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Development of Dutch occupancy and heating profiles for building simulation

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ABSTRACT

Building simulations are often used to predict energy demand and to determine the financial feasibility of the low-carbon projects. However, recent research has documented large differences between actual and predicted energy consumption. In retrofit projects, this difference creates uncertainty about the payback periods and, as a consequence, owners are reluctant to invest in energy-efficient technologies. The differences between the actual and the expected energy consumption are caused by inexact input data on the thermal properties of the building envelope and by the use of standard occupancy data. Integrating occupancy patterns of diversity and variability in behaviour into building simulation can potentially foresee and account for the impact of behaviour in building performance. The presented research develops and applies occupancy heating profiles for building simulation tools in order to create more accurate predictions of energy demand and energy performance. Statistical analyses were used to define the relationship between seven most common household types and occupancy patterns in the Netherlands. The developed household profiles aim at providing energy modellers with reliable, detailed and ready-to-use occupancy data for building simulation. This household-specific occupancy information can be used in projects that are highly sensitive to the uncertainty related to return of investments.

KEYWORDS

energy demand; heating; occupancy profiles; occupant behaviour; performance simulation; personas; retrofit; simulation tools

Introduction

The building stock in the Netherlands consists of 7.5 million dwellings (CBS, 2014). Dwellings of the post-war period account for approximately one-third of the residential stock (Itard & Meijer, 2008); a large number of these properties are in need of renovation. Housing associations are important stakeholders in this context. There are approximately 400 housing associations in the Netherlands that manage 2.4 million residential properties, constituting 34% of the total housing stock (Aedes, 2013). Dutch housing associations have the ambition of achieving an energy rating of C for 80% of their properties and an average rating B by 2020 (Aedes, 2013), while currently the average rating for the post-war building according to AgentschapNL (2011) is D–E (approximately 350–400 kWh/m²/year primary energy), resulting in an expected energy consumption of approximately 20 000 kWh/dwelling/year. Therefore, the energy retrofit of post-war buildings offers great potential for carbon reductions. However, there is a lack of fast, affordable and robust processes for large-scale building renovation. This problem is magnified in

multi-family rented buildings in which the incentives for saving energy and increasing indoor comfort are split between owners and tenants, therefore increasing the risk of a large gap between the predicted and actual energy consumption.

This study focuses on a retrofit approach that is currently under development by a consortium of academic and industry partners in the Netherlands. It addresses the challenges of retrofitting the existing building stock and is sponsored by the European Union Climate-KIC's flagship Building Technology Accelerator (BTA) project and the Dutch TKI/Energy programme. To support the transformation of the built environment, the BTA aims to stimulate the large-scale dissemination and acceleration of new low-carbon technologies into the market.

This paper focuses on the challenge related to the effect of building operation and occupants' behaviour on the energy expectations of renovation projects, thus tackling the so-called prebound effect (Sunikka-Blank & Galvin, 2012). The prebound effect refers to a gap between the expected and the actual energy consumption caused by households using less energy than expected

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before the renovation due to the lack of consideration of actual behaviour of buildings' occupants. This effect has implications for the economic viability of energy retrofit programmes (Sunikka-Blank & Galvin, 2012). For example, the payback periods for low-carbon technologies would be longer than calculated. The goal of this research is the development of occupancy and heating profiles that can be applied to building simulation tools to predict more accurately and to fine-tune the energy performance of the building.

The objective of this study is to define more accurate occupancy profiles per household type that can lead to more accurate predictions of energy demand. More certainty on the occupancy behaviour before a retrofit could potentially help to reduce the financial risks associated with the rebound effect. The rebound effect is not tackled in this phase of the project, since measures to reduce it should be implemented in the post-renovation phase of the process. The rebound effect is thus outside the scope of this paper.

Influence of occupant behaviour in building simulation

Energy simulation tools can be used during the design phase to predict energy demand and help designers choose and size different fabrics (for the external envelope) and mechanical systems (Azar & Menassa, 2012). However, recent research has widely documented the differences between the actual and the predicted energy consumption (Virote & Neves-Silva, 2012), which are thought to be caused by faults in the building envelope or commissioning of the systems, occupants' behaviour being different than assumed, and the interaction between occupants and building technology. According to Yu, Fung, Haghghat, Yoshino, & Morofsky (2011), energy consumption is determined by climate, building characteristics, occupants' behaviour, socio-economic factors and indoor environmental quality. While the impact of climate, building characteristics and indoor environmental quality requirements can be readily investigated and tested in current building simulation software, the impact of user-related characteristic and occupant behaviour are still not fully incorporated into simulation tools.

It is important to understand both the existing behaviour and the drivers causing the behaviour (Wei, Jones, & de Wilde, 2014). Researchers have found significant relationships between occupancy characteristics and socio-economical factors (Guerra-Santin & Itard, 2010). Employment, house ownership, income and educational level have been found to have an effect on energy consumption. However, some factors depend greatly on

the country of study. For example, McLoughlin, Duffy, and Conlon (2012) used household social class as an indicator of income and found that higher professionals (high and intermediate managers and professionals) consume more electricity per household per year than middle and lower social classes (supervisory positions, skilled, semi-skilled and unskilled workers, the unemployed) in the UK; while Guerra Santin, Itard, and Visscher (2009) found no relationship between income and energy consumption in the Netherlands.

Therefore, occupancy profiles and occupant behaviour not only differ per household type but also can vary between regions. Regional responsive data can help to achieve better predictions (Al-Mumin, Khattab, & Sridhar, 2003). According to Kane, Firth, & Lomas (2015), understanding heating patterns in British homes is crucial for energy policy formulation, the design of new controls and heating systems, and for accurate stock modelling. Therefore, the development of occupancy profiles for the specific region of study is necessary.

