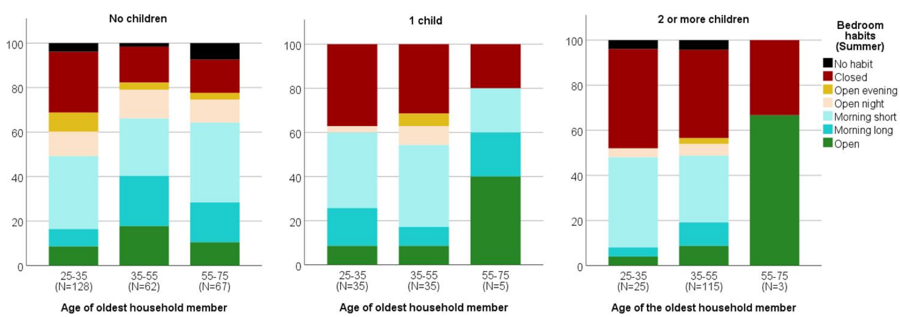


Figure 8.6: Habits in the bedroom in summertime according to number of children and age of the oldest household member.

Education level and employment

No significant differences in window use habits were observed for different education levels (e.g. bedroom - winter: $\chi^2(18)=10.857$, p=.900; summer:$\chi^2(18)=16.170$, p=.581) or employment types (e.g. bedroom - winter: $\chi^2(6)=8.747$, p=.188; summer:$\chi^2(6)=11.879$, p=.065).

8.1.3 Prediction of window use habits based on building and household characteristics

Multinomial logistic regression is applied to predict the window use habits based on building and household characteristics, since the habits are nominal variables with more than two categories. The multinomial regression model predicts the probabilities of the different possible outcomes -having a specific habit- taking one category as reference. The equations are as follows:

$$ln(\frac{P(Y=i)}{P(Y=1)}) = a_1 + b_{1i} * x_1 + b_{2i} * x_2 + ... + b_{ni} * x_n = Z_i \tag{8.1}$$

P(Y=i) is the probability for a household Y to have habit i, with i ranging from 1 to M with M the total number of categories, with i=1 the reference category, and with x_1,x_2,..., x_n the explanatory variables.

In this way the probability of category i is:

$$P(Y=i) = \frac{e^{Z_i}}{1+\sum_{h=2}^{M} e^{Z_h}} \tag{8.2}$$

And the probability of the reference category is:

$$P(Y=1) = \frac{1}{1+\sum_{h=2}^{M} e^{Z_h}} \tag{8.3}$$

In the previous section it was observed that some household characteristics were correlated, therefore it would be beneficial to include interaction terms in the model as well. However, including interaction terms in the analysis was not possible since the sample sizes were too small. The results of the analysis revealed that a few building and household characteristics can be included to predict the window use habits in the different rooms and when going to bed or leaving the dwelling, however, their predictive power is rather small with Nagelkerke R^2-values between .029 and .157 (Table 8.1). The analysis was conducted for both winter and summer.

8.1.4 Habits in other rooms

In a study conducted by Delghust [61] it was revealed that the heating behaviour between rooms was linked. Similar heating behaviour was often reported in different rooms, or there was a clear connection between the behaviour in the rooms (e.g high heating set-points in the living room

Table 8.1: Goodness-of-fit statistics for the prediction of window use habits based on building and household characteristics. The 'x' indicates variables that were found significant to include for the prediction of the window use habits. All results are significant with p<.01.

	Living room		Kitchen		Bathroom		Bedroom		Leaving		Going-to-bed	
	W	S	W	S	W	S	W	S	W	S	W	S
Vent. syst.	x	x		x	x	x	x	x	x	x		x
Building	x		x	x	x							
Windows	x	x	x			x						x
# children							x					
Employment								x				
χ^2	25,541	59,097	34,082	32,320	39,295	53,252	78,997	75,824	12,111	35,924	13,840	47,261
R^2	.072	.131	.097	.087	.125	.155	.157	.152	.029	.082	.032	.106

often meant high set-points in the bedroom as well, but not necessarily the same). Therefore, it was hypothesised that the window use across rooms might be linked as well. For example, a household that always leaves the bedroom windows open might more likely leave the windows in the living room open for a long time, in contrast to a household that never opens the bedroom window. To test this hypothesis the relationship between the habits in the different rooms is assessed as well.

The other room-habits were much better predictors for the presence of a certain habit than the building and household characteristics, as can be shown by the results of the multinomial regression analysis in Table 8.2. The Nagelkerke R^2-values are significant with values ranging between .153 and .548. This means that habits in different rooms are linked and that these other room-habits are better predictors than the building and household characteristics. It should be noted that this does not necessarily mean that the same habits are present in each room. It only indicates that when a certain habit is present in one room, it is a good predictor for the habit in another room.

Table 8.2: Goodness-of-fit statistics for the prediction of window use habits based on habits in other rooms. All results are significant with p<.01.

	Living room		Kitchen		Bathroom		Bedroom		Leaving		Going-to-bed	
	W	S	W	S	W	S	W	S	W	S	W	S
Living	-	-	x	x	x		x			x		
Kitchen	x	x	-	-								
Bathroom					-	-	x	x				
Bedroom	x	x			x	x	-	-	x	x	x	x
χ^2	136,916	261,463	101,710	178,946	95,051	71,274	103,550	80,506	89,383	63,962	219,291	144,178
$R_N{}^2$	.414	.548	.287	.413	.306	.197	.283	.210	.193	.153	.405	.268

Additionally, it can be hypothesised that the habits are linked across seasons as well. E.g. a household that rarely opens windows in wintertime, might leave the windows often closed in summertime as well. To check this assumption a multinomial logistic regression analysis was conducted with as predictor variable the habit in the other season (winter/summer). The results are given in Table 8.3. The habits in the other season can predict the habits in the bedroom and bathroom equally well as the habits in the other rooms. While the living room-habits were predicted more accurately with the habits of the other rooms than with the living room habit in the other season.

Habits are very personal and the formation of these habits is influenced by

Table 8.3: Goodness-of-fit statistics for the prediction of window use habits based on the habits in the other season. All results are significant with p<.01.

	Living room		Kitchen		Bathroom		Bedroom		Leaving		Going-to-bed	
	W	S	W	S	W	S	W	S	W	S	W	S
χ^2	45,986	29,424	32,774	54,230	168,886	171,698	129,594	124,952	212,946	212.946	107.693	136.377
$R_N{}^2$	.123	.066	.095	.140	.457	.418	.241	.233	.408	.408	.221	.255

a lot of factors such as attitudes, upbringing, education, etc. Therefore, it is very difficult to predict which habits will be present based on a limited set of building and household characteristics. However, significant relationships were found between the habits in the different rooms and between the habits in the different seasons. This creates an opportunity to predict habits based on this habit coherence across rooms and season.

8.1.5 Habit-coherence across rooms and seasons

Based on the observations in the previous section it became clear that habits can not be evaluated at room-level, since predicting individual habits for individual rooms will lead to unrealistic window use across rooms (e.g. always open in the living room, while always closed in all other rooms) which might have an important impact on the energy use and indoor climate (see Chapter 12). Therefore, the window use habits should be evaluated at household-level, so the coherence between rooms and seasons could be included.

For that reason the habits across the four rooms (living room, kitchen, bathroom, bedroom) are assessed jointly by creating a four-digit number based on the habit in each room, this for both winter and summer. The number is composed as living-kitchen-bathroom-bedroom with for each room-habit a number assigned according to Table 8.4. For example, a household that always closes all windows will be denoted as 1111, while a household that opens the windows in the bedroom shortly will be defined as 1112.

Table 8.4: Number assignment for room-habits.

	Habit
0	no habit
1	always closed
2	opened shortly (morning, presence, cooking, shower, evening)
3	always open
4	open at night
x	no window in the room

Theoretically 625 different habit combinations are possible, however, in wintertime only 57 combinations were present in this study both due to the relatively small sample size (N=499<625) and due to the fact that some combinations occur multiple times in the study. In summertime 135 different combinations were observed. An overview of the most common household habits (N≥5) in winter and summer as detected in the online survey are given in Table 8.5. The most common combinations in winter are 'keeping all windows closed', 'keeping all windows closed except for the bedroom window', and 'opening all windows shortly'. The habits are more diverse in summertime, but the most common habits are 'keeping all windows always open', 'opening all windows shortly' and 'keeping all windows always open except for the living room window'.

Table 8.5: Most common household habits in winter and summer.

Winter	
All windows closed	23.05%
All windows closed, bedroom short	13.63%
All windows opened shortly	9.42%
Dayzone closed, Nightzone short	4.41%
All windows closed, bedroom open	4.01%
All windows closed, bedroom open night	3.61%
All windows closed, bathroom short	3.61%
All windows shortly, living room closed	3.41%
All windows shortly, kitchen closed	3.41%
Dayzone closed, bedr open, bath short	2.40%
All windows shortly, kitchen no habit	2.20%
All windows shortly, living room no habit	1.60%
No habit in all rooms	1.40%
All windows closed, kitchen short	1.40%
All windows shortly, bedroom open night	1.40%
Liv/bed short, kit/bath closed	1.40%
Dayzone closed, bedr open night, bath short	1.40%
All windows closed, kitchen no habit	1.20%
All windows closed, bathroom no habit	1.00%
All windows no habit, bedroom short	1.00%
Living closed, kit/bath short, bedroom open	1.00%
Other	14.04%

Summer	
All windows always open	8.02%
All windows opened shortly	7.82%
All windows open, living short	5.41%
All windows shortly, bedroom open night	4.01%
All windows closed	2.61%
All windows shortly, bedroom open	2.00%
Liv/bath short, kit no habit, bedr open night	1.40%
Dayzone short, nightzone open	1.40%
All windows open at night	1.40%
No habit in all rooms	1.20%
All windows open, bedroom short	1.20%
Dayzone no habit, nightzone short	1.00%
All windows shortly, kitchen open	1.00%
Liv short, kit open, bedr open night, bath closed	1.00%
Liv short, kit/bath open, bedr open night	1.00%
Other	59.53%

8.2 Model development

8.2.1 Approach

Based on the results from the previous section, a model is developed to generate window use profiles by means of predicted windows use habits. As discussed previously some generalisation could be made of habits across rooms. While in winter clearly some building-level window use habits could be distinguished, this was less clear in the summertime with many different combinations of room-habits. Additionally, a seasonal link between the different room-habits was found in Section 8.1.4 as well. Therefore, the window use habits are predicted by first determining the household winter window use habit and subsequently determining through the seasonality link the habits in summer as well.

For the creation of the habit-based window use model, the data-set is randomly split in a training-set with 399 households for the development of the model (this section) and a data-set with 100 households for the validation (section 8.3). The random division of the data-set resulted in a validation-set and training-set with similar households and dwellings, and no significant difference in household habits was observed between the two data-sets ($\chi^2(4)$=2.684, p=.612). Only in the training-set slightly more households have a mechanical ventilation system (35,5%) compared to the validation-set (27,4%).

8.2.2 Household-habit

The model starts by assigning a winter household-habit to each household (Figure 8.7 – (1)). The different household winter window habits as detected in Section 8.1.5 could be generalised in five different categories:

- **All windows closed** (24.6%)
- **All windows shortly opened** (20.5%)
- **Bedroom window opened more than the windows in other rooms** (25.6%) (e.g. all windows closed except for bedroom window, or all windows opened shortly except for bedroom window which is always open)
- **Clear distinction between habits in the day-zone and night-zone** (20.3%) (e.g. windows in dayzone always closed while in nightzone shortly opened or windows in dayzone shortly opened while in nightzone always closed)
- **Clear distinction between habits in the most occupied zones (living room, bedrooms) and in the less occupied zones (kitchen, bathroom)** (9.0%) (e.g. window in living room and bedroom shortly opened and in kitchen and bathroom always closed)

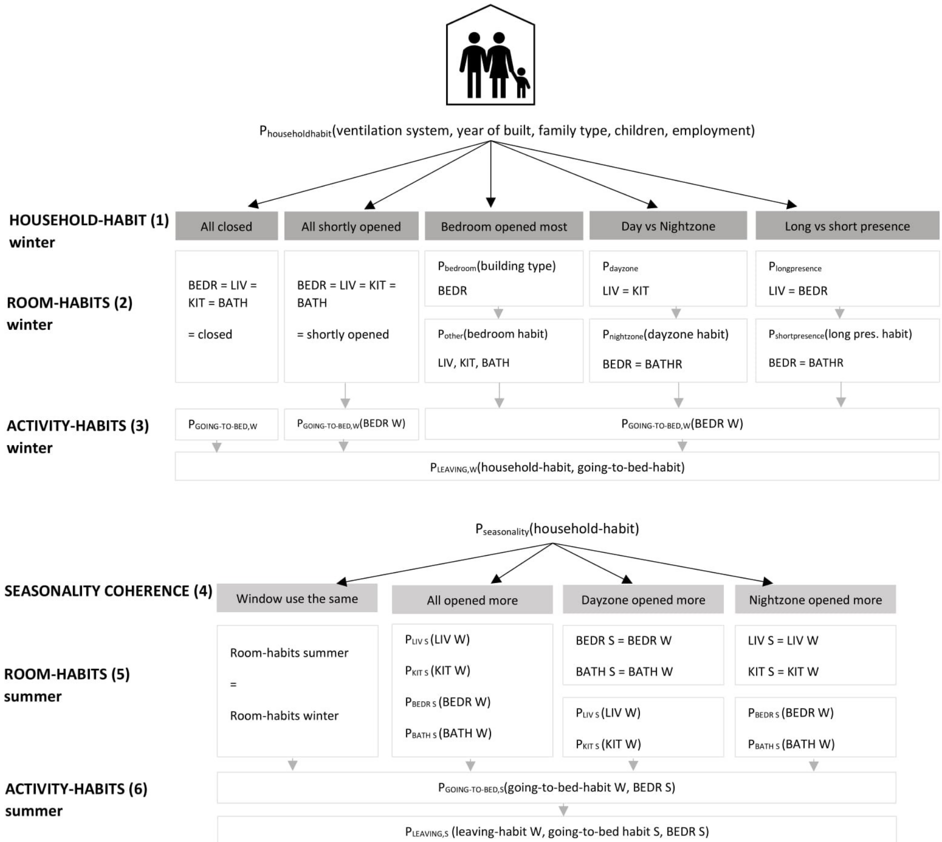


Figure 8.7: Schematic overview of the habit-based window use model (W=winter, S=summer).

The room-habits in winter for each participant of the survey with the corresponding household-habit are given in the Appendix 14.4.

The assignment of these household-habits is based on some household and building characteristics, namely the type of ventilation system, the year of built, the type of family (single, couple, ...), the presence of children and the employment types of the household members. The multinomial regression estimates for the predictions of the household habits are given in Table 8.6 and the goodness of fit indicators in Table 8.7. The explanatory variables in Table 8.6 are all defined as binary variables (e.g. 'family type couple' is 1 when the household is a couple without children and is 0 otherwise). It should be noted that the increase in predictive power by adding the household and building characteristics is significant but rather small. This denotes again that habits are difficult to predict based on a limited set of household and building characteristics.

Table 8.6: Regression parameters for the multinomial logistic regression model of the household-habits.

Estimates	Household-habit							
	All windows (shortly) opened		Day vs nightzone		Bedroom window opened most		Short vs long occupied rooms	
	B	Std. error	B	Std. error	B	Std. error	B	Std. error
Intercept	-1.855	0.943	-1.723	0.888	0.527	0.695	-2.730	1.146
No vent. system	3.009	0.705	2.191	0.586	1.355	0.469	0.462	0.635
Exhaust ventilation	2.278	0.705	0.958	0.585	0.229	0.498	0.666	0.615
Year of built <1950	0.075	0.487	0.786	0.579	-0.576	0.498	0.207	0.715
Year built 1951-1975	-0.081	0.527	1.148	0.588	-0.609	0.528	0.833	0.697
Year built 1976-2005	0.037	0.606	1.378	0.656	0.916	0.546	0.223	0.907
Year built 2006-2015	0.149	0.599	1.281	0.667	-0.208	0.531	0.020	0.797
Year built >2015	-0.733	0.923	1.087	0.828	-0.043	0.655	0.971	0.815
Family type single	-1.108	0.887	-0.495	0.830	-1.848	0.864	1.422	1.157
Family type couple	-0.440	0.753	-0.610	0.728	-1.153	0.671	0.937	1.052
Pres. of student(s)	2.062	1.127	0.717	1.297	1.409	1.127	2.828	1.212
Pres. of unemployed	1.370	1.121	1.253	1.134	0.598	1.149	3.017	1.171
Pres. of child(ren)	-1.040	0.731	-1.486	0.719	-1.478	0.647	0.252	1.030

The reference category is 'all windows closed'.

Table 8.7: Goodness of fit estimators for the multinomial logistic regression model of the household-habits.

	AIC	χ^2	Nagelkerke R^2
Intercept only	589.158		
Model	539.751	145.407	0.327

Based on the household-habits, the winter habits in the different rooms are assigned (Figure 8.7 – (2)). For the 'always closed' household-habit this is straightforward, since all windows are always closed in winter. If the household-habit is 'bedroom opened most', the bedroom-habit is first determined, afterwards the habits in the other rooms are determined based on the bedroom-habit. Similarly, for the 'dayzone vs nightzone' and 'short vs long presence' for which respectively first the dayzone-habit and the habits in the long presence rooms are predicted and afterwards the habits in the other rooms. Based on the winter room-habits, the winter leaving- and going-to-bed-habits are determined (Figure 8.7 - (3)).

8.2.3 Seasonality

In the next step, the seasonality coherence is determined (Figure 8.7 - (4)). As discussed in Section 8.1.4 the room-habits are correlated with the room-habits in the other season. The four-digit household-habits as defined in section 8.1.5 are compared for the different seasons. The household-habits are for some households extended throughout the year, while others reveal other window opening behaviours in summer.

Four categories could be defined:

- Windows use is the same as in winter (18.0%)
- All windows opened more (46.6%)
- Windows in the dayzone opened more (25.3%)
- Windows in the nightzone opened more (10.0%)

The room-habits in summer for each participant of the survey with the corresponding seasonality coherence are as well given in the Appendix 14.4.

The assignment of these categories is based on the household-habit. The parameter estimates and goodness of fit estimators can be found in Table 8.8 and Table 8.9 respectively. The room-habits in summer are determined based on this seasonality coherence and the room habits in winter (Figure 8.7 - (5)). The habits when leaving the dwelling and going to bed in summer are determined based on these habits in winter and the room-habits in summer (Figure 8.7 - (6)). In this way, the habits are determined for each household for both summer and winter.

Table 8.8: Regression parameters for the multinomial logistic regression model of the seasonality coherence. (HH= household-habit)

Estimates	Seasonality coherence: All windows opened more		Dayzone opened more		Nightzone opened more	
	B	Std. Error	B	Std. Error	B	Std. Error
Intercept	0.647	0.372	-1.299	0.651	-2.398	1.044
HH: all windows closed	1.186	0.485	0.424	0.841	1.705	1.158
HH: all windows opened	-0.686	0.466	0.439	0.744	2.136	1.086
HH: dayzone vs nightzone	0.452	0.510	2.398	0.739	1.386	1.197
HH: bedroom opened most	0.334	0.503	2.706	0.727	2.110	1.134

The reference category is ‘Window use the same as in winter’.

Table 8.9: Goodness of fit estimators for the multinomial logistic regression model of the seasonality coherence.

	AIC	χ^2	Nagelkerke R^2
Intercept only	183.896		
Model	87.856	120.041	0.283

8.2.4 Creation of window use profiles

Finally, these habits are coupled to stochastic occupancy and activity profiles, to predict the window use per time step. In this case the occupancy and activity model developed by Aerts et al. [203, 204] as present in the StROBe-model is applied, but other models can be used as well. The StROBe-model generates three-state occupancy profiles (away, asleep, active) for the individuals of each household based on their employment type. Activity probabilities are applied to determine the performance of specific energy consuming activities. The translation of the habits to discrete window use sequences is straightforward, since the habits relate the window use purely to changes in the occupancy state and the performance of activities. For example, in Figure 6 the creation of window use profiles is illustrated for a household which opens the bedroom window at night, the living room window shortly in the morning and the bathroom window when taking a shower.

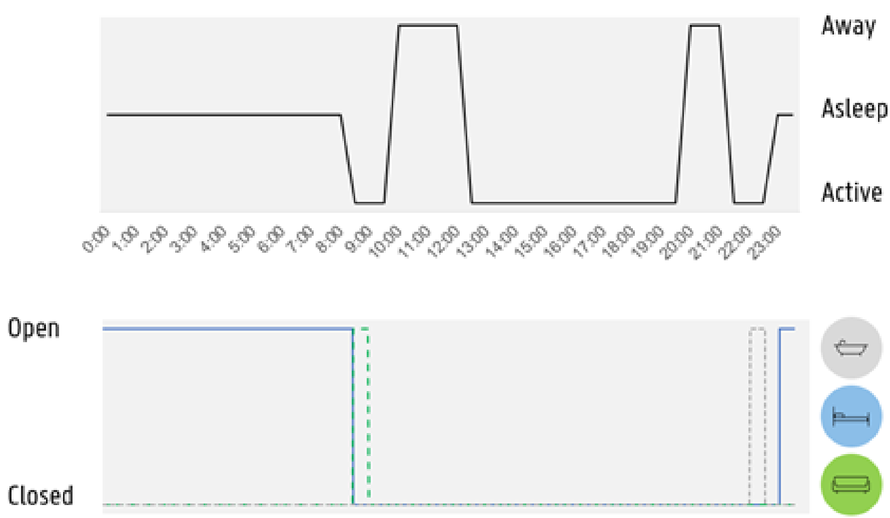


Figure 8.8: Example of translation of habits to window use profiles (bottom) based on the occupancy profile (top)

Since the occupancy and activity profiles are stochastic, and therefore do not predict exactly the same occupancy and activities each day, the resulting window use profiles are variable as well, and do not represent fixed schedules. Most window use habits can directly be related to activities and occupancy, however, habits that define that the window is opened shortly after or before the performance of an activity need some additional information. For these activities it is assumed that short duration is 30 minutes (defined in the survey as < 2 hours) and long duration (defined in the survey as > 2 hours) is 3 hours.

Since only habits were queried for winter and summertime, the year is divided in only those periods, with half of spring and autumn included in each season. This means winter runs from 6 November to 5 May, and summer from 6 May to 5 November. As discussed in Section 5.1.4, this is an arbitrary switching point and further research is necessary to define this more accurately.

8.3 Validation

The model is validated in two ways. First an internal validation is performed to assess if the model developed based on the training set is able to predict the observed window use habits for the validation set. Secondly, the model is validated based on window use data gathered in another Belgian case study, independently of the data on which the model is based, to assess if the model allows for extrapolation to other contexts in a similar climate and culture.

8.3.1 Internal validation

The correct assignment of the household-habit is hard to obtain since habits depend on a large set of different drivers which are difficult to measure. Regardless of the fact that this model may not be able to correctly predict the household-habit for a specific household, it may be able to predict the variability in window use across households and in that way be a good representation for the occurrence of the habits in the building stock. Therefore, the first step in the validation procedure was to check if the proportional prediction of the different winter household-habits and seasonality coherence was met. The results of 10 simulations for each household of the validation-set (1000 simulations in total) and the training-set are given for both the household habits (Figure 8.9) and the seasonality coherence (Figure 8.12). The simulation for the training-set revealed very good results. For the validation set the predictions deviate more than for the training-set, which is logical, but it still results in a relatively good prediction.

To assess the capability of the model it is more interesting to check the predictions for a sample with different building and household properties than the training-set. Therefore, four sub-samples of the validation-set are created which do not have the same building and household properties as in the training set. Set A consists of households without a ventilation system (69 households), while set B only contains households with a mechanical ventilation system (31 households). Set C consists of the 50 smallest households (1-3 persons), while set D consists of the 50 largest households (3-6 persons). The results of the simulations with these sub-samples for both the household habits and seasonality coherence are given in Figures 8.10, 8.11, 8.13 and 8.14 and in Table 8.10. The figures show that not for all sub-samples the derived habits from the survey follow the same distribution as in the training-set, and that for most of the sub-samples these distributions are captured relatively well. Only the predictions for sub-sample B (with ventilation systems) deviate much from the habits derived from the survey. The accuracy of the predictions with the habit-model is compared to that with a naive approach assuming the same distribution as in the training-set. Accuracy is defined here as the sum of the differences between derived and predicted proportions of each habit. The results, as shown in Table 8.10, reveal that the naive approach works equally well or is even better for the prediction of the household habits in most sub-samples, but is less accurate for the prediction of the seasonality coherence.

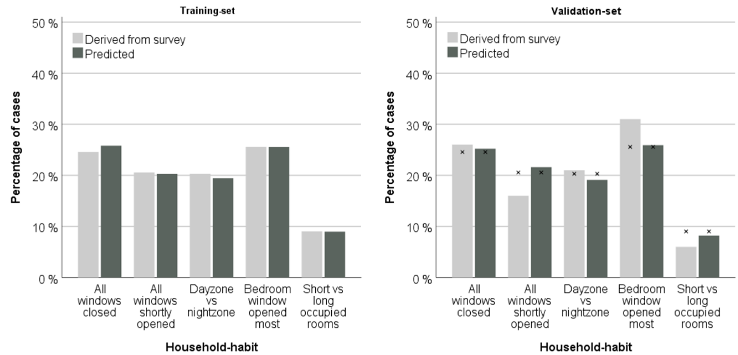


Figure 8.9: Predicted household-habits compared to household-habits derived from the survey both for the training-set and the validation-set. 'x' marks the occurrence in the training-set.

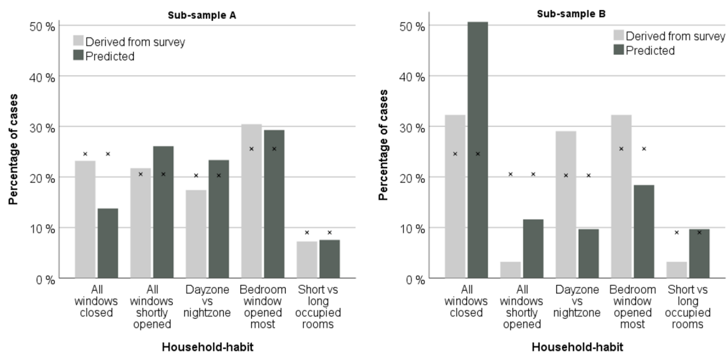


Figure 8.10: Predicted household-habits compared to household-habits derived from the survey both for sub-sample A (without ventilation system) and sub-sample B (with ventilation system) of the validation-set.'x' marks the occurrence in the training-set.

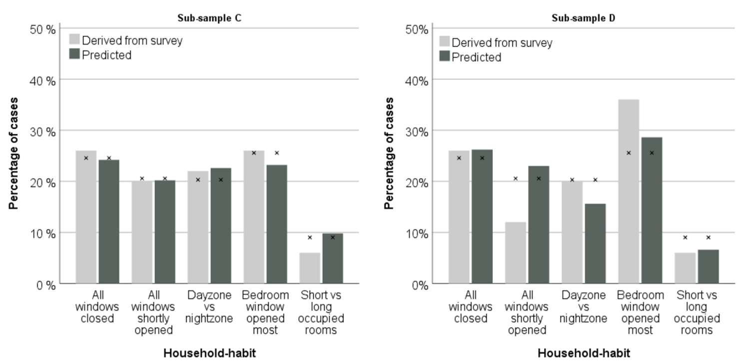


Figure 8.11: Predicted household-habits compared to household-habits derived from the survey both for sub-sample C (small families) as for sub-sample D (large families) of the validation-set.'x' marks the occurrence in the training-set.

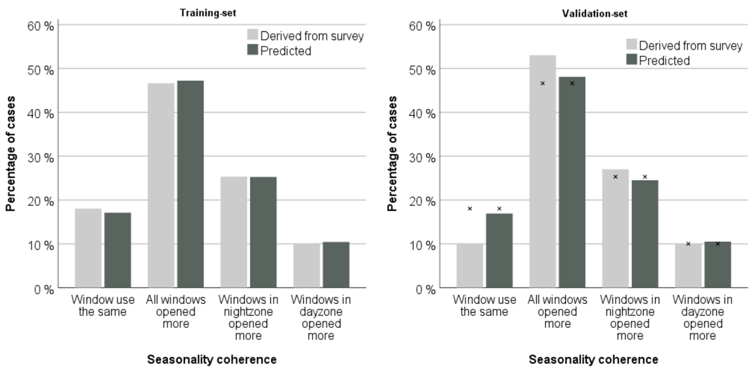


Figure 8.12: Predicted seasonality coherence compared to seasonality coherence derived from the survey both for the training-set and the validation-set.'x' marks the occurrence in the training-set.

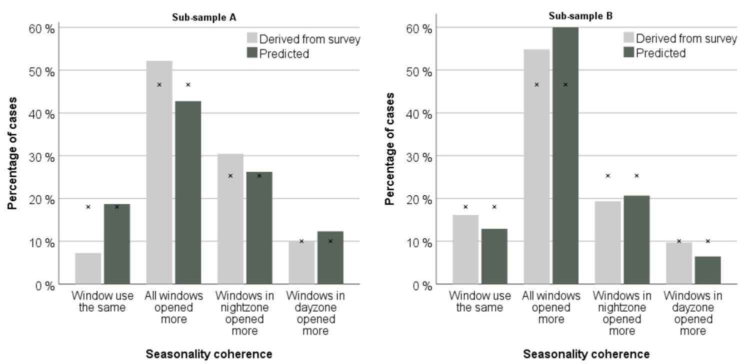


Figure 8.13: Predicted seasonality coherence compared to seasonality coherence derived from the survey both for sub-sample A (without vent. system) and sub-sample B (with vent. system) of the validation-set.'x' marks the occurrence in the training-set.

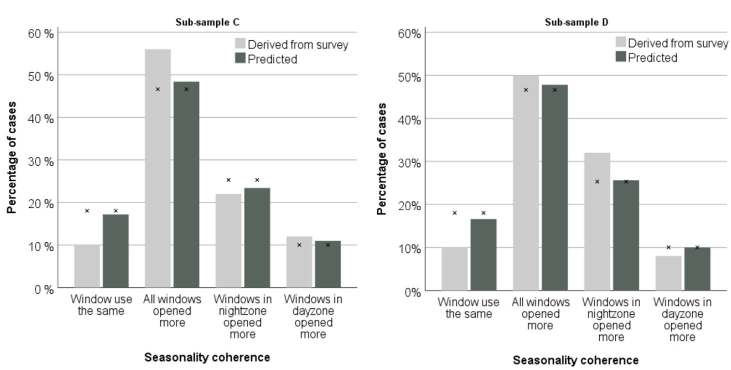


Figure 8.14: Predicted seasonality coherence compared to seasonality coherence derived from the survey both for sub-sample C (small families) as for sub-sample D (large families) of the validation-set.'x' marks the occurrence in the training-set.

Table 8.10: Summary of the proportion of household habits and seasonality coherences as derived from the survey and as predicted with the habit-model for both the training-set, validation-set and the four sub-samples. Additionally, the accuracy defined as the sum of the differences between the proportion derived from the survey and the predicted proportion is given. For comparison the accuracy when assuming the distribution of the training-set is given as well.

	Training		Validation		Sub-sample A		Sub-sample B		Sub-sample C		Sub-sample D	
	Der.	Pred.	Der.	Pred.	Der.	Pred.	Der.	Pred.	Der.	Pred.	Der.	Pred.
All windows closed	24.56	25.79	26.00	25.20	23.19	13.77	32.26	50.65	26.00	24.20	26.00	26.20
All windows shortly opened	20.55	20.28	16.00	21.60	21.74	26.09	3.23	11.61	20.00	20.20	12.00	23.00
Dayzone vs nightzone	20.30	19.42	21.00	19.10	17.39	23.33	29.03	9.68	22.00	22.60	20.00	15.60
Bedroom window opened most	25.56	25.54	31.00	25.90	30.43	29.28	32.26	18.39	26.00	23.20	36.00	28.60
Short vs long occupied rooms	9.02	8.97	6.00	8.20	7.25	7.54	3.23	9.68	6.00	9.80	6.00	6.60
Accuracy: Habit-model	*2.45*		*15.60*		*21.15*		*66.44*		*9.20*		*23.60*	
Accuracy: Proportion trainingset	-		*15.15*		*12.11*		*46.24*		*7.15*		*23.75*	
Window use the same	18.05	17.09	10.00	16.90	7.25	18.70	16.13	12.90	10.00	17.20	10.00	16.60
All windows opened more	46.62	47.22	53.00	48.10	52.17	42.75	54.84	60.00	56.00	48.40	50.00	47.80
Windows in the nightzone opened more	25.31	25.26	27.00	24.50	30.43	26.23	19.35	20.65	22.00	23.40	32.00	25.60
Windows in the dayzone opened more	10.03	10.43	10.00	10.50	10.14	12.32	9.68	6.45	12.00	11.00	8.00	10.00
Accuracy: Habit-model	*2.01*		*14.80*		*27.25*		*12.92*		*17.20*		*17.20*	
Accuracy: Proportion trainingset	-		*16.15*		*21.58*		*16.45*		*22.71*		*20.15*	

In the next step the accuracy of the habit prediction is evaluated. It is checked if the room-habit is predicted correctly for the validation set, when assuming the right assignment of the household-habit. In Figure 8.15, the percentages of correctly predicted room- and activity-habits are given for both the training- and validation-set. Additionally, the results are given for a random simulation (probability for all habits is the same) and a weighted random simulation (probability based on the habit occurrence in the sample of that household-habit). On average, the model predicts the habits in winter-time with approximately 50%-accuracy. While in summer this is reduced to approximately 30%. There are different reasons for the lower predictability in summer. First, in summer a wider variety of habits are performed, consequently the probability of correctly predicting habits drops with more choices. Secondly, in this analysis it is assumed that the winter household-habit is correctly predicted, while no such assumption is made regarding the seasonality coherence. The habit-model works significantly better than a random prediction. The weighted prediction of some habits (living room, kitchen, going-to-bed, leaving) in only slightly less accurate (approx. 4%) than the habit-model, while the bedroom and bathroom habits are predicted significantly better with the habit-model (approx. 20%).

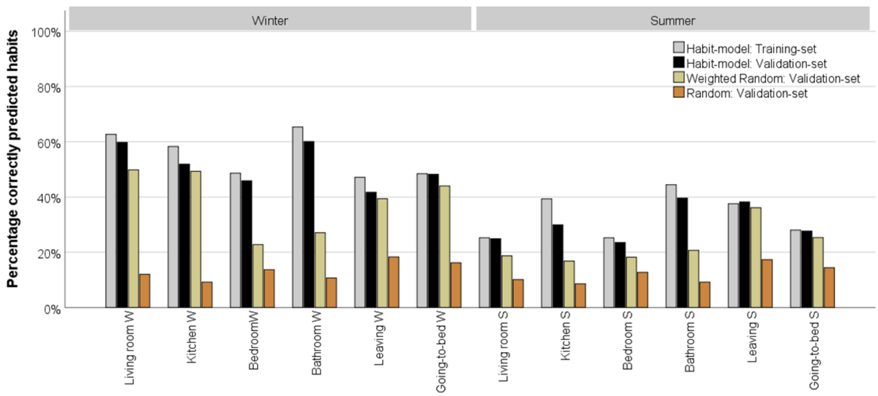


Figure 8.15: Correctly predicted habits for the validation-set with the habit-model, weighted random prediction and naive random prediction. The results of the habit-model for the training-set are given for comparison.

These results indicate that the model is able to correctly predict a significant share of the habits, better than a random and weighted assignment of the habits, but overall the habits are accurately predicted for less than 50% of the households.

It is important to notice that even if some habits may be divergent, the impact on the window use itself may be small. For example, the opening of the bathroom window shortly after taking a shower may coincide with opening the window in the morning. While these two habits are distinct and will not indicate a correct evaluation in the analysis, the impact of this wrongful prediction may have not such a large impact on the predicted window use.

However, predicting the windows 'always open' compared to 'always closed' is a large fault. Therefore, the predicted window use was compared to the window use translated from the reported habits from the survey. The reported habits were translated to discrete window use sequences based on the same occupancy and activity profiles as generated for the predicted habits. Notice that the comparison is not between the observed window use since these data are not available, but rather a synthetic 'observed' window use based on reported habits. The predictive accuracy is evaluated based on the opening percentage, number of opening actions and the discrimination accuracy [108, 142]. The opening percentage and number of opening actions are good first criteria to evaluate the general window use prediction, however, these metrics do not take into account when the windows are open or closed. Therefore, we also evaluate the discrimination accuracy. This by evaluating the true positive rate (TPR - proportion of actual open states which are correctly predicted open), the false positive rate (FPR - proportion of actual closed states which are falsely predicted open) and the accuracy (proportion of correct classifications).

The obtained validation parameters are given in Table 8.11. The predicted average opening percentages and number of opening actions are in good comparison with the synthetic window use profiles based on reported habits. The model can predict the window use with reasonable accuracy, since the TPR is significantly higher than the FPR for all rooms. The obtained accuracy ranges from 68% for the bedroom to 84% in the kitchen. These results are comparable to the results obtained in the validation studies of Schweiker et al. [142] and Haldi and Robinson [108]. The predictions in the bedroom are the least accurate, probably due to the higher variability of window use in the bedroom. While the accuracy of the habit-model is much better than that of a naive random approach, the accuracy of the weighted random approach is similar to that of the habit-model. This indicates that predicting the habits based on the occurrence in the training-set will lead to equally accurate window use predictions for each room-habit individually. A similar analysis was conducted for sub-samples A and B (with and without mechanical ventilation system)(Table 8.12), which led to the same conclusion, that a good accuracy is obtained for both the habit-model and the weighted random approach.

However, this evaluation does not consider the relationship between the different habits. While the weighted random approach will be able to predict the habits equally well across the sample resulting in a correct distribution of the habits, the relationship between the different room-habits and between the different seasons might not be captured. This may lead to unrealistic combinations of room-habits across seasons. Due to the limited sample size in this study we can not define which combinations are "unrealistic". For example, it seems unrealistic to always open all windows except for the bedroom window in winter, however, it is possible that there is a household that portrays such behaviour. A larger study needs to be conducted to be able to determine realistic and unrealistic combinations of room-habits.

Table 8.11: Validation parameters: true positive rate, false positive rate, accuracy, opening percentage and average number of opening actions per day.