Integrating occupancy patterns diversity and variability in behaviour into building simulation can potentially foresee and overcome the impact of behaviour in building performance (Stokes et al. cited in Richardson, Thomson, & Infield, 2008; Lee & Malkawi, 2014). Occupancy is considered to have a great influence in occupants' heating and ventilation behaviour, as well as on electricity consumption patterns (D'Oca & Hong, 2015). Therefore, determination of occupancy profiles and heating and ventilation patterns that more accurately reproduce building operation are considered crucial in the area of building simulation (Johansson, Bagge, & Lindstrij, 2011; Virote & Neves-Silva, 2012).

In this context, occupancy behaviour refers to how the building would be operated (heating, air-conditioning, ventilation systems), what would be the occupancy level (number of people present at a determined time), and what would be the internal heat gains related to the presence and use of lighting and appliances (Hopfe & Hensen, 2011; Ryan and Sanquist, 2014).

Several models have integrated the influence of occupants' behaviour into building simulation programmes, however only focusing on a limited set of parameters, for example a simplified and schematic representation of the operation of heating controls or windows (Azar & Menassa, 2012; Lee & Malkawi, 2014; Wei et al., 2014; Yu et al., 2011). In addition, current simulation tools, for both energy performance certification or design, lack an approach to evaluate the impact of occupants' characteristics (Martinaitis, Zavadskas, & Motuziene, 2015).

A number of building simulation studies have focused on understanding the effect of occupants' behaviour on

specific designs or low-carbon technologies. For example, occupancy profiles can be defined with a specific purpose such as improving the design of buildings (Flores Larsen, Filippin, Beascochea, & Lesino, 2008), improving the efficiency of ventilation systems (Johansson et al., 2011), or determining the influence of specific internal or external building conditions (Ampatzi & Knight, 2012).

However, there is no standard method to assign the heating set-point for building simulation. Occupancy patterns are defined from standards or estimates (Wei et al., 2014). For example, The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1. 2004 provides standardized occupancy factors for different building types which can be used to design when occupancy schedules are unknown.

In current simulation tools, occupancy level and intensity of use of appliances and lighting are considered for the calculation of internal heat gains; while building operation is included as a 'standard' or 'average' fixed schedule for the thermostat-setting and window operation (Lee & Malkawi, 2014; Wei et al., 2014). Heating and ventilation patterns that reflect the diversity of occupancy profiles followed by different households could produce more realistic and reliable predictions (Kane et al., 2015).

Several studies have focused on the development and use of occupancy profiles. These determine occupancy input based on surveys or datasets. For example, Santos Silva and Ghisi (2014) analysed uncertainties in building simulation through a probabilistic approach. Uncertainties of the user behaviour and physical parameters were obtained through a literature review and field survey. Martinaitis et al. (2015) performed an analysis on the effect of domestic occupancy profiles on the performance of energy-efficient houses and assessed the applicability of default simulation software occupancy profiles. The daily occupancy patterns were created according to the Harmonized European Time Use Survey.

In general, the methods used in current studies to determine occupancy and occupancy behaviour profiles can be classified as statistical analysis such as regression, logistic regression, cluster analysis (Guerra Santin et al., 2009), engineering methods such as load profiles (Capasso, Grattieri, Lamedica, & Prudenzi, 1994; McLoughlin et al., 2012; Wilden & Wackelgard, 2010; Yao and Steemers, 2005), and machine-learning algorithms, for example neural networks, Markov chains, data-mining, genetic algorithms and agent-based models (Davis & Nutter, 2010; Duarte, van den Wymelenberg, & Rieger, 2013; D'Oca & Hong, 2015; Jovanovic, Sretenovic, & Zivkovic, 2015; Mahdavi & Tahmasebi, 2015; Virote & Neves-Silva, 2012).

Conventional statistical analysis has been used and reported extensively in this area of research. The main purpose of these studies has been to identify relationships between different factors affecting energy consumption. For example, regression analysis has been used to identify factors influencing energy use and their relative importance. For a complete review on these studies, see Guerra Santin et al. (2009).

Engineering models use information such as appliance power ratings and end-use characteristics to build a bottom-up description of electricity consumption patterns (McLoughlin et al., 2012). In engineering models, appliance, lighting and electricity load profiles are generated using either metered data or a combination of time-use data, appliance ownership and power information about the appliances. McLoughlin et al. (2012) give some examples in their review (see also Capasso et al., 1994; Wilden & Wackelgard, 2010; Yao and Steemers, 2005).

Machine-learning algorithms have been more recently used in the area of building simulation to develop occupancy profiles. Occupancy profiles can be classified into deterministic models and stochastic models. In deterministic schedules, a standard day profile is usually the same for all weekdays and both weekend days. For these models, data-mining can be used to obtain information on user–building interaction. Depending on the available data, this method assumes no change in occupancy schedules throughout the year (Duarte et al., 2013). Other studies have focused on the development of stochastic occupancy profiles with data from monitoring campaigns. Diversity profiles, generated by these models, represent typical probability profiles and are derived from long-term monitored data. The probabilistic models generate random non-repeating daily profiles of occupancy for a long-term (annual) building performance simulation (Mahdavi & Tahmasebi, 2015). These models can be used to randomly generate multiple building occupancy patterns to evaluate the uncertainties related to occupant behaviour. For these models, diverse machine-learning algorithms are used such as Markov chains or artificial neural networks (Davis & Nutter, 2010; Jovanovic et al., 2015; Virote & Neves-Silva, 2012). Prediction models aim to generate artificial occupancy patterns that are similar to the actual (measured) patterns. Thus, the limitations of studies using monitoring data is that the mined or predicted occupancy profiles are circumstantial to the given dataset (D'Oca & Hong, 2015; Virote & Neves-Silva, 2012).

In building-simulation studies, the method used to define occupancy depends on the purpose of the study and the availability of the data. The following sections describe the approach taken in this study.

Methods and data

As there are large differences in energy consumption between households, it is very important to get clear insights into the relationship between type of occupancy and energy use. For example, in the context of this research, these insights will help to assess the feasibility of the ‘zero-on-the-meter’ (in Dutch: *nul-op-de-meter*) target in the retrofit of apartment complexes, to evaluate the effectiveness of technological measures, and to reduce the risks of unexpected energy bills. In the Netherlands, zero-on-the-meter is defined as a building (usually renovated social residential buildings) in which the yearly building-related and user-related energy consumption in MJ equals the generated energy in the building and surrounding area (RVO, 2015).

This study consists of the definition of household types and corresponding occupancy patterns. The process to define household types and occupancy patterns can be seen in Figure 1. As a first step, household types are defined as the most representative household typologies on a national sample in terms of demographics. As a second step, occupancy patterns are defined with exploratory factor analysis. Occupancy profiles are defined, in the context of this study, as a set of building operation patterns, for example heating patterns, ventilation patterns and presence at home. As a third step, analysis of variance (ANOVA) tests are used to determine household profiles as the specific occupancy patterns followed by a determined household type. Household profiles are determined based on the relationship between household types and occupancy patterns. The main goal of the

household profiles is to characterize the intensity on the use of the building, installations and appliances.

The occupancy patterns linked to the household types will be used to calculate the expected energy consumption through building simulation. A different combination of household profiles can be used to determine worst- and best-case occupancy scenarios, as well as average scenarios. The occupancy scenarios can be examined to determine whether the energy targets are reached in all instances. The results can be compared with the results from a common approach to calculate energy consumption (*i.e.* using an ‘average’ household). These results would indicate how realistic are the energy targets of a determined project. These steps are, however, outside the scope of this paper. The definitions of household types, occupancy patterns and household profiles are presented in the following sections.

This investigation, on the effect of occupancy and behaviour profiles diversity, aims to be integrated into renovation processes. Therefore, the method to determine the expected building performance accounting for household variation should be predefined, readily usable and representative for the region of study (the Netherlands).

It is anticipated that housing associations would be able to determine in advance the household’s typology in the building to be renovated based on their client portfolio and, thus, deterministic occupancy profiles per household are preferred to stochastic and predictive models. Deterministic models would be also more easily and readily applied to building simulation tools.

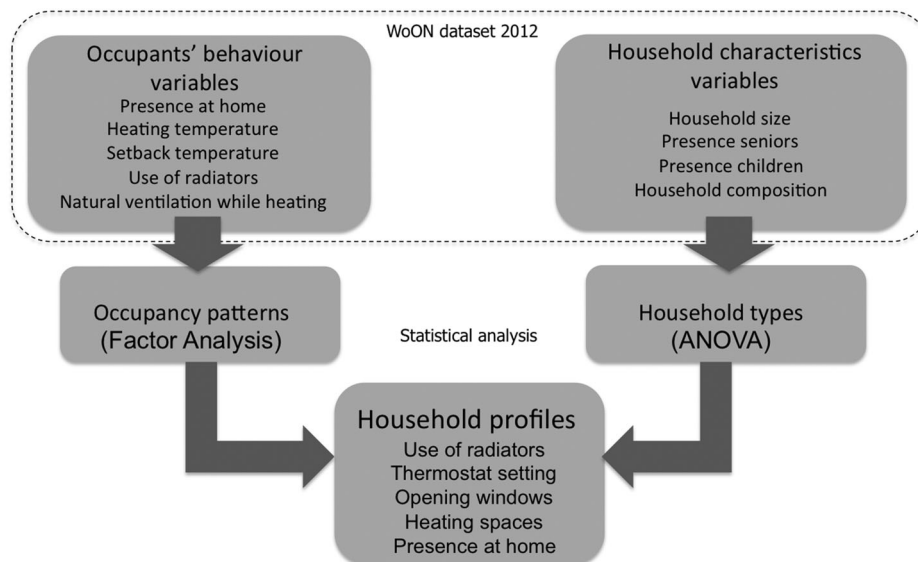


Figure 1. Household type, reference users, user profiles and occupancy patterns.

The use of survey self-reported data is in this case preferable to monitored data because of the complexities of collecting data in buildings to be renovated; however, the authors acknowledge the fact that self-reporting data are not exempt from errors. Furthermore, the use of survey data with a large number of cases is preferable to monitoring data based on a limited number of dwellings, as the aim is to investigate the impact of different households representing the variability within the country.

Since simulation tools only focus on building-related energy demand, the profiles discussed here are only related to space heating and ventilation. Occupancy (the presence of people at home), lighting and appliances use are defined only to calculate internal heat gains.