		Discrimination			Opening percentage	Openings per day
		TPR	FPR	Accuracy		
Derived from survey	living room				15	1.32
	kitchen				11	1.12
	bedroom				25	1.00
	bathroom				14	0.91
Habit-model: Training	living room	39	8	84	12	1.33
	kitchen	29	7	85	9	1.40
	bedroom	51	22	66	28	1.02
	bathroom	20	6	83	8	0.83
Habit-model: Validation	living room	35	7	82	11	1.39
	kitchen	29	6	84	9	1.34
	bedroom	53	22	68	28	1.04
	bathroom	25	7	81	9	0.99
Weighted random: Validation	living room	43	9	83	14	1.53
	kitchen	35	7	84	11	1.25
	bedroom	47	16	70	22	1.18
	bathroom	40	11	80	15	1.37
Random: Validation	living room	38	33	62	33	2.77
	kitchen	25	21	71	21	2.42
	bedroom	48	33	60	35	1.34
	bathroom	33	24	70	25	2.60

Table 8.12: Validation parameters: true positive rate, false positive rate, accuracy and opening percentage for sub-sample A and B.

Sub-sample A		discrimination			Opening percentage
		TPR	FPR	Accuracy	
Derived from survey	Living room				16
	Kitchen				14
	Bedroom				27
	Bathroom				18
Habit-model	Living room	45	8	82	13
	Kitchen	37	8	82	11
	Bedroom	56	25	67	32
	Bathroom	32	8	79	11
Weighted random	Living room	44	8	83	14
	Kitchen	34	7	84	11
	Bedroom	48	17	70	22
	Bathroom	42	11	79	16
Random	Living room	38	33	61	34
	Kitchen	24	21	71	21
	Bedroom	50	34	60	36
	Bathroom	33	24	69	26

Sub-sample B		discrimination			Opening percentage
		TPR	FPR	Accuracy	
Derived from survey	Living room				13
	Kitchen				12
	Bedroom				28
	Bathroom				9
Habit-model	Living room	45	8	84	13
	Kitchen	39	10	84	14
	Bedroom	53	23	67	32
	Bathroom	41	11	82	13
Weighted random	Living room	41	11	82	15
	Kitchen	37	8	85	11
	Bedroom	44	14	71	21
	Bathroom	42	11	79	16
Random	Living room	38	31	65	32
	Kitchen	28	21	73	21
	Bedroom	43	31	59	33
	Bathroom	33	23	72	24

8.3.2 External validation

The previous discussed validation-analysis was based on data collected in the same study as for which the model was developed. An external validation is necessary to evaluate the window use prediction with measured window use data. Therefore, the simulated window use with the habit model is compared to the measured window use data of the case study (Chapter 2). The window use is simulated 50 times for each household living in a house of the Venning-neighbourhood for which measured data is available (N=12). The results of the simulation are given in Figure 8.16. It is observed that the variability in window use is captured well with the newly developed model. The range of opening percentages is slightly wider than the observed window use, however, this is logical since the measured window use is only from 12 households while the simulated window use is from 600 households (50 x 12 households). We can conclude that the model is able to capture the large diversity in window use as present in reality.

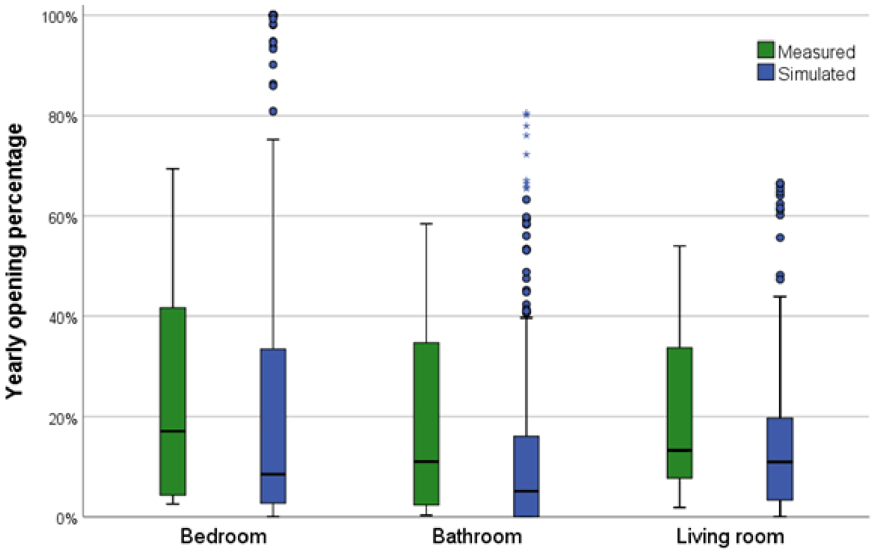


Figure 8.16: Comparison between simulated window use with the habit-model and measured window use.

8.4 Discussion

The main advantages of the window use habit model are that the model is able to predict the diversity in window use, predicts realistic actions in the day-to-day life of the occupants and allows for easy implementation in different energy simulations programs.

Diversity

As discussed in Section 8.3, this window use habit model allows for predicting the large diversity in window use observed in the building stock but is not able to predict the exact window use for a specific household. Nevertheless, if the window use for a specific household has to be simulated the range in possible behaviours can be limited by conducting a short survey. Since habits are easily query-able, conducting this short optional habit-survey will allow for a more accurate prediction of the window use for that specific household compared to the general prediction with the model without further knowledge of the habits.

Realistic actions

By connecting the window use directly to occupancy and activity profiles the window use actions are predicted at realistic (representing things as they are in real life [62]) moments in the day. Furthermore, the model captures the important inter-room and inter-season relationship between the habits. In this way, the window use across seasons and rooms for one household is coherent and represented in a realistic manner.

Easy implementation

The model as developed in this study can be readily implemented in building energy simulations. The model, which is written in Python, determines the window use based on the predicted occupancy and activity sequences of the occupants. In this case the StROBe-model for occupancy and activity is used which is as well developed in Python. Based on the combination of the two python models text-files are generated with a time sequence of the window use. These text-files can be easily used as inputs in a variety of energy simulation software.

To simulate the model for a household a few input variables can be defined such as number of persons, employment of the household members, type of ventilation system, ... However, it is not necessary to define these inputs. If no inputs are defined the window use is simulated for a random household. Additionally, the habits themselves can as well be defined in order to simulate a specific household with specific habits. This flexibility makes the approach comprehensible, convenient and reproducible.

Deviation from the habitual behaviour

Currently the model is only based on habits, however, other variables might still have an influence on the window use. Furthermore, when extremes are present within the season it is probable that the habit will not be performed any more. For example, with very high temperatures (>35°C) windows are more often kept closed instead of following the usual habit. As stated before, habits are only performed in stable contexts, and when the context is not stable the behaviour is based on conscious reasoning. Therefore further research could focus on the definition of this stable context, and in which circumstances, the behaviour deviates from the baseline habitual behaviour and is based on other window use drivers. The combination of the window use habits with other window use drivers is a promising future development.

8.5 Conclusion

It was found that window use habits in specific rooms are significantly related to the habits in the other rooms, indicating habit coherence across the different rooms. Therefore, a window use model was created based on an initial classification of the households according to the habit-coherence across the rooms in winter and the seasonality coherence. The validation of the model revealed a good performance of the model at stock-level in the Belgian context, with much better results compared to a random prediction. Nevertheless, the use of a weighted random prediction revealed similar accuracies. However, the weighted random prediction is not able to capture the important inter-room and inter-season relationship between the habits which is difficult to evaluate.

The window use habit model allows for a realistic prediction of the window use and captures the inter-occupant diversity very well. Additionally, the model is easy to implement in building performance simulation tools. Habits can be easily derived by asking a limited number of questions, resulting in convenient, realistic and fast predictions of the window use of those queried occupants. The further development of the habit model in combination with other window use drivers seems promising.

9

Event-based OB-model

As discussed in Chapter 7, an event-based approach is regarded as the best fitting for the inclusion of habits in an OB-model. In Chapter 8 a first step was already made by predicting window use habits and thereby relating window use to specific events in the occupant's daily life. In this chapter a more comprehensive event-based OB-model is developed.

9.1 Model structure

The Event-based Residential Occupant Behaviour (EROB) model is developed using the modelling approach of the StROBe-model. As discussed in Section 7.3, the StROBe-model is a good starting point, however, some adaptations need to be made to improve the model and to include the OB-habits.

- **Predicting occupancy on room-level instead of building-level.** Since many habits are linked to the presence in the zone it is necessary to model the occupancy on room-level. Additionally, predicting the occupancy on zone-level will allow for a better prediction of the heating energy use due to adequate assignment of the internal heat gains and better prediction of the lighting loads.

- **Moving from an agent-based model to an event-based model.** For the inclusion of habits it is often not necessary to known the exact behaviour of each individual occupant, rather it is necessary to know when different domestic activities are executed that are linked to the performance of activities (regardless of who exactly performs this activity). Furthermore, the predicted electricity use with the StROBe-model was relatively high due to the agent-based approach, with multiple occupants using the same appliance simultaneously without the consideration of shared use. A move to an event-based approach can solve these issues.

- **Improvement of domestic hot water model.** The amount of domestic hot water predicted with the StROBe-model was as well relatively high. This could be attributed to the assigned flow rates, number of tappings per day and tapping durations. The domestic hot water model was therefore ameliorated with data received from the Instal2020-project [205].

- **Update the model with more recent data.** The StROBe-model is based on occupancy and appliance data from 2005. Therefore the model is updated with more recent data. The new model uses data from a time use survey (TUS) and household budget survey (HBS) of 2013 in Belgium, which is provided by the 'Algemene Directie Statistiek-Statistics Belgium' and of which a limited overview can be found on the TUS-website [206].

The new EROB-model has a similar structure as the StROBe-model. In first instance the occupancy and activity profiles of the household and its individual members are defined based on some characteristics of the household. The other types of occupant behaviour (electricity use, heating behaviour, internal heat gains, domestic hot water use and window use) are subsequently linked to these profiles. The modelling of each of these steps is described in detail in the following sections.

9.2 Initialisation

9.2.1 Household

The occupancy profiles are generated based on occupancy clusters that vary according to the employment type of the household members. Therefore, it is necessary to define the household for which the occupant behaviour is simulated, and more specifically the occupation of the members. The members can be categorised according to 6 different employment types (StrOBe, TUS2013):

- Full Time Employment (FTE)
- Part Time Employment (PTE)
- Unemployed
- Retired
- Student (> 18 years)
- School (10-18 years)

So a household of two Full-time employed adults will be denoted as (FTE,FTE). If the household is not given as input, it can be randomly selected out of a list of households (TUS 2013). When only the number of persons is given as input, a household of similar size is randomly selected from the list of households. Since in the time-use survey no data is collected about children less than 10 years old, these are not included in the model.

9.2.2 Bedrooms

For each household member it should be defined in which room they sleep. This is important for the determination of the internal heat gains, lighting use, and window use in the separate rooms. The first step is the determination of the number of bedrooms. This can be either defined as input or can be selected based on the number of persons in the household. The probabilities related to this second option are given in Table 9.1 and are based on the data gathered from the online window use survey (section 5.1.3).

Table 9.1: Probability for number of bedrooms for each household-size.

	Number of bedrooms							
	1	2	3	4	5	6	7	8
1 pers	0.431	0.314	0.216	0.020	0.020	0.000	0.000	0.000
2 pers	0.143	0.351	0.363	0.113	0.024	0.006	0.000	0.000
3 pers	0.000	0.202	0.646	0.111	0.040	0.000	0.000	0.000
4 pers	0.000	0.055	0.614	0.260	0.055	0.008	0.008	0.000
5+ pers	0.000	0.000	0.185	0.630	0.093	0.037	0.000	0.056

When the number of bedrooms is determined, the household members are assigned a bedroom, this can be given as input as well, or can be determined based on the employment type of the household members. If the first two members of the household are adults, it is assumed they are a couple and are assigned to the same bedroom. The other household members are divided over the remaining bedrooms, assuming optimal spreading and with a maximum of 3 persons sleeping together in one room.

9.2.3 Appliances

In order to determine the internal heat gains and electricity use, the presence of different energy consuming appliances needs to be defined. A set of appliances is assigned based on ownership statistics from the household budget survey (HBS), which was conducted together with the time-use survey. For the appliances not covered in the HBS, the ownership statistics of the StROBe-model, were used.

Following appliances are included: Fridge-Freezer, Freezer, Refrigerator, TV (incl. TV-receiver), Computer/Laptop (incl. router), Smartphone, HiFi, Iron, Vacuum, Dishwasher, Hob , Oven, Microwave, Washing machine, Washer-dryer, Tumble dryer.

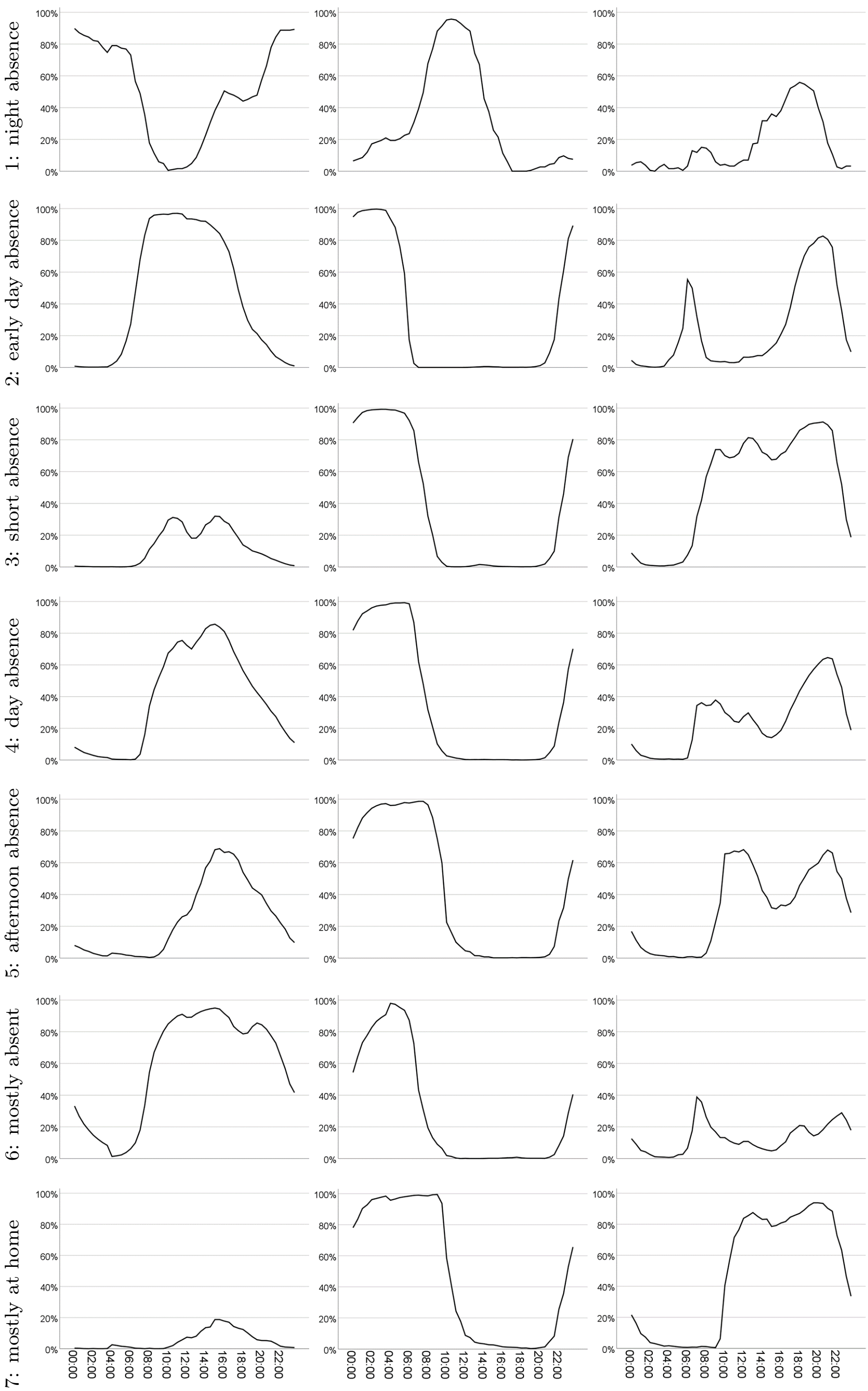
While most appliances are only present once in the household, multiple tv's, computers and smartphones may be present. The number of these appliances is determined based on the household size, with a probability of owning a specific number of appliances per household size (TUS 2013, HBS 2013).

9.3 Occupancy

After the initialisation, the next step is to define the occupancy-profiles of the different occupants, since this will be the base for the determination of the other types of occupant behaviour. The occupancy-state is defined as (1) present and awake, (2) present and asleep or (3) away from home.

9.3.1 Occupancy clusters

As discussed previously the occupancy is determined based on occupancy clusters assigned according to the different employment types. Occupancy clusters are clusters in which the occupancy is similar, and for which separate occupancy probabilities are defined. The occupancy clusters were determined by applying hierarchical clustering in SPSS based on the waking-up time and the duration of absence of the different persons that participated in the TUS of 2013. There are 7 different occupancy clusters (Figure 9.1), resembling occupancy patterns of (1) night-time absence, (2) daytime absence - early wake up, (3) short daytime absence, (4) daytime absence, (5) afternoon absence, (6) mostly absent and (7) mostly at home.



(a) Absent (b) Asleep (c) Active

Figure 9.1: Probability to be absent (a), asleep (b) and active (c) for each occupancy cluster per 10 minutes.

For each occupation the probability is defined to belong to a certain occupancy cluster, for each day of the week (StROBe, TUS 2013). The occupancy clusters are mostly identical for each day of the week, but differ on Saturdays and Sundays. However, FTE and Students have deviating occupancy clusters on Fridays, and the PTE and School-going children on Wednesdays (half day off in most Belgian schools). Therefore the occupancy clusters are corrected for these 'special' days of the week. In general, an occupancy cluster is determined for weekdays and this cluster is assigned to each individual weekday. For the 'special' days a separate occupancy cluster is determined and assigned only to that specific day. For Saturday and Sunday separate occupancy clusters are determined as well. In this way occupancy clusters are defined for each household member for each day of the week. In Table 9.2 the probabilities for Sunday are given as illustration. In Appendix 14.5 the probabilities for the other days are given.

Table 9.2: Probabilities for occupancy clusters on Sunday for each employment type.

	FTE	PTE	Unemployed	Retired	School	Student
Night absence	0.011	0	0.005	0	0	0
Early day absence	0.027	0.023	0.01	0.006	0	0
Short absence	0.497	0.615	0.623	0.732	0.403	0.309
Day absence	0.219	0.165	0.099	0.181	0.121	0.122
Afternoon absence	0.1	0.088	0.106	0.045	0.15	0.216
Mostly absent	0.038	0.017	0.003	0.008	0.029	0.036
Mostly at home	0.108	0.091	0.128	0.028	0.297	0.317

9.3.2 Determination of occupancy profiles

Discrete Markov chain simulations are used to determine the occupancy state for each household member for each day of the week. The occupancy cluster includes the probability of the starting state (asleep, away or active) at 4am, the duration probability and the transition probability. Based on the starting state probability a start state is determined. When a certain state is started the duration of this state is determined using the duration probability based on the time of day. At the end of this duration it is determined what the next state will be based on the transition probability. This is the probability of changing to a certain state after the previous state has ended. In this way occupancy profiles can be generated for each day of the week.

For the simulation of the first day the start-state at 4 am is used, but for the other days the end-state of the previous day is applied. The occupancy simulations are carried out with a time-step of 10 minutes, however, to avoid empty probability slots (when no occupancy change occurs during the time bin(TUS 2013)) the transition and duration probabilities are given per 30 min. An example of the transition probability for the occupancy cluster daytime absence is given in Figure 9.2.

The occupancy profiles of the individual days are added together to create a weekly profile. This weekly profile is repeated 52 to times to create a yearly

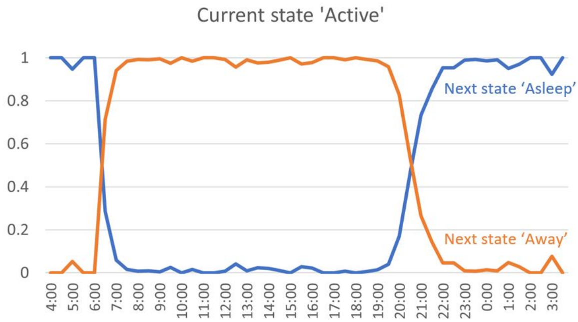


Figure 9.2: Transition probability for the state active for the occupancy cluster daytime absence.

profile. It was specifically chosen to not repeat the simulation for each day of the week, as the occupancy for most occupants is relatively constant over the weeks, and performing daily simulations for an entire year would lead to a too high variability and as well to longer simulation time.

At last a merged occupancy chain is created. This represents the most active state of all household members, ranging from active, asleep to absent. The created occupancy profiles are the base on which the rest of the model is constructed.

9.4 Activities

In order to model the habitual behaviour it is necessary to determine when specific activities are performed that lead to habitual actions or when location specific activities are performed that can determine the presence in the different zones (e.g. taking a shower is linked to the bathroom, cooking is linked to the kitchen). Additionally, the execution of other energy-consuming activities needs to be determined to predict the electricity use. The approach for the activity-model is based on the work of Aerts et al. [203, 204] in which a distinction is made between individual activities and household tasks.

- **Household tasks** = activities such as doing laundry and cooking that are usually performed by one person and the frequency of performing this activity is dependent on the size of the household.

- **Individual activities** = activities such as taking a shower or using a computer which are independently performed from other household members.

For each type of activity a separate modelling approach is used. The data used in this section regarding the performance of activities (start probability, duration probability) is derived from the TUS-data. For every execution of the specific activity in the data-set the starting times are gathered and this info is used to determine the starting probabilities, sometimes depending on other characteristics such as household size. Similarly for every execution of the specific activity the corresponding duration of that activity is gathered to created the duration probabilities.

9.4.1 Household tasks

Household tasks are activities such as doing laundry and cooking that are usually performed by one person and the frequency of performing this activity is dependent on the size of the household (E.g. doing laundry will be performed more often in larger households). The execution of a household task is predicted for the household as a whole and then assigned to the most suitable household member to perform it.

At least one member of the household should be active for a household task to be performed. To predict the start of a household task a starting probability is used which is dependent on the time of day and on the size of the household. When an activity is started, a duration probability is used to determine the length of the activity. At the end of the activity it is determined which household member performs this household task by checking the availability and the member probability. The availability defines whether or not an occupant is active for the entire duration of the household task and the member probability is the probability for specific members to perform the task based on their employment type. E.g. the member probability for cooking will be higher for FTE adults than for school-going children. None of the household tasks can be combined as for these activities multi-tasking is not an option.

The modelling approach of the household tasks is illustrated in Figure 9.3. First the tasks (green bars) are determined on household-level (HH). Then each task is assigned to the most suited occupant. For the first two tasks in the example it is clear that the only person that can perform this activity is person 1. The third activity can be performed by either person 2 or 3. In this case the member probability of person 2 was higher, leading to the assignment of the task to person 2.

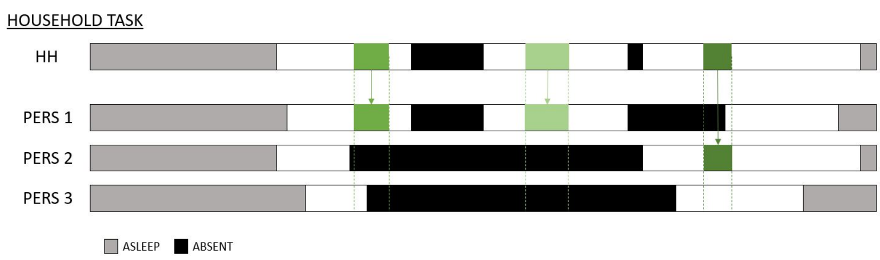


Figure 9.3: Illustration of the assignment of household tasks (green).

9.4.2 Location specific individual activities

Next, the execution of location specific activities is determined for each individual separately. Occupants are present in the bedroom when sleeping and a specific time before and after sleeping for getting (un)dressed (orange bars with arrow in Figure 9.4). Additionally, students and children are present in their respective bedrooms when studying or using the pc (orange bars without arrow in Figure 9.4). Occupants are present in the bathroom when showering or bathing, but as well when brushing teeth, etc (blue bars in Figure 9.4). And occupants are present in the kitchen when preparing meals (with or without appliances). Otherwise occupants are assumed to be in the day-zone.

The modelling of the location specific individual activities is done on individual level, so for each occupant separately. An occupant can perform a location specific activity when the occupant is active and not performing a household task. The presence in the bedroom is determined by the duration of the morning and evening routines, which are determined by a duration probability. The other location specific activities are determined with a start probability based on the time of day, employment type and occupancy cluster. When the activity is started the duration is determined with a duration probability as well.

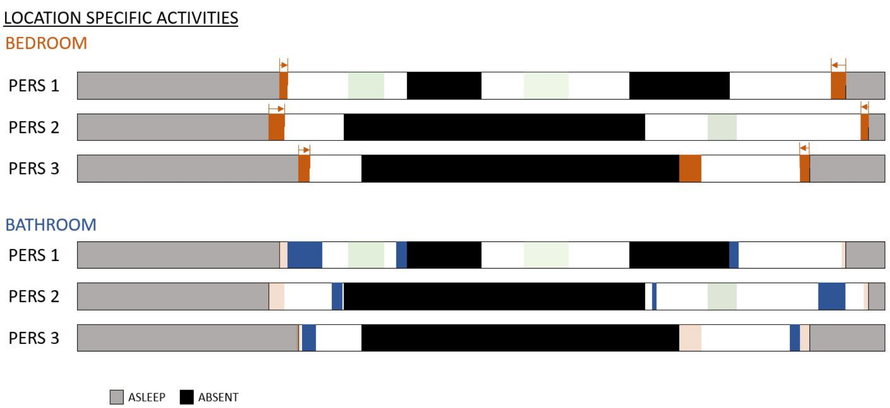


Figure 9.4: Illustration of the assignment of location specific activities. Activities performed in the bedroom (red) or in the bathroom (blue). The green boxes represent the previously determined household activities.

9.4.3 Energy consuming individual activities

Finally, the performance of other energy consuming activities is determined. The approach is similar as for the location specific activities, with the exception that some of these activities can be combined with other activities. E.g. if the occupant is already ironing, he/she is still able to listen to music. An overview of activities that are compatible can be found in Table 9.3. The starting probabilities for these activities are based on the time of day, day of the week and employment type. The activity is only assigned to the occupant if there is no conflict regarding the compatibility of activities. For example, in Figure 9.5 the hatched bar overlaps with other previously defined activities, but since no compatibility issues occur the activity can be assigned.

The start probabilities of the activities, as defined above, are multiplied by a calibration factor, so that the average activity duration or the average number of cycles is in correspondence with the observed data from the time-use survey.

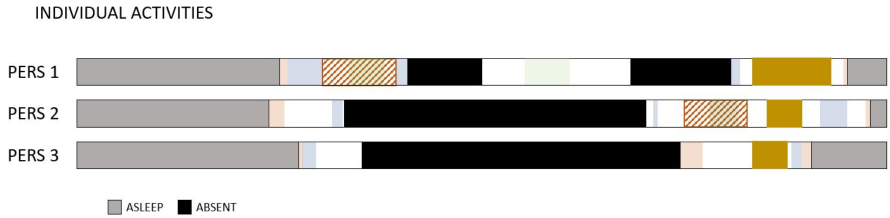


Figure 9.5: Illustration of the assignment of individual activities (orange - hatched). The green boxes represent the previously determined household activities, the red boxes the presence in the bedroom and the blue boxes the presence in the bathroom.

Table 9.3: Compatibility matrix activities. + indicates compatible activities, - indicates non-compatible activities.

	PC	TV	Audio	Work/study
Household tasks				
Dishes	-	+	+	-
Vacuum	-	-	-	-
Iron	-	+	+	-
Wash	-	-	+	-
Dry	-	-	+	-
Cook	-	+	+	-
Location specific				
(Un)dress	-	-	+	-
Bathroom	-	-	+	-
Individual activities				
PC	-	-	+	-
TV	-	-	-	-
Audio	+	-	-	+
Work/ Study	-	-	+	-

9.5 Metabolic rate

Based on the defined activities, the metabolic rate for the different occupants can be determined and with that the corresponding internal heat gains and produced CO_2. In Table 9.4 the values for the metabolic rate for a set of activities is given [207]. A normal distribution is applied to allow for some variation across different occupants. Interpolation is performed to determine the produced CO_2 that corresponds with a specific metabolic rate based on the study of Persily and de Jonge [207] (Table 9.5). Since the EROB-model does not determine the sex and age of the occupants, the average of the CO_2-production of male and female adults between 30 and 40 years old is used. If multiple activities are performed at the same time the metabolic rate of the most 'active' activity is used.

Table 9.4: Determination of metabolic rate [207].

	metabolic rate
sleeping	0.95
cleaning, ironing, vacuuming	3.8
watching tv, sitting	1.2
working in kitchen	3.3
light effort, other activities	1.5

Table 9.5: Determination of heat-production and CO_2-production based on the metabolic rate. CO_2-production is the average of the CO_2-production of a male and a female of 30 to 40 years [207].

Heat	0.80 met	70 W
	1.25 met	110 W
CO_2	1.00 met	0.0033 l/s
	1.60 met	0.0054 l/s

9.6 Electricity use and internal heat gains by appliances

The properties for the different appliances as present in the StROBe-model were updated, to represent more recent data. For this the data of a Dutch study from 2018 are used [208].

Based on the activities, defined in the activity model, the use of the different appliances can be determined. For some activities an appliance is used for the entire duration of the activity (e.g. listening to audio, watching tv, using pc, ironing, vacuuming). During the performance of the activity the load of that appliance is assigned. For other activities the appliance is used when the activity is finished (e.g. doing laundry - both washing and drying). For these activities the cycle length is determined based on the properties of the appliance and the load is assigned during this duration. Finally, for some activities the appliance is not used the entire time (e.g. use of a pc when studying) or different appliances can be used (e.g. hob, oven, microwave or kettle can be used to prepare food). For these activities, a probability is determined for the use of the appliance during the performance of this specific activity. Additionally, a cycle length is defined since it is possible that the use of the appliance is shorter than the activity duration. When the appliances are not in use a standby load is assigned.

There are some appliances that are not related to the performance of an activity (e.g. cooling appliances). For these appliances a cycle length and delay time are determined based on a normal distribution of these metrics as defined for the specific appliance. The load will be assigned for the cycle length and the standby load will be assigned for the delay length. This is continuously repeated.

Finally, some appliances are present multiple times in the household (e.g. pc, tv). For these appliances, it is checked for each household member if there is still an appliance that is not in use. If this is the case, an appliance is assigned to that person for the duration of the activity. If there is no free appliance, it is assumed the occupants are sharing the appliance, and no additional load is assigned.

The internal heat gains produced by each appliance are determined by a factor that determines the fraction of the electricity use that is converted in radiative and convective heat. This factor is defined for each appliance separately, as for some appliances more heat will be transferred by radiation or convection than for others. The values as defined in the StROBe-model are used.

9.7 Electricity use and internal heat gains by lighting

The lighting use is based on the presence in the house and irradiance-levels. When at least one occupant is active in a room and the solar radiation is below 200W/m^2, the lighting load of that room is assigned (dayzone 100W, other rooms 20W). Since in the dayzone multiple lights are present which may not be turned on all at once, an adaptive model is included based on the model of Widen [209]. When a change in solar radiation level occurs, a stochastic model is incorporated that allows for adjustment per 25W. Internal heat gains are assigned in a similar way as for the appliances. The modelling approach and model assumptions are the same as in the StROBe-model. An update to this part of the model, taking into account architectural properties and/or indoor illuminance levels, is still required to allow for correct lighting use predictions.

9.8 Heating behaviour

The heating profiles are based on the study of Leidelmeijer and Van Grieken [210], similar as in the StROBe-model. Based on surveys conducted in the Netherlands in 2005, they defined 7 heating-profiles with temperatures for when the occupants are active in the house, asleep or away. For each heating-profile some options are available for heated rooms. Unheated rooms are assigned a set-point temperature of 12°C. The heating set-points and related heated rooms are assigned based on the occurrence statistics of the study of Leidelmeijer and Van Grieken.

Table 9.6: Temperature setpoints according to Leidelmeijer and Van Grieken

	Active	Asleep	Away	Heated rooms
1	17.0	14.0	15.0	none, dayzone, dayzone & nightzone, all
2	18.5	15.0	18.5	dayzone & bathroom
3	20.0	15.0	19.5	dayzone, dayzone & bathroom, dayzone & nightzone
4	20.0	11.0	19.5	dayzone, dayzone & nightzone
5	20.0	14.5	15.0	dayzone
6	21.0	20.5	21.0	all
7	21.5	15.5	21.5	dayzone & bathroom

9.9 Domestic hot water use

In essence, the domestic hot water use is determined in the same way as the appliance loads. When an occupant is present or performing a specific activity it can lead to the use of hot water. In the StROBe-model the domestic hot water was severely overestimated, therefore a new domestic hot water model is created based on data from the Instal2020 project [205].

If someone is present in the bathroom, the shower or bath can be used. Based on the start probabilities based on the time of day and household size the tapping can be started. If a tapping is started a duration is determined and subsequently a flow rate is determined according to the tap point.

For the other tap points the approach is similar. For the dishes the activity doing the dishes has to be performed and no dishwasher should be present, before the starting probabilities are applied. For other tappings (e.g. washing hands) starting probabilities are evaluated when someone is present in the dwelling. The start probabilities are further calibrated based on the number of tappings per household per year at that tap point. The duration probabilities are based on a distribution for these tap points based on the Instal2020-data as given in Table 9.7. The flow rate is determined based on a gaussian distribution of the average flow rate.

Table 9.7: Probability distribution functions for the tap durations [205].

	distribution	shape	location	scale
shower	weibull min	1.71	0.96	8.04
bath	normal	-	10	1
dish washing	loglaplace	1.32	-0.0042	3
other (sec)	genextreme	-1.12	2.39	2.16

Based on 100 simulations the average domestic hot water use per day per household is 62 l, which is in good comparison with the 63 l per household measured in the study of Gerin et al. [211]. The average value of 30 l/pp/day is as well in good comparison to the values per person set out by Pidpa (34 l/pp/day) and by the Belgian Building Research Institute (30 l/pp/day) [212].

9.10 Window use

The habitual window use model as developed in Chapter 8 is included in the EROB-model.

9.11 Discussion & Conclusion

The EROB-model as discussed in this section is a first step in the development of an occupant behaviour model based on habits. Due to the prediction of the occupancy states and specific activities it allows for easy linkage between certain types of occupant behaviour and the daily-life of the occupants, and in this way performs great for the inclusion of habitual behaviour.

While for now only the habits related to the window use are included, habits in other types of OB can be easily added later on. The solar shading use is not yet included, since too little data was available, but a habit-approach could prove interesting for that as discussed in Section 6.2. Currently, the heating behaviour is already linked to the occupancy states, however, improvements could be made regarding the differentiation between rooms and as well with some links to the performance of activities. Additionally, the model could benefit from an update of the lighting use model. Finally, the model does not provide a connection between the different types of OB (e.g. closing the window when turning the heating on). Providing such connections between the different types of OB will improve the model as well. The impact of this connection can be important and will be discussed in Section 11.5.

Part III

Evaluate the impact on the energy use and IEQ

In the previous parts the importance of building control habits were discussed and a new event-based occupant behaviour model based on habits was created. This habit-based approach has some advantages such as the prediction of inter-occupant diversity, easy implementation in BES and the prediction of realistic actions that fit in the occupants' day-to-day life. However, for application purposes it can be questioned if the inclusion of these habits makes a significant impact on the energy use and indoor climate. Therefore, this third part focusses on the last objective, namely, assessing the impact of the habit-based approach on the energy use and indoor climate predictions.

First, in Chapter 10, the modelling of one of the houses of the case study is explained. This model will be used in the further analyses. In Chapter 11, the impact of the use of the EROB-model in building simulations is assessed. The simulations are carried out for both the overall model and for a base-model including only one type of OB, to evaluate which type of OB has the most influence. In Chapter 12 the focus is more specifically on the window use habit model. The model is evaluated for its influence on the energy use and indoor environmental quality predictions by comparing the model to other window use models from the literature. Additionally, the importance of predicting realistic window use actions, one of the intrinsic characteristics of the habit-based approach, is assessed.

10

Model setup and approach

In order to evaluate the energy use and IEQ, one of the houses from the case study neighbourhood (Chapter 2) has been modelled in Modelica. The modelling approach, library components and modelling assumptions are clarified in this chapter.

10.1 Model environment and libraries

The model is created in the object-oriented modelling language Modelica, which is tailored for the modelling of complex systems containing mechanical, electrical, electronic, hydraulic, thermal, control or process-oriented sub-components. The equations used in the language do not have a pre-defined causality which makes the language very suitable for the modelling of physics, and more specifically, dynamic multi-zone energy models. The Modelica code is constructed in the simulation environment Dymola. This model is created based on components of the Modelica 3.2.3 and the IDEAS 2.1.0 library [202].

10.2 Case study model

The model is based on one of the houses from the case-study neighbourhood. It represents a 2-storey terraced house with 3 bedrooms, with a total surface area of 100 m^2. The house is fitted with a balanced mechanical ventilation system with heat recovery, all windows are operable and on some windows external solar screens are provided. In reality the house is heated with radiators connected to a district-heating system, however, in the model an ideal heating system is applied which directly compensates the heat losses. The model uses climate data from Uccle, Belgium. The overview of the model is given in Figure 10.1.

The model is a representation of the as-built situation. However, to assess the influence of different building properties and systems, additional components for the building structure, ventilation system and heating system are modelled as well, creating a multitude in options for the simulation of the house. The model including the different options is developed in cooperation with K. Simić (model of the heating system) and K. Van den Brande (part of the building structure model) as part of the SBO-project NEPBC [15]. The modelling details and the different options are discussed in the next sections.

10.2.1 Building structure

The building structure components consist of 9 zones representing the different rooms (Figure 10.2). The properties of the structure models were adapted to create buildings of different energy performance levels while preserving the geometry and orientation. Adaptations were made to the insulation levels and airtightness of the building envelope, and to the built-up and solar thermal properties of the windows. Three building structures were created:

- Good energy performance: as-built situation (NZEB).
- Medium energy performance: building envelope compatible to energy performance standards of 2006, at the start of the EPB regulative framework in Flanders (E100).

- Poor energy performance: building envelope compatible to building practices in the seventies. This means low or no insulation thicknesses, simple double glazing with a high solar factor and a very poor airtightness (Y70).

The properties of the different building envelopes are given in Figure 10.3.

The windows are modelled by a combination of two components. One component to model the thermal performance (window-component from the IDEAS.Buildings-library), and a second component to model the air flow. The air flow window-component is given in Figure 10.4. This component calculates the flow rate through a window and then assigns the flow to the zone by using air flow pumps. The air flow pumps are components in IDEAS that allow to model an air flow rate by mimicking the operation of a fan. The air flow rate is calculated with the equation of Phaff for single sided ventilation which is based on the temperature difference and wind speed [63] (Equation 10.1), since in most rooms the windows are only situated at one side of the room. This approach was chosen over the use of the window/door-airflow component of IDEAS, since it results in faster simulations. The opening angle used in the equation represents a tilted window, as this was the most common window state according to the online survey. Further research is necessary to create a model that can predict the variations in opening angles.

The flow rate by infiltration is simulated per zone based on the airtightness. The infiltration-component (interzonalairflow) represents a fixed mass flow rate that is directly injected into and extracted from the zone. The mass flow rate is computed from the zone airtightness (n50). Additionally, door-components are included that allow for air flow between the zones. The doors are assumed to be always closed, however, air flow between the zones can still occur through ventilation grids in the door.

$$q_v = \frac{A_{open}}{1000} * \sqrt{2500 + 250 * v^2 + 900 * (T_i - T_e) * h} \tag{10.1}$$

$$A_{open} = A * J(\theta)$$

With q_v the air flow rate (m^3/s), A_{open} the open area of the window (m^2), v the wind speed (m/s), T_i the indoor temperature (°C), T_e the outdoor temperature (°C), h the height of the window (m), A the surface area of the window (m^2) and $J(\theta)$ a correction factor determined by the opening angle of the window.

Solar shades can be assigned to the thermal window components. In this case an external screen is present in the south-oriented rooms and on the roof windows. The opening of windows and lowering of solar shades is controlled by the WindowUse input and SolarShading input. The Occupancy input provides the number of persons present in each zone, based on this input the metabolic heat gains and CO_2-production are determined.

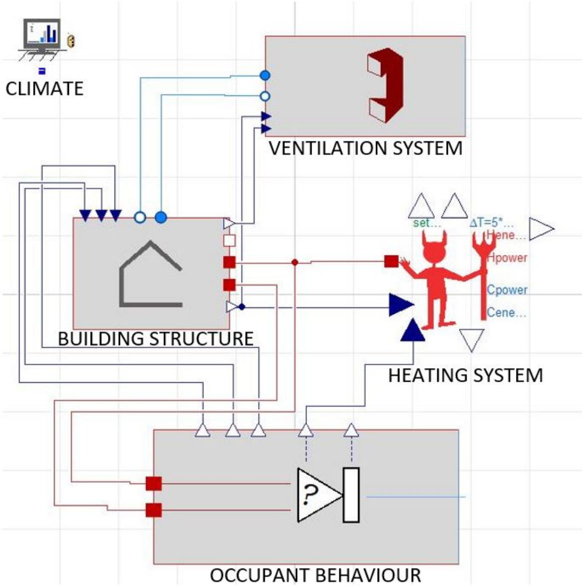


Figure 10.1: Overview of the model of a house from the Venning neighbourhood in Modelica.

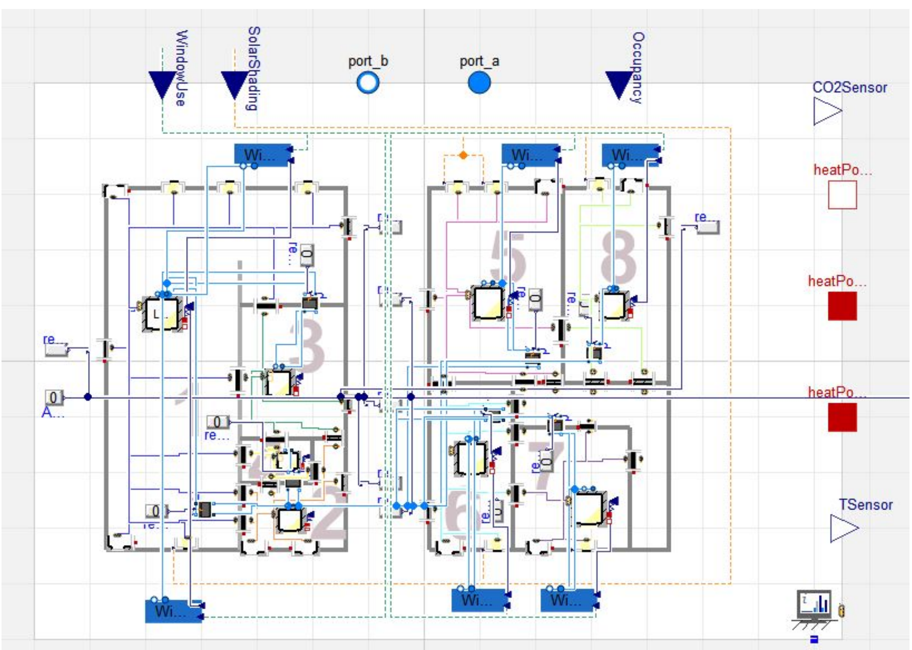


Figure 10.2: Overview of the building structure in Modelica.

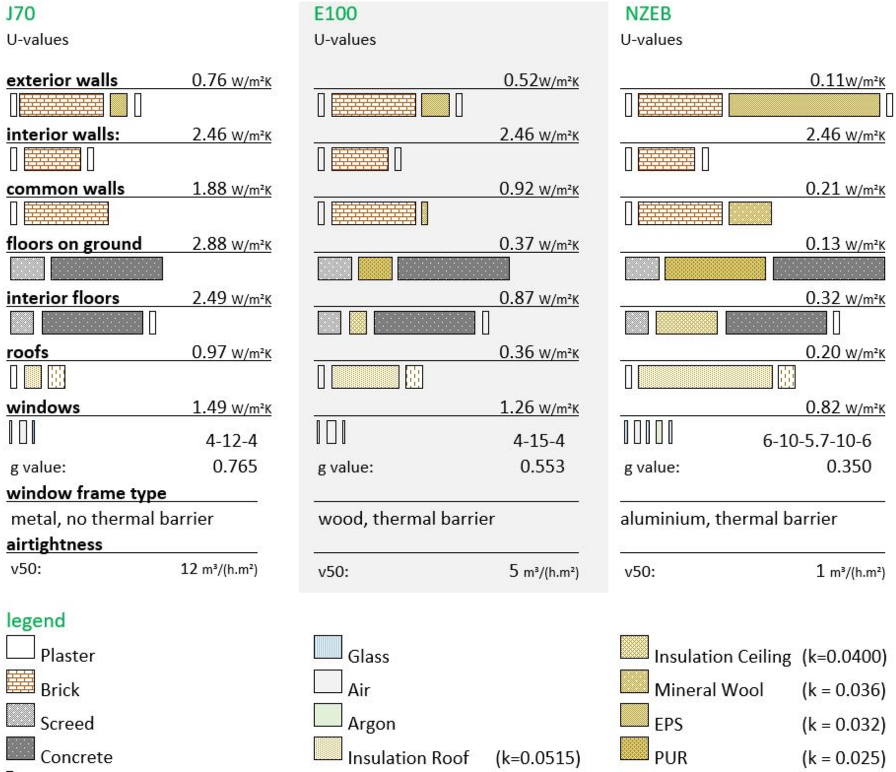


Figure 10.3: Overview of the properties of the building envelopes.

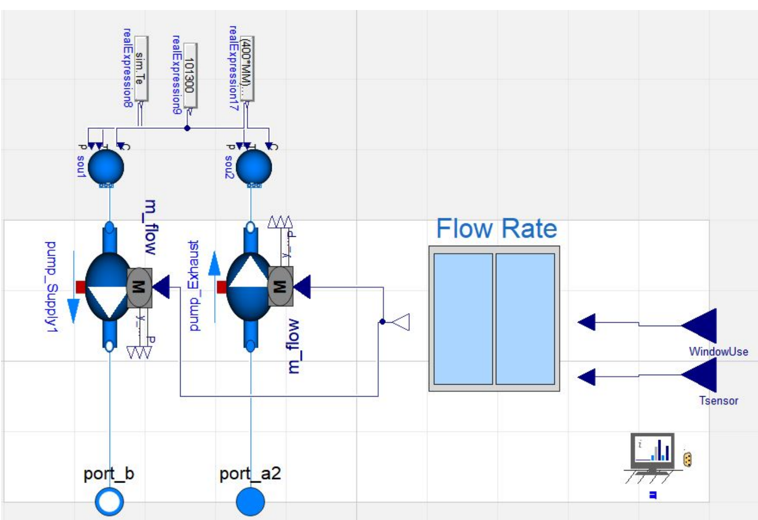


Figure 10.4: Overview of the air flow window-component in Modelica.

10.2.2 Ventilation system

For the ventilation system as well different options were created:

- Balanced ventilation system with heat recovery and summer by-pass (as-built situation).
- Exhaust ventilation system with fixed flow rate
- Demand-driven exhaust ventilation system
- No ventilation system (only infiltration and window airing)

All ventilation systems are modelled using one or multiple pump-components that represent the air flow initiated by a fan. The balanced ventilation system is equipped with pumps to provide the supply and exhaust flow rate (Figure 10.5). A heat recovery component is included with the option to by-pass it in summer. The bypass is activated when the indoor air temperature is above 21°C and the outdoor air temperature is above 9°C. The effectiveness of the heat recovery is 80%.

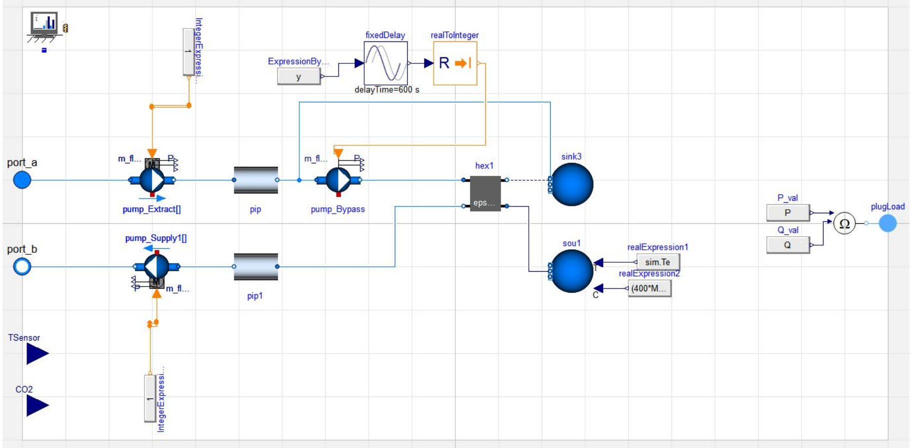


Figure 10.5: Overview of the balanced ventilation system in Modelica.

The exhaust ventilation system with fixed flow rate is modelled in a similar way, with pumps for both supply and exhaust at the fixed ventilation rate. The supply air is in this way simplified by a pump instead of inlet openings. Both systems with fixed flow rate operate at the operative flow rate as defined by the Flemish EPB-calculation, which is 51% of the design flow rate for this specific building. The design flow rate is given in Table 10.1.

For the demand controlled exhaust ventilation system the flow rate is based on the CO_2-concentration in the individual rooms (Figure 10.6). If the CO_2-concentration rises above 800 ppm the ventilation rate is increased from 20% of the design flow rate to 100%. The increase in ventilation rate is balanced out across rooms, so when the exhaust ventilation rate in the bathroom is increased the supply rate is increased as well. Finally, there is as well the option that there is no ventilation system present. For this option the ventilation component is omitted.

10.2.3 Heating system

The building is coupled to an ideal heating system that can compensate the energy losses of all concerned zones of the dwellings. The applied system can be considered to match the properties of an electrical heating system that instantly transfers heat by convection without power restrictions.

Table 10.1: Design flow rate in the different rooms.

	flow rate [m^3/h]
Supply [m^3/h]	
Living	115
Bedroom 1	55
Bedroom 2	35
Bedroom 3	35
Exhaust [m^3/h]	
Kitchen	100
Bathroom	65
Storage	50
Toilet	25

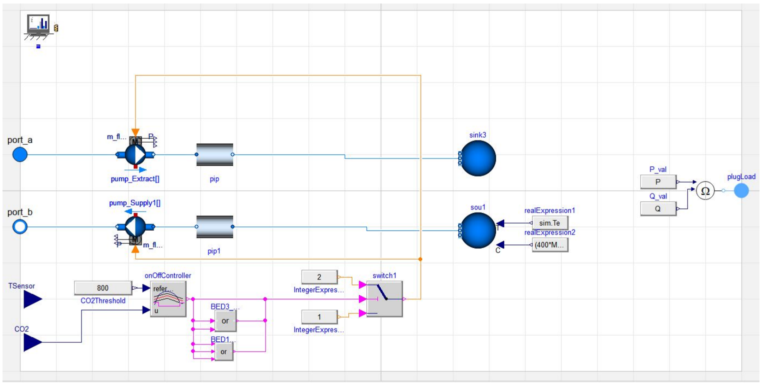


Figure 10.6: Overview of the demand driven exhaust ventilation system in Modelica.

10.2.4 Occupant

Finally, the occupant component (Figure 10.7) provides input for the other components related to the occupant behaviour. The component provides for the building structure per zone the occupancy, the window use, the use of solar shades, and the internal heat gains (both convective and radiative). Additionally, the heating set-points in each zone and the demand of domestic hot water is given to the heating system. Finally, the total electricity use is as well provided.

The component reads in the required OB-data from text-files calculated with a separate OB-model. This can for example be the StROBe-model (Section 7.3) or the newly developed EROB-model (Chapter 9).

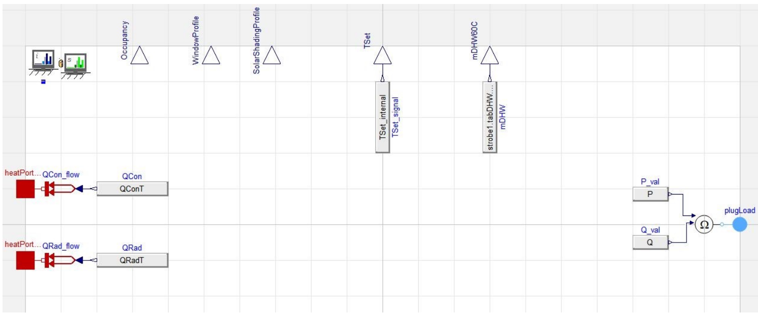


Figure 10.7: Overview of the occupant behaviour component in Modelica.

10.3 Approach

To assess the impact of the modelled OB on the energy use and IEQ, the outputs of the EROB-model are used as inputs in the Modelica model of the case study. To assess as well the impact of different building properties, some of the simulations were carried out for three variations of the building:

- Y70: building structure from the seventies without a ventilation system
- E100: building structure with E-level of 100 with a demand-controlled exhaust ventilation system
- NZEB: NZEB-building structure with a balanced heat-recovery ventilation system

Since the OB-model is stochastic, 30 households were simulated to get a representative result sample. For each of the households, first the occupancy and activity-profiles are created. These occupancy and activity profiles are used as input for the full simulations of these 30 households for each of the three buildings. Identical profiles are used for each building only the window use deviates as it is dependent on the installed ventilation system. In this way 90 different households have been simulated.

The presence-level of the households varied between 57% and 99%, with for larger families often high presence-levels. The OB-model often predicts unheated bedrooms and bathrooms (Table 10.2). These are given a default heating setpoint of 12°C, to prevent unrealistically low indoor temperatures. Consequently, the average heating set-points are often low, as can be seen in the average heating set-points of the households in Figure 10.8. The window opening percentages are different for each household and each building since these are dependent on the ventilation system. A high diversity in window use is observed between the simulated households (Figure 10.9). It is assumed that the shades are not used, since a solar shading model is currently lacking in the EROB-model. These 90 households are used in the building energy simulations in the next chapters.

Table 10.2: Setpoint temperatures when occupants are active, asleep or away, and heated rooms for each of the 30 simulated households.

HH	Setpoint temperatures			Heated rooms		
	Active	Asleep	Away	Bedroom	Bathroom	Living room
1	20	14.5	15			x
2	20	15	19.5			x
3	20	14.5	15			x
4	21	20.5	21	x	x	x
5	20	15	19.5		x	x
6	20	15	19.5			x
7	20	15	19.5		x	x
8	21.5	15.5	21.5		x	x
9	18.5	15	18.5		x	x
10	20	14.5	15			x
11	20	11	19.5	x		x
12	17	14	15	x	x	x
13	20	14.5	15			x
14	20	14.5	15			x
15	21.5	15.5	21.5		x	x
16	20	11	19.5			x
17	21.5	15.5	21.5		x	x
18	21	20.5	21	x	x	x
19	20	14.5	15			x
20	20	14.5	15			x
21	21.5	15.5	21.5		x	x
22	21	20.5	21	x	x	x
23	18.5	15	18.5		x	x
24	20	15	19.5			x
25	20	15	19.5	x		x
26	21.5	15.5	21.5		x	x
27	18.5	15	18.5		x	x
28	18.5	15	18.5		x	x
29	20	15	19.5		x	x
30	20	11	19.5			x

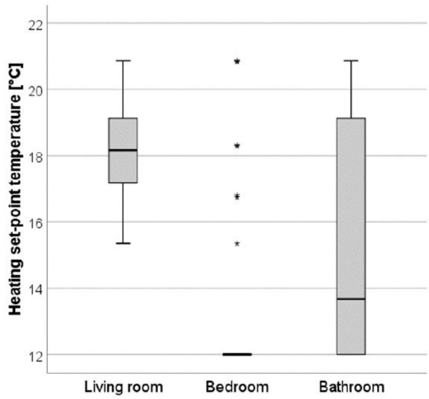


Figure 10.8: Time-averaged heating set-point for the different households in the different rooms.

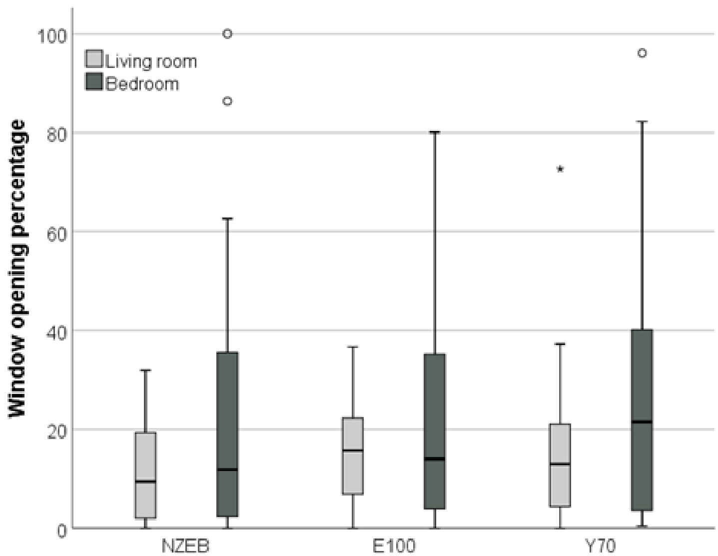


Figure 10.9: Window opening percentage for the different households in the living room and bedroom.

11

Impact of EROB-model

In Chapter 9 an event-based occupant behaviour model based on habits was created. This habit-based approach has some advantages such as the prediction of the inter-occupant diversity and realistic actions that fit in the occupants' day-to-day life, and easy implementation in BES. However, for application purposes it can be questioned whether the inclusion of these habits has a significant impact on the energy use and indoor climate. Therefore, the impact of including OB in building energy simulations is assessed, as well as the importance of each individual type of OB.

11.1 Methods

The simulations are carried out for the EROB-model coupled to the model of the case study house in Modelica for the 30 different households. The evaluation of the impact is based on three criteria: the net energy use for space heating, the CO_2-concentration as a measure for IAQ and the overheating.

To assess the influence of including the different types of OB, the simulations were carried out as well for each type of behaviour separately (occupancy/activity, heating behaviour, and window use). The DHW was not considered in this comparison as it has no influence on the energy use for space heating or the indoor environmental quality. For the comparison only the behaviour under review was changed while the other types of behaviour remained fixed as in a base-model. The base-model represents a simple OB-model by assuming default settings:

- The heating set-point is always 20°C in all rooms.
- The windows are always closed.
- The solar shades are not used.
- An average occupancy and activity profile is selected to account for the internal heat gains (persons and appliances).

11.2 Impact on heating energy

The results of the simulations for the energy use for space heating are given in Figure 11.1. The base-model predicts a yearly energy use for space heating of 1683 kWh/year, 5609 kWh/year and 13991 kWh/year, for respectively the NZEB-building, E100-building and Y70-building (surface area is 100 m^2).

The inclusion of the different occupancy-profiles leads to a range (90th-10th percentile) in heating energy use between 486 kWh/year and 2015 kWh/year for the different buildings (Table 11.1). While the 90th percentile of the energy use for heating for the occupancy profiles is approximately 1.1 times higher then the 10th percentile in the Y70 and E100-buildings, the factor increases to almost 2 for the NZEB-building. Due to the already low heating energy use in the NZEB-building, the relative impact of the diversity in occupancy profiles is more important than in the other buildings.

As expected, the heating behaviour has a large influence on the total heating energy demand. The range is respectively 1513 kWh/year, 3181 kWh/year and 6531 kWh/year, for the NZEB, E100 and Y70-buildings. This amounts to a proportion (high-low) of 3.29, 2.11, and 1.78 respectively, showing again a greater proportional impact of the heating behaviour in the energy efficient buildings. Additionally, the average heating energy use is significantly lower compared to the base-model for all buildings. This can be attributed to the uniform choice of heating set-point of 20°C in the base-model, while the OB-model often predicts unheated bedrooms and bathrooms (Section 10.3 - Figure 10.8), and therefore a lower heating demand.

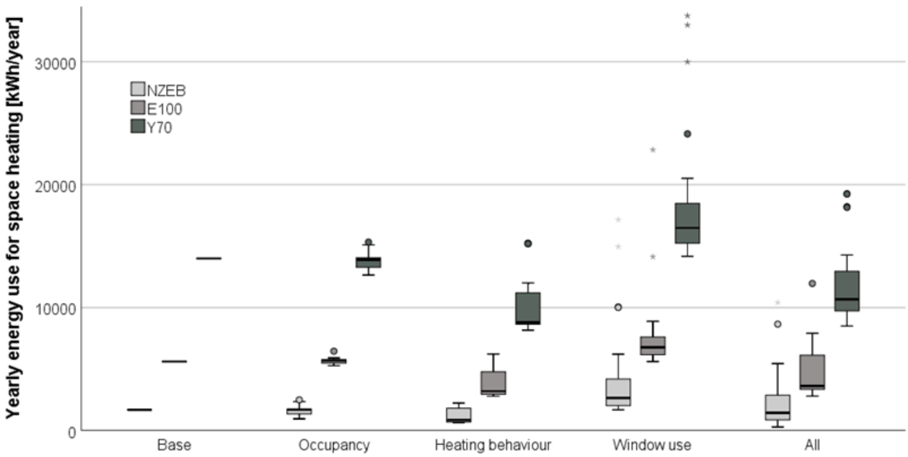


Figure 11.1: Yearly energy use for space heating for three different buildings for the different types of occupant behaviour.

The inclusion of the window opening behaviour results in the highest variability in heating energy use, with a range of more than 3000 kWh/year for the E100-building and even more than 8000 kWh/year for the other two buildings. It is observed that the impact of including window use is proportionally smaller in the E100-building compared to the other buildings. Since the opening of windows reduces the CO_2-concentration the ventilation system will operate less in boost-mode, reducing the ventilation flow rates of the ventilation system and thus the heating demand. While in the Y70 and E100 building the distribution of the heating energy use for the different window use profiles is approximately normal distributed, a slightly skewed distribution is observed in the NZEB-building towards the lower energy use. This can be attributed to the higher share of low opening percentages in the NZEB-building (Section 10.3).

The inclusion of the window use leads to the highest average energy use for heating (4138 kWh/year, 7656 kWh/year, 18421 kWh/year). The opening of the windows when the heating set-point is 20°C results in high energy losses, especially in wintertime. For households that open the windows often in wintertime the heating energy use is significantly higher. In this way a E100-building in which the windows are often opened can have the same energy use for heating as a Y70-building where the windows are never opened. Since the range in heating energy use is extremely high, this leads to high proportional influences for all buildings, but especially for the energy efficient ones with up to a factor 5 difference between minimum (10th percentile) and maximum (90th percentile) heating energy use. It should be noted that in reality the range might not be that extreme as some occupants may turn off the heating when they open a window. The effect of the connection between types of OB is investigated further in Section 11.5. In Chapter 12 the impact of the window use habit model on the energy use and IEQ is analysed in more detail.

Table 11.1: Yearly heating energy use per building per OB-type: mean, median, 10th percentile, 90th percentile, range (90th perc-10 th perc), proportion high-low (90th perc/10th perc) and proportion median (range/median)

		Mean	Median	10th percentile	90th percentile	Range	Proportion high-low	Proportion median
Base	NZEB	1683						
	E100	5609						
	Y70	13991						
Occupancy	NZEB	1603	1685	1164	2278	1114	1.96	0.66
	E100	5653	5675	5366	5852	486	1.09	0.09
	Y70	13779	13891	12987	15003	2015	1.15	0.14
Heating	NZEB	1159	849	661	2174	1513	3.29	1.78
	E100	3818	3202	2866	6048	3181	2.11	0.99
	Y70	10016	8792	8339	14870	6531	1.78	0.74
Window	NZEB	4138	2649	1742	10046	8304	5.77	3.13
	E100	7656	6765	5724	8848	3124	1.54	0.46
	Y70	18421	16473	14697	29989	15292	2.04	0.93
All	NZEB	2314	1438	443	5391	4948	12.17	3.44
	E100	4740	3618	3095	7246	4151	2.34	1.15
	Y70	11768	10673	8697	18203	9506	2.09	0.89

The average heating energy use when all types of OB are jointly considered is respectively 2314 kWh/year, 4740 kWh/year and 11768 kWh/year for the different buildings. This average energy use is higher than the base-model load for the NZEB-building, and lower for the E100 and Y70-building. This difference can be attributed to the combination of the heating behaviour and window use. While the inclusion of the window use increased the energy use compared to the base-model, the lower heating set-points reduced the energy use. Since the heating behaviour has a smaller impact in the NZEB-building the average energy use increased, while for the other buildings the average energy use decreased. Similar trends were observed in performance gap research (Section 1.1.3), with overestimations of the energy use in older buildings and underestimations in more energy efficient dwellings. This might indicate indeed that the modelling of occupant behaviour can play an important role in the reduction of the performance gap.

Based on the simulation results the importance of the performance gap reduction can be illustrated. For this dwelling the base model predicts savings of 8382 kWh/year and 12308 kWh/year going from Y70 to E100 and to NZEB respectively, while the simulation with the OB-model only predicts a saving of 7028 kWh/year and 9454 kWh/year. Thus savings by improving the Y70 building to respectively an E100-building or NZEB-building according to the simulation with the OB-model are 84% and 77% of the ones according to the base model. The overestimation of the energy use savings by the base model might lead to wrongful stimulation of specific energy measures, as others might be more effective for the reduction of the energy use.

The variability in heating energy use is large with a range of almost 5000 kWh/year for the NZEB and E100 buildings and almost 10000 kWh/year for the Y70-building. Nevertheless, due to the fact that the NZEB-building already has a low heating energy demand, the proportional impact (range/median) is high (factor 3.4) while a much smaller proportional impact is observed in the E100 (1.1) and Y70-building (0.9).

It can be concluded that the heating energy use can differ significantly in a specific building depending on the household that lives in it. The diversity between households is therefore very important to consider, especially in highly energy efficient buildings. For all types of OB the impact on the heating energy demand is significant, however, the OB with the most influence is the window use followed by the heating behaviour.

11.3 Impact on indoor air quality

Next to the heating energy demand, the OB will as well influence the indoor environmental quality. In this section, the impact on the indoor air quality is assessed using the CO_2-concentration as evaluation criterion. The average yearly CO_2-concentrations as simulated for the bedroom and living room are given in Figure 11.2 and Figure 11.3.

The type of ventilation system and type of building have an important influence on the average CO_2-concentration in the rooms. The average yearly CO_2-concentration is the highest for the Y70-building, followed by the NZEB-building and the E100-building. The fixed flow rate of the balanced ventilation system (51% of the design flow rate) in the NZEB-building is not always sufficient leading to higher CO_2-concentrations compared to the demand driven ventilation system (E100) for which the flow rate is increased to 100% design flow rate when the threshold of 800 ppm is exceeded. The Y70-building is the least airtight, but has no ventilation system, resulting in the highest CO_2-concentrations. The CO_2-concentrations for one day in the bedroom and living room are given in Figure 11.4 and Figure 11.5 for the base model to illustrate the impact of the building type and ventilation system.

The inclusion of different occupancy profiles results in wide variations in average CO_2-concentrations, especially in the NZEB and Y70-building. Due to the demand driven threshold of 800 ppm, the variation in CO_2-concentration is rather limited in the E100-building. The window use impacts the average CO_2-concentration as well. While the maximum CO_2-concentration is observed for the base-model (all windows closed), it was significantly reduced by the opening of windows. An example for the living room of the NZEB-building is given in Figure 11.6. The effect is most notorious in the seventies building, as the efficient use of the windows can reduce the CO_2-concentrations to similar levels as in buildings were ventilation systems are installed.

It can be concluded that the predicted CO_2-concentration is as well highly impacted by the inclusion of OB in the simulations. A wide range in CO_2-concentrations is observed for the different occupancy profiles of the households. While for some households in the NZEB-building, the provided air flow rate was sufficient to allow for a good indoor air quality, for others the ventilation rate should be increased. This emphasizes the importance of a good fitting of the ventilation system to the needs of the different households. The inclusion of window use in the simulations resulted in significant lower CO_2-concentrations. Therefore it is necessary to consider the window use to obtain accurate assessments of the indoor air quality.

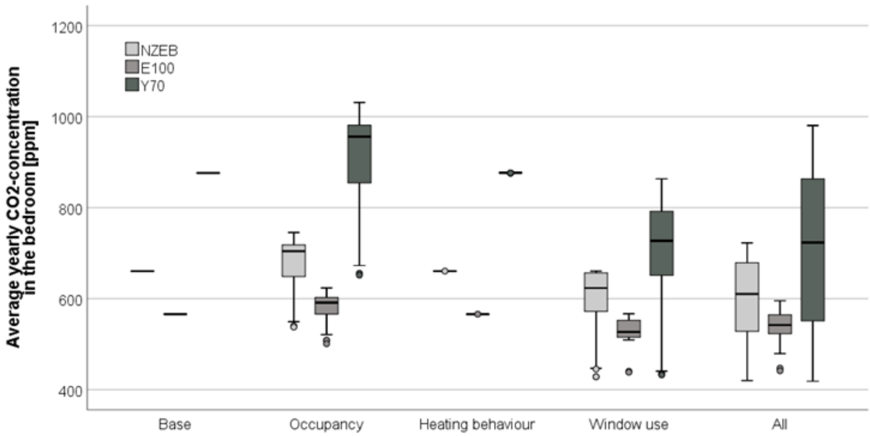


Figure 11.2: Average CO_2-concentration in the master bedroom, as a measure for the indoor air quality, for three different buildings and for the different types of occupant behaviour.

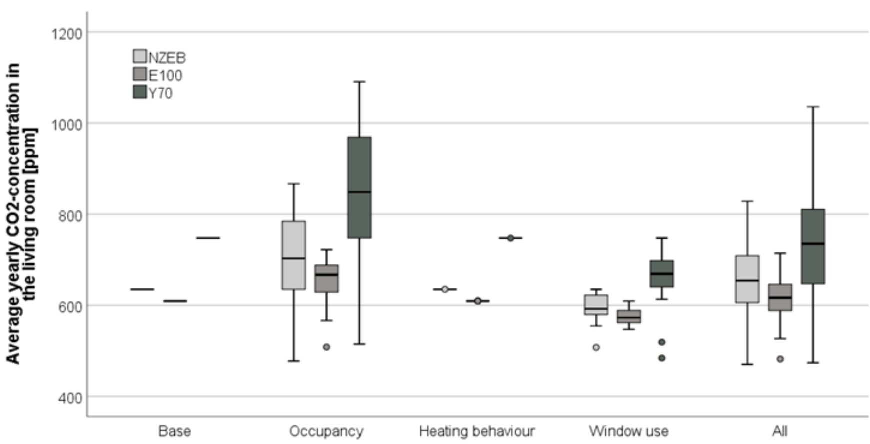


Figure 11.3: Average CO_2-concentration in the living room, as a measure for the indoor air quality, for three different buildings and for the different types of occupant behaviour.

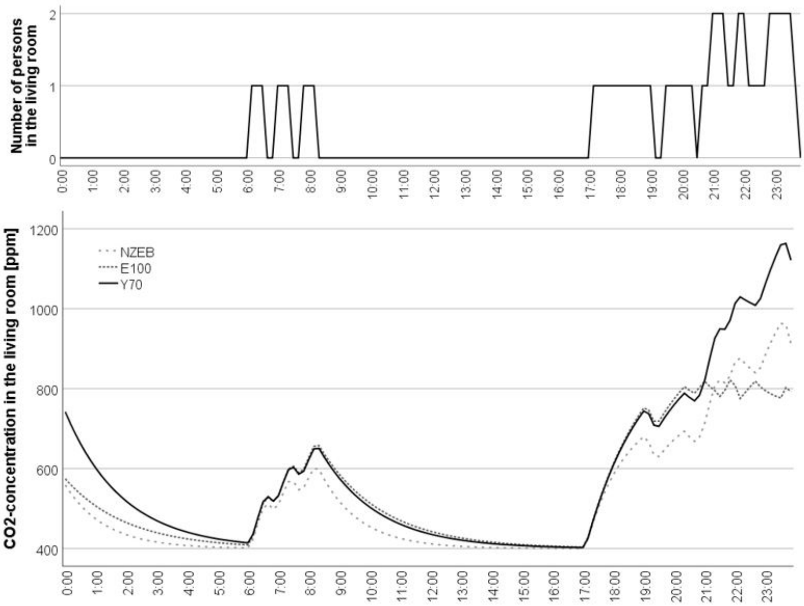


Figure 11.4: Occupancy and CO_2-concentration for one day in the living room for the three different buildings.

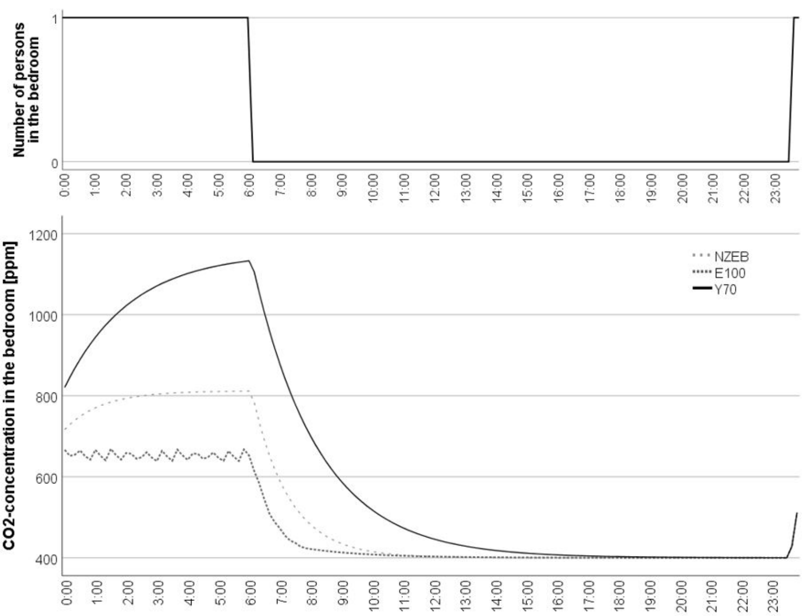


Figure 11.5: Occupancy and CO_2-concentration for one day in the bedroom for the three different buildings.

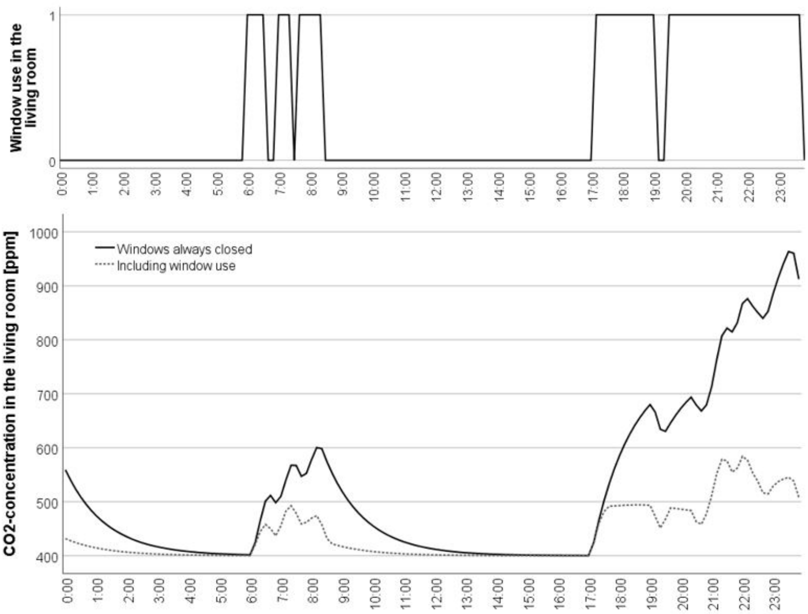


Figure 11.6: CO_2-concentration for one day in the bedroom of the NZEB-building for different window use.

11.4 Impact on overheating

Finally, occupant behaviour has an impact on the overheating as well. In this section, an assessment is made of the impact on the overheating predictions by including OB in building simulations. The overheating is expressed in Kelvin hours above 26°C. In Figure 11.7 and Figure 11.8 the overheating is shown for respectively the living room and bedroom.

Overheating is more common in the NZEB and E100-buildings due to the high insulation-levels, especially in the living rooms. Nevertheless, in the bedroom the NZEB-building has the least overheating, this is due to the presence of a summer bypass in the ventilation system, which allows for fresh air to enter instead of pre-heated air when the indoor temperature is above 21°C and the outdoor temperature above 9°C. But this can as well be attributed to the high insulation level of the roof and windows, reducing the heat gains significantly. In the E100-building overheating is more common even though in these buildings the supply air is always unheated. This can be attributed to the lower ventilation rate when nobody is present in the room. At the hottest moments of the day the bedroom tends to be unoccupied and the reduced ventilation rate is not able to cool down the room. In Figure 11.10 and Figure 11.11 this is illustrated with the operative temperatures in respectively the living room and bedroom for an exemplary day for the three different buildings. Figure 11.9 gives the outdoor temperatures for that day.