To develop country representative occupancy and heating patterns, a nationwide dataset is used. Statistical analyses were used to determine the most common types of households in the Netherlands. The Woononderzoek Nederland (WoON) dataset 2012 (see www.rijksoverheid.nl) was used to carry out this analysis. It is based on a nationwide survey carried out by the Dutch Ministry of the Interior and Kingdom Relations (BZK). The WoON dataset 2012 is the third survey carried out; the first and second surveys were carried out in 2006 and 2009 respectively. (The WoON dataset 2015 is not yet available.) The goal of the survey is to determine how Dutch people live and want to live. The dataset includes information regarding household composition, housing needs, energy consumption and building operation. The advantage of using this dataset is that it has been previously used for behavioural research (Guerra Santin, 2010; Jeeninga, Uytterlinde, & Uitzinger, 2001) since the dataset is openly available to researchers. In addition, the survey was carried out several times, and so the type of data collection and data coding has improved at every iteration.

The dataset consists of the compilation of 4800 dwelling audits and over 69 000 household questionnaires, which are also linked to external data (Tigchelaar and Leidelmeijer, 2013). The building audits aim to gather data on building characteristics, while the household questionnaire collects data regarding occupants' behaviour and household characteristics, among others. The WoON dataset (version 2006) has previously proved useful in the study of occupant behaviour in residential buildings (Guerra-Santin & Itard, 2010).

Results

This section presents the results of the statistical analyses to define the household types, occupancy patterns and household profiles.

Household types

The WoON dataset was used to determine households types in relation to their size, composition, age, and the absence or presence of seniors and children, which are important variables on energy consumption (Guerra-Santin & Itard, 2010). Eleven types of households were identified in the sample. Four groups were too small in the sample and therefore were not further studied. Table 1 shows the descriptive statistics of the groups.

ANOVA tests were conducted to investigate the relation of these types of households with electricity, gas and water consumption, as an indicator of domestic hot water (see Table 2 for descriptive statistics). The results showed that gas consumption ($F(6,16\ 080) = 659.1$, $p < 0.001$ Welch statistic), electricity consumption ($F(6,16\ 059) = 3054.8$, $p < 0.001$ Welch statistic) and water consumption ($F(6,15\ 546) = 73059.5$, $p < 0.001$ Welch statistic) are statistically significantly different for the seven types of households. Post-hoc Tukey comparisons were used to ascertain differences between specific household on energy and water use.

For gas consumption, post-hoc comparisons showed that there are statistically significant differences between all groups except between 'one senior' and 'two seniors', 'two seniors' and 'nuclear family', and 'two seniors' and 'three adults'. For electricity consumption, post-hoc comparisons showed that there are statistically significant differences between all groups. For water consumption, post-hoc comparisons showed that there are statistically significant differences between all groups except between the groups 'two adults' and 'two seniors'.

Table 1. Descriptive statistics of households types in the Woononderzoek Nederland (WoON) dataset survey.

Household type	Frequency in the sample	% in the sample
1 senior (> 65 years old)	6667	9.6
1 adult (18–64 years old)	11 598	16.7
2 adults (partners or not)	13 910	20.1
2 adults, at least 1 senior	8266	11.9
3–4 adults	9925	14.3
5 or more adults ^a	2458	3.5
3 or more adults, at least one senior ^a	471	0.7
1 adult and one or more children	2211	3.1
2 adults and 1–3 children	13 034	18.8
2 adults with more than 4 children ^a	764	1.1
3 or more people, children and a senior ^a	38	0.1
Total	69 339	100

Note: ^aEliminated households.

Table 2. Mean and standard deviation (SD) for gas, electricity and water consumption per household type.

Household type	Number of cases in the sample	Gas (m ³ /year)		Electricity (kWh/year)		Water (m ³ /year)	
		Mean	SD	Mean	SD	Mean	SD
1 senior	6667	1521.0	908.2	2162.2	1143.7	61.8	10.1
1 adult	11 598	1310.3	790.2	2341.3	1397.4	62.4	9.3
2 adults	13 086	1682.6	858.0	3479.4	1609.9	101.6	11.0
2 seniors	8252	1876.8	987.1	3358.3	1503.8	101.8	10.7
Single parent	2211	1572.5	749.6	3193.9	1528.3	116.3	25.8
3 adults	3903	1914.6	856.7	4681.2	1816.4	147.8	18.0
Nuclear family	13 034	1859.5	831.8	4309.1	1708.6	157.2	16.4
Total	58 751	1668.6	887.4	3341.4	1752.3	105.3	38.5

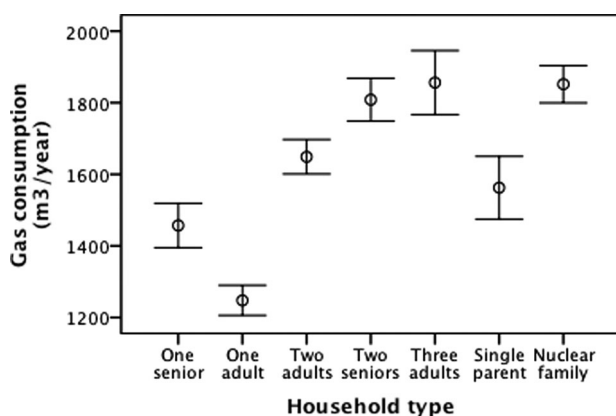
**Figure 2.** Gas consumption per household type in the Dutch building stock (m³/year).