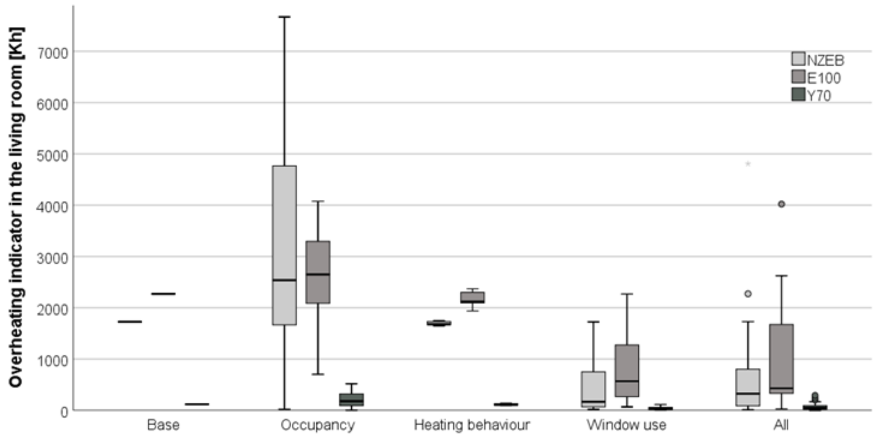


Figure 11.7: Overheating indicator in the living room for three different buildings and for the different types of occupant behaviour.

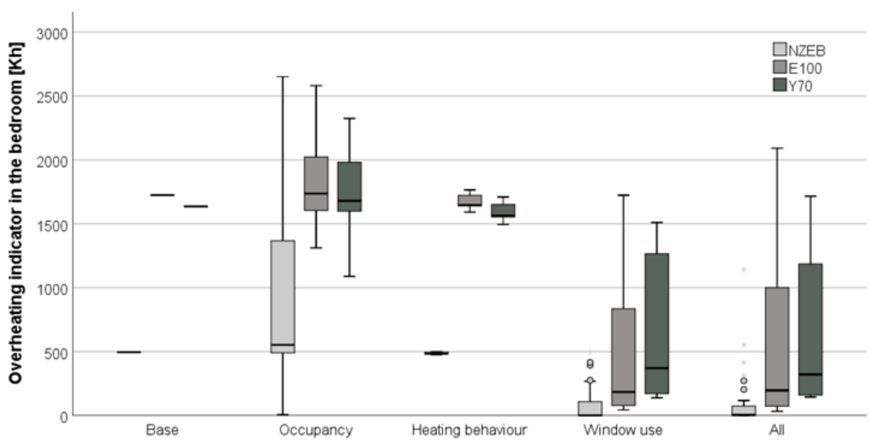


Figure 11.8: Overheating indicator in the bedroom for three different buildings and for the different types of occupant behaviour.

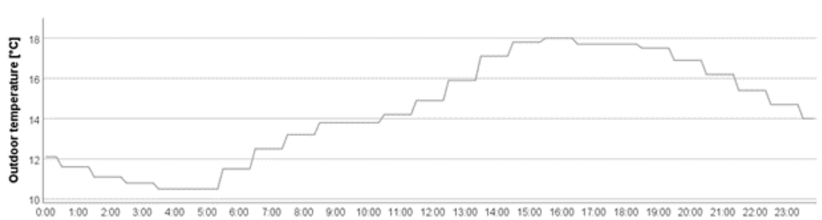


Figure 11.9: Outdoor temperature on the exemplary day.

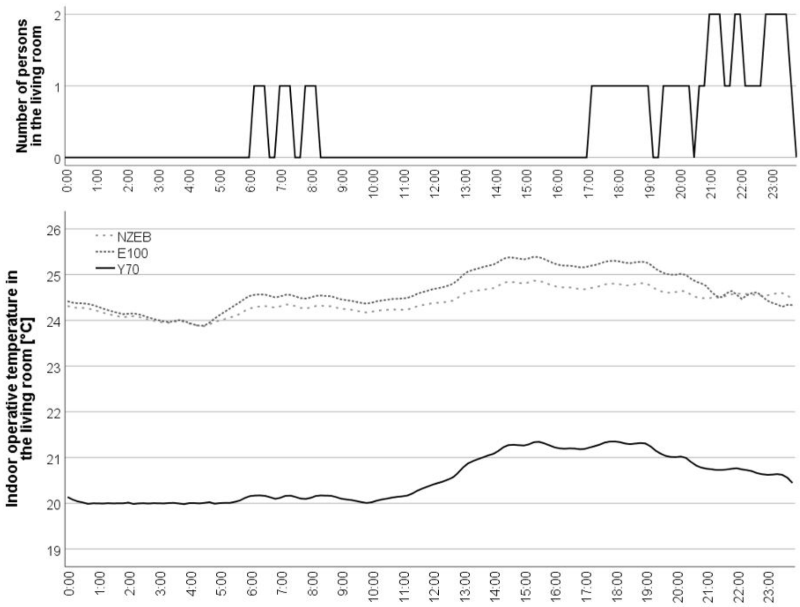


Figure 11.10: Indoor operative temperature in the living room for three different buildings.

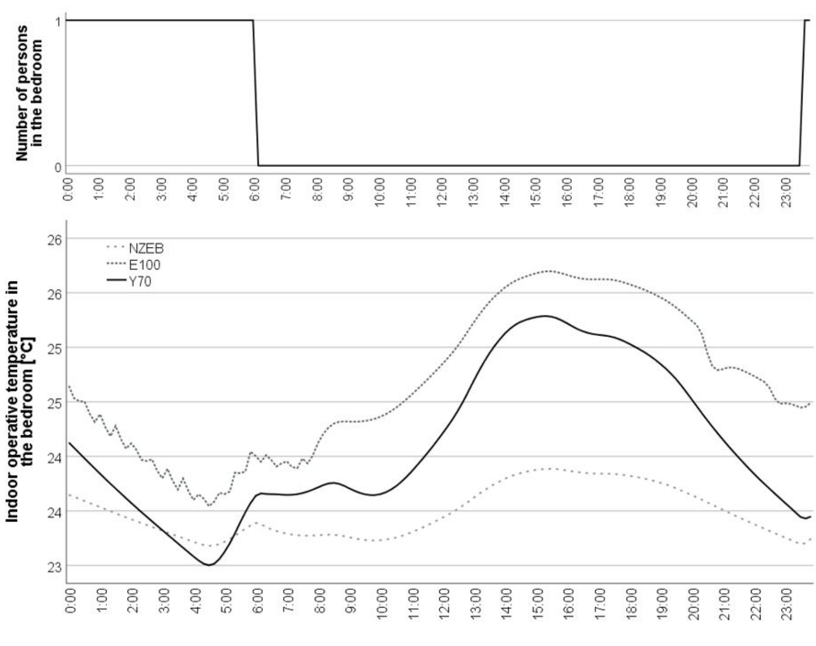


Figure 11.11: Indoor operative temperature in the bedroom for three different buildings.

The variation in occupancy profiles has a significant impact on the overheating prediction, especially, in the energy efficient buildings, with for some households serious overheating (almost 8000 Kh in the living room) while other households in the same building had rarely any overheating (minimum 22 Kh in the living room). Due to the increased insulation levels of the energy efficient buildings the internal heat gains due to persons and appliances are longer kept inside the buildings, leading to more overheating, but as well larger variations due to the occupancy.

Again the window use has a significant impact on the overheating, with the maximum overheating occurring when the windows are always closed and no overheating at all when the windows are frequently used. The distribution of the overheating due to the varying window use is strongly skewed to the lower end, even though the window use itself is only slightly skewed for the NZEB-building and normal distributed for the other buildings (Section 10.3). This indicates that most of the predicted window use profiles are already sufficient to lower the overheating significantly. An example of the effect of including window use on the overheating is given in Figure 11.12 for the living room of the NZEB-building.

It can be concluded that the predicted overheating in the building is as well seriously impacted by the inclusion of OB in the building simulation. Again, the diversity in occupancy and window use had the most fundamental impact. A significant reduction of the overheating was observed for most window use profiles in all types of buildings, indicating that opening the windows for a short time can already be sufficient to limit overheating.

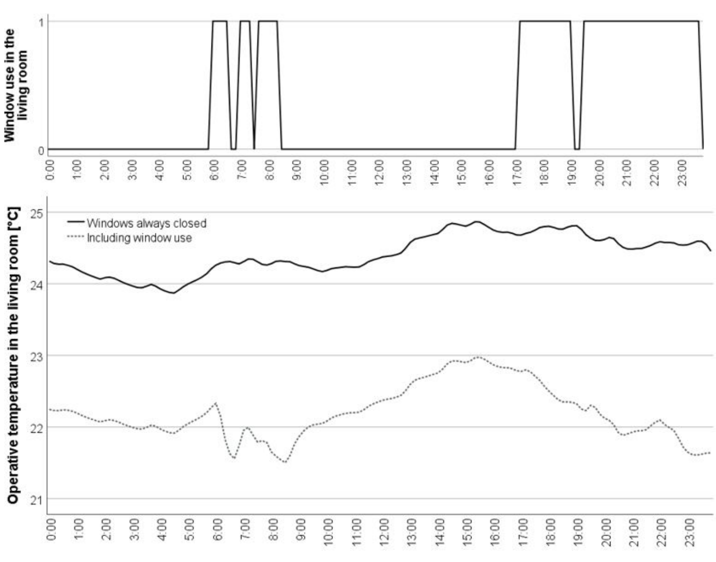


Figure 11.12: Indoor operative temperature in the living room of the NZEB-building with and without the inclusion of window use.

11.5 Combination of different types of OB

In the previous simulations the different types of OB were simulated separately. While there is a connection between the occupancy and the other behaviours, a more in depth link could be assumed. For example window use is possibly closely interrelated with the heating behaviour, as many occupants will close the window when turning on the heating or the other way around. Based on the research conducted in this dissertation no information is available on this connection between behaviours and possibly as well habits in the different rooms. For example, occupants that have a habit of always leaving the bedroom windows open might have the habit of never heating that room.

To assess the impact of the combination of different types of behaviours, the complete model as discussed above is compared with a similar model but including the restriction that the heating is turned off when the window is opened. The results of these simulations for each of the three buildings are given in Figure 11.13 and Table 11.2.

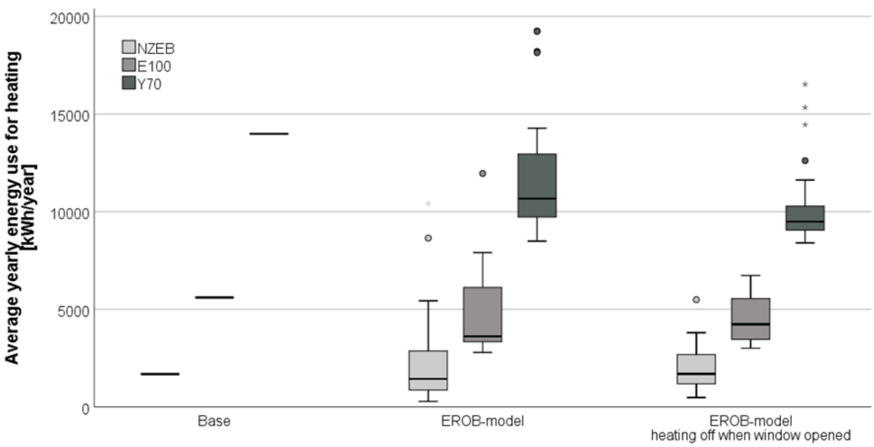


Figure 11.13: Yearly energy use for heating for three different buildings for the combination of all OB and for the combination of all OB with the adaptation of turning the heating down when opening window.

Table 11.2: Yearly heating energy use per building per OB-type: mean, median, 10th percentile, 90th percentile, range (90th perc-10 th perc), proportion high-low (90th perc/10th perc) and proportion median (range/median)

		Mean	Median	10th percentile	90th percentile	Range	Proportion high-low	Proportion median
EROB-model	NZEB	2314	1438	443	5391	4948	12.17	3.44
	E100	4740	3618	3095	7246	4151	2.34	1.15
	Y70	11768	10673	8697	18203	9506	2.09	0.89
Heating off when window open	NZEB	1977	1693	534	3486	2952	6.53	1.74
	E100	4583	4235	3198	6606	3408	2.06	0.80
	Y70	10272	9491	8670	14634	5963	1.69	0.63

The heating energy use decreased when the heating was turned off with window openings. While the median energy use decreased only slightly, the high profiles with very high energy use were reduced more significantly, with that reducing the range of the heating energy use.

Along with this illustration of possible relations between different types of OB many others may be present. Currently, few studies have been conducted that investigate the relationship between the different types of OB.

11.6 Discussion: Application in practice

In Section 7.2 some demands were set out to which OB-models should comply in order to be applied in practice. The OB-models should be easy to implement in standard BES-software, should not require advanced knowledge of the practitioner and the computational time should be limited. The EROB-model complies with all of these demands. In this section, it is clarified how this OB-model might be used in practice and for which purposes.

11.6.1 Use of detailed model

First, the model in its current form (as discussed in Chapter 9) can be used to perform detailed dynamic multi-zone simulations. These detailed OB predictions are not only useful for the energy use predictions (as discussed above) but are useful for a multitude of applications. For example, they can be used to determine the stability of the energy grid [213] or for the analysis of the performance of building systems (e.g. legionella control in DHW-installations [214], performance of heating systems [215], performance of ventilation systems [216]).

The model as developed in Chapter 9 can be directly used to predict the OB in time steps of 10 minutes, or the outputs can be aggregated to a larger time step (e.g. 30 minutes, 1 hour, 1 day). However, as discussed in Section 7.2 the majority of practitioners rarely perform detailed dynamic simulations but rather base their decisions on the EPB-calculation results.

11.6.2 Application in EPB

Therefore, it is assessed in which ways the insights regarding the OB from this dissertation can be applied to the Belgian EPB-calculation. First of all, the primary goal of the EPB is the labelling of dwellings. But the EPB-calculation is often used as well to guide the design of the buildings and included systems, and to determine the energy reduction measures. Especially for these latter uses it is important that the EPB provides accurate energy use predictions. See for example the importance of reducing the performance gap for defining energy saving measures in Section 11.2.

Two possible options to include OB in the EPB-calculation are put forward. The first option keeps the EPB-calculation procedures in its current form by just improving the OB-parameters that are currently included, while the second option rethinks the way the EPB-calculation is performed by working with distributions.

Improve values for OB parameters

Currently, the energy use predictions are based on fixed values (e.g. average of a distribution, or a chosen default) of the OB-parameters (e.g. set-point temperatures or ventilation rates). Based on these fixed values the energy use is predicted, resulting in 1 value for the energy use. This is illustrated in the top part of Figure 11.14.

For this option, the possibilities for improvement are situated in the amelioration of the choice of the fixed value. This might be done by including a monthly additional ventilation rate due to window airing, which varies over the seasons, and is as well dependent on the type of ventilation system (since this was one of the predictors for the window use habits). This will still represents an average user, however, the values are more realistic than always keeping the windows closed (during the heating season).

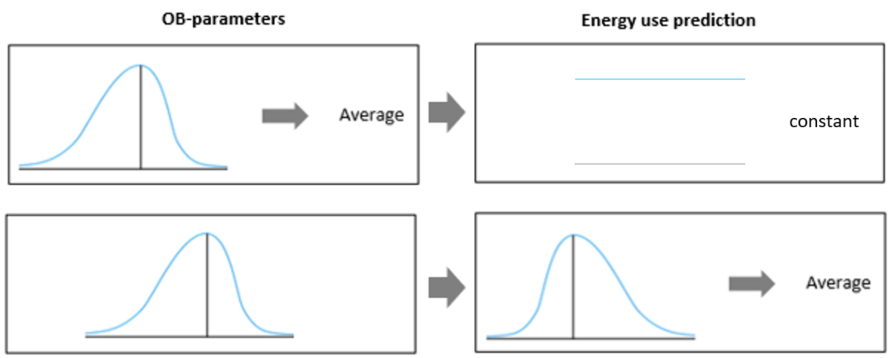


Figure 11.14: Schematic overview of the connection between the OB-parameters and the energy use predictions for the two different scenarios.

Distribution of OB parameters

However, by reducing the stochasticity of the OB-parameters already in the first step, the accuracy of the energy use predictions is reduced. As the result of simulations with average values will not be the same as the average of the results of multiple simulations with the OB-parameters according to their distributions (Figure 11.14 - bottom).

By keeping the stochasticity of the OB-parameters in the first step, a distribution of the energy use or any other metric can be defined when running a multitude of simulations. For window use an additional ventilation rate per month might be defined based on the window use habits. This ventilation rate will differ for each simulation with different habits and different occupancy and activity patterns. These simulations will result in a distribution of the predicted energy use, overheating and IAQ, for which not all of the metrics might be normally distributed. As seen in the previous section, the energy use for the different window use profiles is approximately normally distributed, but the CO_2-concentration and overheating are strongly skewed to the lower end, indicating that certain window use habits might lead to a significant reduction in overheating while maintaining an average heating energy use. This approach results in a distribution for the end-metric which allows for more informed design decisions, but as well for more informed buyers.

If the distribution of the energy use is for example very narrow it indicates that the energy use is stable for the different behaviours and therefore can be used as a good predictor of the actual energy use. However, if the distribution is wide, a high variability in energy use is observed over the different behaviours and the average energy use will be less accurate. This may inform designers on the robustness of the building and systems.

Furthermore, it can help buyers to make a more informed decision when they can position their current behaviour in the distributions to find a dwelling that is most fitting for their specific behaviour. An illustration: If for example there are two houses on the market with the same average energy use but with different distributions of this energy use. The one house has a narrow distribution slightly skewed to the left, while the other has a very wide distribution. A household that is very conscious about the energy use will probably have a lower energy use with the house with the wide distribution, while occupants with less energy conscious behaviour might have a lower energy use with the other house.

The inclusion of this diversity in OB-parameters might help to reduce the performance gap. This approach is feasible as it does not require fundamental changes to the way the EPB-calculations are performed. The calculation should be repeated multiple times with different values of the OB-parameters to arrive at a distribution. Labelling can still be done based on the selection of a pre-determined value from this distribution (e.g. average, median, 75-percentile,...).

11.7 Conclusion

The results revealed that occupant behaviour is important to take into consideration, not only for energy use predictions but as well for overheating and IAQ, especially in more energy efficient buildings. The use of the OB-model will not only benefit the energy use predictions but as well the design and control of different systems such as for ventilation or cooling.

The average energy use of the NZEB-building increased when the OB-model was included compared to the base-model, while it decreased for the other two buildings, revealing a similar trend as was observed with the performance gap. This indicates that occupant behaviour may be an important part of the explanation of the performance gap. To further improve the OB-models research regarding the combination of different behaviours would be beneficial.

Finally, some options for the application of the OB-model in practice are given to illustrate the possibilities of the model.

12

Impact of window use habit model

This chapter focusses on the impact of the application of the window use habit-model in building energy simulations. It is assessed how the window use habit model compares to other window use models from the literature and what the impact is on the predicted energy use and IEQ. Additionally the importance of predicting window use actions at realistic moments in the occupants day, one of the key characteristics of the window use habit model, is assessed as well.

12.1 Comparison with window use models from the literature

Over the years many different window use models have been developed. In this section the newly developed window use habit model is compared to four other models from the literature, namely, the Humphrey's adaptive algorithm [147] and the models of Maeyens and Janssens [125], Andersen et al. [126], and Haldi and Robinson [108]. For this assessment simulations are carried out for 30 households in the NZEB-building. To be able to compare the models easily all window use simulations are performed with the same 30 households. In this way thirty simulations are conducted with each window use model with identical inputs for comparability.

12.1.1 Applied window use models

The newly developed window use habit model is compared to four other models from the literature. These four models capture the window use in a different way. The Humphrey's adaptive algorithm (Rijal et al.) [147] is specifically focussed on the deliberative window actions to maintain thermal comfort. The models of Andersen et al. [126] and Maeyens and Janssens [125] are as well solely focussed on deliberative actions but include some factors related to the presence in the building. Maeyens and Janssens by including a correction factor for occupancy, Andersen et al. by including the CO_2-concentration which may be seen as a proxy for the occupancy. Finally, the discrete-time Markov model of Haldi and Robinson [108] as developed for offices which includes more explicitly the habitual behaviour with separate probabilities for three distinct periods in the day of the occupant. The four models are described in more detail below.

Humphrey's adaptive algorithm (Rijal et al.)

The Humphrey's adaptive algorithm [147] links the use of windows directly to thermal comfort. Windows are opened or closed only when comfort is disrupted. In a first step, it is determined if the thermal conditions are satisfying or not, by comparing the comfort temperature (T_{comf}) to the operative temperature (T_{op}), taking into account a dead-band of +-2°C.

The comfort temperature is calculated as follows:
if $T_{rm} > 10°C$:

$$T_{comf} = 0.33 * T_{rm} + 18.8 \tag{12.1}$$

else:

$$T_{comf} = 0.09 * T_{rm} + 22.6 \tag{12.2}$$

With T_{rm} the daily running mean outdoor temperature.

When the comfort requirements are not met an action may be undertaken. When it is too cold the window may be closed or when it is too hot the window may be opened. The probability that an action is taken is based on the indoor operative and outdoor temperature.

$$logit(P_{open}) = 0.171 * T_{op} + 0.166 * T_e – 6.4 \tag{12.3}$$

This model calculates the window use with a timestep of one hour. The model is applied when occupants are present in the building, during unoccupied periods the window state is assumed the same as before departing.

Model of Maeyens and Janssens

The model of Maeyens and Janssens [125] predicts the hourly probability that a window is opened (P_{open}) based on the global horizontal solar radiation (SR [W/m²]), the outdoor temperature (T_e[°C]), the wind speed (v [m/s]) and a correction factor for presence (F) [217]. This factor denotes the probability that occupants are at home (Figure 12.1). The opening probability is initially determined based on the solar radiation and outdoor temperature (Equation 12.4) and is further corrected for the wind speed and the presence (Equation 12.5).

$$\begin{aligned} \text{if SR} > 300\ \text{W/m}^2\text{:}\ P_{open} &= (2.10 * T_e + 3)/100 \\ \text{else:}\ P_{open} &= (1.16 * T_e + 3)/100 \end{aligned} \tag{12.4}$$

$$\begin{aligned} \text{if v} > 3\ \text{m/s:}\ P_{open,corr} &= (1.550 - 0.183 * v) * F * P_{open} \\ \text{else:}\ P_{open,corr} &= F * P_{open} \end{aligned} \tag{12.5}$$

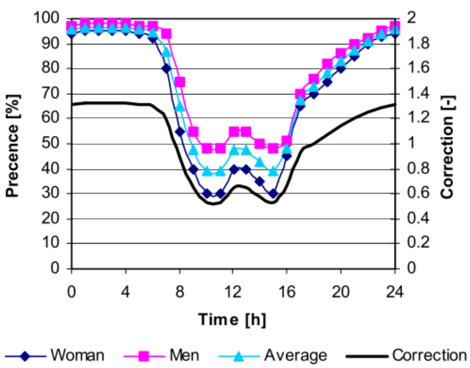


Figure 12.1: Correction factor for presence as defined by Fracastoro and Lyberg [217].

In this model the occupancy is included with a correction factor for presence, therefore the model is applied during the full simulation time without limitations during unoccupied periods.

Model of Andersen et al.

The model of Andersen et al. [126] is based on a multitude of physical environmental variables and is one of the few window use models that include the CO_2-concentration. The model predicts if an opening action occurs when the window is closed and if a closing action occurs when the window is open per 10 minutes. They developed four different models depending on the presence of a mechanical ventilation system and the ownership of the dwelling. A distinction is made between window use in the different seasons and in the different rooms (bedroom and living room). They assume that the window use in other rooms, such as the kitchen and bathroom, is similar as in the living room. In this paper, the model for rented dwellings with a mechanical ventilation system is applied (Group 4). The equations for the bedroom in summertime are given below.

$$\begin{aligned} logit(P_{open,bed}) = &- 18.53–0.019 * T_e + 0.18 * log(SR) + 0.057 * SH \qquad (12.6) \\ &+ 0.029 * RH_e + 0.26 * log(Il) + 0.1 * T_i + 1.16 * log(CO_2) \\ logit(P_{close,bed}) = &- 4.94–0.057 * T_e + 0.13 * log(SR) - 0.089 * SH \qquad (12.7) \\ &- 0.028 * RH_e + 0.063 * RH_i \end{aligned}$$

With SH the number of solar hours of the day [h], $RH_{e/i}$ the outdoor (e) and indoor (i) relative humidity [%], Il the illuminance [lux], T_e the outdoor temperature [°C], SR the global horizontal solar radiation [W/m²] and CO_2 the CO_2-concentration [ppm].

In this study no data regarding the occupancy of the residents was available. The occupancy patterns were derived from CO_2-measurements. They assumed that the room was unoccupied if the CO_2 decreased and continued to decrease below 420 ppm, or when the concentration was below 420 ppm and the window was closed. Additionally, when the window was open it was assumed that the dwelling was occupied. This stems from the fact that a common reason for closing the window was leaving the dwelling. Therefore, this model is applied during the occupied periods and during unoccupied periods the windows are assumed to be closed.

Model of Haldi and Robinson

The final model is based on a discrete-time Markov process [108]. Haldi and Robinson found that most window actions occur at arrival or departure from the office, with very few intermediate actions. Therefore, the model distinguishes the probabilities of opening and closing a window for three occupancy-states: arrival, during occupancy and departure. The probabilities of closing and opening a window on arrival are based on the indoor and outdoor temperature. Additionally, the probability of opening is as well based on the occurrence of rain (F_r[0/1]) and if the duration of the preceding absence was longer than 8 hours ($F_{abs,prev}$ [0/1]).

$$P_{open,arr} = -13.7 + 0.308 * T_i + 0.0395 * T_e + 1.826 * F_{abs,prev} - 0.43 * F_r \quad (12.8)$$

$$P_{close,arr} = 3.95 - 0.286.T_i - 0.0500 * T_e \quad (12.9)$$

The intermediate probabilities are based on the indoor and outdoor temperature, the occurrence of rain and the duration of the presence (F_{pres}).

$$P_{open,int} = -11.78 + 0.236 * T_i + 0.0394 * T_e - 0.0009 * F_{pres} - 0.336 * F_r \quad (12.10)$$

$$P_{close,int} = -4.14 + 0.026 * T_i - 0.0625 * T_e \quad (12.11)$$

The probabilities at departure are not based on the momentarily outdoor temperature but on the daily mean outdoor temperature ($T_{e,dm}$). Additionally, the indoor temperature, the fact if the duration of the following absence period is longer than 8 hours ($F_{abs,next}$[0/1]) and the fact if the office is situated at the ground floor (F_{gf} [0=ground floor/1=not on ground floor]) have an impact on the window action probabilities.

$$P_{open,dep} = -8.72 + 0.1352 * T_{e,dm} + 0.85 * F_{abs,next} + 0.82 * F_{gf} \quad (12.12)$$

$$P_{close,dep} = -8.68 + 0.222 * T_i - 0.0936 * T_{e,dm} + 1.534 * F_{abs,next} - 0.845 * F_{gf} \quad (12.13)$$

This model is developed for offices, but Schweiker et al. [142] found that it performs well for living rooms in residential settings as well. This model is applied in this study in two different ways. First, only the probability of intermediate actions are applied during occupied periods (as Schweiker et al. did in their study). Secondly, the model is applied in its entirety. Additional to the intermediate action probability, the probabilities of arrival are applied when arriving in a room, and the probabilities of departing when leaving the room. This model is applied with a time-step of 5 minutes.

12.1.2 Results

The window use is evaluated based on both the prediction of the state (opening percentage) and the actions, and is compared to measured data from the Venning-neighbourhood. Additionally, the impact on the energy use and IEQ is assessed as well.

Prediction of window state

The average yearly opening percentages in the bedroom, bathroom and living room are given in Figure 12.2, Figure 12.3 and Figure 12.4 for respectively a year, a winter-month and a summer-month. For comparison, in the study of Rijal et al. [147] the average proportion of open windows was 38% and in the study of Haldi and Robinson [108] it was 15%.

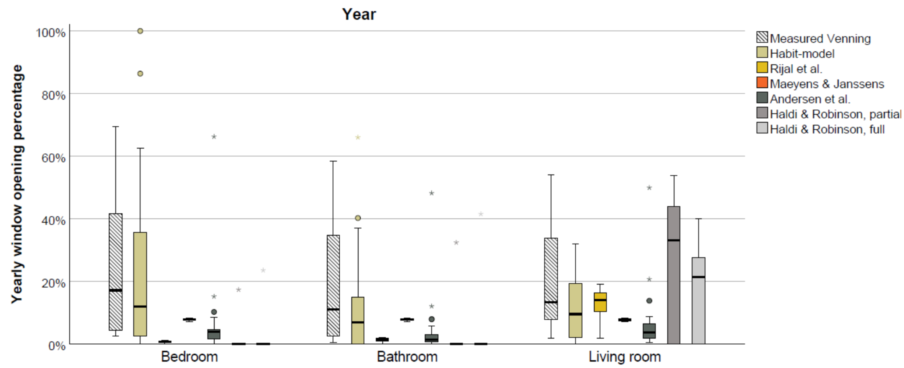


Figure 12.2: Average yearly opening percentage in the bedroom, bathroom and living room as simulated with the different window opening models.

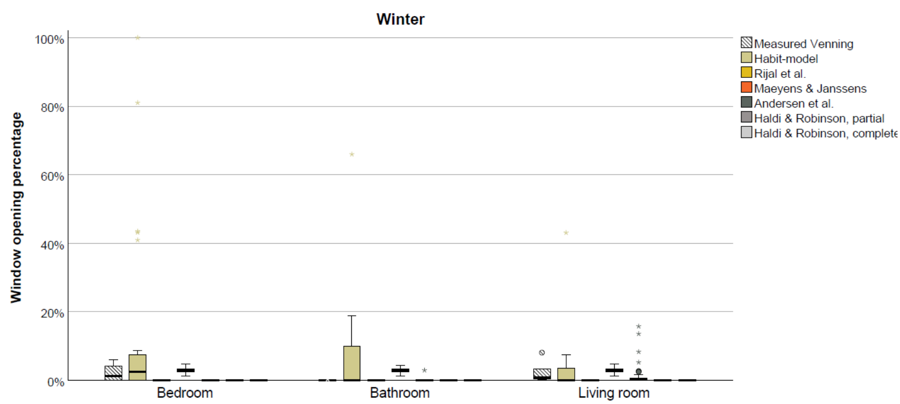


Figure 12.3: Average opening percentage in January (winter) in the bedroom, bathroom and living room as simulated with the different window opening models.

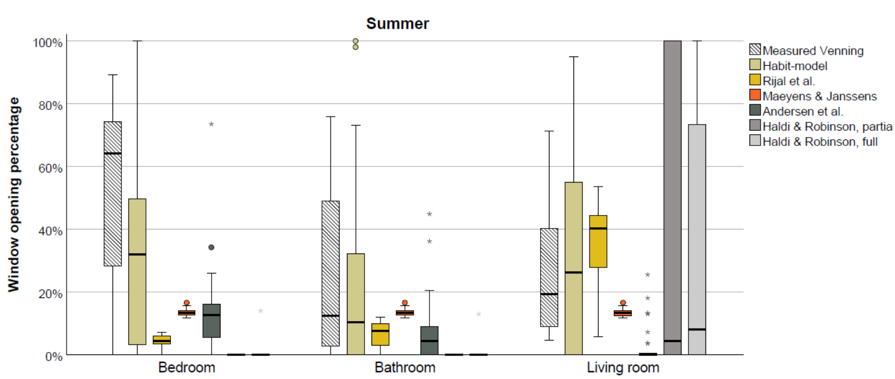


Figure 12.4: Average opening percentage in June (summer) in the bedroom, bathroom and living room as simulated with the different window opening models.

The average opening percentage in the bedroom as observed in the Venning-neighbourhood is 25%. The habit-model captures the window use relatively well, with an average opening percentage of 21% and a similar variability across households. The model of Maeyens and Janssens predicts a lower average opening percentage of 8%, and does not capture the high diversity in window use with a very small range (1%). The model of Andersen et al. predicts some diversity in window use but the average opening percentage is severely underestimated (6%). The other models predict little to no window opening time (Rijal et al. 0.7%, Haldi and Robinson part. 0.6% and complete 1.3%).

In the living room, the average observed opening percentage is 21%. In general, the window use models predict higher opening percentages in the living room compared to the bedroom or bathroom, however, the opening percentages are still underestimated (habit-model 11%, Rijal et al. 13%, Maeyens and Janssens 8%, Andersen et al. 6%). The average opening percentages of the models of Haldi and Robinson, both the partial and the complete model, are significantly higher (28% and 17%).

In wintertime, the windows are not opened according to the models of Rijal et al. and Haldi and Robinson. In the livingroom, the observed window use (5%) is predicted accurately by the habit-model (3%), the model of Andersen et al. (2%) and the model of Maeyens and Janssens (3%). This last model is, however, not able to predict the variability in window use across the households.

In summertime, in the bedroom, all models underestimate the opening percentage. The windows are still barely opened according to the model of Haldi and Robinson (partial 0.0%, complete 0.8%), and the opening percentage is very low for the model of Rijal et al. (4%). In the bathroom the average opening percentage is predicted relatively good by most models, except for the model of Haldi and Robinson. The window use predictions in the living room are quite diverse with lower average opening percentages for some models (Andersen et al. 3%, Maeyens and Janssens 13%) and higher opening percentages for others (Habit-model 28%, Haldi and Robinson 32-33%, Rijal et al. 35%) compared to the observed window use (27%).

Overall, the habit-model is able to predict the window use accurately across the rooms and seasons, including the high diversity. The model of Rijal et al. predicts the window use in the summer relatively well in the living room but underestimates the window use in the bedroom and in wintertime. This can be attributed to the assumption in the model that actions only occur when comfort is disrupted. In the bedroom, the heating set-points are relatively low, and overheating is not common, therefore the occupant will rarely be 'too hot' and the window will be rarely opened. The model works better in the living room since overheating is a more common problem in that room.

The model of Maeyens and Janssens does predict window openings with an average opening percentage slightly lower than the average measured window use, but the difference between rooms is not captured, with similar opening percentages in all rooms, and the variability across households is very low. Since the model is not dependent on the occupancy profile of the household but is based on outdoor weather variables and a presence probability, the window use predictions for each household and each room are similar, with only a slight variation due to the use of the stochastics for presence. The model of Andersen et al. predicts relatively low opening percentages throughout the year, but does capture some of the variability in window use. The low opening percentages could be attributed to the low opening probabilities, as illustrated in Figure 12.5 for a winterday (Te=5°C) and a summerday (Te=25°C).

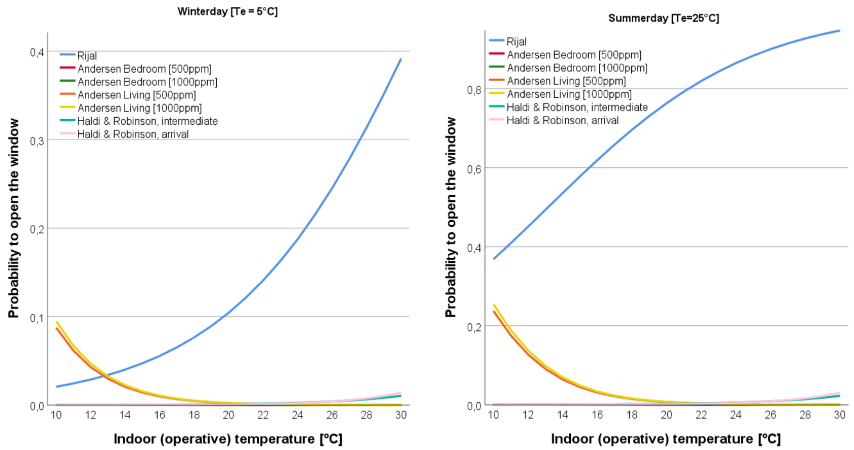


Figure 12.5: Probability to open window according to different indoor temperatures for the different models for a winterday and summerday. Other required variables are kept constant (SR=200W/m^2, SH=5h, RH$_e$=75%, RH$_i$=45%, Il=300lux, F$_r$=0, F$_{abs}$=0, F$_{pres}$=60)

Similarly, very low opening percentages are predicted with the model of Haldi and Robinson due to the low opening probabilities. In the living room some higher opening percentages are noted. When a window is opened it remains open for a long time, since the closing percentages are very low as well. Consequently, high opening percentages are predicted for some dwellings. This can be more clearly illustrated by evaluating the number of actions.

Prediction of window actions

As explained in the previous section, very few window actions are predicted with the window use models that are based on the indoor temperature or thermal comfort (Table 12.1). The model of Maeyens and Janssens and the habit-model on the other hand predict 3 to 4 actions per day. While the number of actions simulated with the model of Maeyens and Janssens is similar as that of the habit-model, it should be noted that not all of these actions are predicted at realistic moments (e.g. the occupant is asleep or not at home). This can be attributed to the use of the correction factor for occupancy instead of the occupancy profiles.

Table 12.1: Number of opening and closing actions per day as simulated with the different models.

	Living room			Bedroom			Bathroom		
	mean	min	max	mean	min	max	mean	min	max
Habit-model	3.20	0.00	15.96	3.22	0.00	12.93	4.09	0.00	21.67
Rijal et al.	0.12	0.02	0.19	0.02	0.00	0.03	0.02	0.00	0.03
M & J	3.24	2.99	3.48	3.24	2.99	3.48	3.24	2.99	3.45
Andersen et al.	0.12	0.01	0.59	0.05	0.01	0.10	0.03	0.00	0.09
H & R, part.	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00
H & R, compl.	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01

Impact on heating energy use and indoor environmental quality

The window use predictions with the different models are highly diverse. Therefore it is important to assess the impact of the use of the different window use models on the predicted energy use for heating and on the indoor climate.

In Figure 12.6 the heating energy use is given as simulated based on the window use predictions of the different models. In general, the average heating energy use is similar for the different models, with slightly higher energy use for the models that predict high opening percentages for some of the households (Habit-model 2314 kWh, Rijal et al. 917 kWh, Maeyens and Janssens 1490 kWh, Andersen et al. 1399 kWh, Haldi and Robinson 2323 kWh and 1634 kWh). However, it should be noted that when the variability in window use is larger, a much wider range of heating energy use is predicted, emphasising the importance of correctly predicting the variability in window use. The range of the habit-model is for example 10200 kWh, while the range for the model of Rijal et al. is only 1100 kWh.

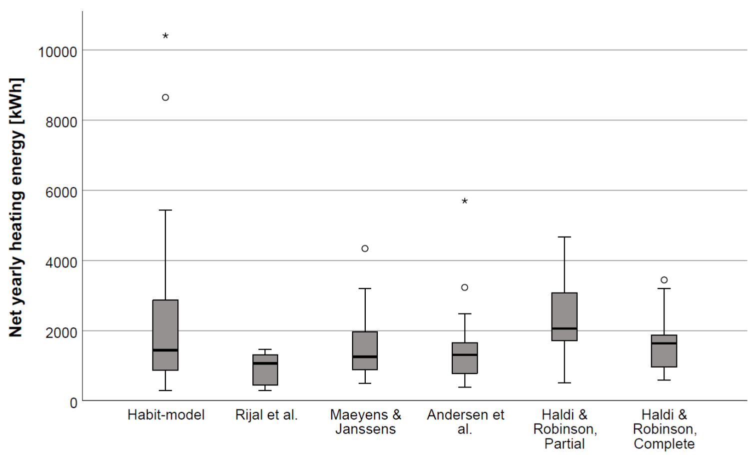


Figure 12.6: Net heating energy use for the NZEB-building based on the different window use predictions

In Figure 12.7, the average yearly CO_2-concentration is given for both the bedroom and the bathroom. In the bedroom, the low opening percentages of some of the models lead to higher average CO_2-concentrations and the variability is smaller as well. In the living room the models of Haldi and Robinson predict the lowest indoor CO_2-concentrations, due to the extremely long opening actions. Finally, in Figure 12.8 the overheating indicator is given for both the bedroom and living room. Again the importance of correctly predicting the window use is shown, with more overheating for the models which predict very little opening time.