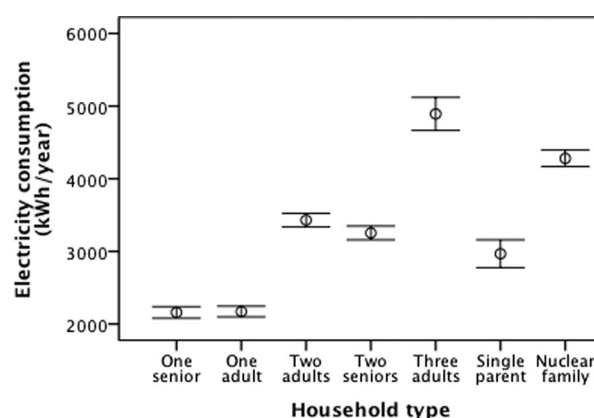
Figure 2 shows that one-person households use the least amount of gas followed by single-parent households, while larger households and those with two seniors use more gas. Figure 3 shows that for electricity the important factors are household size and the presence of children. For water consumption, the main determining factor is household size.

Occupancy patterns

This section defines the occupancy patterns that Dutch households are more likely to follow.

Occupancy patterns are defined as the use of the heating system, opening windows, preferences for temperature settings and presence at home. To define the occupancy patterns for heating, it is assumed that households with similar composition will have the same occupants' behaviour regardless of other socio-economical variables. This assumption allows an investigation of regional household profiles. In addition, research has shown larger effects of socio-economical variables on electricity use than on energy for space heating.

Exploratory factor analysis is a technique used to reduce the number of variables, and it can help to

**Figure 3.** Electricity consumption per household type in the Dutch building stock (kWh/year).

determine related behaviours. The variables used refer to self-reported heating-related behaviour at home, namely: presence at home, thermostat setting, use of radiators and ventilation while heating (Table 3).

Factor analysis describes the variability among variables in terms of factors. The behaviour factors resulting from the analysis (groups of related variables) were further analysed in relation to the intensity of behaviour they represent and their relation to the previously determined household types. According to Field (2005), a factor can be described in terms of the variables measured and the relative importance of these variables to that factor.

Eighteen variables were used in the analysis. They were first examined to determine whether factor analysis was a suitable method, examining the correlation between them. All variables correlated at least .3 with other variables, thus suggesting reasonable factorability. The initial Eigen values showed that the first factor explained 20.1% of the variance, the second 17.3%, the third 10.1%, the fourth 7.7%, the fifth 6.6% and the sixth 6.2%. Factors 7–18 could each explain less than 5%. After examining the Eigen values in each of the resulting factors, and analysing the scree plot, the

Table 3. Behavioural variables used for factor analysis.

Type of variable and values		Mean	SD	Number of cases in the analysis	Number of missing cases ^a
Days at home, 06:00–09:00	Continuous – number of days per week	4.89	1.5170	4490	2021
Days at home, 09:00–12:00		2.95	1.319	4490	2021
Days at home, 12:00–15:00		2.87	1.334	4490	2021
Days at home, 15:00–18:00		3.48	1.445	4490	2021
Days at home, 18:00–23:00		5.04	1.266	4490	2021
Days at home, 23:00–06:00		5.66	1.190	4490	2021
Temperature, 06:00–09:00	Continuous – C°	17.66	2.309	4490	432
Temperature, 09:00–15:00		18.95	1.927	4490	382
Temperature, 15:00–18:00		19.40	1.710	4490	373
Temperature, 18:00–23:00		20.12	1.427	4490	347
Temperature, 23:00–06:00		16.06	1.927	4490	491
Temperature with nobody at home		16.57	2.231	4490	456
Kitchen heating	Categorical – frequency (1 = Always; 2 = Sometimes; 3 = Seldom or Never)	1.47	.561	4490	2335
Bathroom heating		1.64	.842	4490	159
Main bedroom heating		2.59	.758	4490	154
Other bedroom heating		2.57	.706	4490	454
Natural ventilation in other rooms	Categorical – frequency (1 = Always; 2 = Regularly; 3 = Sometimes; 4 = Seldom or Never)	3.19	.910	4490	694
Natural ventilation in the living room		3.33	.824	4490	694

Note: ^aFor each variable, missing values are replaced with the variable mean.

solution that included six factors and explained 68% of the variance was preferred. The factor loading matrix (contribution of each variable to the solution) and communalities (common variance shared with other variables) are shown in Table 4.

Scores were created for each factor based on the mean of the variables that have their primary loadings on each factor. The composite scores were named after the variables contributing to each factor. The factors represent the occupancy behaviour, these are: *Presence at home*, *Day temperature*, *Setback temperature*, *Radiators in bedrooms*, *Ventilation while heating* and *Radiators in service rooms* (Table 5).

In order to maintain a large number of cases for further analysis, missing values were replaced with the mean (Table 3). However, since this method could suppress the true value of the standard deviation (SD), pairwise analysis was also executed to make sure that replacing the missing values with the mean did not affect the results. The results of both analysis were very similar and, thus, the results of the first analysis are used.

Household profiles

The household profiles are the specific occupancy patterns followed by a determined household type. To

determine the household profiles, analysis of variance (ANOVA) tests were carried out between the factor scores (occupancy patterns) and the household types (for statistics, see Table 6). All behavioural factors were statistically significant different between household groups, except for factor 5, *Ventilation while heating* (Table 6, column 1). Previous studies have also failed to find statistical correlation between ventilation habits and household types (Guerra-Santin & Itard, 2010) suggesting too little variability on ventilation patterns between Dutch households. The second, third and fourth columns of Table 6 show the household types scoring lower, average or higher on each factor, representing the intensity of the behaviour per household type. This clustering was made in accordance to the ANOVA post-hoc Tukey tests. This information was used to identify the intensity of the use of the building and building systems (e.g. thermostats setting, use of radiators, ventilation, presence).