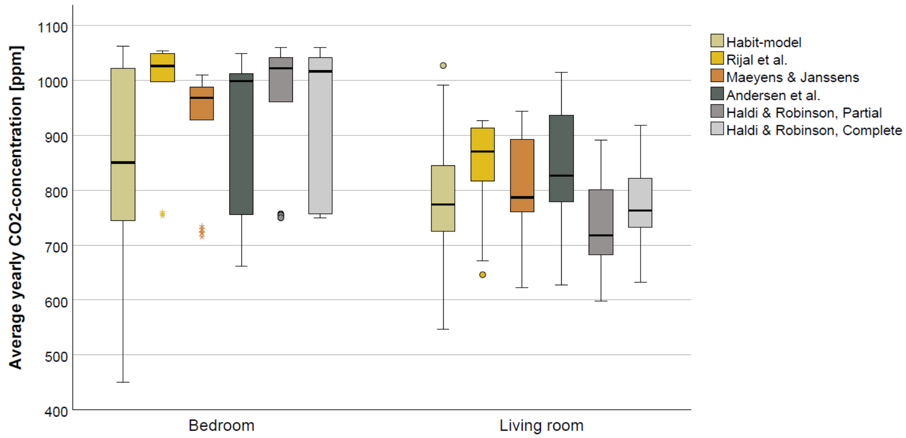


Figure 12.7: Yearly average CO_2-concentration in the bedroom and living room for the NZEB-building based on the different window use predictions

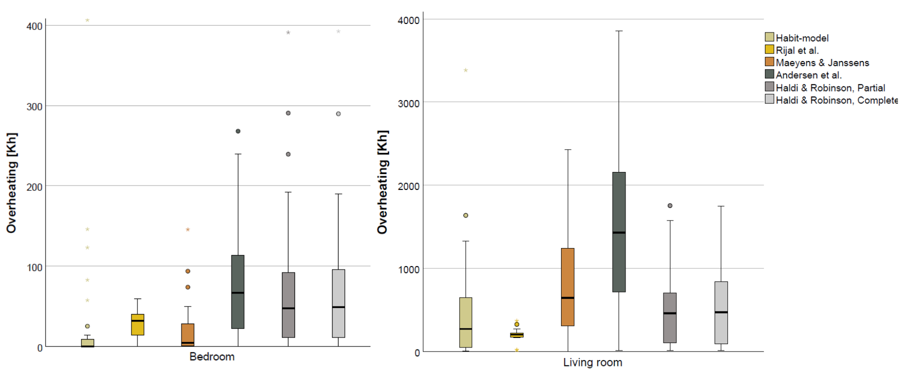


Figure 12.8: Overheating indicator in the bedroom and living room for the NZEB-building based on the different window use predictions

12.1.3 Conclusion

The habit-model is clearly able to predict the diversity in window use in the different rooms to a greater extent than the other window use models. While the model of Andersen et al. and Rijal et al. showed as well good results for the living rooms, in the rooms with lower heating set-points the models were not able to grasp the window use accurately.

Furthermore, the habit-model requires very little simulation time in contrast to the other models which are based on the indoor environmental conditions. These models require simulation of the indoor environment (indoor temperature, indoor relative humidity, CO_2-concentration) to determine when the window will be opened or closed, while the habit-model only requires an occupancy and activity profile, which is as well needed for the other models (with the exception of the model of Maeyens and Janssens). Furthermore, even when for both models (habit and physical environmental based) the same indoor environmental variables are calculated the simulation time will still be shorter with the habit-model as it does not require the iterative process caused by the dependence of the window use on indoor environment and vice versa.

12.2 Prediction of realistic window actions

It has been emphasized that predictions of window actions at the correct moment in the day are essential, which is one of the main advantages of the habits-based model. However, it can be questioned if the prediction of more realistic actions, at logical moments in the day, effectively makes a difference in the energy use and indoor climate predictions. Therefore, the energy use, indoor air quality and overheating predictions with the window use habit model are compared to simulations with window use with a similar opening percentage per day but at a random timing.

12.2.1 Impact on heating energy

The difference between the heating energy for the predicted window use and for the randomised window use is very minimal, with the average heating energy for the predicted window use only slightly higher than that of the randomised window use (98 kWh/year) (Figure 12.9 and Figure 12.10). The predicted window use occurs frequently when occupants are present in the building, while the randomised window use happens throughout the day. Since presence-levels often coincide with lower outdoor temperatures (morning, evening), opening the windows at these times will result in higher heating energy use. The difference is slightly higher for the less energy efficient buildings, nevertheless, the heating energy use is as well much higher in those buildings. The proportional impact is respectively 3.1%, 2.3% and 0.9% in the NZEB, E100 and Y70-building, indicating a proportional higher impact in the energy efficient buildings.

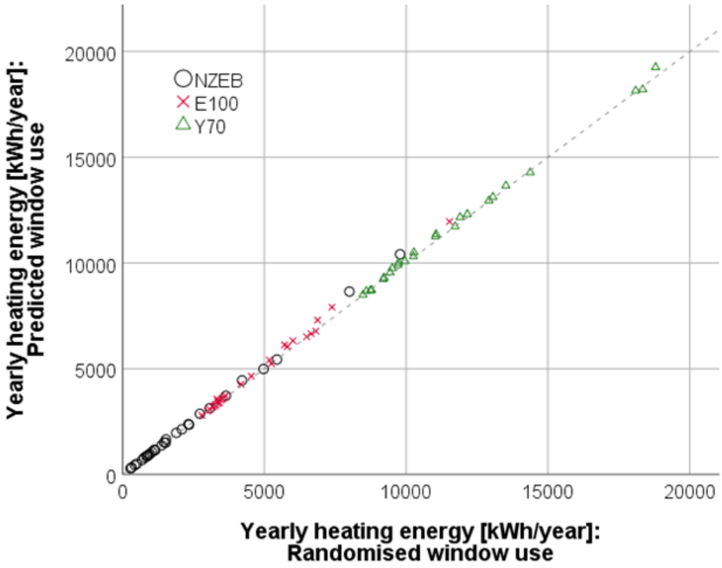


Figure 12.9: Heating energy use for the predicted window use versus the randomised window use.

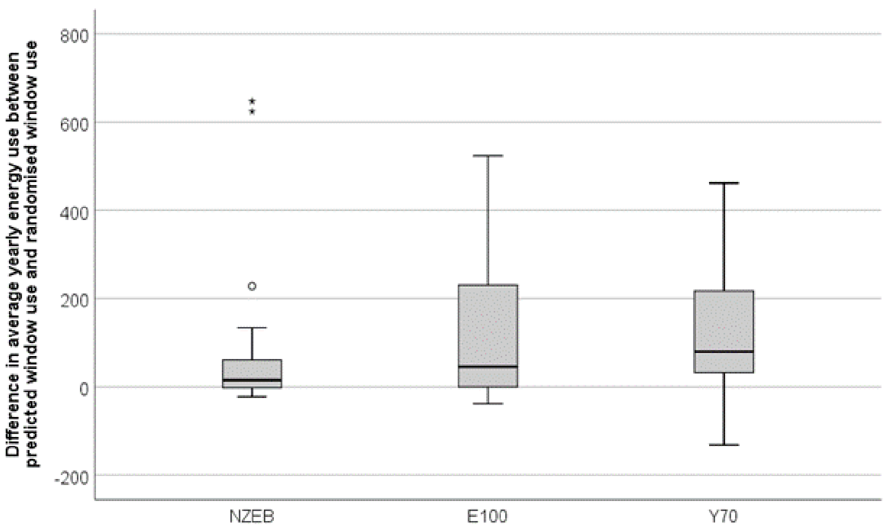


Figure 12.10: Difference in heating energy use between the predicted window use and the randomised window use for the three different buildings.

12.2.2 Impact on indoor air quality

In Figure 12.11 and Figure 12.12 the average yearly CO_2-concentrations are given for respectively the living room and bedroom for the different window uses.

A minimal difference is observed between the predicted window use and randomised window use. The average difference is 1 ppm in the living room and 5 ppm in the bedroom (Figure 12.13), which is negligible. However, when the profiles are examined in more detail, higher deviations can be observed especially for certain habits. For example when the living room window is opened when someone is present in the room (Figure 12.14), the CO_2-concentration during the presence was lower compared to the randomised window use. Since good IAQ is mainly required during the presence, the evaluation was repeated as well for the occupied periods only in Section 12.2.4.

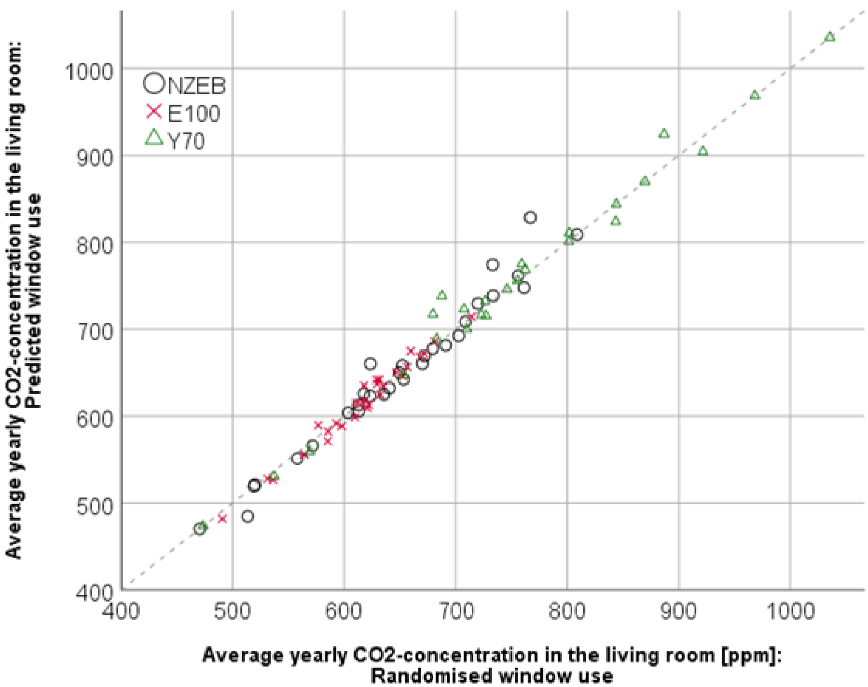


Figure 12.11: Average yearly CO_2-concentration in the living room for the predicted window use versus the randomised window use.

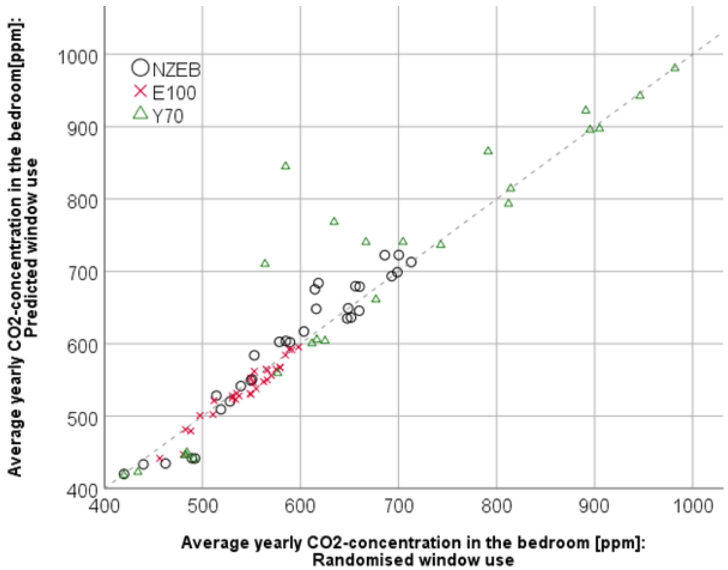


Figure 12.12: Average yearly CO_2-concentration in the bedroom for the predicted window use versus the randomised window use.

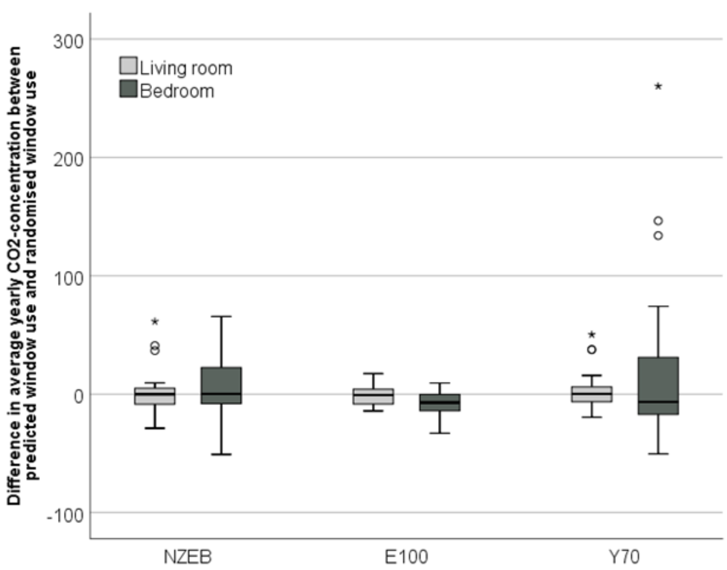


Figure 12.13: Difference in CO_2-concentration between the predicted window use and the randomised window use for the three different buildings.

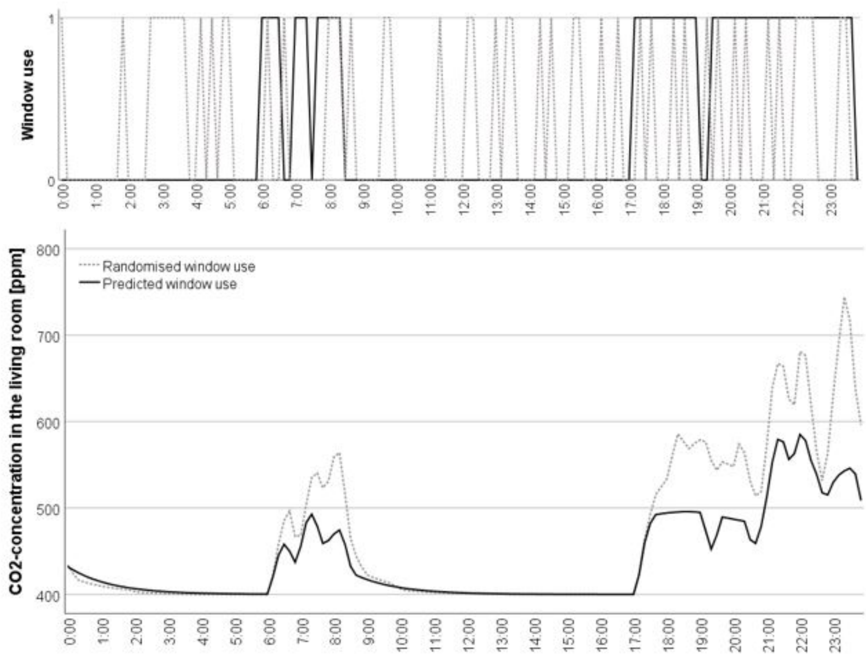


Figure 12.14: CO_2-concentration in the living room of an NZEB-building for both predicted and randomised window use.

12.2.3 Impact on overheating

The timings of the window actions may as well have influence on the overheating. In Figure 12.15 and Figure 12.16 the overheating indicators are given for respectively the living room and bedroom for the different window uses. Again a minimal difference is observed between the predicted window use and the randomised window use. The average difference is 10 Kh in the bedroom and 31 Kh in the living room (Figure 12.17). In general the overheating is more prevalent with the predicted window use compared to the randomised window use. As discussed previously, the predicted window use often occurs when occupants are present in the building, which is when the lowest outdoor temperatures occur. While the randomised window use may predict open windows during the hottest moments of the day providing some cooling when occupants are not present. This is illustrated with a daily profile of the living room temperature of an NZEB-building in Figure 12.18. While during presence (when the windows are opened), the temperature is approximately the same for the random and predicted window use, the temperature is higher when nobody is present. Since overheating is only a problem when it affects the occupants comfort, the evaluation may be more relevant when assuming only the occupied periods.

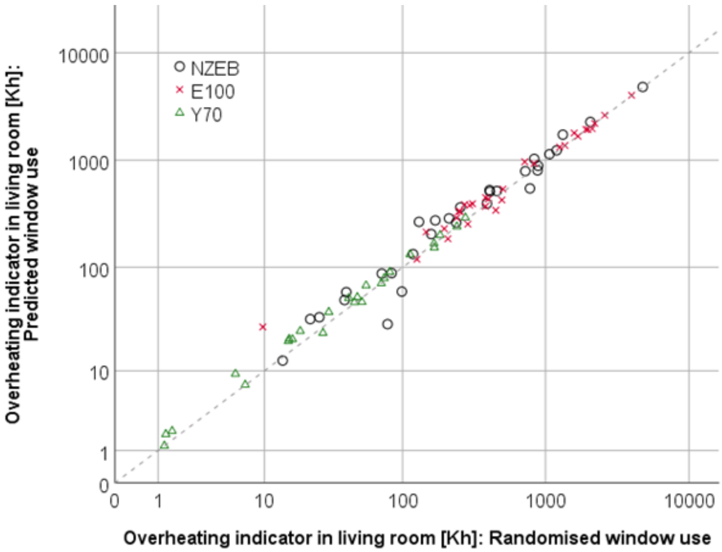


Figure 12.15: Overheating indicator in the living room for the predicted window use versus the randomised window use.

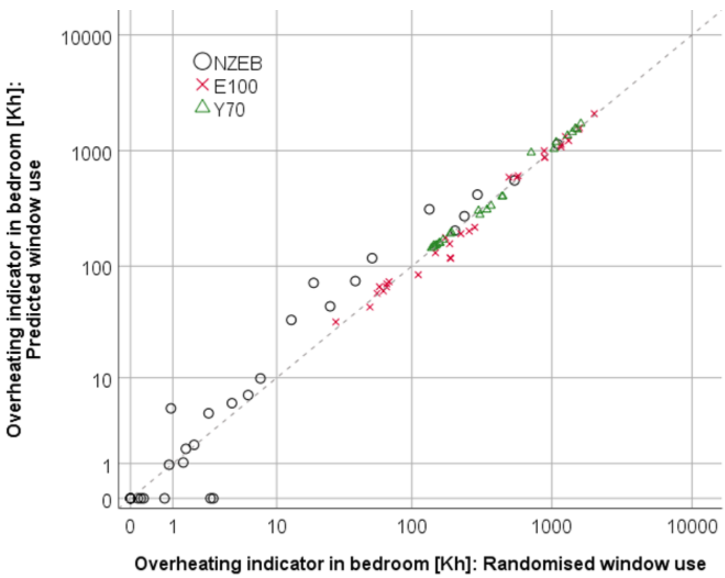


Figure 12.16: Overheating indicator in the bedroom for the predicted window use versus the randomised window use.

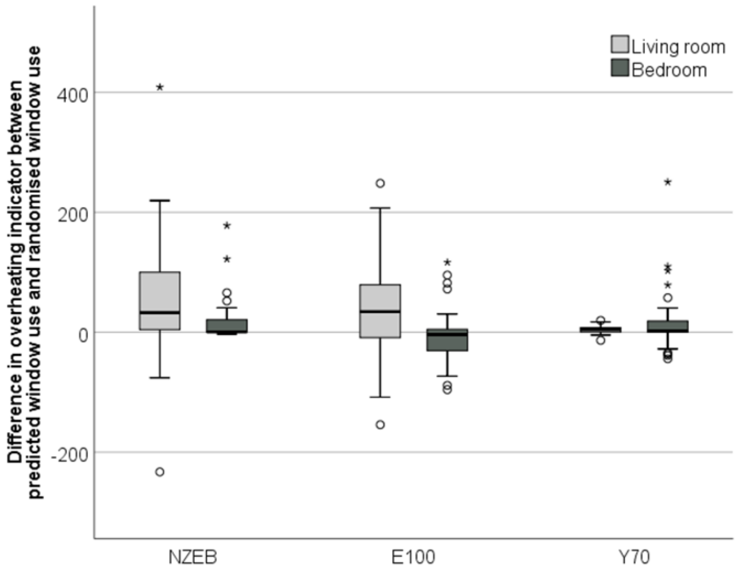


Figure 12.17: Difference in overheating indicator between the predicted window use and the randomised window use for the three different buildings.

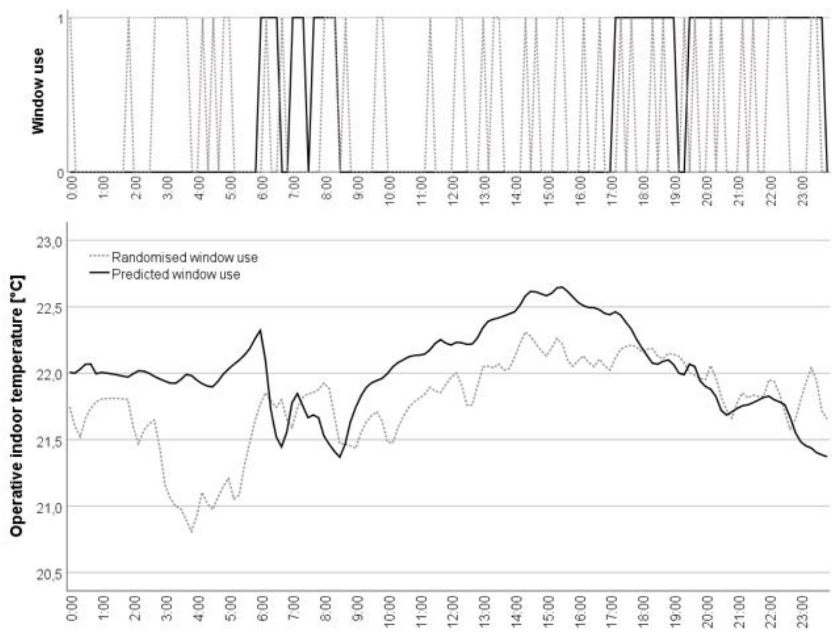


Figure 12.18: Indoor operative temperature in the living room of an NZEB-building for both predicted and randomised window use.

12.2.4 Corrected for occupied periods

The analysis is repeated for the occupied periods only, since a poor IAQ and overheating is mostly problematic for the occupant's comfort and health. While the average difference in CO_2-concentration between the predicted window use and randomised window use was negligible when the full simulation period was considered, it is slightly negative when only the occupied periods are assumed in the living room (Figure 12.19). Since the windows in the living room are often opened linked to the presence or performed activities in the living room the CO_2-concentration will decrease during these periods, while the random use is more dispersed over the day. For the bedroom the average difference is approximately the same only the range is larger. The habits in the bedrooms are more diverse with habits of opening the windows when present but as well a number of habits that indicate window openings when leaving the room (e.g. opened in the morning, opened during the day). Consequently, the CO_2-concentration when present is in certain households influenced in a negative way and in others in a positive way.

The highest overheating is detected during the day, when the presence is lower, consequently less overheating is noted when observing only the occupied periods and as well smaller differences between predicted and randomised window use (Figure 12.20). In the bedroom, the difference between predicted and randomised window use is mostly positive indicating that more overheating occurs with the predicted window use. As discussed in the previous paragraph, the randomised window use leads to window actions throughout the day, but the predicted window use varies with sometimes opening actions when present but often as well when leaving the room. When the windows are not opened during the night the overheating will be higher compared to random openings during the night which provide passive cooling.

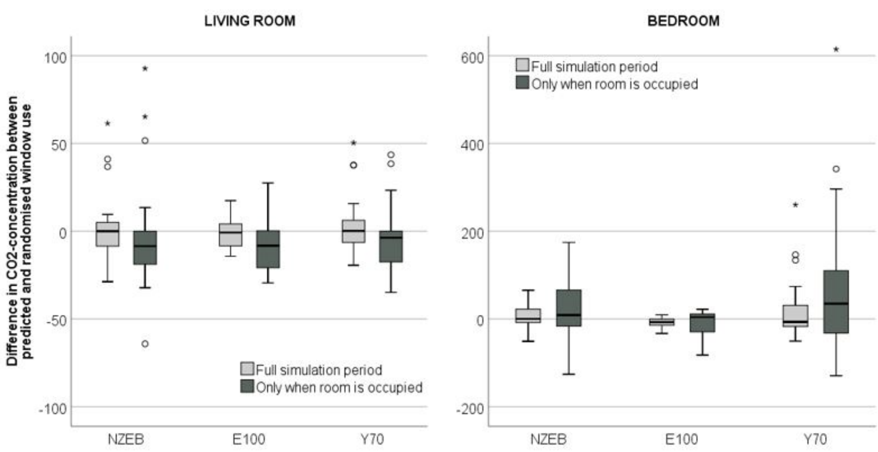


Figure 12.19: Difference in average yearly CO_2-concentration between the predicted window use and the randomised window use for the three different buildings for both the full simulation period and only the occupied period.

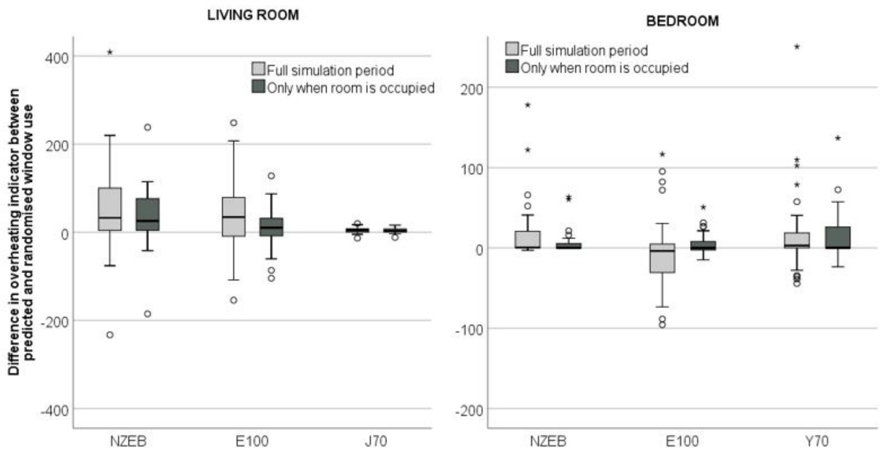


Figure 12.20: Difference in overheating indicator between the predicted window use and the randomised window use for the three different buildings for both the full simulation period and only the occupied period.

12.2.5 Discussion

The effect of including realistic window actions instead of random actions during the day is small on the heating energy use. While the effect is more significant on the IAQ and overheating. Especially when the windows are opened when present, large deviations could be observed during the occupied periods.

We can conclude that for the purpose of heating energy use evaluations it is most important to correctly predict the opening percentage on the day, and that the timings of these actions are less influential. By using the window use habit model for the prediction of the opening percentage and then combining it with BES on a daily basis the heating energy use will still be accurately predicted, and the simulation time may decrease significantly. The step to monthly values as suggested in Section 11.6.2, might consequently be acceptable for the heating energy use predictions. It should be noted, however, that due to the decrease in heating energy use due to the evolution to more energy efficient buildings, the proportional impact of including the correct timings increases. For other purposes that are related to the indoor air quality or overheating, it is advised to go to more detailed calculations since the impact of the correct timings are still significant.

12.3 Conclusion

In this chapter the window use habit model is evaluated for its impact on the heating energy and indoor environmental climate. The results emphasised the main advantages of the window use habit model.

Independence of the indoor environment

From the comparison with window use models from the literature the importance of the independence of indoor environmental variables in the habit-model is highlighted. Most models based on indoor environmental variables predicted very few openings in the bedrooms and in wintertime. Additionally, the independence of indoor environmental variables leads as well to much faster window use simulations because of the possibility of decoupling the OB-model from the building simulation model.

Diversity

Additionally, the variability in window use across households has an important impact on the predicted indoor climate. Good indoor climate predictions are essential to evaluate the occupants' comfort, but as well for the design and development of different building systems and components. Therefore, it is important that a window use model can accurately capture this diversity.

Realistic actions

Another important characteristic of the habit-model is its ability to predict window actions at realistic moments in the day of the occupants. The analysis of this impact on the heating energy use, did not reveal a significant difference with randomised window use assuming similar opening percentages per day. The impact was more important on the IAQ and overheating, and depended highly on the type of window use habit of the household.

13

Conclusions & Perspectives

13.1 Conclusions

The current approach towards OB-modelling is predominantly based on the assumption that occupant behaviour is deliberative, however, behavioural studies indicate that not all actions are deliberative, and that especially in a stable context such as a residential building, the actions are often performed without conscious thought, out of habit. Since building control habits were rarely explicitly studied, the objectives of this dissertation were to gather knowledge regarding building control habits in the residential setting, develop an OB-model which includes these findings and evaluate this model for the impact on the energy use and IEQ.

In Part I, knowledge is gathered regarding building control habits (RQ 1). The results of Chapter 4 indicate that window use in residential settings might be a habitual behaviour. The study showed that a large share of the observed variance in window opening behaviour can be attributed to the season and the household-ID, indicating that the window use varied across the year but was rather stable within one season, and that these behaviours differ significantly between households. Indicating that the window use is a repetitive behaviour, and that there might be window use habits in residential buildings. It can not be confirmed that the observed or reported repetitive behaviour are habits as there was no evaluation of the consciousness of the behaviour. However, for the purpose in this dissertation (prediction of the window use) this distinction is less important.

In the dissertation different methods were used to detect habits. A combination of monitoring data and surveys/interviews would be advisable, but surveys alone can capture much information, as indicated in Chapter 5. The online survey conducted in Belgian households revealed that almost all occupants perform some kind of habit with at least one window. Most habits are related to the performance of specific activities (e.g. cooking, cleaning, sleeping) and the presence in a specific room. A comparative study with window opening behaviour in the US revealed that habits are as well present in other contexts and that the cultural aspect is influential on the type and distribution of the habits across the population.

Furthermore, in Chapter 6, two limited studies indicate that habitual behaviour might not be constricted to window use alone, but might be as well present in clothing behaviour and solar shading use.

In Part II, an OB-model is developed which takes the findings on building control habits into account (RQ2). In Chapter 8, the possibility to predict window use habits was evaluated. Since habits are very personal and can originate through a wide set of multi-disciplinary factors, habits can not easily be predicted. While some correlations were found with the type of ventilation system, type of windows, building type, family type, employment type and age, the window use habits were mostly related to the habits in the remaining rooms, indicating habit coherence across the different rooms and across seasons. Consequently, window use habits can be predicted based on an initial classification of the households according to the habit-coherence across the rooms in winter and the seasonality coherence. These predicted habits are coupled to an occupancy and activity model to predict window use profiles. The validation procedure revealed good results for different applications.

This approach towards window use modelling has a some important advantages.The window use habit model allows for predicting the large diversity in window use observed in the building stock, is able to predict realistic window use actions (both for the timing during the day, as the coherence across rooms and seasons) and is easy implementable in BES-software due to the simplicity of the output and the independence of indoor environmental variables.

In Chapter 9, the window use habit model was combined with other types of OB in an event-based OB-model. The model allows to predict the occupancy and activity profiles of the households and linked to that the window use, heating set-points, domestic hot water use, electricity use, internal heat gains and CO_2-production.

In Part III, the the impact of the habit-based OB-model on the building performance assessment is evaluated (RQ3). In Chapter 11, it is revealed that there is a significant impact on the energy use and indoor climate predictions due to the inclusion of OB in BES, especially by the window use and especially in energy efficient buildings. A similar trend as with the performance gap was observed leading to the assumption that OB is partially responsible for the performance gap. Even though certain systems or buildings perform well under general use, as defined in standards and codes, the performance differentiates highly due to the diversity of the households living in it. Therefore, it is important to take into account the different possible behaviours.

As the impact of the OB is important it should as well be considered in practice. While the detailed OB-models are already frequently used in the research field, applications in practice are rather limited. Possibilities exist to include the OB in the EPB-calculation (Section 11.6.2) either in a simplified aggregated way or by allowing a distribution of end-metrics.

Finally, in chapter 12, simulation results proved that the habit model is able to predict the diversity to a larger extent than the models based on indoor environmental variables, as most of these models predict very few openings in rooms that are unheated or have low heating set-points. The results showed as well that the models which were originally developed for residential settings performed better than the models developed for offices, emphasising the importance of the context in which the model is created. Predicting realistic timings of the window actions did not have a large effect on the heating energy, but was important for the evaluation of the IAQ and the overheating. However, the impact strongly depended on the type of window use habit performed by the household.

It can be concluded that the window use in residential buildings is strongly repetitive, with many occupants reporting window use habits in the different rooms of their residence. The model based on the window use habits was able to more accurately predict the diversity in window use compared to other studies from literature. Additionally, the model is able to predict realistic actions, allows for easy implementation in BES and gives fast results. The simulation results of three buildings with different performance levels revealed that including OB in energy predictions may indeed be a way to reduce the performance gap, and with that allows to define more accurate measures to reduce the energy use to comply with the climate targets.

13.2 Limitations & Perspectives

13.2.1 Sociological/psychological studies

An important limitation of this study is that there is no indication whether the identified habits are effectively habits, they may just as well be repetitive deliberate actions guided by factors that were not observed in this study. The deployed surveys were a good way to gather information regarding the repetitive behaviour, however, to evaluate the fact that the actions occur without conscious thought more in depth studies are needed from a multi-disciplinary perspective. As discussed in Section 5.1.4, a possible way to assess the consciousness is by evaluating the thoughts and emotions during the performance of the behaviour.

Currently, information on the origins of the habits is lacking. More information on the social narrative behind the habit might ameliorated the prediction of the window use habits for specific households and may provide a sturdier base for the switching point between the habits, which are currently defined as seasonal. It may as well provide insights on how to influence this habitual behaviour. Furthermore, the social narratives behind the window use habits may as well allow for the prediction of other OB-habits. For example, the preference for fresh air may lead to opening the windows frequently but as well to other building control habits such as defining lower heating set-points. Currently, no connection between the different occupant behaviours is provided which may lead to unrealistic behavioural combinations (e.g. high heating set-points with frequent window use). The simulation results showed that including a basic connection between window use and heating behaviour already impacted the heating energy use significantly. Many other possible connections between the types of occupant behaviour might be present.

13.2.2 Definition of stable context

The developed window use model is currently solely based on the habitual, repetitive behaviour. The definition of habits as used in this dissertation indicates that these habits, the baseline behaviour, are only executed when the context is stable, otherwise the behaviour is based on intentions. Therefore, it is necessary to know in which situations the habits are performed and at which moments, in which circumstances the occupant deviates from this behaviour. When the context is unstable, the window use might be influenced by environmental and time-dependent variables. A combination of a sociological study and a monitoring campaign may provides some insights in the definition of the stable context, which may vary for different types of OB and for different households.

13.2.3 Sample size limitations

In this dissertation, the sample size was rather limited for most of the studies. For the window use study 499 responses were gathered, which in the end proved too little to capture the different possible household habits. As a consequence, it is unsure if all possible room-habit combinations are captured and if some important other habits might be neglected. A higher response rate on the online survey would provide with a more sound window use habit model.

Next to that, the focus of this study was limited to the window use habits in the Belgian context. While the study on American data revealed that habits are probably as well present in other contexts. Since the survey was developed for online deployment, the extension to other cultural and climatological contexts seems a promising and feasible further venture.

13.2.4 Application in EPB

Finally, in this dissertation some suggestive options were given to include OB-modelling in practice. Many practitioners and building owners/buyers base their decisions on the EPB-calculation results. The inclusion of OB in these calculations would allow for a more targeted approach toward energy use reduction in residential buildings. In Section 11.6, some possible implementations were suggested, with their consequences. Developing these ideas further and applying them into practice will make a real life impact.

14

Appendix

14.1 Parameter estimates log. regression model

14.1.1 Opening percentage

Table 14.1: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening percentage in the bedroom based on physical environmental variables.

BEDROOM	Rn^2	AIC	intercept	Te	Ti	SR	v
YEAR							
Te	0.218	17275.645	-13.559	0.605			
Te, Ti	0.239	17207.877	-2.617	0.816	-0.611		
Te, Ti, SR	0.248	17178.008	-1.100	0.722	-0.694	0.013	
Te, Ti, SR, v	0.251	17171.919	-0.159	0.733	-0.705	0.012	-0.363
WINTER							
-							
SUMMER							
Te, Ti	0.075	4718.651	23.516	0.435	-1.305		
Te, Ti, SR	0.089	4710.882	24.052	0.638	-1.347	-0.018	
Te, Ti, SR, v	0.089	4712.857	24.303	0.632	-1.347	-0.018	-0.066

Table 14.2: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening percentage in the bathroom based on physical environmental variables.

BATHROOM	Rn^2	AIC	intercept	Te	v	RHe	precip.
YEAR							
Te	0.189	20607.963	-13.603	0.568			
Te, v	0.195	20586.111	-12.395	0.566	-0.582		
WINTER							
RHe, precip.	0.018	3939.046	-14.181			0.050	-0.051
SUMMER							
-							

Table 14.3: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening percentage in the living room based on physical environmental variables.

LIVING	Rn^2	AIC	intercept	Te	Ti	SR	RHi	RHe
YEAR								
Te	0.190	17045.853	-6.703	0.381				
Te, Ti	0.264	16777.153	13.327	0.567	-0.945			
Te, Ti, SR	0.271	16755.513	13.532	0.507	-0.956	0.007		
Te, Ti, RHi	0.267	16772.025	15.509	0.610	-0.972		-0.043	
Te, Ti, RHe	0.267	16770.962	16.019	0.544	-0.946			-0.032
WINTER								
Te, Ti, RHi	0.162	4051.797	-2.613	0.249	0.318		-0.240	
SUMMER								
Te, Ti	0.447	3933.800	51.860	0.730	-2.519			
Te, Ti, SR	0.451	3931.793	52.067	0.806	-2.536	-0.007		
Te, Ti, RHe	0.453	3929.100	42.213	0.879	-2.543	0.088		

Table 14.4: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening percentage in the apartments based on physical environmental variables.

APARTMENTS	Rn^2	AIC	intercept	Ti,liv	Ti,bed	SR	RHi
YEAR							
Ti,liv	0.037	25795.041	-10.551	0.380			
Ti,bed	0.026	25848.835	-6.991		0.239		
Ti,liv, SR	0.041	25776.344	-9.781	0.329		0.003	
Ti,liv, SR, RHi	0.042	25772.495	-10.486	0.320		0.003	0.019
WINTER							
Ti,liv	0.029	8704.662	-11.846	0.434			
Ti,bed	0.006	8740.995	-5.774		0.167		
Ti,liv, SR	0.033	8700.882	-11.967	0.424		0.005	
SUMMER							
Ti,liv	0.006	3885.454	-5.509	0.174			
Ti,bed	0.012	3880.988	-6.527		0.223		

14.1.2 Opening actions

Table 14.5: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening actions in the bedroom based on physical environmental variables.

BEDROOM	Rn^2	AIC	intercept	Te	Ti	SR	RHe	v
YEAR								
Te	0.021	8194.147	9.829	-0.085				
Ti	0.021	8181.929	13.760		-0.223			
Te, Ti, SR, RHe	0.029	8136.561	14.487	-0.013	-0.190	-0.001	-0.015	
WINTER								
Te	0.010	1626.768	10.285	-0.156				
Ti	0.087	1501.350	25.849		-0.786			
Ti, SR, v	0.111	1465.924	27.423		-0.817	-0.003		-0.215
SUMMER								
Ti	0.006	3310.508	2.963		0.188			

Table 14.6: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening actions in the bathroom based on physical environmental variables.

BATHROOM	Rn^2	AIC	intercept	Te	SR
YEAR					
Te	0.012	8203.829	10.668	-0.102	
SR	0.010	8215.459	9.619		-0.002
Te, SR	0.015	8180.704	10.574	-0.085	-0.001
WINTER					
-					
SUMMER					
SR	0.003	2543.819	8.397		-0.001

Table 14.7: Goodness-of-fit indicators and parameter estimates for logistic models to predict window opening actions in the living room based on physical environmental variables.

LIVING	Rn^2	AIC	intercept	Te	Ti	v	RHe	RHi	SR
YEAR									
Ti	0.002	220968.9	3.054		0.085				
RHi	0.004	220570.2	6.480					-0.030	
Ti, RHi, SR	0.018	217716.1	3.364		0.172			-0.045	-0.001
Te, Ti, v, RHe, RHi	0.017	217835.6	1.974	0.029	0.158	0.010	0.030	-0.067	
Te, Ti, v, RHe, RHi, SR	0.020	217186.3	2.992	0.042	0.147	0.024	0.020	-0.069	-0.001
WINTER									
Ti	0.002	53487.03	8.438		-0.137				
RHi	0.001	53599.25	5.804					-0.011	
Ti, RHi, SR	0.015	52835.06	10.228		-0.160			-0.025	-0.002
SUMMER									
Ti	0.013	27119.74	-0.819		0.228				
RHi	0.006	27297.18	8.294					-0.054	
Ti, RHi, SR	0.028	26734.95	1.809		0.235			-0.045	-0.001
Te, Ti, v, RHe, RHi	0.042	26351.62	-1.326	0.070	0.257	-0.087	0.061	-0.103	

14.2 Questionnaire window use habits

Het gebruik van ramen in woningen

In deze enquête wordt het raamopeningsgedrag in woningen bevraagd. Dit naar aanleiding van een doctoraatsonderzoek rond gebruikersgedrag in gebouwen.

De enquête vraagt slechts enkele minuten van uw tijd (MAX 10 min) en de resultaten zullen anoniem worden verwerkt.
Er zijn GEEN foute antwoorden, de enquête dient enkel om een realistisch beeld te krijgen over het gebruik van ramen in residentiële gebouwen.

Indien u vragen of opmerkingen hebt, aarzel dan niet om mij te contacteren: Silke.verbruggen@ugent.be
Alvast bedankt!
*Vereist

Gegevens over uw woning

In eerste instantie hebben we een aantal gegevens nodig over uw woning.

1. Is er een ventilatiesysteem aanwezig in uw woning? *

   Markeer slechts één ovaal.

   - Neen, er is geen ventilatiesysteem aanwezig *Ga naar vraag 3*
   - Ja, er is een ventilatiesysteem aanwezig *Ga naar vraag 2*

Gegevens over uw woning

2. Welk type ventilatiesysteem is er aanwezig? *

   Markeer slechts één ovaal.

   - Systeem C (aanvoer door ventilatieroosters, mechanische afvoer)
   - Systeem D (mechanische aan- en afvoer)
   - Ik weet niet welk type ventilatiesysteem er aanwezig is
   - Anders: ______________________

Gegevens over uw woning

3. In welk jaar is uw woning ongeveer gebouwd? indien u niet het exacte bouwjaar weet is een periode voldoende

   ____

4. In wat voor type woning woont u? *

Markeer slechts één ovaal.

- Rijwoning
- Half-open bebouwing
- Open bebouwing
- Appartement
- Studio
- Duplex
- Anders: ______________________

5. Hoeveel slaapkamers zijn er in uw woning? *

____

Gewoontes in winter

In de volgende sectie worden er vragen gesteld rond het raamgebruik in winter. Stel u daarom de vorige winter-periode voor (temperatuur onder 10°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met extreme temperaturen (kouder als -5°C) buiten beschouwing. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

6. U gaat slapen. Welke actie onderneemt u met uw ramen? *

Markeer slechts één ovaal.

- Ik sluit alle ramen in de woning
- Ik sluit alle toegankelijke ramen in de woning (inbraakbeveiliging)
- Ik sluit alle ramen behalve die in de slaapkamer
- Ik sluit enkel de ramen in de slaapkamer
- Ik verander niets aan de stand van de ramen
- Anders: ______________________

7. U verlaat de woning. Welke actie onderneemt u met uw ramen? *

Markeer slechts één ovaal.

- Ik sluit alle ramen in de woning
- Ik sluit alle toegankelijke ramen in de woning (inbraakbeveiliging)
- Ik verander niets aan de stand van de ramen
- Anders: ______________________

Gewoontes in zomer

In de volgende sectie worden er vragen gesteld rond het raamgebruik in de zomer. Stel u daarom de vorige zomer-periode voor (temperatuur boven 20°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met zeer hoge temperaturen buiten beschouwing (>35°C). Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

8. U gaat slapen. Welke actie onderneemt u met uw ramen? *

Markeer slechts één ovaal.

- Ik sluit alle ramen in de woning
- Ik sluit alle toegankelijke ramen in de woning (inbraakbeveiliging)
- Ik sluit alle ramen behalve die in de slaapkamer
- Ik sluit enkel de ramen in de slaapkamer
- Ik verander niets aan de stand van de ramen
- Anders: ______

9. U verlaat de woning. Welke actie onderneemt u met uw ramen? *

Markeer slechts één ovaal.

- Ik sluit alle ramen in de woning
- Ik sluit alle toegankelijke ramen in de woning (inbraakbeveiliging)
- Ik verander niets aan de stand van de ramen
- Anders: ______

Raamopeningsgedrag in de leefruimte (zitkamer + eetkamer)

10. Zijn er ramen aanwezig in uw leefruimte (zitkamer + eetkamer) ? *

Markeer slechts één ovaal.

- Ja, er zijn ramen in de leefruimte
- Ja, er zijn ramen in de leefruimte maar deze kunnen niet open (vaste ramen) *Ga naar vraag 16*
- Neen, er zijn geen ramen in de leefruimte *Ga naar vraag 16*

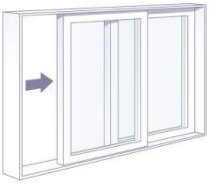
Raamopeningsgedrag in de leefruimte (zitkamer + eetkamer)

11. Welke soorten ramen zijn er aanwezig in uw leefruimte? (meerdere antwoorden zijn mogelijk) *

Vink alle toepasselijke opties aan.

☐ Draai-ramen (geen kiep-mogelijkheid)

☐ Kiep-ramen (geen draai-mogelijkheid)



☐ Draai-kiep ramen

☐ Schuiframen

☐ Dakramen

☐ Vaste ramen (niet opengaand)

Anders: ☐ ______________

12. Heeft u bepaalde raamopeninggewoontes in de leefruimte in WINTER? *

Stel u de vorige winter-periode voor (temperatuur onder 10°C) en op welke manier u toen meestal met de ramen bent omgegaan. Laat dagen met extreme temperaturen (kouder als -5°C) buiten beschouwing. Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

◯ De ramen blijven meestal gesloten in winter *Ga naar vraag 14*

◯ De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)

◯ De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)

◯ De ramen worden geopend wanneer iemand aanwezig is

◯ De ramen worden gesloten wanneer iemand aanwezig is

◯ De ramen staan meestal open in winter

◯ Ik heb geen specifieke gewoonte in de leefruimte in winter *Ga naar vraag 14*

◯ Anders: ______________

Raamopeningsgedrag in de leefruimte (zitkamer + eetkamer)

13. Hoe ver zet u de ramen open? (specifiek voor de winter) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15 cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in de leefruimte (zitkamer + eetkamer)

14. Heeft u bepaalde raamopeninggewoontes in de leefruimte in ZOMER? *

Stel u de vorige zomer-periode voor (temperatuur boven 20°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met zeer hoge temperaturen buiten beschouwing (>35°C). Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- ◯ De ramen blijven meestal gesloten in de zomer *Ga naar vraag 16*
- ◯ De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- ◯ De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- ◯ De ramen worden geopend wanneer iemand aanwezig is
- ◯ De ramen worden gesloten wanneer iemand aanwezig is
- ◯ De ramen in de leefruimte staan meestal open in de zomer
- ◯ De ramen worden geopend gedurende de nacht en gesloten overdag
- ◯ Ik heb geen specifieke gewoonte in de leefruimte in de zomer *Ga naar vraag 16*
- ◯ Anders: ____________

Raamopeningsgedrag in de leefruimte (zitkamer + eetkamer)

15. Hoe ver zet u de ramen open? (specifiek voor de zomer) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in de keuken

16. Zijn er ramen aanwezig in uw keuken? *

Markeer slechts één ovaal.

- ◯ Ja, er zijn ramen in de keuken
- ◯ Ja, er zijn ramen in de keuken maar deze kunnen niet open (vaste ramen) *Ga naar vraag 22*
- ◯ Neen, er zijn geen ramen in de keuken *Ga naar vraag 22*

Raamopeningsgedrag in de keuken

17. Welke soorten ramen zijn er aanwezig in uw keuken? (meerdere antwoorden zijn mogelijk) *

Vink alle toepasselijke opties aan.

- [ ] Draai-ramen (geen kiep-mogelijkheid)
- [ ] Kiep-ramen (geen draai-mogelijkheid)
- [ ] Draai-kiep ramen
- [ ] Schuiframen
- [ ] Dakramen
- [ ] Vaste ramen (niet opengaand)

Anders: [ ] ______________________

18. Heeft u bepaalde raamopeninggewoontes in de keuken in WINTER? *

Stel u de vorige winter-periode voor (temperatuur onder 10°C) en op welke manier u toen meestal met de ramen bent omgegaan. Laat dagen met extreme temperaturen (kouder als -5°C) buiten beschouwing. Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- ◯ De ramen blijven meestal gesloten in winter *Ga naar vraag 20*
- ◯ De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- ◯ De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- ◯ De ramen worden geopend wanneer iemand aan het koken is
- ◯ De ramen worden geopend na het koken
- ◯ De ramen in de keuken staan meestal open in winter
- ◯ Ik heb geen specifieke gewoonte in de keuken in winter *Ga naar vraag 20*
- ◯ Anders: ______________________

Raamopeningsgedrag in de keuken

19. Hoe ver zet u de ramen open? (specifiek voor de winter) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15 cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in de keuken

20. Heeft u bepaalde raamopeninggewoontes in de keuken in ZOMER? *

Stel u de vorige zomer-periode voor (temperatuur boven 20°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met zeer hoge temperaturen buiten beschouwing (>35°C). Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- De ramen blijven meestal gesloten in de zomer *Ga naar vraag 22*
- De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- De ramen worden geopend wanneer iemand aan het koken is
- De ramen worden geopend na het koken
- De ramen in de keuken staan meestal open in de zomer
- De ramen worden geopend gedurende de nacht en gesloten overdag
- Ik heb geen specifieke gewoonte in de keuken in de zomer *Ga naar vraag 22*
- Anders: ____

Raamopeningsgedrag in de keuken

21. Hoe ver zet u de ramen open? (specifiek voor de zomer) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in de badkamer

22. Zijn er ramen aanwezig in uw badkamer? *

Markeer slechts één ovaal.

- Ja, er zijn ramen in de badkamer
- Ja, er zijn ramen in de badkamer maar deze kunnen niet open (vaste ramen) *Ga naar vraag 28*
- Neen, er zijn geen ramen in de badkamer *Ga naar vraag 28*

Raamopeningsgedrag in de badkamer

23. Welke soorten ramen zijn er aanwezig in uw badkamer? (meerdere antwoorden zijn mogelijk) *

Vink alle toepasselijke opties aan.

- [ ] Draai-ramen (geen kiep-mogelijkheid)
- [ ] Kiep-ramen (geen draai-mogelijkheid)
- [ ] Draai-kiep ramen
- [ ] Schuiframen
- [ ] Dakramen
- [ ] Vaste ramen (niet opengaand)
- Anders: [ ] ____

24. Heeft u bepaalde raamopeninggewoontes in de badkamer in WINTER? *

Stel u de vorige winter-periode voor (temperatuur onder 10°C) en op welke manier u toen meestal met de ramen bent omgegaan. Laat dagen met zeer extreme temperaturen (kouder als -5°C) buiten beschouwing. Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- De ramen blijven meestal gesloten in winter *Ga naar vraag 26*
- De ramen worden geopend wanneer er iemand een douche/bad neemt
- De ramen worden geopend nadat een douche/bad is genomen
- De ramen in de badkamer staan meestal open in winter
- De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- Ik heb geen specifieke gewoonte in de badkamer in winter *Ga naar vraag 26*
- Anders: ____________________

Raamopeningsgedrag in de badkamer

25. Hoe ver zet u de ramen open? (specifiek voor de winter) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15 cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in de badkamer

26. Heeft u bepaalde raamopeninggewoontes in de badkamer in ZOMER? *

Stel u de vorige zomer-periode voor (temperatuur boven 20°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met zeer hoge temperaturen buiten beschouwing (>35°C). Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- De ramen blijven meestal gesloten in de zomer *Ga naar vraag 28*
- De ramen worden geopend wanneer er iemand een douche/bad neemt
- De ramen worden geopend nadat een douche/bad is genomen
- De ramen in de badkamer staan meestal open in de zomer
- De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- Ik heb geen specifieke gewoonte in de badkamer in de zomer *Ga naar vraag 28*
- Anders: ____________________

Raamopeningsgedrag in de badkamer

27. Hoe ver zet u de ramen open? (specifiek voor de zomer) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15cm)	Half open	Volledig open
Grootte van de raamopening	⬭	⬭	⬭	⬭

Raamopeningsgedrag in de slaapkamer

28. Zijn er ramen aanwezig in uw slaapkamer(s)? *

Markeer slechts één ovaal.

- ⬭ Ja, er zijn ramen in de slaapkamer(s)
- ⬭ Ja, er zijn ramen in de slaapkamer(s) maar deze kunnen niet open (vaste ramen) *Ga naar vraag 34*
- ⬭ Neen, er zijn geen ramen in de slaapkamer(s) *Ga naar vraag 34*

Raamopeningsgedrag in de slaapkamer

29. Welke soorten ramen zijn er aanwezig in uw slaapkamer(s)? (meerdere antwoorden zijn mogelijk) *

Vink alle toepasselijke opties aan.

- ☐ Draai-ramen (geen kiep-mogelijkheid)
- ☐ Kiep-ramen (geen draai-mogelijkheid)
- ☐ Draai-kiep ramen
- ☐ Schuiframen
- ☐ Dakramen
- ☐ Vaste ramen (niet opengaand)

Anders: ☐ ________________

30. Heeft u bepaalde raamopeninggewoontes in de slaapkamer in WINTER? *

Stel u de vorige winter-periode voor (temperatuur onder 10°C) en op welke manier u toen meestal met de ramen bent omgegaan. Laat dagen met extreme temperaturen (kouder als -5°C) buiten beschouwing. Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- ⬭ De ramen blijven meestal gesloten in winter *Ga naar vraag 32*
- ⬭ De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- ⬭ De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- ⬭ De ramen worden geopend voor een korte periode vooraleer te gaan slapen
- ⬭ De ramen worden geopend gedurende de nacht en gesloten overdag
- ⬭ De ramen in de slaapkamer staan meestal open in winter
- ⬭ Ik heb geen specifieke gewoonte in de slaapkamer in winter *Ga naar vraag 32*
- ⬭ Anders: ________________

Raamopeningsgedrag in de slaapkamer

31. Hoe ver zet u de ramen open? (specifiek voor de winter) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15 cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in de slaapkamer

32. Heeft u bepaalde raamopeninggewoontes in de slaapkamer in ZOMER? *

Stel u de vorige zomer-periode voor (temperatuur boven 20°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met zeer hoge temperaturen buiten beschouwing (>35°C). Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- ◯ De ramen blijven meestal gesloten in de zomer *Ga naar vraag 34*
- ◯ De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- ◯ De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- ◯ De ramen worden geopend voor een korte periode vooraleer te gaan slapen
- ◯ De ramen worden geopend gedurende de nacht en gesloten overdag
- ◯ De ramen in de slaapkamer staan meestal open in de zomer
- ◯ Ik heb geen specifieke gewoonte in de slaapkamer in de zomer *Ga naar vraag 34*
- ◯ Anders: ______________________

Raamopeningsgedrag in de slaapkamer

33. Hoe ver zet u de ramen open? (specifiek voor de zomer) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Raamopeningsgedrag in het toilet

34. Zijn er ramen aanwezig in uw toilet? *

Markeer slechts één ovaal.

- ◯ Ja, er zijn ramen aanwezig in het toilet.
- ◯ Ja, er zijn ramen in het toilet maar deze kunnen niet open (vaste ramen) *Ga naar vraag 40*
- ◯ Neen, er zijn geen ramen aanwezig in het toilet *Ga naar vraag 40*
- ◯ Er is geen apart toilet aanwezig *Ga naar vraag 40*

Raamopeningsgedrag in het toilet

35. Welke soorten ramen zijn er aanwezig in uw toilet? (meerdere antwoorden zijn mogelijk) *

Vink alle toepasselijke opties aan.

- [ ] Draai-ramen (geen kiep-mogelijkheid)
- [ ] Kiep-ramen (geen draai-mogelijkheid)
- [ ] Draai-kiep ramen
- [ ] Schuiframen
- [ ] Dakramen
- [ ] Vaste ramen (niet opengaand)

Anders: [ ] ______________________

36. Heeft u bepaalde raamopeninggewoontes in het toilet in WINTER? *

Stel u de vorige winter-periode voor (temperatuur onder 10°C) en op welke manier u toen meestal met de ramen bent omgegaan. Laat dagen met extreme temperaturen (kouder als -5°C) buiten beschouwing. Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- ( ) De ramen blijven meestal gesloten in winter *Ga naar vraag 38*
- ( ) De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- ( ) De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- ( ) De ramen worden geopend wanneer iemand aanwezig is
- ( ) De ramen worden geopend nadat iemand aanwezig was
- ( ) De ramen in het toilet staan meestal open in winter
- ( ) Ik heb geen specifieke gewoonte in het toilet in winter *Ga naar vraag 38*
- ( ) Anders: ______________________

Raamopeningsgedrag in het toilet

37. Hoe ver zet u de ramen open? (specifiek voor de winter) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15 cm)	Half open	Volledig open
Grootte van de raamopening	( )	( )	( )	( )

Raamopeningsgedrag in het toilet

38. Heeft u bepaalde raamopeninggewoontes in het toilet in ZOMER? *

Stel u de vorige zomer-periode voor (temperatuur boven 20°C) en op welke manier u toen met de ramen bent omgegaan. Laat dagen met zeer hoge temperaturen buiten beschouwing (>35°C). Indien u slechts af en toe een bepaalde handeling uitvoert, duidt u "Ik heb geen specifieke gewoonte" aan. Indien het voor u relevant antwoord niet in de lijst staat, kan u het antwoord "Anders" aanduiden en daarbij uw antwoord specificeren.

Markeer slechts één ovaal.

- De ramen blijven meestal gesloten in de zomer *Ga naar vraag 44*
- De ramen worden geopend in de ochtend, na het opstaan, voor een korte periode (<2uur)
- De ramen worden geopend in de ochtend, na het opstaan, voor een lange periode (>2 uur)
- De ramen worden geopend wanneer iemand aanwezig is
- De ramen worden geopend nadat iemand aanwezig was
- De ramen in het toilet staan meestal open in de zomer
- Ik heb geen specifieke gewoonte in het toilet in de zomer *Ga naar vraag 44*
- Anders: ______________________

Raamopeningsgedrag in het toilet

39. Hoe ver zet u de ramen open? (specifiek voor de zomer) *

Markeer slechts één ovaal per rij.

	Kiertje (< 1cm)	Kiep of kleine opening (< 15cm)	Half open	Volledig open
Grootte van de raamopening	◯	◯	◯	◯

Ligging van de woning

40. In welke omgeving is uw woning gelegen? *

Markeer slechts één ovaal.

- Stadscentrum
- Stedelijk gebied (excl. stadscentrum)
- Landelijk gebied langs drukke weg
- Landelijk gebied (andere)
- Industrieel gebied
- Anders: ______________________

41. Ondervindt u soms hinder door de ligging van uw woning (vb. geluidshinder, verkeer,...) waardoor u de stand van de ramen zal aanpassen? *

Markeer slechts één ovaal.

- Nee, ik ondervind geen hinder door de ligging van mijn woning *Ga naar vraag 44*
- Ja, ik ondervind soms hinder door de ligging van mijn woning

Ligging van de woning

42. In welke kamers ondervindt u soms hinder? *

Vink alle toepasselijke opties aan.

- [ ] Leefruimte
- [ ] Keuken
- [ ] Badkamer
- [ ] ALLE slaapkamers
- [ ] SOMMIGE slaapkamers
- [ ] Toilet

43. Welke hinder ondervindt u in deze kamer(s)?

Raamopeningsgedrag bij activiteiten

Deze sectie bevraagt het raamopeningsgedrag bij het uitvoeren van specifieke activiteiten.

44. Opent u een of meerdere ramen wanneer u volgende activiteiten uitvoert? *

Markeer slechts één ovaal per rij.

	Ja	Nee	Soms	Niet van toepassing
Strijken	○	○	○	○
Drogen van kleding	○	○	○	○
Stofzuigen	○	○	○	○
Kuisen (excl. kuisen van de ramen)	○	○	○	○

45. Zijn er andere activiteiten/omstandigheden waarvoor u ramen opent? (vb. bezoek, sporten, geurhinder,...)

46. Zijn er andere activiteiten/omstandigheden waarvoor u ramen sluit? (vb. huisdieren aanwezig, weersomstandigheden, ...)

47. Mag er binnen gerookt worden? *

Markeer slechts één ovaal.

- Ja *Ga naar vraag 48*
- Nee *Ga naar vraag 50*
- Soms *Ga naar vraag 48*

Raamopeningsgedrag bij actviteiten

48. Wanneer er binnen gerookt wordt, opent u dan een raam? *

Markeer slechts één ovaal.

- Ja
- Nee, Ik zet wel de dampkap aan
- Nee

Raamopeningsgedrag

49. Heeft u nog opmerkingen over uw raamgebruik in de woning die voordien nog niet bevraagd zijn?

Gegevens over de bewoners

Als laatste hebben we nog een aantal gegevens nodig over de bewoners van de woning

50. Met hoeveel personen woont u in de woning? *

Markeer slechts één ovaal.

- 1 *Ga naar vraag 51*
- 2 *Ga naar vraag 54*
- 3 *Ga naar vraag 57*
- 4 *Ga naar vraag 60*
- 5 *Ga naar vraag 63*
- 6 *Ga naar vraag 66*
- 7 *Ga naar vraag 69*
- 8 *Ga naar vraag 72*
- Anders:

Gegevens over de bewoners

51. Wat is de leeftijd van de bewoner? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭	⬭

52. Wat is het beroep van de bewoner? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaan((kleuter/lager/mid(
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

53. Wat is het opleidingsniveau van de bewoner?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭

Gegevens over de bewoners

54. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 2	⬭	⬭	⬭	⬭	⬭	⬭	⬭

55. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaan((kleuter/lager/mid(
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 2	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

56. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯

Ga naar vraag 75

Gegevens over de bewoners

57. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1	◯	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯	◯

58. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaan((kleuter/lager/midc
Bewoner 1	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯	◯	◯	◯

59. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯

Ga naar vraag 75

Gegevens over de bewoners

60. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1							
Bewoner 2							
Bewoner 3							
Bewoner 4							

61. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaan (kleuter/lager/midc
Bewoner 1									
Bewoner 2									
Bewoner 3									
Bewoner 4									

62. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1						
Bewoner 2						
Bewoner 3						
Bewoner 4						

Ga naar vraag 75

Gegevens over de bewoners

63. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1	◯	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯	◯

64. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaan (kleuter/lager/mid
Bewoner 1	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯	◯	◯	◯

65. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯

Ga naar vraag 75

Gegevens over de bewoners

66. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 2	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 3	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 4	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 5	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 6	⬭	⬭	⬭	⬭	⬭	⬭	⬭

67. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaand (kleuter/lager/midc
Bewoner 1	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 2	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 3	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 4	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 5	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭
Bewoner 6	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭	⬭

68. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯
Bewoner 6	◯	◯	◯	◯	◯	◯

Ga naar vraag 75

Gegevens over de bewoners

69. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1	◯	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯	◯
Bewoner 6	◯	◯	◯	◯	◯	◯	◯
Bewoner 7	◯	◯	◯	◯	◯	◯	◯

70. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaand (kleuter/lager/midd
Bewoner 1	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 6	◯	◯	◯	◯	◯	◯	◯	◯	◯
Bewoner 7	◯	◯	◯	◯	◯	◯	◯	◯	◯

71. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1	◯	◯	◯	◯	◯	◯
Bewoner 2	◯	◯	◯	◯	◯	◯
Bewoner 3	◯	◯	◯	◯	◯	◯
Bewoner 4	◯	◯	◯	◯	◯	◯
Bewoner 5	◯	◯	◯	◯	◯	◯
Bewoner 6	◯	◯	◯	◯	◯	◯
Bewoner 7	◯	◯	◯	◯	◯	◯

Ga naar vraag 75

Gegevens over de bewoners

72. Wat is de leeftijd van de bewoners? *

Markeer slechts één ovaal per rij.

	<12 jaar	12-18 jaar	18-25 jaar	25-35 jaar	35-55 jaar	55-75 jaar	> 75 jaar
Bewoner 1							
Bewoner 2							
Bewoner 3							
Bewoner 4							
Bewoner 5							
Bewoner 6							
Bewoner 7							
Bewoner 8							

73. Wat is het beroep van de bewoners? *

Markeer slechts één ovaal per rij.

	Voltijds werk, dagwerk	Voltijds werk, 1-2 dagen in de week thuiswerk	Voltijds werk, thuiswerk	Voltijds werk, shiften	Halftijds werk	Gepensioneerd	Werkloos	Niet schoolgaand kind	Schoolgaan((kleuter/lager/mid(
Bewoner 1									
Bewoner 2									
Bewoner 3									
Bewoner 4									
Bewoner 5									
Bewoner 6									
Bewoner 7									
Bewoner 8									

74. Wat is het opleidingsniveau van de bewoners?
Selecteer het hoogst behaalde diploma.

Markeer slechts één ovaal per rij.

	Geen diploma	Lager onderwijs	Secundair onderwijs	Bachelor	Master	Doctor
Bewoner 1						
Bewoner 2						
Bewoner 3						
Bewoner 4						
Bewoner 5						
Bewoner 6						
Bewoner 7						
Bewoner 8						

Ga naar vraag 75

Huisdieren

75. Heeft u huisdieren? *

Markeer slechts één ovaal.

- Ja
- Nee *Ga naar sectie 48 (Bedankt voor uw deelname!)*

Huisdieren

76. Welke huisdieren heeft u en hoeveel?

Bedankt voor uw deelname!

Bij vragen en/of opmerkingen aarzel dan niet om mij te contacteren: silke.verbruggen@ugent.be

U bevestigt uw antwoorden door op de knop 'Verzenden' te drukken.

14.3 Questionnaire clothing behaviour

Enquête kledingsgedrag

Datum:
Uur:

Enquête kledingsgedrag

Deze enquête peilt naar het kledingsgedrag van personen in hun eigen leefomgeving.
U kan de enquête alleen invullen wanneer u zich in uw eigen leefomgeving bevindt (thuis, app, studio, ...).
Dus niet wanneer u op verplaatsing bent (winkel, werk, school, ...).

Alle resultaten worden vertrouwelijk behandeld. Er bestaan geen foute antwoorden!

Dit is een korte enquête die ongeveer 3 minuten zal duren. De enquête loopt van 11 maart t.e.m. 7 april 2019 en kan meermaals door eenzelfde persoon ingevuld worden, maximum 1x per dag. Ook kinderen vanaf 7 jaar kunnen hier aan mee doen. Onder de deelnemers worden 10 bioscooptickets verloot. Hoe vaker u hebt deelgenomen, hoe groter de kans op een ticket.

Bij vragen of opmerkingen bent u vrij te mailen naar Els.DeCeuster@UGent.be.
Bedankt voor uw medewerking!

*Vereist

Thuisomgeving

1. **Bent u nu thuis?** *
   Bevindt u zich nu in uw vertrouwde woning? Dit kan een app, een studio, een woning, ... zijn.
   Markeer slechts één ovaal.

   - Ja *Ga naar vraag 3.*
   - Nee *Ga naar vraag 2.*

Thuisomgeving

Het is belangrijk om deze enquête uit te voeren wanneer u zich in een vertrouwde omgeving bevindt. Hier wordt uw kledingskeuze minder beïnvloed door anderen, en bent u vrij om aan te doen wat u zelf verkiest.

2. *Markeer slechts één ovaal.*

   - Oké *Stop met het invullen van dit formulier.*

Algemeen

3. **Naam** *
   Dit kan uw echte naam of een pseudoniem zijn.

4. **Leeftijd** *

5. **Geslacht** *
   Markeer slechts één ovaal.

   - Man
   - Vrouw
   - Andere

Enquête kledingsgedrag

6. **Bezoekers** *
   Bent u momenteel alleen thuis of in gezelschap? Zoja, wie is er nog aanwezig?
   Vink alle toepasselijke opties aan.

- [ ] Ik ben alleen thuis
- [ ] Kinderen
- [ ] Partner
- [ ] Ouders/Broers/Zussen
- [ ] Andere

Kledingsgedrag

7. **Kleren** *
   Welke kleren draagt u op dit moment?
   Vink alle toepasselijke opties aan.

- [ ] Onderbroek
- [ ] Beha
- [ ] Kousen
- [ ] Extra kousen
- [ ] Korte broek
- [ ] Lange broek
- [ ] Joggingbroek
- [ ] Pyjamabroek
- [ ] Badjas
- [ ] Onderhemd
- [ ] T - shirt zonder mouwen
- [ ] T - shirt
- [ ] T - shirt met lange mouwen
- [ ] Hemd
- [ ] Hemd met lange mouwen
- [ ] Korte jurk met korte mouwen
- [ ] Korte jurk met lange mouwen
- [ ] Lange jurk met korte mouwen
- [ ] Lange jurk met lange mouwen
- [ ] Korte rok
- [ ] Lange rok
- [ ] Dunne trui
- [ ] Dunne trui met kap
- [ ] Dikke trui
- [ ] Dikke trui met kap
- [ ] Pantoffels
- [ ] sneakers of sportschoenen
- [ ] Schoenen
- [ ] Schoenen tot boven enkel
- [ ] Sjaal

Enquête kledingsgedrag

8. **Andere:**
vb. jeansvest, kousenbroek, beenverwarmers, ...

9. **Zitten/liggen op/onder**
Indien u niet rechtstaat, op wat voor meubelstuk bevindt u zich?
Vink alle toepasselijke opties aan.

- [ ] Houten stoel
- [ ] Plastieken stoel
- [ ] Metalen stoel
- [ ] Bureaustoel
- [ ] Zetel
- [ ] Onder een dekentje
- [ ] Bed (matras + deken)

10. **Andere:**
vb. op de mat, op een schapenvacht, ...

11. **Kledingspatronen** *
Komen de kleren die u nu aanheeft overeen met wat u afgelopen dagen aan had?
Markeer slechts één ovaal.

- ◯ Ik draag veel minder kleren dan afgelopen dagen.
- ◯ Ik draag minder kleren dan afgelopen dagen.
- ◯ Ik draag iets minder kleren dan afgelopen dagen.
- ◯ Ik draag ongeveer hetzelfde.
- ◯ Ik draag iets meer kleren dan afgelopen dagen.
- ◯ Ik draag meer kleren dan afgelopen dagen.
- ◯ Ik draag veel meer kleren dan afgelopen dagen.

12. **In de periode dat u vandaag thuis was, hoe vaak heeft u kledingstukken uitgedaan?** *
Hierbij tellen de kledingsaanpassingen die gebeuren wanneer u net bent opgestaan of wanneer u net bent thuisgekomen (van werk, school, winkel, ...) OOK mee. Bijvoorbeeld pyjama uitdoen bij het opstaan, werkkleren uitdoen bij thuiskomen en om 16u thuis een trui en pantoffels uitdoen = 3x kleren uitgedaan.
Markeer slechts één ovaal.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

13. **In de periode dat u vandaag thuis was, hoe vaak heeft u kledingstukken aangedaan?** *
Hierbij tellen de kledingsaanpassingen die gebeuren wanneer u net bent opgestaan of wanneer u net bent thuis gekomen (van werk, school, winkel, ...) OOK mee. Bijvoorbeeld kleren aandoen bij het opstaan, andere kleren aandoen bij het thuis komen van het werk = 2x kleren aangedaan.
Markeer slechts één ovaal.

0	1	2	3	4	5	6	7	8	9	10
◯	◯	◯	◯	◯	◯	◯	◯	◯	◯	◯

Enquête kledingsgedrag

14. **Waarom/wanneer deed u vandaag kleren aan/uit?** *
    Vink alle toepasselijke opties aan.

    - [ ] Bij het opstaan / slapen
    - [ ] Te warm / te koud
    - [ ] Voor comfort (vb. werkkleren omwisselen in jogging, ...)
    - [ ] Buiten -> binnen / binnen -> buiten
    - [ ] Bezoekers / gezelschap
    - [ ] Andere

15. **Andere:**

    ____

Comfort

16. **Hoe voelt u zich op dit moment?** *
    Markeer slechts één ovaal.

    - ( ) Te warm
    - ( ) Warm
    - ( ) Een beetje warm
    - ( ) Neutraal
    - ( ) Een beetje fris
    - ( ) Fris
    - ( ) Koud

17. **Comfort** *
    Hoe uit dat gevoel zich in comfortniveau?
    Markeer slechts één ovaal.

    - ( ) Aangenaam
    - ( ) Juist voldoende aangenaam
    - ( ) Juist niet aangenaam
    - ( ) Onaangenaam

18. **Comfort aanpassen** *
    Hoe zou je de tempratuur in je omgeving willen aanpassen?
    Markeer slechts één ovaal.

    - ( ) Veel kouder
    - ( ) Koeler
    - ( ) Iets frisser
    - ( ) Zoals nu is goed
    - ( ) Iets warmer
    - ( ) Warmer
    - ( ) Veel warmer

Temperatuur

Enquête kledingsgedrag

19. **Ruimte** *
In welke ruimte bevindt u zich?
Markeer slechts één ovaal.

- Woonkamer
- Leefruimte (living)
- Keuken
- Slaapkamer
- Badkamer
- Toilet
- Gang/hal
- Kot/Studio
- Anders: ______

20. **Temperatuur in de ruimte** *
Kunt u de temperatuur in de ruimte waarin u zich bevindt aflezen van een thermostaat?
Markeer slechts één ovaal.

- Ja
- Nee

21. **Indien ja, wat is de temperatuur in de ruimte?**

______

22. **Indien nee, kunt u kijken op welke stand de radiator staat?**

Markeer slechts één ovaal.

0	1	2	3	4	5
◯	◯	◯	◯	◯	◯

Enquête kledingsgedrag

Einde enquête

Bedankt om mee te doen aan deze enquête.

Bij vragen of opmerkingen bent u vrij te mailen naar Els.DeCeuster@UGent.be.

23. **Wilt u graag een cinematicket winnen?**
    Markeer slechts één ovaal.
    - Ja
    - Nee

24. **Zou u deze enquête in de volgende dagen nog eens willen invullen?**
    Markeer slechts één ovaal.
    - Ja, stuur mij een mail om me er aan te herinneren.
    - Misschien
    - Nee

25. **Zou u op het einde van het onderzoek graag de resultaten krijgen?**
    Markeer slechts één ovaal.
    - Ja, stuur mij een mail.
    - Nee.

26. **E-mailadres**
    Gelieve uw e-mailadres in te geven indien u kans wilt maken op een cinematicket, eraan herinnert wilt worden om deze enquête nog een keer uit te voeren, of wanneer u graag de resultaten van dit onderzoek zou krijgen.

14.4 Classification household-habits and seasonality coherence

Table 14.8: Window use habits for all survey participants in both winter and summer (living-kitchen-bedroom-bathroom), with corresponding assignment of household-habit and seasonality coherence.