Figure 4 summarizes graphically the results from the ANOVA tests, showing the factor scores (columns) for each of the household types (colours). It shows that seniors (singles and couples) and nuclear families tend to be more time at home, while adults (especially single adults) spend less time at home. The thermostat setting in seniors households seems to be the highest, while adults tend to set their thermostat lower. Single adults

Table 4. Factor loadings and communalities based on a principal components analysis for 18 variables of occupant behaviour ($N = 4490$).

	Components						Communalities
	1	2	3	4	5	6	
Days at home, 06:00–09:00	.787						.579
Days at home, 09:00–12:00	.776						.586
Days at home, 12:00–15:00	.772						.638
Days at home, 15:00–18:00	.764						.602
Days at home, 18:00–23:00	.760						.610
Days at home, 23:00–06:00	.740						.642
Temperature, 6:00–09:00		.892					.585
Temperature, 9:00–15:00		.862					.801
Temperature, 15:00–18:00		.707					.840
Temperature, 18:00–23:00			.851				.550
Temperature, 23:00–06:00			.775				.757
Temperature with nobody at home			.728				.659
Main bedroom heating				.897			.709
Other bedrooms heating				.890			.611
Natural ventilation in other rooms while heating					.852		.808
Natural ventilation in the living room while heating					.842		.812
Kitchen heating						.839	.716
Bathroom heating						.744	.728

Notes: Rotation method: Varimax with Kaiser normalization.

Factor loadings < .4 are suppressed.

The Kaiser–Meyer–Olkin measure of sampling adequacy was .742, above the recommended value of .6. The diagonals of the anti-image correlation matrix were all above .5, supporting the inclusion of each item in the factor analysis. Finally, the communalities were all above .3, further confirming that each item shared some common variance with other items. Given these overall indicators, factor analysis was conducted with all 18 variables.

Table 5. Factors analysis – variables contributing to each factor score.

Factor and name	Variable contributing
Factor 1. Presence home factor score	Presence at home, 06:00–09:00 Presence at home, 09:00–12:00 Presence at home, 12:00–15:00 Presence at home, 15:00–18:00 Presence at home, 18:00–23:00 Presence at home, 23:00–06:00
Factor 2. Temperature day factor score	Thermostat settings, 09:00–15:00 (°C) Thermostat settings, 15:00–18:00 (°C) Thermostat settings, 18:00–23:00 (°C)
Factor 3. Temperature setback factor score	Thermostat settings, 06:00–09:00 (°C) Thermostat settings, 23:00–06:00 (°C)Thermostat settings, when nobody home (°C)
Factor 4. Bedroom radiators factor score	Radiators on in the main bedroom Radiators on in other bedrooms
Factor 5. Ventilation factor score	Natural ventilation in the living room while heating Natural ventilation in other rooms while heating
Factor 6. Other rooms' radiators factor score	Radiators on in the kitchen Radiators on in the bathroom

seem to have the lowest thermostat setback; while nuclear families and single seniors have the highest thermostat setbacks. Households with children seem to heat the bedrooms more frequently, while households with two seniors, three adults and nuclear families tend to heat service rooms such as the kitchen and bathroom more frequently. Ventilation preferences seem to be similar in all household types, only the single-parent

households seem to differ from other households, ventilating more frequently while the heating is on.

Definition of occupancy patterns for building simulation

To develop the occupancy patterns, this study is based on the dynamic building simulation programme Bink

Table 6. Results for the analysis of variance (ANOVA) test: factors analysis scores per household type. Welch statistics are presented.

Factor	Lower scores	<i>u</i>	Higher scores
1. Presence home factor score $F(6, 1224.5) = 28.74, p < .001$	Single adult Two adults (less often)	3 adults Single parent	Two seniors Single senior Nuclear family (more often)
2. Temperature day factor score $F(6, 1211.5) = 49.20, p < .001$	Single adult (lower)	Two adults 3 adults Nuclear family Single parent	Two seniors Single senior (higher)
3. Temperature setback factor score $F(6, 1216.9) = 9.1, p < .001$	Single adult Single parent Two seniors Two adults (lower setting)	n.a.	3 adults Single senior Nuclear family (higher setting)
4. Bedroom radiators factor score $F(6, 1223.9) = 5.0, p = .001$	Single parent Nuclear family (more frequently)	Single adult Single senior Two adults Two seniors	3 adults (less frequently)
5. Ventilation factor score $F(6, 1226.5) = 1.86$ n.s.	(more)	Single senior Single adult Nuclear family 3 adults Two adults Two seniors	Single parent (less)
6. Other rooms' radiators factor score $F(6, 1232.8) = 24.1, p < .001$	Two seniors 3 adults (more frequently)	Nuclear family Single senior Two adults	Single parent Single adult (less frequently)

Note: n.a. = Not available; n.s. = not statistically significant.