Habits Winter	Household-habit	Habits Summer	Seasonality coherence
0111	All Closed	2041	All windows opened more
1011	All Closed	2031	All windows opened more
1110	All Closed	0002	All windows opened more
1111	All Closed	4421	All windows opened more
1111	All Closed	2342	All windows opened more
1111	All Closed	2341	All windows opened more
1111	All Closed	2041	All windows opened more
1111	All Closed	2200	All windows opened more
1111	All Closed	2342	All windows opened more
1111	All Closed	2333	All windows opened more
1111	All Closed	2222	All windows opened more
1111	All Closed	2343	All windows opened more
1111	All Closed	2242	All windows opened more
1111	All Closed	3333	All windows opened more
1111	All Closed	2241	All windows opened more
1111	All Closed	3333	All windows opened more
1111	All Closed	2321	All windows opened more
1111	All Closed	444x	All windows opened more
1111	All Closed	2231	All windows opened more
1111	All Closed	2142	All windows opened more
1111	All Closed	2220	All windows opened more
1111	All Closed	4141	All windows opened more
1111	All Closed	2130	All windows opened more
1111	All Closed	4441	All windows opened more
1111	All Closed	4443	All windows opened more
1111	All Closed	3122	All windows opened more
1111	All Closed	3232	All windows opened more
1111	All Closed	2131	All windows opened more
1111	All Closed	4442	All windows opened more
1111	All Closed	4421	All windows opened more
1111	All Closed	4040	All windows opened more
1111	All Closed	2341	All windows opened more
1111	All Closed	2032	All windows opened more
1111	All Closed	2221	All windows opened more
1111	All Closed	3321	All windows opened more
1111	All Closed	224x	All windows opened more
1111	All Closed	444x	All windows opened more
1111	All Closed	2321	All windows opened more
1111	All Closed	2341	All windows opened more
1111	All Closed	3320	All windows opened more

1111	All Closed	0000	All windows opened more
1111	All Closed	2331	All windows opened more
1111	All Closed	2222	All windows opened more
1111	All Closed	2231	All windows opened more
1111	All Closed	2041	All windows opened more
1111	All Closed	2042	All windows opened more
1111	All Closed	0100	All windows opened more
1111	All Closed	0341	All windows opened more
1111	All Closed	2042	All windows opened more
1112	All Closed	3242	All windows opened more
1112	All Closed	33x2	All windows opened more
1211	All Closed	2341	All windows opened more
1211	All Closed	2222	All windows opened more
111x	All Closed	222x	All windows opened more
111x	All Closed	213x	All windows opened more
111x	All Closed	333x	All windows opened more
111x	All Closed	220x	All windows opened more
111x	All Closed	234x	All windows opened more
111x	All Closed	224x	All windows opened more
111x	All Closed	004x	All windows opened more
111x	All Closed	213x	All windows opened more
111x	All Closed	233x	All windows opened more
111x	All Closed	332x	All windows opened more
111x	All Closed	333x	All windows opened more
111x	All Closed	242x	All windows opened more
11xx	All Closed	22xx	All windows opened more
1x11	All Closed	3x23	All windows opened more
1x11	All Closed	3x30	All windows opened more
1x11	All Closed	2x22	All windows opened more
1x11	All Closed	3x21	All windows opened more
1x11	All Closed	2x32	All windows opened more
1x11	All Closed	2x21	All windows opened more
1x11	All Closed	2x02	All windows opened more
1x11	All Closed	2x21	All windows opened more
1x11	All Closed	4x23	All windows opened more
1x11	All Closed	2x21	All windows opened more
1x11	All Closed	2x23	All windows opened more
1x11	All Closed	4x40	All windows opened more
1x11	All Closed	0x41	All windows opened more
1x11	All Closed	2x3x	All windows opened more
1x1x	All Closed	0x3x	All windows opened more
1x1x	All Closed	0x0x	All windows opened more
1x1x	All Closed	2x3x	All windows opened more
1x1x	All Closed	2x4x	All windows opened more
1x1x	All Closed	2x4x	All windows opened more
1x1x	All Closed	2x2x	All windows opened more
1x1x	All Closed	2x4x	All windows opened more
1x1x	All Closed	4x0x	All windows opened more
1x1x	All Closed	2x3x	All windows opened more
1x1x	All Closed	2x2x	All windows opened more
x111	All Closed	x233	All windows opened more

x112	All Closed	x322	All windows opened more
xx11	All Closed	xx22	All windows opened more
xx1x	All Closed	xx2x	All windows opened more
1011	All Closed	2211	Dayzone windows opened more
1101	All Closed	0000	Dayzone windows opened more
1111	All Closed	0011	Dayzone windows opened more
1111	All Closed	4313	Dayzone windows opened more
1111	All Closed	3311	Dayzone windows opened more
1x11	All Closed	2x11	Dayzone windows opened more
0111	All Closed	0042	Nightzone windows opened more
1111	All Closed	1101	Nightzone windows opened more
1112	All Closed	1022	Nightzone windows opened more
1112	All Closed	1222	Nightzone windows opened more
2112	All Closed	1142	Nightzone windows opened more
111x	All Closed	1x3x	Nightzone windows opened more
1x11	All Closed	1x33	Nightzone windows opened more
x110	All Closed	x100	Nightzone windows opened more
x111	All Closed	x132	Nightzone windows opened more
x112	All Closed	x332	Nightzone windows opened more
1111	All Closed	1111	Window use the same
1111	All Closed	1111	Window use the same
1111	All Closed	1111	Window use the same
1111	All Closed	1111	Window use the same
1111	All Closed	1111	Window use the same
1111	All Closed	1212	Window use the same
1111	All Closed	1111	Window use the same
1111	All Closed	1111	Window use the same
1112	All Closed	1112	Window use the same
111x	All Closed	101x	Window use the same
111x	All Closed	111x	Window use the same
1x1x	All Closed	1x1x	Window use the same
x111	All Closed	x111	Window use the same
xx11	All Closed	xx11	Window use the same
0020	All Shortly Opened	3030	All windows opened more
0020	All Shortly Opened	2042	All windows opened more
0122	All Shortly Opened	2243	All windows opened more
0122	All Shortly Opened	2233	All windows opened more
0201	All Shortly Opened	4243	All windows opened more
0222	All Shortly Opened	3333	All windows opened more
0222	All Shortly Opened	3233	All windows opened more
2122	All Shortly Opened	3333	All windows opened more
2122	All Shortly Opened	3332	All windows opened more
2122	All Shortly Opened	2323	All windows opened more
2122	All Shortly Opened	3342	All windows opened more
2220	All Shortly Opened	2323	All windows opened more
2222	All Shortly Opened	3333	All windows opened more
000x	All Shortly Opened	232x	All windows opened more
0x0x	All Shortly Opened	3x4x	All windows opened more
0x20	All Shortly Opened	2x30	All windows opened more
0x20	All Shortly Opened	4333	All windows opened more
202x	All Shortly Opened	333x	All windows opened more

222x	All Shortly Opened	414x	All windows opened more
2x20	All Shortly Opened	0331	All windows opened more
2x2x	All Shortly Opened	3x3x	All windows opened more
2x2x	All Shortly Opened	333x	All windows opened more
2x2x	All Shortly Opened	044x	All windows opened more
2x2x	All Shortly Opened	3x3x	All windows opened more
x222	All Shortly Opened	3333	All windows opened more
x22x	All Shortly Opened	x33x	All windows opened more
x22x	All Shortly Opened	x03x	All windows opened more
x22x	All Shortly Opened	x33x	All windows opened more
x22x	All Shortly Opened	x33x	All windows opened more
xx2x	All Shortly Opened	xx4x	All windows opened more
xx2x	All Shortly Opened	xx3x	All windows opened more
0000	All Shortly Opened	2300	Dayzone windows opened more
0021	All Shortly Opened	4420	Dayzone windows opened more
0222	All Shortly Opened	2323	Dayzone windows opened more
2022	All Shortly Opened	3323	Dayzone windows opened more
2122	All Shortly Opened	3223	Dayzone windows opened more
2122	All Shortly Opened	3223	Dayzone windows opened more
2222	All Shortly Opened	3323	Dayzone windows opened more
2222	All Shortly Opened	3322	Dayzone windows opened more
2222	All Shortly Opened	3323	Dayzone windows opened more
2222	All Shortly Opened	3323	Dayzone windows opened more
2222	All Shortly Opened	3323	Dayzone windows opened more
202x	All Shortly Opened	002x	Dayzone windows opened more
222x	All Shortly Opened	332x	Dayzone windows opened more
xx2x	All Shortly Opened	3323	Dayzone windows opened more
0002	All Shortly Opened	0022	Nightzone windows opened more
0222	All Shortly Opened	0033	Nightzone windows opened more
0222	All Shortly Opened	2232	Nightzone windows opened more
2022	All Shortly Opened	2333	Nightzone windows opened more
2022	All Shortly Opened	2042	Nightzone windows opened more
2122	All Shortly Opened	2142	Nightzone windows opened more
2122	All Shortly Opened	2232	Nightzone windows opened more
2222	All Shortly Opened	2332	Nightzone windows opened more
2222	All Shortly Opened	2232	Nightzone windows opened more
2222	All Shortly Opened	2343	Nightzone windows opened more
2222	All Shortly Opened	2333	Nightzone windows opened more
0x22	All Shortly Opened	0x42	Nightzone windows opened more
0x22	All Shortly Opened	0x43	Nightzone windows opened more
202x	All Shortly Opened	2333	Nightzone windows opened more
222x	All Shortly Opened	133x	Nightzone windows opened more
222x	All Shortly Opened	2343	Nightzone windows opened more
2x20	All Shortly Opened	2333	Nightzone windows opened more
2x22	All Shortly Opened	2x33	Nightzone windows opened more
2x2x	All Shortly Opened	2x4x	Nightzone windows opened more
2x2x	All Shortly Opened	2x4x	Nightzone windows opened more
2x2x	All Shortly Opened	2x3x	Nightzone windows opened more
2x2x	All Shortly Opened	2x3x	Nightzone windows opened more
2x2x	All Shortly Opened	2x4x	Nightzone windows opened more
0000	All Shortly Opened	0000	Window use the same

0220	All Shortly Opened	0322	Window use the same
0222	All Shortly Opened	0222	Window use the same
2022	All Shortly Opened	2022	Window use the same
2022	All Shortly Opened	2023	Window use the same
2022	All Shortly Opened	x022	Window use the same
2022	All Shortly Opened	2222	Window use the same
2122	All Shortly Opened	2122	Window use the same
2222	All Shortly Opened	2023	Window use the same
2222	All Shortly Opened	2222	Window use the same
2222	All Shortly Opened	2223	Window use the same
2222	All Shortly Opened	2322	Window use the same
2222	All Shortly Opened	2023	Window use the same
2222	All Shortly Opened	2222	Window use the same
000x	All Shortly Opened	000x	Window use the same
000x	All Shortly Opened	000x	Window use the same
00x2	All Shortly Opened	0042	Window use the same
0x2x	All Shortly Opened	0x2x	Window use the same
222x	All Shortly Opened	222x	Window use the same
222x	All Shortly Opened	222x	Window use the same
2x20	All Shortly Opened	2x23	Window use the same
2x22	All Shortly Opened	2x22	Window use the same
2x22	All Shortly Opened	2x22	Window use the same
2x22	All Shortly Opened	2x23	Window use the same
2x22	All Shortly Opened	2x22	Window use the same
x22x	All Shortly Opened	022x	Window use the same
xx22	All Shortly Opened	xx22	Window use the same
xx2x	All Shortly Opened	xx2x	Window use the same
xx3x	All Shortly Opened	2x3x	Window use the same
xx3x	All Shortly Opened	xx3x	Window use the same
1002	Bedroom Opened Most	0033	All windows opened more
1021	Bedroom Opened Most	0031	All windows opened more
1022	Bedroom Opened Most	2042	All windows opened more
1022	Bedroom Opened Most	2242	All windows opened more
1121	Bedroom Opened Most	22x0	All windows opened more
1121	Bedroom Opened Most	2333	All windows opened more
1121	Bedroom Opened Most	0032	All windows opened more
1121	Bedroom Opened Most	2333	All windows opened more
1121	Bedroom Opened Most	2232	All windows opened more
1121	Bedroom Opened Most	2331	All windows opened more
1121	Bedroom Opened Most	2330	All windows opened more
1121	Bedroom Opened Most	3333	All windows opened more
1121	Bedroom Opened Most	2330	All windows opened more
1121	Bedroom Opened Most	2242	All windows opened more
1121	Bedroom Opened Most	2333	All windows opened more
1121	Bedroom Opened Most	2042	All windows opened more
1121	Bedroom Opened Most	3333	All windows opened more
1121	Bedroom Opened Most	2031	All windows opened more
1121	Bedroom Opened Most	2232	All windows opened more
1121	Bedroom Opened Most	2231	All windows opened more
1131	Bedroom Opened Most	2241	All windows opened more
1132	Bedroom Opened Most	2343	All windows opened more

1132	Bedroom Opened Most	2042	All windows opened more
1141	Bedroom Opened Most	2332	All windows opened more
1141	Bedroom Opened Most	2331	All windows opened more
1141	Bedroom Opened Most	2232	All windows opened more
1142	Bedroom Opened Most	2333	All windows opened more
1142	Bedroom Opened Most	2332	All windows opened more
1142	Bedroom Opened Most	3333	All windows opened more
1202	Bedroom Opened Most	0233	All windows opened more
1220	Bedroom Opened Most	2330	All windows opened more
1222	Bedroom Opened Most	2x30	All windows opened more
1222	Bedroom Opened Most	3333	All windows opened more
1222	Bedroom Opened Most	3342	All windows opened more
1222	Bedroom Opened Most	0032	All windows opened more
1242	Bedroom Opened Most	3333	All windows opened more
2231	Bedroom Opened Most	2333	All windows opened more
102x	Bedroom Opened Most	233x	All windows opened more
120x	Bedroom Opened Most	333x	All windows opened more
122x	Bedroom Opened Most	x34x	All windows opened more
1x21	Bedroom Opened Most	2x31	All windows opened more
1x30	Bedroom Opened Most	3x40	All windows opened more
1x42	Bedroom Opened Most	3x33	All windows opened more
1x42	Bedroom Opened Most	2x32	All windows opened more
x032	Bedroom Opened Most	x233	All windows opened more
0242	Bedroom Opened Most	2242	Dayzone windows opened more
1032	Bedroom Opened Most	3333	Dayzone windows opened more
1121	Bedroom Opened Most	3321	Dayzone windows opened more
1121	Bedroom Opened Most	2221	Dayzone windows opened more
1121	Bedroom Opened Most	2321	Dayzone windows opened more
1121	Bedroom Opened Most	4422	Dayzone windows opened more
1121	Bedroom Opened Most	0022	Dayzone windows opened more
1121	Bedroom Opened Most	2321	Dayzone windows opened more
1121	Bedroom Opened Most	0022	Dayzone windows opened more
1121	Bedroom Opened Most	2222	Dayzone windows opened more
1121	Bedroom Opened Most	2222	Dayzone windows opened more
1121	Bedroom Opened Most	3321	Dayzone windows opened more
1121	Bedroom Opened Most	2223	Dayzone windows opened more
1121	Bedroom Opened Most	2222	Dayzone windows opened more
1121	Bedroom Opened Most	2220	Dayzone windows opened more
1121	Bedroom Opened Most	0020	Dayzone windows opened more
1121	Bedroom Opened Most	2123	Dayzone windows opened more
1130	Bedroom Opened Most	2233	Dayzone windows opened more
1131	Bedroom Opened Most	3333	Dayzone windows opened more
1131	Bedroom Opened Most	2130	Dayzone windows opened more
1131	Bedroom Opened Most	2233	Dayzone windows opened more
1131	Bedroom Opened Most	2032	Dayzone windows opened more
1131	Bedroom Opened Most	4231	Dayzone windows opened more
1131	Bedroom Opened Most	4131	Dayzone windows opened more
1131	Bedroom Opened Most	2331	Dayzone windows opened more
1131	Bedroom Opened Most	0031	Dayzone windows opened more
1131	Bedroom Opened Most	3133	Dayzone windows opened more
1132	Bedroom Opened Most	2233	Dayzone windows opened more

1132	Bedroom Opened Most	3333	Dayzone windows opened more
1132	Bedroom Opened Most	2232	Dayzone windows opened more
1141	Bedroom Opened Most	2142	Dayzone windows opened more
1141	Bedroom Opened Most	2341	Dayzone windows opened more
1141	Bedroom Opened Most	444x	Dayzone windows opened more
1142	Bedroom Opened Most	2x42	Dayzone windows opened more
1142	Bedroom Opened Most	2242	Dayzone windows opened more
1220	Bedroom Opened Most	2322	Dayzone windows opened more
1221	Bedroom Opened Most	0221	Dayzone windows opened more
1221	Bedroom Opened Most	0321	Dayzone windows opened more
1222	Bedroom Opened Most	4222	Dayzone windows opened more
1222	Bedroom Opened Most	2222	Dayzone windows opened more
1222	Bedroom Opened Most	2222	Dayzone windows opened more
1222	Bedroom Opened Most	0022	Dayzone windows opened more
1232	Bedroom Opened Most	2333	Dayzone windows opened more
1242	Bedroom Opened Most	2343	Dayzone windows opened more
2042	Bedroom Opened Most	4042	Dayzone windows opened more
2132	Bedroom Opened Most	3333	Dayzone windows opened more
2132	Bedroom Opened Most	3332	Dayzone windows opened more
2231	Bedroom Opened Most	3331	Dayzone windows opened more
0x42	Bedroom Opened Most	2x42	Dayzone windows opened more
122x	Bedroom Opened Most	022x	Dayzone windows opened more
123x	Bedroom Opened Most	203x	Dayzone windows opened more
123x	Bedroom Opened Most	2233	Dayzone windows opened more
123x	Bedroom Opened Most	233x	Dayzone windows opened more
1x21	Bedroom Opened Most	2x22	Dayzone windows opened more
1x21	Bedroom Opened Most	3x20	Dayzone windows opened more
1x21	Bedroom Opened Most	2x21	Dayzone windows opened more
1x21	Bedroom Opened Most	0x22	Dayzone windows opened more
1x31	Bedroom Opened Most	2x32	Dayzone windows opened more
1x32	Bedroom Opened Most	3x32	Dayzone windows opened more
1x32	Bedroom Opened Most	4x32	Dayzone windows opened more
1x32	Bedroom Opened Most	2333	Dayzone windows opened more
1x41	Bedroom Opened Most	2x42	Dayzone windows opened more
x132	Bedroom Opened Most	4233	Dayzone windows opened more
x231	Bedroom Opened Most	x331	Dayzone windows opened more
1121	Bedroom Opened Most	1141	Nightzone windows opened more
1121	Bedroom Opened Most	1131	Nightzone windows opened more
1131	Bedroom Opened Most	1111	Nightzone windows opened more
1132	Bedroom Opened Most	1043	Nightzone windows opened more
1221	Bedroom Opened Most	1232	Nightzone windows opened more
2242	Bedroom Opened Most	2233	Nightzone windows opened more
102x	Bedroom Opened Most	103x	Nightzone windows opened more
104x	Bedroom Opened Most	133x	Nightzone windows opened more
122x	Bedroom Opened Most	123x	Nightzone windows opened more
1x21	Bedroom Opened Most	1x11	Nightzone windows opened more
0042	Bedroom Opened Most	0041	Window use the same
1121	Bedroom Opened Most	1121	Window use the same
1121	Bedroom Opened Most	1122	Window use the same
1121	Bedroom Opened Most	1121	Window use the same
1132	Bedroom Opened Most	1333	Window use the same

1132	Bedroom Opened Most	1132	Window use the same
1141	Bedroom Opened Most	1141	Window use the same
1232	Bedroom Opened Most	1033	Window use the same
2232	Bedroom Opened Most	2232	Window use the same
102x	Bedroom Opened Most	001x	Window use the same
1x21	Bedroom Opened Most	xx01	Window use the same
1x41	Bedroom Opened Most	1x41	Window use the same
1xx2	Bedroom Opened Most	1xx2	Window use the same
2x42	Bedroom Opened Most	2x42	Window use the same
1120	Dayzone vs Nightzone	3333	All windows opened more
1122	Dayzone vs Nightzone	3333	All windows opened more
1122	Dayzone vs Nightzone	3333	All windows opened more
1122	Dayzone vs Nightzone	2232	All windows opened more
1122	Dayzone vs Nightzone	2333	All windows opened more
1122	Dayzone vs Nightzone	0233	All windows opened more
1122	Dayzone vs Nightzone	3132	All windows opened more
1122	Dayzone vs Nightzone	0042	All windows opened more
1122	Dayzone vs Nightzone	2333	All windows opened more
1122	Dayzone vs Nightzone	0233	All windows opened more
1122	Dayzone vs Nightzone	2133	All windows opened more
1122	Dayzone vs Nightzone	2232	All windows opened more
1122	Dayzone vs Nightzone	22x3	All windows opened more
1140	Dayzone vs Nightzone	2333	All windows opened more
021x	Dayzone vs Nightzone	323x	All windows opened more
0x12	Dayzone vs Nightzone	3x42	All windows opened more
0x1x	Dayzone vs Nightzone	3x3x	All windows opened more
112x	Dayzone vs Nightzone	434x	All windows opened more
112x	Dayzone vs Nightzone	2x3x	All windows opened more
112x	Dayzone vs Nightzone	223x	All windows opened more
112x	Dayzone vs Nightzone	224x	All windows opened more
112x	Dayzone vs Nightzone	213x	All windows opened more
112x	Dayzone vs Nightzone	313x	All windows opened more
112x	Dayzone vs Nightzone	3333	All windows opened more
112x	Dayzone vs Nightzone	213x	All windows opened more
112x	Dayzone vs Nightzone	2233	All windows opened more
113x	Dayzone vs Nightzone	444x	All windows opened more
114x	Dayzone vs Nightzone	23xx	All windows opened more
114x	Dayzone vs Nightzone	003x	All windows opened more
11x2	Dayzone vs Nightzone	2033	All windows opened more
1x02	Dayzone vs Nightzone	0x43	All windows opened more
1x22	Dayzone vs Nightzone	2x32	All windows opened more
1x22	Dayzone vs Nightzone	3x33	All windows opened more
1x22	Dayzone vs Nightzone	0x43	All windows opened more
1x22	Dayzone vs Nightzone	2x33	All windows opened more
1x2x	Dayzone vs Nightzone	4x3x	All windows opened more
1x2x	Dayzone vs Nightzone	4x4x	All windows opened more
224x	Dayzone vs Nightzone	020x	All windows opened more
2x3x	Dayzone vs Nightzone	3x4x	All windows opened more
2x4x	Dayzone vs Nightzone	3x3x	All windows opened more
x01x	Dayzone vs Nightzone	x30x	All windows opened more
x122	Dayzone vs Nightzone	x023	All windows opened more

x122	Dayzone vs Nightzone	x323	All windows opened more
x122	Dayzone vs Nightzone	x223	All windows opened more
x21x	Dayzone vs Nightzone	x32x	All windows opened more
0022	Dayzone vs Nightzone	2322	Dayzone windows opened more
0211	Dayzone vs Nightzone	3211	Dayzone windows opened more
1120	Dayzone vs Nightzone	0022	Dayzone windows opened more
1122	Dayzone vs Nightzone	3223	Dayzone windows opened more
1122	Dayzone vs Nightzone	2022	Dayzone windows opened more
1122	Dayzone vs Nightzone	2322	Dayzone windows opened more
1122	Dayzone vs Nightzone	0222	Dayzone windows opened more
1122	Dayzone vs Nightzone	3022	Dayzone windows opened more
1122	Dayzone vs Nightzone	2222	Dayzone windows opened more
1122	Dayzone vs Nightzone	2322	Dayzone windows opened more
1122	Dayzone vs Nightzone	2122	Dayzone windows opened more
110x	Dayzone vs Nightzone	2303	Dayzone windows opened more
112x	Dayzone vs Nightzone	222x	Dayzone windows opened more
112x	Dayzone vs Nightzone	002x	Dayzone windows opened more
112x	Dayzone vs Nightzone	012x	Dayzone windows opened more
112x	Dayzone vs Nightzone	412x	Dayzone windows opened more
112x	Dayzone vs Nightzone	002x	Dayzone windows opened more
112x	Dayzone vs Nightzone	202x	Dayzone windows opened more
112x	Dayzone vs Nightzone	0023	Dayzone windows opened more
112x	Dayzone vs Nightzone	0123	Dayzone windows opened more
113x	Dayzone vs Nightzone	233x	Dayzone windows opened more
113x	Dayzone vs Nightzone	332x	Dayzone windows opened more
113x	Dayzone vs Nightzone	224x	Dayzone windows opened more
114x	Dayzone vs Nightzone	224x	Dayzone windows opened more
114x	Dayzone vs Nightzone	324x	Dayzone windows opened more
1x22	Dayzone vs Nightzone	2x22	Dayzone windows opened more
1x22	Dayzone vs Nightzone	2x2x	Dayzone windows opened more
1x2x	Dayzone vs Nightzone	2x2x	Dayzone windows opened more
1x2x	Dayzone vs Nightzone	2x2x	Dayzone windows opened more
1x2x	Dayzone vs Nightzone	3x2x	Dayzone windows opened more
1x2x	Dayzone vs Nightzone	0x2x	Dayzone windows opened more
1x2x	Dayzone vs Nightzone	0x2x	Dayzone windows opened more
1x3x	Dayzone vs Nightzone	3x3x	Dayzone windows opened more
1x4x	Dayzone vs Nightzone	2x4x	Dayzone windows opened more
1x4x	Dayzone vs Nightzone	3x4x	Dayzone windows opened more
1x4x	Dayzone vs Nightzone	2x4x	Dayzone windows opened more
2x3x	Dayzone vs Nightzone	3x3x	Dayzone windows opened more
x12x	Dayzone vs Nightzone	x02x	Dayzone windows opened more
x12x	Dayzone vs Nightzone	x22x	Dayzone windows opened more
1122	Dayzone vs Nightzone	1342	Nightzone windows opened more
221x	Dayzone vs Nightzone	232x	Nightzone windows opened more
224x	Dayzone vs Nightzone	233x	Nightzone windows opened more
224x	Dayzone vs Nightzone	223x	Nightzone windows opened more
x022	Dayzone vs Nightzone	x332	Nightzone windows opened more
1122	Dayzone vs Nightzone	1122	Window use the same
1122	Dayzone vs Nightzone	1122	Window use the same
1122	Dayzone vs Nightzone	1223	Window use the same
1122	Dayzone vs Nightzone	1222	Window use the same

112x	Dayzone vs Nightzone	132x	Window use the same
1x2x	Dayzone vs Nightzone	1x2x	Window use the same
1x2x	Dayzone vs Nightzone	xx2x	Window use the same
1x3x	Dayzone vs Nightzone	1x3x	Window use the same
224x	Dayzone vs Nightzone	224x	Window use the same
2x3x	Dayzone vs Nightzone	2x4x	Window use the same
x03x	Dayzone vs Nightzone	x03x	Window use the same
x122	Dayzone vs Nightzone	x123	Window use the same
x13x	Dayzone vs Nightzone	x13x	Window use the same
0101	Long vs Short Presence	3041	All windows opened more
2021	Long vs Short Presence	3332	All windows opened more
2120	Long vs Short Presence	1440	All windows opened more
2121	Long vs Short Presence	3131	All windows opened more
2121	Long vs Short Presence	4141	All windows opened more
2121	Long vs Short Presence	3333	All windows opened more
2141	Long vs Short Presence	0x32	All windows opened more
101x	Long vs Short Presence	xx4x	All windows opened more
101x	Long vs Short Presence	404x	All windows opened more
121x	Long vs Short Presence	232x	All windows opened more
121x	Long vs Short Presence	232x	All windows opened more
1x12	Long vs Short Presence	2x22	All windows opened more
1x12	Long vs Short Presence	2x02	All windows opened more
1x12	Long vs Short Presence	3x32	All windows opened more
1x12	Long vs Short Presence	4x42	All windows opened more
1x12	Long vs Short Presence	4x42	All windows opened more
210x	Long vs Short Presence	414x	All windows opened more
212x	Long vs Short Presence	333x	All windows opened more
212x	Long vs Short Presence	414x	All windows opened more
x131	Long vs Short Presence	3243	All windows opened more
x141	Long vs Short Presence	x033	All windows opened more
xx10	Long vs Short Presence	xx20	All windows opened more
xx10	Long vs Short Presence	xx33	All windows opened more
xx12	Long vs Short Presence	xx42	All windows opened more
0121	Long vs Short Presence	3020	Dayzone windows opened more
2121	Long vs Short Presence	0020	Dayzone windows opened more
121x	Long vs Short Presence	231x	Dayzone windows opened more
12x2	Long vs Short Presence	22x2	Dayzone windows opened more
x121	Long vs Short Presence	x222	Dayzone windows opened more
0121	Long vs Short Presence	0032	Nightzone windows opened more
x121	Long vs Short Presence	x132	Nightzone windows opened more
0101	Long vs Short Presence	0100	Window use the same
2020	Long vs Short Presence	2020	Window use the same
2121	Long vs Short Presence	2121	Window use the same
2121	Long vs Short Presence	2120	Window use the same
212x	Long vs Short Presence	212x	Window use the same
212x	Long vs Short Presence	212x	Window use the same
2x21	Long vs Short Presence	2x12	Window use the same
x020	Long vs Short Presence	x222	Window use the same
xx21	Long vs Short Presence	xx22	Window use the same
xx21	Long vs Short Presence	xx23	Window use the same
xx41	Long vs Short Presence	xx41	Window use the same

14.5 Probability for occupancy clusters according to employment

Table 14.9: Probabilities for occupancy clusters on weekdays for each employment type.

	FTE	PTE	Unemployed	Retired	School	Student
Night absence	0.010	0.010	0.003	0	0	0
Early day absence	0.394	0.230	0.019	0.018	0.182	0.153
Short absence	0.101	0.349	0.743	0.834	0.160	0.246
Day absence	0.364	0.315	0.116	0.096	0.588	0.407
Afternoon absence	0.007	0.030	0.043	0.025	0.006	0.025
Mostly absent	0.123	0.060	0.018	0.007	0.063	0.153
Mostly at home	0.001	0.006	0.059	0.021	0.000	0.017

Table 14.10: Probabilities for occupancy clusters on Saturday for each employment type.

	FTE	PTE	Unemployed	Retired	School	Student
Night absence	0.005	0.018	0.003	0.000	0.000	0.021
Early day absence	0.007	0.055	0.008	0.013	0.005	0.000
Short absence	0.478	0.477	0.611	0.749	0.377	0.277
Day absence	0.281	0.283	0.168	0.157	0.216	0.170
Afternoon absence	0.112	0.055	0.084	0.031	0.162	0.191
Mostly absent	0.074	0.080	0.057	0.026	0.059	0.128
Mostly at home	0.043	0.031	0.068	0.024	0.181	0.213

Table 14.11: Probabilities for occupancy clusters on Wednesday for PTE and School-going children.

	PTE	School
Night absence	0.000	0.000
Early day absence	0.083	0.089
Short absence	0.514	0.536
Day absence	0.266	0.321
Afternoon absence	0.064	0.000
Mostly absent	0.073	0.036
Mostly at home	0.000	0.018

Table 14.12: Probabilities for occupancy clusters on Friday for FTE and students.

	FTE	Student
Night absence	0.008	0.000
Early day absence	0.346	0.077
Short absence	0.126	0.154
Day absence	0.301	0.231
Afternoon absence	0.008	0.026
Mostly absent	0.211	0.231
Mostly at home	0.008	0.051

15

Publications

15.1 Journal publications

15.1.1 First author

S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens, "Evaluation of the relationship between window use and physical environmental variables: consistency, seasonality and diversity," *Journal of Building Performance Simulation*, vol. 14, no. 4, pp. 366-382, 2021. doi:10.1080/19401493.2021.1942209

S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens, "Habitual window opening behaviour in residential buildings," *Energy and Buildings*, accepted 2021. doi:10.1016/j.enbuild.2021.111454

15.1.2 Co-author

A. Mahdavi, C. Berger, H. Amin, E. Ampatzi, R.K. Andersen, E. Azar, V.M. Barthelmes, M. Favero, J. Hahn, D. Khovalyg, H.N. Knudsen, A. Luna-Navarro, A. Roetzel, F.C. Sangogboye, M. Schweiker, M. Taheri, D. Teli, M. Touchie and S. Verbruggen, "The Role of Occupants in Buildings' Energy Performance Gap: Myth or Reality?," *Sustainability*, vol.13, 2021. doi:10.3390/su13063146

W. O'Brien, F. Tahmasebi, R.K. Andersen, E. Azar, V. Barthelmes, Z.D. Belafi, C. Berger, D. Chen, M. De Simone, S. d'Oca, T. Hong, Q. Jin, D. Khovalyg, R. Lamberts,

V. Novakovic, J.Y. Park, M. Plagmann, V.S. Rajus, M. Vellei, S. Verbruggen, A. Wagner, E. Willems, D. Yan and J. Zhou, “An international review of occupant-related aspects of building energy codes and standards,” *Building and Environment*, Vol. 179, 2020. doi:10.1016/j.buildenv.2020.106906.

15.2 Publications in proceedings of conferences

15.2.1 First author

S. Verbruggen, J. Laverge, M. Delghust and A. Janssens, “Comparative window use study: habits versus deliberative actions in residential buildings,” in *Proceedings of Building Simulation 2021: 17th Conference of IBPSA*, Bruges, Belgium, 2021.

S. Verbruggen, J. Laverge, M. Delghust and A. Janssens, “Window use habits in Belgian households,” in *16th International Conference on Indoor Air Quality and Climate (INDOOR AIR 2020)*, Seoul, Korea, 2020. pp. 1006-1011

S. Verbruggen, J. Hertoge, M. Delghust, J. Laverge, and A. Janssens, “The use of solar shading in a nearly zero-energy neighbourhood,” in *12th Nordic Symposium On Building Physics (NSB 2020)*, Tallinn, Estonia, 2020, vol. 172.

S. Verbruggen, E. De Ceuster, M. Delghust, and J. Laverge, “Clothing behaviour in Belgian homes,” in *12th Nordic Symposium On Building Physics (NSB 2020)*, Tallinn, Estonia, 2020, vol. 172.

S. Verbruggen, J. Laverge, M. Delghust, and A. Janssens, “Stochastic occupant behaviour model: impact on residential energy use,” in *Proceedings of Building Simulation 2019: 16th Conference of IBPSA*, Rome, Italy, 2019, vol. 16, pp. 2310-2317.

S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens, “Impact of an occupancy and activity based window use model on the prediction of the residential energy use and thermal comfort,” in *From energy crisis to sustainable indoor climate: 40 years of AIVC*, Ghent, Belgium, 2019, pp. 912-919.

S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens, “Inclusion of window opening habits in a window model based on activity and occupancy patterns,” in *CLIMA 2019 Congress*, Bucharest, Romania, 2019, vol. 111.

S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens,“The influence of window opening habits on the residential energy use in nearly zero energy buildings,” in *Proceedings of the 7th International Building Physics Conference*, Syracuse, NY, USA, 2018, pp. 685–690.

15.2.2 Co-author

K. Simić, H. Monteyne, J.B. Bastero, S. Verbruggen, W. Beyne, J. Laverge and M. De Paepe, “Numerical and experimental assessment of the energy performance of a multi-zone building with the use of transient detailed models,” in *33rd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact* *of Energy Systems (ECOS 2020)*, Osaka, Japan, 2020.

A. Janssens, W. Bracke, M. Delghust, E. Himpe, S. Verbruggen, and J. Laverge, “Utilization of heat recovery ventilation: steady-state two-zone heat loss analysis and field studies,” in *Proceedings of the 7th International Building Physics Conference*, Syracuse, NY, USA, 2018, pp. 691-696.

J. Laverge, M. Delghust, E. Himpe, and S. Verbruggen, “Window opening behaviour in a nearly zero energy social housing development in Belgium,” in *Healthy Buildings 2017 Asia: The Proceedings*, Tainan, Taiwan, 2017, pp. 285–286.

Bibliography

[1] IPCC, "Climate Change 2014," Tech. Rep. October, 2014.

[2] Intergovernmental Panel on Climate Change, "Climate change 2021 The Physical Science Basis - Summary for Policymakers," tech. rep., 2021.

[3] W. Brock and A. Xepapadeas, "The Economy, Climate Change and Infectious Diseases: Links and Policy Implications," *Environmental and Resource Economics*, vol. 76, pp. 811–824, aug 2020.

[4] G. C. Daily and P. R. Ehrlich, "Global change and human susceptibility to disease," *Annual Review of Energy and the Environment*, vol. 21, no. 1, pp. 125–144, 1996.

[5] European Comission, "2020 Climate & Energy package," 2009.

[6] European Environment Agency, "Trends and drivers of EU greenhouse gas emissions."

[7] European Environment Agency, "Share of renewable energy in gross final energy consumption."

[8] European Comission, "2030 climate & energy framework."

[9] European Comission, "2050 long-term strategy."

[10] Eurostat, *Energy data*. 2020.

[11] Eurostat, "Eurostat Data Explorer."

[12] "Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings," tech. rep.

[13] V. regering, "Besluit van de Vlaamse Regering houdende algemene bepalingen over het energiebeleid," 2010.

[14] Vlaamse Regering, "Langetermijnstrategie Voor De Renovatie Van Vlaamse Gebouwen," 2020.

[15] "NEPBC: Next generation building energy assessment methods towards a carbon neutral building stock."

[16] M. Sunikka-Blank and R. Galvin, "Introducing the prebound effect: The gap between performance and actual energy consumption," *Building Research and Information*, vol. 40, no. 3, pp. 260–273, 2012.

[17] D. Majcen, L. C. M. Itard, and H. Visscher, "Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications," *Energy Policy*, vol. 54, pp. 125–136, 2013.

[18] G. Dall'O, L. Sarto, A. Galante, and G. Pasetti, "Comparison between predicted and actual energy performance for winter heating in high-performance residential buildings in the Lombardy region (Italy)," *Energy and Buildings*, vol. 47, pp. 247–253, 2012.

[19] V. Fabi, R. V. Andersen, S. P. Corgnati, and B. W. Olesen, "A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings," *Building Simulation*, vol. 6, no. 4, pp. 415–427, 2013.

[20] T. Maier, M. Krzaczek, and J. Tejchman, "Comparison of physical performances of the ventilation systems in low-energy residential houses," *Energy and Buildings*, vol. 41, no. 3, pp. 337–353, 2009.

[21] D. Calì, T. Osterhage, R. Streblow, and D. Müller, "Energy performance gap in refurbished German dwellings: Lesson learned from a field test," *Energy and Buildings*, vol. 127, pp. 1146–1158, 2016.

[22] O. Guerra-Santin and L. Itard, "Occupants' behaviour: Determinants and effects on residential heating consumption," *Building Research and Information*, vol. 38, no. 3, pp. 318–338, 2010.

[23] F. Stevenson and A. Leaman, "Evaluating housing performance in relation to human behaviour: new challenges," *Building Research & Information*, vol. 38, no. 5, pp. 437–441, 2010.

[24] S. Verbruggen, M. Delghust, A. Janssens, and Vlaams Energie Agentschap, "Onderzoek naar de relatie tussen het E-peil, het berekende energieverbruik in de EPB-aangifte en het werkelijke energieverbruik op basis van enquêtegegevens en gegevens opgevraagd bij de netbeheerder," tech. rep., 2020.

[25] M. Delghust, W. Roelens, T. Tanghe, Y. D. Weerdt, and A. Janssens, "Regulatory energy calculations versus real energy use in high-performance houses," *http://dx.doi.org/10.1080/09613218.2015.1033874*, vol. 43, pp. 675–690, nov 2015.

[26] H. Yoshino, T. Hong, and N. Nord, "IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods," *Energy and Buildings*, vol. 152, pp. 124–136, 2017.

[27] H. Polinder, M. Schweiker, A. V. D. Aa, K. Schakib-Ekbatan, V. Fabi, R. Andersen, N. Morishita, C. Wang, S. Corgnati, P. Heiselberg, D. Yan, B. Olesen, T. Bednar, and A. Wagner, "Final Report Annex 53 - Volume II: Occupant behavior and modeling," 2013.

[28] R. Andersen, *Occupant behaviour with regard to control of the indoor environment.* PhD thesis, Technical University of Denmark, 2009.