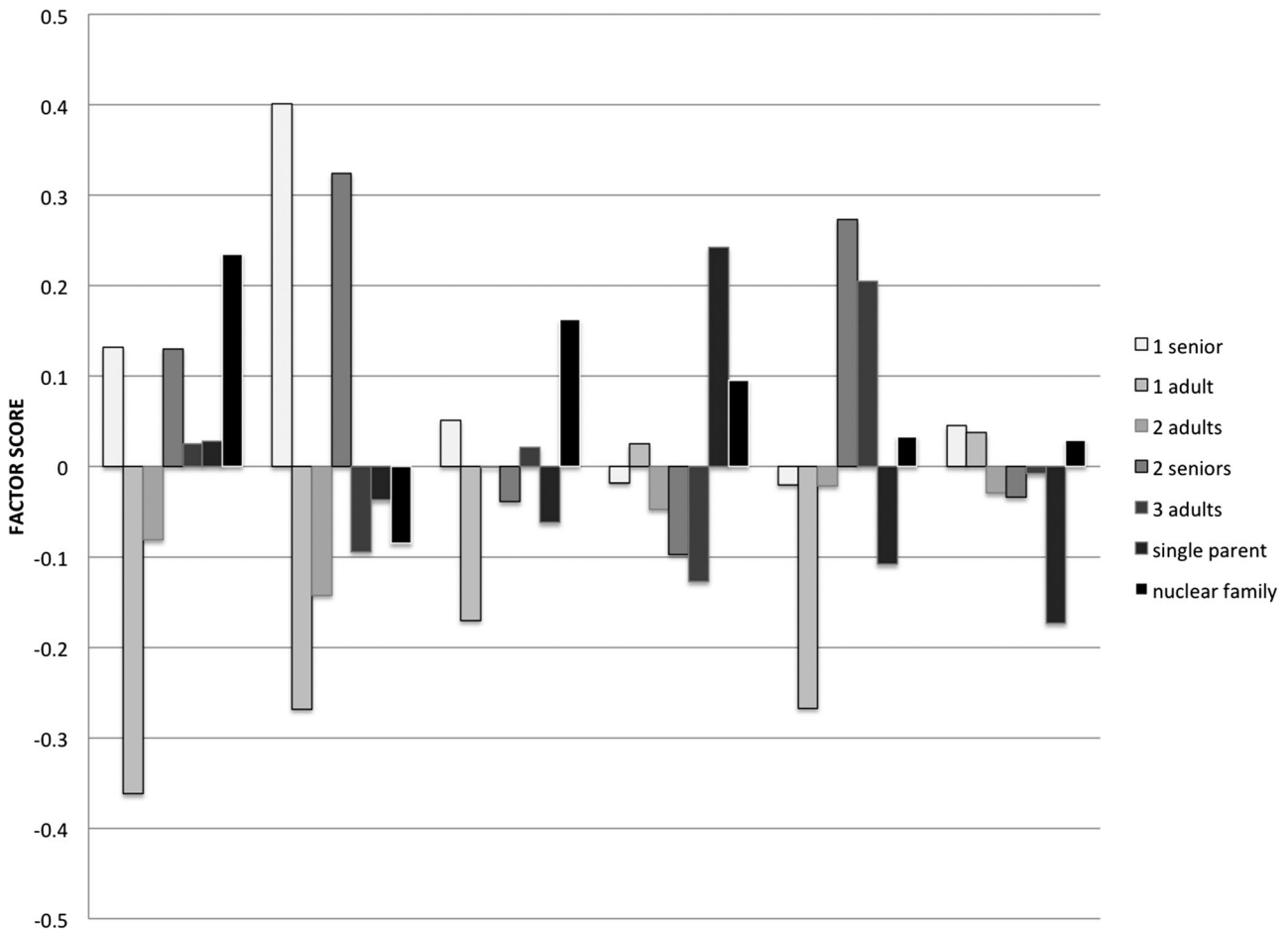


Figure 4. ANOVA tests: factor scores for each of the household types.

Table 7. Household profiles: intensity of heating behaviours and presence.

	Presence	Temperature	Setback	Radiators in the bedroom	Ventilation while heating	Radiators, others
1 senior	More	Warm	Wasteful	Semi-open	Higher rate	Semi-open
2 seniors	More	Warm	Setback	Semi-open	Average rate	Open
1 adult	Less	Cool	Setback	Semi-open	Higher rate	Closed
2 adults	Less	Average	Setback	Semi-open	Average rate	Semi-open
3 adults	Average	Average	Wasteful	Closed	Average rate	Open
Single parent	Average	Average	Setback	Open	Lower rate	Closed
Nuclear family	More	Average	Wasteful	Open	Higher rate	Semi-open

DYWAG, which has been developed according to NEN-EN-ISO 15255, 15256, 13792 (see Binksoftware.nl). The household profiles have been defined in accordance to the required input values in this software. In the software, the authors can define specific heating patterns per day, week, month or year, as well as the presence of people, heat gains and artificial lighting and appliances use in each room.

In the Netherlands, individual rooms are usually heated by radiators fitted with thermostatic radiator valves (TRVs), the valves modulate the flow to the radiator in response to the locally sensed temperature, enabling different rooms to achieve different temperatures (Kane et al., 2015). From previous studies, it is known that in Dutch houses the radiators are usually left closed or half open in the least-used rooms (Guerra-Santin & Itard, 2010). In addition, authors have found that large amounts of energy are wasted due to unoccupied space. In order to take into account the influence of the thermostatic valves in the simulation, more than one thermostat is defined per household, reflecting the state of the radiator in a room as open, semi-open or closed. A similar approach has been followed by Monetti, Fabrizio, and Filippi (2015). For each household profile, up to three thermostat programmes are defined; each thermostat can be linked to different rooms depending on the household type and building layout. For example, a first thermostat set to 22°C can be linked to the living room (or the room with the thermostat) where the radiators are kept completely open; a second thermostat set to 16°C can be linked to the kitchen, bathroom and other rooms where radiators are left closed; and a third thermostat set to 19°C can be linked to the bedrooms where the radiators are kept half open.

The Bink simulation program does not allow the specification of the natural ventilation patterns per hour; natural ventilation can be only defined based on outdoor and indoor temperature. Therefore, the windows will be simulated to be closed during the winter.