[29] Z. M. Gill, M. J. Tierney, I. M. Pegg, and N. Allan, "Low-energy dwellings: The contribution of behaviours to actual performance," *Building Research and Information*, vol. 38, no. 5, pp. 491–508, 2010.

[30] R. C. Sonderegger, "Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating," *Energy and Buildings*, vol. 1, no. 3, pp. 313–324, 1978.

[31] O. Guerra Santin, L. Itard, and H. Visscher, "The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock," *Energy and Buildings*, vol. 41, pp. 1223–1232, nov 2009.

[32] A. Mahdavi, C. Berger, H. Amin, E. Ampatzi, R. K. Andersen, E. Azar, V. M. Barthelmes, M. Favero, J. Hahn, D. Khovalyg, H. N. Knudsen, A. L. Navarro, A. Roetzel, F. C. Sangogboye, M. Schweiker, M. Taheri, D. Teli, M. Touchie, and S. Verbruggen, "The role of occupants in buildings' energy performance gap: Myth or reality?," *Sustainability*, vol. 13, mar 2021.

[33] R. Gupta, M. Kapsali, and A. Howard, "Evaluating the influence of building fabric, services and occupant related factors on the actual performance of low energy social housing dwellings in UK," *Energy and Buildings*, vol. 174, pp. 548–562, 2018.

[34] A. R. Hansen, K. Gram-Hanssen, and H. N. Knudsen, "How building design and technologies influence heat-related habits," *Building Research and Information*, vol. 46, pp. 83–98, jan 2018.

[35] E. Cuerda, O. Guerra-Santin, J. J. Sendra, and F. J. Neila, "Understanding the performance gap in energy retrofitting: Measured input data for adjusting building simulation models," *Energy and Buildings*, vol. 209, p. 109688, 2020.

[36] A. Al Amoodi and E. Azar, "Impact of human actions on building energy performance: A case study in the United Arab Emirates (UAE)," *Sustainability*, vol. 10, may 2018.

[37] J. Rouleau, L. Gosselin, and P. Blanchet, "Robustness of energy consumption and comfort in high-performance residential building with respect to occupant behavior," *Energy*, vol. 188, dec 2019.

[38] J. Rouleau, L. Gosselin, and P. Blanchet, "Understanding energy consumption in high-performance social housing buildings: A case study from Canada," *Energy*, vol. 145, pp. 677–690, feb 2018.

[39] I. Mojic, M. Lehmann, S. V. Velsen, and M. Haller, "ImmoGap – Analysis of the performance gap of apartment buildings," *E3S Web of Conferences 111, CLIMA 2019*, 2019.

[40] P. Pascal Housez, U. Pont, and A. Mahdavi, "A comparison of projected and actual energy performance of buildings after thermal retrofit measures," *Original Article Journal of Building Physics*, vol. 38, no. 2, pp. 138–155, 2014.

[41] U. Lehmann, J. Khoury, and M. K. Patel, "Actual energy performance of student housing: Case study, benchmarking and performance gap analysis," in *Energy Procedia*, vol. 122, pp. 163–168, Elsevier Ltd, 2017.

[42] J. R. Littlewood and I. Smallwood, "Occupant interaction with as-designed smart heating: Impacts upon energy use & thermal comfort," in *Smart Innovation, Systems and Technologies*, vol. 131, pp. 403–412, 2019.

[43] S. Moeller, I. Weber, F. Schröder, A. Bauer, and H. Harter, "Apartment related energy performance gap – How to address internal heat transfers in multi-apartment buildings," *Energy and Buildings*, vol. 215, p. 109887, may 2020.

[44] A. Hamburg, K. Kuusk, A. Mikola, and T. Kalamees, "Realisation of energy performance targets of an old apartment building renovated to nZEB," *Energy*, vol. 194, p. 116874, mar 2020.

[45] N. Vetterli, M. Sulzer, and U. P. Menti, "Energy monitoring of a low temperature heating and cooling district network," in *Energy Procedia*, vol. 122, pp. 62–67, Elsevier Ltd, sep 2017.

[46] R. V. Jones, A. Fuertes, and P. De Wilde, "The Gap Between Simulated and Measured Energy Performance: A Case Study Across Six Identical New-Build

Flats in the UK," in *14th Conference of International Building Performance Simulation Association*, pp. 2248–2255, 2015.

[47] S. Cozza, J. Chambers, A. Geissler, K. Wesselmann, C. Gambato, G. Branca, G. Cadonau, L. Arnold, and M. K. Patel, "GAPxPLORE: Energy Performance Gap in existing, new, and renovated buildings Learning from large-scale datasets," tech. rep., 2019.

[48] A. Gonzalez-Caceres and T. A. Vik, "Improving the Energy Performance Certificate recommendations accuracy for residential building through simple measurements of key inputs," in *IOP Conference Series: Materials Science and Engineering 609*, pp. 1–6, 2019.

[49] M. Delghust, J. Laverge, A. Janssens, E. Cnockaert, and T. Davidson, "The influence of energy performance levels on the heating demand in dwellings: Case-study analyses on neighbourhoods," *Thermal Performance of the Exterior Envelopes of Whole Buildings - 12th International Conference*, 2013.

[50] J. Hahn, P. Schumacher, W. Lang, and W. Jensch, "Performance gap and occupant behavior – review and analysis of high-efficiency residential buildings in Germany," in *Proceedings of the 33rd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems (ECOS2020)*, (Osaka, Japan), pp. 2010–2022, 2020.

[51] J. Kragh, J. Rose, H. Knudsen, and O. Jensen, "Possible explanations for the gap between calculated and measured energy consumption of new houses," *Energy Procedia*, vol. 132, pp. 69–74, 2017.

[52] G. Branco, B. Lachal, P. Gallinelli, and W. Weber, "Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data," *Energy and Buildings*, 2004.

[53] O. Guerra Santin, "Occupant behaviour in energy efficient dwellings: Evidence of a rebound effect," *Journal of Housing and the Built Environment*, vol. 28, pp. 311–327, jun 2013.

[54] G. Hunter, S. Hoyne, and L. Noonan, "Evaluation of the Space Heating Calculations within the Irish Dwelling Energy Assessment Procedure Using Sensor Measurements from Residential Homes," in *Energy Procedia*, vol. 111, pp. 181–194, Elsevier Ltd, mar 2017.

[55] A. Hamburg and T. Kalamees, "How well are energy performance objectives being achieved in renovated apartment buildings in Estonia?," *Energy and Buildings*, vol. 199, pp. 332–341, sep 2019.

[56] E. Lambie, M. Senave, I. Van De Vyver, and D. Saelens, "Experimental analysis of indoor temperature of residential buildings as an input for building simulation tools," in *Energy Procedia*, vol. 132, pp. 123–128, Elsevier Ltd, oct 2017.

[57] E. Cayre, B. Allibe, and M.-H. Laurent, "There are people in the house!: How the results of purely technical analysis of residential energy consumption are misleading for energy policies," in *ECEEE 2011 Summer Study*, pp. 1675–1683, 2011.

[58] M. Delghust, J. Laverge, A. Janssens, C. Van Erck, and C. Taelman, "The influence of user behaviour on energy use in old dwellings : case-study analysis of a social housing neighbourhood," *5th International Building Physics Conference, Proceedings*, vol. 36, pp. 809–816, 2012.

[59] D. Teli, T. Dimitriou, P. A. James, A. S. Bahaj, L. Ellison, and A. Waggott, “Fuel poverty-induced ’prebound effect’ in achieving the anticipated carbon savings from social housing retrofit,” in *Building Services Engineering Research and Technology*, vol. 37, pp. 176–193, SAGE Publications Ltd, mar 2016.

[60] D. Majcen, L. Itard, and H. Visscher, “Statistical model of the heating prediction gap in Dutch dwellings: Relative importance of building, household and behavioural characteristics,” *Energy and Buildings*, vol. 105, pp. 43–59, aug 2015.

[61] M. Delghust, *Improving the Predictive Power of Simplified Residential Space Heating Demand Models : a Field Data and Model Driven Study.* PhD thesis, Universiteit Gent, 2016.

[62] Oxford Advanced Learner’s Dictionary, “Realistic (adjective) - Oxford Advanced Learner’s Dictionary.”

[63] C. Dubrul, “Inhabitant Behaviour with Respect to Ventilation - a Summary Report of IEA Annex VIII,” Tech. Rep. 23, AIVC, 1988.

[64] V. Fabi, R. V. Andersen, S. Corgnati, and B. W. Olesen, “Occupants’ window opening behaviour: A literature review of factors influencing occupant behaviour and models,” *Building and Environment*, vol. 58, pp. 188–198, dec 2012.

[65] V. Fabi, R. Andersen, and S. Corgnati, “Description of occupant behaviour in building energy simulation: state-of-art and concepts for improvements,” *Building Simulation 2011: 12th Conference of International Building Performance Simulation Association, Sydney, 14-16 November*, pp. 2882–2889, 2011.

[66] C. Peng, D. Yan, R. Wu, C. Wang, X. Zhou, and Y. Jiang, “Quantitative description and simulation of human behavior in residential buildings,” *Building Simulation*, vol. 5, no. 2, pp. 85–94, 2012.

[67] F. Stazi, F. Naspi, and M. D’Orazio, “A literature review on driving factors and contextual events influencing occupants’ behaviours in buildings,” *Building and Environment*, vol. 118, pp. 40–66, 2017.

[68] C. Foulds, J. Powell, and G. Seyfan, “Investigating the performance of everyday domestic practices using building monitoring,” *Building Research and Information*, vol. 41, no. 6, pp. 622–636, 2013.

[69] A. Wagner and L. O’brien, “Annex 79 Factsheet: Occupant-centric Building Design and Operation,” tech. rep., IEA Energy in Buildings and Communities, 2019.

[70] F. Haldi, D. Calì, R. K. Andersen, M. Wesseling, and D. Müller, “Modelling diversity in building occupant behaviour: a novel statistical approach,” *Journal of Building Performance Simulation*, vol. 10, no. 6, pp. 527–544, 2017.

[71] W. O’Brien and H. . B. Gunay, “Occupant Behaviour Diversity Modelling And Its Applications,” *eSIM Building Performance Simulation Conference*, pp. 734–742, 2016.

[72] S. D’Oca and T. Hong, “A data-mining approach to discover patterns of window opening and closing behavior in offices,” *Building and Environment*, vol. 82, pp. 726–739, 2014.

[73] B. Hauge, “The air from outside: Getting to know the world through air practices,” *Journal of Material Culture*, vol. 18, no. 2, pp. 171–187, 2016.

[74] S. Herkel, U. Knapp, and J. Pfafferott, "Towards a model of user behaviour regarding the manual control of windows in office buildings," in *Building and Environment*, vol. 43, pp. 588–600, 2008.

[75] F. Haldi and D. Robinson, "Interactions with window openings by office occupants," *Building and Environment*, vol. 44, no. 12, pp. 2378–2395, 2009.

[76] J. A. Ouellette and W. Wood, "Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior.," *Psychological Bulletin*, vol. 124, no. 1, pp. 54–74, 1998.

[77] I. Ajzen, "Residual Effects of Past on Later Behavior: Habituation and Reasoned Action Perspectives," *Personality and Social Psychology Review*, vol. 6, no. 2, pp. 107–122, 2002.

[78] B. Verplanken, H. Aarts, A. Van Knippenberg, and A. Moonen, "Habit versus planned behaviour: A field experiment," *British Journal of Social Psychology*, vol. 37, no. 1, pp. 111–128, 1998.

[79] C. A. Klöckner, "A comprehensive model of the psychology of environmental behaviour-A meta-analysis," *Global Environmental Change*, vol. 23, no. 5, pp. 1028–1038, 2013.

[80] D. Kahneman, "Thinking, fast and slow," 2011.

[81] S. H. Lo, G. J. Y. Peters, G. J. van Breukelen, and G. Kok, "Only reasoned action? An interorganizational study of energy-saving behaviors in office buildings," *Energy Efficiency*, vol. 7, pp. 761–775, oct 2014.

[82] M. Mulville, K. Jones, and J. Powell-Greig, "Energy-saving occupant behaviours in offices: change strategies. Energy-saving occupant behaviours in offices: change strategies,"

[83] E. Himpe, A. Janssens, and J. E. V. Rebollar, "Energy and comfort performance assessment of monitored low energy buildings connected to low-temperature district heating," *Energy Procedia*, vol. 78, pp. 3465–3470, 2015.

[84] A. Janssens, J. Vaillant Rebollar, E. Himpe, and M. Delghust, "Transforming social housing neighbourhoods into sustainable carbon neutral districts," *Energy Procedia*, vol. 132, pp. 549–554, 2017.

[85] E. Himpe, J. V. Rebollar, and A. Janssens, "ECO-life monitoring report BE 1/2: ECO-life deliverable D.8.1.4," tech. rep., 2014.

[86] B2Ai, "Sociale woonwijk Venning Kortrijk - Projecten - B2Ai."

[87] F. Stazi and F. Naspi, "Triggers for Users' Behaviours," pp. 19–29, Springer, Cham, 2018.

[88] T. Hong, "Annex 66: Definition and Simulation of Occupant Behavior in Buildings," tech. rep., 2017.

[89] A. Heydarian, C. McIlvennie, L. Arpan, S. Yousefi, M. Syndicus, M. Schweiker, F. Jazizadeh, R. Rissetto, A. L. Pisello, C. Piselli, C. Berger, Z. Yan, and A. Mahdavi, "What drives our behaviors in buildings? A review on occupant interactions with building systems from the lens of behavioral theories," *Building and Environment*, vol. 179, jul 2020.

[90] H. A. Simon, "A Behavioral Model of Rational Choice," *The Quarterly Journal of Economics*, vol. 69, no. 1, pp. 99–118, 1955.

[91] I. Ajzen and M. Fishbein, "Attitude-behavior relations: A theoretical analysis and review of empirical research," *Psychological Bulletin*, vol. 84, no. 5, pp. 888–918, 1977.

[92] I. Ajzen, “From Intentions to Actions: A Theory of Planned Behavior,” in *Action Control*, pp. 11–39, 1985.

[93] I. Ajzen, “The theory of planned behavior: Frequently asked questions,” *Human Behavior and Emerging Technologies*, vol. 2, no. 4, pp. 314–324, 2020.

[94] M. Bratman, *Intentions, Plans, and Practical Reason.* 1987.

[95] A. S. Rao and M. P. Georgeff, “Decision Procedures for BDI Logics,” *Journal of Logic and Computation*, vol. 8, no. 3, pp. 293–342, 1998.

[96] P. Caillou, B. Gaudou, A. Grignard, C. Q. Truong, and P. Taillandier, “Advances in Social Simulation 2015,” in *Advances in Social Simulation 2015: Advances in Intelligent Systems and Computing*, vol. 528, pp. 15–29, 2017.

[97] C. J. Andrews, D. Yi, U. Krogmann, J. A. Senick, and R. E. Wener, “Designing buildings for real occupants: An agent-based approach,” *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, vol. 41, no. 6, pp. 1077–1091, 2011.

[98] X. Zhao, J. Venkateswaran, and Y.-J. Son, “Modeling Human Operator Decision-Making in Manufacturing Systems Using BDI Agent Paradigm,” in *IIE Annual Conference and Exposition 2005*, 2005.

[99] S. H. Schwartz, “Normative Influences on Altruism 1,” in *Advances in experimental social psychology*, pp. 221–279, 1977.

[100] H. Aarts, B. Verplanken, and A. Knippenberg, “Predicting Behavior From Actions in the Past: Repeated Decision Making or a Matter of Habit?,” *Journal of Applied Social Psychology*, vol. 28, no. 15, pp. 1355–1374, 1998.

[101] B. Verplanken, “Beyond frequency: Habit as mental construct,” *British Journal of Social Psychology*, vol. 45, no. 3, pp. 639–656, 2006.

[102] J. R. Grove and I. Zillich, “Conceptualisation and measurement of habitual exercise (abstract),” *Australian Journal of Psychology*, vol. 55, p. 183, 2003.

[103] G. D. Gregory and M. D. Leo, “Repeated Behavior and Environmental Psychology: The Role of Personal Involvement and Habit Formation in Explaining Water Consumption1,” *Journal of Applied Social Psychology*, vol. 33, no. 6, pp. 1261–1296, 2003.

[104] K. Maréchal, “Not irrational but habitual: The importance of ”behavioural lock-in” in energy consumption,” *Ecological Economics*, vol. 69, pp. 1104–1114, mar 2010.

[105] H. C. Triandis, “Values, attitudes, and interpersonal behavior,” in *Nebraska Symposium on Motivation*, pp. 195–259, 1979.

[106] B. Verplanken and H. Aarts, “Habit, Attitude, and Planned Behaviour: Is Habit an Empty Construct or an Interesting Case of Goal-directed Automaticity?,” *European Review of Social Psychology*, vol. 10, no. 1, pp. 101–134, 1999.

[107] W. Wood, J. M. Quinn, and D. A. Kashy, “Habits in everyday life: Thought, emotion, and action,” *Journal of Personality and Social Psychology*, vol. 83, no. 6, pp. 1281–1297, 2002.

[108] F. Haldi and D. Robinson, “Interactions with window openings by office occupants,” *Building and Environment*, vol. 44, pp. 2378–2395, dec 2009.

[109] H. B. Gunay, W. O’Brien, I. Beausoleil-Morrison, and S. Gilani, “Development and implementation of an adaptive lighting and blinds control algorithm,” *Building and Environment*, vol. 113, pp. 185–199, feb 2017.

[110] P. R. Boyce, J. A. Veitch, G. R. Newsham, C. C. Jones, J. Heerwagen, M. Myer, C. M. Hunter, and L. Bedocs, "Occupant use of switching and dimming controls in offices," *Lighting Research and Technology*, vol. 38, no. 4, pp. 358–378, 2006.

[111] T. Moore, D. Carter, and A. Slater, "Long-term patterns of use of occupant controlled office lighting," *Lighting Research & Technology*, vol. 35, pp. 43–57, mar 2003.

[112] D. R. Hunt, "The use of artificial lighting in relation to daylight levels and occupancy," *Building and Environment*, vol. 14, no. 1, pp. 21–33, 1979.

[113] D. Calì, R. K. Andersen, D. Müller, and B. W. Olesen, "Analysis of occupants' behavior related to the use of windows in German households," *Building and Environment*, vol. 103, pp. 54–69, 2016.

[114] B. Jeong, J. W. Jeong, and J. S. Park, "Occupant behavior regarding the manual control of windows in residential buildings," *Energy and Buildings*, vol. 127, pp. 206–216, 2016.

[115] M. Yao and B. Zhao, "Window opening behavior of occupants in residential buildings in Beijing," *Building and Environment*, vol. 124, pp. 441–449, nov 2017.

[116] D. Lai, S. Jia, Y. Qi, and J. Liu, "Window-opening behavior in Chinese residential buildings across different climate zones," *Building and Environment*, vol. 142, pp. 234–243, 2018.

[117] S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens, "Evaluation of the relationship between window use and physical environmental variables: consistency, seasonality and diversity," *Journal of Building Performance Simulation*, vol. 14, no. 4, pp. 366–382, 2021.

[118] S. Verbruggen, J. Laverge, M. Delghust, and A. Janssens, "Stochastic Occupant Behaviour Model: Impact on residential energy use," in *Proceedings of Building Simulation 2019 : 16th Conference of IBPSA*, (Rome), pp. 2310–2317, 2020.

[119] Vlaamse Regering, "Energiebesluit Bijlage V: Bepalingsmethode EPW," 2018.

[120] M. Frontczak, R. V. Andersen, and P. Wargocki, "Questionnaire survey on factors influencing comfort with indoor environmental quality in Danish housing," *Building and Environment*, vol. 50, pp. 56–64, 2012.

[121] H. Erhorn, "Influence of meteorological conditions on inhabitants' behaviour in dwellings with mechanical ventilation," *Energy and Buildings*, vol. 11, no. 1-3, pp. 267–275, 1988.

[122] M. D. Lyberg, "Residents and windows, chapter 2: Airing," tech. rep., Statens institut för byggnadsforskning, Gävle, 1983.

[123] G. W. Brundrett and G. H. Poultney, "Use of natural ventilation," in *3rd AIC Conference: Energy Efficient domestic ventilation systems For Achieving Acceptable Indoor Air Quality*, (London, UK), 1982.

[124] G. Conan, *Domestic gas consumption, household behaviour patterns, and window opening.* PhD thesis, Brunel University, 1981.

[125] J. Maeyens and A. Janssens, "A stochastic ventilation model regarding leakage and user behaviour," in *2nd international conference on building physics*, (Leuven), pp. 737–748, Department of Architecture and Urban Planning, Ghent University, 2003.

[126] R. Andersen, V. Fabi, J. Toftum, S. P. Corgnati, and B. W. Olesen, "Window opening behaviour modelled from measurements in Danish dwellings," *Building and Environment*, vol. 69, pp. 101–113, nov 2013.

[127] R. V. Jones, A. Fuertes, E. Gregori, and A. Giretti, "Stochastic behavioural models of occupants' main bedroom window operation for UK residential buildings," *Building and Environment*, vol. 118, pp. 144–158, 2017.

[128] H. B. Rijal, "Window opening behaviour in Japanese dwellings," in *Sustainable Houses and Living in the Hot-Humid Climates of Asia*, pp. 271–282, Springer Singapore, jun 2018.

[129] D. Calì, M. T. Wesseling, and D. Müller, "WinProGen: A Markov-Chain-based stochastic window status profile generator for the simulation of realistic energy performance in buildings," *Building and Environment*, vol. 136, pp. 240–258, 2018.

[130] J. Chapman, P. O. Siebers, and D. Robinson, "On the multi-agent stochastic simulation of occupants in buildings," *Journal of Building Performance Simulation*, vol. 11, no. 5, pp. 604–621, 2018.

[131] J. Langevin, J. Wen, and P. L. Gurian, "Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors," *Building and Environment*, vol. 88, pp. 27–45, jun 2015.

[132] Y. S. Lee and A. M. Malkawi, "Simulating multiple occupant behaviors in buildings: An agent-based modeling approach," *Energy and Buildings*, vol. 69, pp. 407–416, feb 2014.

[133] K. J. Kalvelage, M. C. Dorneich, U. Passe, C. C. Krejci, K. Kalvelage, and C. Krejci, "Task-Based Approach to Define Occupant Behaviour in Agent-Based Modelling," tech. rep.

[134] R. Markovic, E. Grintal, D. Wölki, J. Frisch, and C. van Treeck, "Window opening model using deep learning methods," *Building and Environment*, vol. 145, pp. 319–329, nov 2018.

[135] V. M. Barthelmes, C. Becchio, V. Fabi, and S. P. Corgnati, "Occupant behaviour lifestyles and effects on building energy use: Investigation on high and low performing building features," in *Energy Procedia*, vol. 140, pp. 93–101, Elsevier Ltd, 2017.

[136] G. Conan, "Variations in householders' window opening patterns," in *3rd AIC Conference: Energy Efficient domestic ventilation systems For Achieving Acceptable Indoor Air Quality*, (London), pp. 3.1–3.19, 1982.

[137] P. Wouters and D. De Baets, "A detailed statistical analysis of window use and its effect on the ventilation rate in 2400 Belgian social houses," in *7th AIC Conference: Occupant interaction with ventilation systems*, (Stratford-upon-Avon), pp. 33–53, 1986.

[138] H. B. Rijal, P. Tuohy, F. Nicol, M. A. Humphreys, A. Samuel, and J. Clarke, "Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings," *Journal of Building Performance Simulation*, vol. 1, no. 1, pp. 17–30, 2008.

[139] P. Tuohy, H. B. Rijal, M. a. Humphreys, J. F. Nicol, A. Samuel, and J. Clarke, "Comfort driven adaptive window opening behavior and the influence of building design," in *Building simulation*, (Beijing), pp. 717–724, University of Strathclyde Institutional Repository, 2007.

[140] V. M. Barthelmes, Y. Heo, R. K. Andersen, V. Fabi, and S. P. Corgnati, “Towards A Comprehensive Model Of Window Control Behaviour: A Survey-based Investigation On Interdisciplinary Drivers In Danish Dwellings,” tech. rep.

[141] F. Haldi and D. Robinson, “On the behaviour and adaptation of office occupants,” *Building and Environment*, vol. 43, no. 12, pp. 2163–2177, 2008.

[142] M. Schweiker, F. Haldi, M. Shukuya, and D. Robinson, “Verification of stochastic models of window opening behaviour for residential buildings,” *Journal of Building Performance Simulation*, vol. 5, no. 1, pp. 55–74, 2012.

[143] B. Griefahn, A. Schuemer-Kohrs, R. Schuemer, U. Moehler, and P. Mehnert, “Physiological, subjective, and behavioural responses during sleep to noise from rail and road traffic.,” *Noise & health*, vol. 3, no. 9, pp. 59–71, 2000.

[144] F. Tahmasebi and A. Mahdavi, “An inquiry into the reliability of window operation models in building performance simulation,” *Building and Environment*, vol. 105, pp. 343–357, 2016.

[145] G. Y. Yun, P. Tuohy, and K. Steemers, “Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models,” *Energy and Buildings*, vol. 41, no. 5, pp. 489–499, 2009.

[146] S. Verbruggen, A. Janssens, J. Laverge, and M. Delghust, “Window opening behavior in a CO2-neutral neighborhood.” 2017.

[147] H. B. Rijal, P. Tuohy, M. A. Humphreys, J. F. Nicol, A. Samuel, and J. Clarke, “Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings,” *Energy and Buildings*, vol. 39, pp. 823–836, jul 2007.

[148] IBM Corporation, “IBM SPSS Statistics for Windows, version 25,” 2018.

[149] S. Verbruggen, M. Delghust, J. Laverge, and A. Janssens, “Habitual window opening behaviour in residential buildings,” *Energy & Buildings*, 2021.

[150] Statistiek België, “Gebouwenpark — Statbel.”

[151] FOD Economie, “Analyse van het energieverbruik van huishoudens in België,” pp. 2010–2016, 2017.

[152] B. Verplanken and S. Orbell, “Reflections on Past Behavior: A Self-Report Index of Habit Strength1,” *Journal of Applied Social Psychology*, vol. 33, no. 6, pp. 1313–1330, 2003.

[153] G. D. Date, “Towards a better understanding of indoor exposure to air pollutants: Window opening occurrence in U.S. residences,” tech. rep., 2017.

[154] M. Fountain, G. Brager, and R. De Dear, “Expectations of indoor climate control,” *Energy and Buildings*, vol. 24, pp. 179–182, oct 1996.

[155] D. Yan, W. O. Brien, T. Hong, X. Feng, H. B. Gunay, F. Tahmasebi, and A. Mahdavi, “Occupant behavior modeling for building performance simulation : Current state and future challenges,” *Energy & Buildings*, vol. 107, pp. 264–278, 2015.

[156] G. R. Newsham, “Clothing as a thermal comfort moderator and the effect on energy consumption,” *Energy and Buildings*, vol. 26, no. 3, pp. 283–291, 1997.

[157] F. Haldi and D. Robinson, “Modelling occupants’ personal characteristics for thermal comfort prediction,” *International Journal of Biometeorology*, vol. 55, pp. 681–694, sep 2011.

[158] S. Karjalainen, “Gender differences in thermal comfort and use of thermostats in everyday thermal environments,” *Building and Environment*, vol. 42, pp. 1594–1603, apr 2007.

[159] W. Liu, D. Yang, X. Shen, and P. Yang, “Indoor clothing insulation and thermal history: A clothing model based on logistic function and running mean outdoor temperature,” *Building and Environment*, vol. 135, pp. 142–152, may 2018.

[160] P. O. Fanger, “Thermal comfort. Analysis and applications in environmental engineering.,” *Thermal comfort. Analysis and applications in environmental engineering.*, 1970.

[161] K. C. Parsons, “The effects of gender, acclimation state, the opportunity to adjust clothing and physical disability on requirements for thermal comfort,” in *Energy and Buildings*, vol. 34, pp. 593–599, jul 2002.

[162] S. Schiavon and K. H. Lee, “Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures,” *Building and Environment*, vol. 59, pp. 250–260, jan 2013.

[163] M. De Carli, B. W. Olesen, A. Zarrella, and R. Zecchin, “People’s clothing behaviour according to external weather and indoor environment,” *Building and Environment*, vol. 42, pp. 3965–3973, dec 2007.

[164] C. Morgan and R. de Dear, “Weather, clothing and thermal adaptation to indoor climate,” *Climate Research*, vol. 24, no. 3, pp. 267–284, 2003.

[165] N. Baker and M. Standeven, “Thermal comfort for free-running buildings,” *Energy and Buildings*, vol. 23, no. 3, pp. 175–182, 1996.

[166] American Society of Heating Refrigerating and Air-Conditioning Engineers, “Thermal Environmental Conditions for Human Occupancy,” in *ANSI/ASHRAE Standard 55-2010*, 2010.

[167] “ISO 7730 - Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria,” tech. rep., 2015.

[168] A. Janssens and A. . Vandepitte, “Analysis of indoor climate measurements in recently built Belgian dwellings,” *Annex 41 Moist-Eng Working Meeting Lyon*, no. May, pp. 1–7, 2006.

[169] S. H. Hong, J. Gilbertson, T. Oreszczyn, G. Green, and I. Ridley, “A field study of thermal comfort in low-income dwellings in England before and after energy efficient refurbishment,” *Building and Environment*, vol. 44, no. 6, pp. 1228–1236, 2009.

[170] S. A. Sadeghi, P. Karava, I. Konstantzos, and A. Tzempelikos, “Occupant interactions with shading and lighting systems using different control interfaces: A pilot field study,” *Building and Environment*, vol. 97, pp. 177–195, feb 2016.

[171] C. F. Reinhart, “Lightswitch-2002: a model for manual and automated control of electric lighting and blinds,” Tech. Rep. 1, 2004.

[172] C. F. Reinhart, *Daylight availability and manual lighting control in office buildings : simulation studies and analysis of measurement.* PhD thesis, Universitat Karlsruhe, 2001.

[173] A. Mahdavi and C. Pröglhöf, “Toward Empirically-based Models of People’s Presence and Actions in Buildings,” in *Building Simulation*, pp. 537–544, 2009.

[174] F. Haldi, *Towards a Unified Model of Occupants' Behaviour and Comfort for Building Energy Simulation.* PhD thesis, École Polytechnique Fédérale de Lausanne, 2010.

[175] Y. Zhang and P. Barrett, "Factors influencing occupants' blind-control behaviour in a naturally ventilated office building," *Building and Environment*, vol. 54, pp. 137–147, aug 2012.

[176] Y. Sutter, D. Dumortier, and M. Fontoynont, "The use of shading systems in VDU task offices: A pilot study," *Energy and Buildings*, vol. 38, pp. 780–789, jul 2006.

[177] P. Correia da Silva, V. Leal, and M. Andersen, "Occupants interaction with electric lighting and shading systems in real single-occupied offices: Results from a monitoring campaign," *Building and Environment*, vol. 64, pp. 152–168, jun 2013.

[178] I. A. Raja, J. F. Nicol, K. J. McCartney, and M. A. Humphreys, "Thermal comfort: Use of controls in naturally ventilated buildings," *Energy and Buildings*, vol. 33, no. 3, pp. 235–244, 2001.

[179] M. Foster and T. Oreszczyn, "Occupant control of passive systems: The use of Venetian blinds," *Building and Environment*, vol. 36, pp. 149–155, feb 2001.

[180] I. Gaetani, P. J. Hoes, and J. L. Hensen, "On the sensitivity to different aspects of occupant behaviour for selecting the appropriate modelling complexity in building performance predictions," *Journal of Building Performance Simulation*, vol. 10, no. 5-6, pp. 601–611, 2017.

[181] H. B. Gunay, W. O'Brien, and I. Beausoleil-Morrison, "Implementation and comparison of existing occupant behaviour models in EnergyPlus," *Journal of Building Performance Simulation*, vol. 9, no. 6, pp. 567–588, 2016.

[182] T. Hong, S. C. Taylor-Lange, S. D'Oca, D. Yan, and S. P. Corgnati, "Advances in research and applications of energy-related occupant behavior in buildings," *Energy and Buildings*, vol. 116, pp. 694–702, 2016.

[183] D. Yan, T. Hong, B. Dong, A. Mahdavi, S. D. Oca, I. Gaetani, and X. Feng, "IEA EBC Annex 66 : Definition and simulation of occupant behavior in buildings," *Energy & Buildings*, vol. 156, pp. 258–270, 2017.

[184] R. D. Heap, "Heat requirements and energy use in British houses," *Energy and Buildings*, vol. 1, no. 4, pp. 347–366, 1978.

[185] G. R. Newsham, "Manual Control of Window Blinds and Electric Lighting: Implications for Comfort and Energy Consumption," *Indoor and Built Environment*, vol. 3, no. 3, pp. 135–144, 1994.

[186] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," *Proceedings of the National Academy of Sciences*, vol. 99, no. Supplement 3, pp. 7280–7287, 2002.

[187] D. Simeone, Y. E. Kalay, H. Achten, J. Pavlicek, J. Hulin, and D. Matejovska, "An Event-Based Model to Simulate Human Behaviour in Built Environments," in *Ecaade 2012, Vol 1*, vol. 1, pp. 525–532, 2012.

[188] W. Shen, Q. Shen, and Q. Sun, "Building Information Modeling-based user activity simulation and evaluation method for improving designer-user communications," *Automation in Construction*, vol. 21, pp. 148–160, jan 2012.

[189] D. Schaumann, Y. E. Kalay, S. W. Hong, and D. Simeone, "Simulating Human Behavior in not-yet Built Environments by means of Event-based Narratives," pp. 1047–1054.

[190] V. Tabak, B. de Vriesh, and J. Dijkstra, “Simulation and validation of human movement in building spaces,” *Environment and Planning B: Planning and Design*, vol. 37, no. 4, pp. 592–609, 2010.

[191] W. O’Brien, F. Tahmasebi, R. K. Andersen, E. Azar, V. Barthelmes, Z. D. Belafi, C. Berger, D. Chen, M. De Simone, S. d’Oca, T. Hong, Q. Jin, D. Khovalyg, R. Lamberts, V. Novakovic, J. Y. Park, M. Plagmann, V. S. Rajus, M. Vellei, S. Verbruggen, A. Wagner, E. Willems, D. Yan, and J. Zhou, “An international review of occupant-related aspects of building energy codes and standards,” *Building and Environment*, vol. 179, jul 2020.

[192] Standard Norge, “Energy Performance of Buildings Calculation of Energy Needs and Energy Supply SN/TS 3031:2016,” tech. rep., Oslo, 2016.

[193] Building and Construction Authority Singapore, “Green Mark for Non-residential Buildings,” tech. rep., Singapore, 2015.

[194] Australia Building Codes Board (ABCB), “National Construction Code (NCC) 2016,” tech. rep., Canberra, 2016.

[195] National Research Council Canada (NRC), “National Energy Code of Canada for Buildings 2017,” tech. rep., Ottawa, 2017.

[196] ANSI/ASHRAE/IES, “Standard 90.1, Energy Standard for Buildings Except Low-Rise Residential Buildings,” tech. rep., Atlanta, 2016.

[197] V. regering, “Energiebesluit Bijlage VI: Bepalingsmethode EPU/EPN,” 2018.

[198] Centre Scientifique et Technique du Bâtiment (CSTB), “Reglementation thermique 2012,” tech. rep., 2012.

[199] T. Abuimara, B. Gunay, and J. K. Day, “Designing for Occupants: A Review of the Integrated Design Practice Definition and Simulation of Occupant Behavior in Buildings View project Occupant modelling in building design View project,” tech. rep., 2018.

[200] W. O’brien, I. Gaetani, S. Gilani, S. Carlucci, P.-J. Hoes, and J. Hensen, “International survey on current occupant modelling approaches in building performance simulation,” *Journal of Building Performance Simulation*, vol. 10, no. 6, pp. 653–671, 2017.

[201] R. Baetens and D. Saelens, “Modelling Uncertainty in District Energy Simulations by Stochastic Residential Occupant Behaviour,” *Journal of Building Performance Simulation*, vol. 9, no. 4, pp. 431–447, 2016.

[202] F. Jorissen, G. Reynders, R. Baetens, D. Picard, D. Saelens, and L. Helsen, “Implementation and verification of the IDEAS building energy simulation library,” *Journal of Building Performance Simulation*, vol. 11, pp. 669–688, nov 2018.

[203] D. Aerts, J. Minnen, I. Glorieux, I. Wouters, and F. Descamps, “Discrete occupancy profiles from time-use data for user behaviour modelling in homes,” *Proceedings of BS2013*, pp. 2421 – 2427, 2013.

[204] D. Aerts, J. Minnen, I. Glorieux, I. Wouters, and F. Descamps, “A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison,” *Building and Environment*, vol. 75, pp. 67–78, 2014.

[205] J. De Schutter, I. Verhaert, and M. De Pauw, “A methodology to generate realistic random behavior profiles for space heating and domestic hot water simulations,” in *Proceedings of the REHVA Annual Meeting Conference*, pp. 1–8, 2018.

[206] I. Glorieux, J. Minnen, and T. van Tienoven, "Belgisch tijdsbudgetonderzoek," 2015.

[207] A. Persily and L. de Jonge, "Carbon dioxide generation rates for building occupants," *Indoor Air*, vol. 27, no. 5, pp. 868–879, 2017.

[208] Shift Innovatie, "Een vernieuwde analyse over huishoudelijke apparaten," pp. 1–81, 2018.

[209] J. Widén, A. M. Nilsson, and E. Wäckelgård, "A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand," *Energy and Buildings*, vol. 41, no. 10, pp. 1001–1012, 2009.

[210] K. Leidelmeijer and P. V. Grieken, "Stook en ventilatiegedrag van huishoudens," tech. rep., 2005.

[211] O. Gerin, B. Bleys, and K. De Cuyper, "Seasonal variation of hot and cold water consumption in apartment buildings," tech. rep., 2014.

[212] E. Janssen, "Conceptfiches voor de productie en distributie van sanitair warm water," tech. rep., Universiteit Antwerpen, 2018.

[213] C. Protopapadaki, *A probabilistic framework towards metamodeling the impact of residential heat pumps and PV on low-voltage grids.* PhD thesis, KU Leuven, 2018.

[214] E. V. Kenhove, "Coupled Thermohydraulic and Biologic Modelling of Legionella Pneumophila Proliferation in Domestic Hot Water Systems," 2018.

[215] K. Simic, I. T'Jollyn, W. Faes, J. Borrajo Bastero, J. Laverge, and M. De Paepe, "Modelling of a gas-fired heating boiler unit for residential buildings based on publicly available test data," *Energy and Buildings*, p. 111451, sep 2021.

[216] Universiteit Gent, "Ontwikkeling van een simulatietool voor Duco Ventilation & Sun Control — Vakgroep Architectuur en Stedenbouw."

[217] G. Fracastoro and M. D. Lyberg, "Guiding principles concerning design of experiments, instrumentation and measuring techniques (Annex 3)," tech. rep., Swedish council for building research D11:1983, 1983.