As previously stated, each household profile was defined based on household type and their relationship

with the occupancy patterns (defined with factor analysis). For each household, the intensity of the behaviour (e.g. *thermostat setting, presence at home*) was determined based on the results of the ANOVA tests carried out between household type and the occupancy patterns (shown in Table 6). For example, a household type scoring higher in *temperature setting* would have a higher intensity behaviour for thermostat setting (i.e. temperature setting is higher) than a household with a low score. The household profiles are defined in terms of the presence in the dwelling, thermostat setting, thermostat setback, use of radiators and natural ventilation frequency (when the heating is on). The use of appliances and artificial lighting is based on the presence of occupants in the dwelling. Table 7 shows the resulting household profiles, which consist of a relative measure for intensity of behaviour (e.g. seniors use higher set-points than singles). The actual input values for the simulation are obtained from descriptive statistics from the same dataset (Table 8). The input values are defined in the following section and summarized in Table 9.

Presence

The household profiles consist of the schedule for the presence for a whole week. The presence of the occupants is based on the mean number of days that the occupants reported to be at home. It was assumed that all households were more often at home at the beginning of the week and on weekdays than on weekends since previous research has shown that households have an irregular schedule at weekends. This assumption has, however, no implications for the results of the simulation, but it simplifies the input into the software. To determine the number of people present in a room, the rooms of the building were categorized as (1) living area (living room and kitchen), (2) sleeping area (bedrooms), and (3) short-presence spaces (corridors, bathrooms). The short-presence areas were considered to be always empty, while the living area was considered to be occupied during day hours, and sleeping areas during night hours. In the case of singles and couples

Table 8. Descriptive statistics for behavioural variables per household type.

	06:00–09:00		09:00–12:00		12:00–15:00		15:00–18:00		18:00–23:00		23:00–06:00	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
<i>How many weekdays is there someone at home between ... ?</i>												
1 senior	5.3	1.8	3.8	1.7	3.5	1.7	3.6	1.8	4.9	1.7	5.7	1.7
1 adult	4.3	2.3	2.4	1.8	2.2	1.8	2.6	2.0	4.4	1.9	5.4	1.8
2 adults	4.7	2.2	2.8	1.7	2.7	1.8	3.3	1.9	5.0	1.7	5.6	1.7
2 seniors	5.5	1.8	3.9	1.7	3.9	1.7	4.0	1.8	5.1	1.6	5.8	1.7
3 adults	4.9	1.9	2.8	1.6	2.8	1.7	3.6	1.8	5.2	1.6	5.8	1.5
Single parent	5.2	1.8	2.5	1.8	2.4	1.7	3.7	1.9	5.5	1.5	5.8	1.3
Nuclear family	5.2	1.7	3.1	1.5	3.2	1.6	4.2	1.7	5.6	1.3	5.9	1.3
Total	4.9	2.0	2.9	1.8	2.9	1.8	3.5	1.9	5.0	1.7	5.7	1.6
<i>Average temperature weekdays when someone at home between ...</i>												
1 senior	17.8	2.5	19.8	1.7	20.0	1.6	20.5	1.6	16.4	2.2	17.1	2.5
1 adult	17.0	2.5	18.3	2.3	18.8	2.1	19.7	1.7	15.8	2.1	15.9	2.4
2 adults	17.6	2.3	18.6	2.0	19.1	1.9	20.1	1.2	16.0	1.9	16.4	2.3
2 seniors	17.6	2.4	19.6	1.5	19.8	1.4	20.4	1.5	16.0	2.1	17.0	2.4
3 adults	17.7	2.5	18.7	2.0	19.3	1.6	20.2	1.2	15.9	2.1	16.6	2.4
Single parent	17.7	2.7	18.9	2.5	19.5	2.1	20.1	2.0	15.8	2.1	16.1	2.3
Nuclear family	18.3	2.2	18.8	1.9	19.5	1.5	20.0	1.4	16.2	1.8	16.7	2.1
Total	17.6	2.4	18.9	2.0	19.4	1.8	20.1	1.5	16.1	2.0	16.6	2.3

Table 9. Definition of specific occupancy profiles for building simulation.

	1 senior	2 seniors	1 adult	2 adults	3 adults	Single parent	Nuclear family
<i>Presence</i> For each time period (e.g. from 06:00 to 09:00 hours) the mean number of days present at home per household is used	Mean presence per household	Mean presence per household	Mean presence per household	Mean presence per household	Mean presence per household	Mean presence per household	Mean presence per household
<i>Thermostat setting</i> Mean temperature per household	1 SD above the mean	1 SD above the mean	1 SD below the mean	Mean	Mean	Mean	Mean
Setback setting	Same as thermostat setting	Mean for setback	Mean for setback	Mean for setback	Same as thermostat setting	Mean for setback	Same as thermostat setting
Radiators in bedrooms	Same as the living room with a maximum of media temperature in the living room	Same as the living room with a maximum of media temperature in the living room	Same as the living room with a maximum of media temperature in the living room	Same as the living room with a maximum of media temperature in the living room	Lowest temperature in the living room	Same as the living room	Same as the living room
Ventilation	Higher rate	Average rate	Higher rate	Average rate	Average rate	Lower rate	Higher rate
Radiators in other rooms	Same as the living room with a maximum of media temperature in the living room	Same as thermostat setting	Lowest temperature in the living room	Same as the living room with a maximum of media temperature in the living room	Same as thermostat setting	Lowest temperature in the living room	Same as the living room with a maximum of media temperature in the living room

Table 10. Occupancy profiles (number of people indicated by numbers) and artificial lighting profiles (background colour) per household type.

		23:00–06:00 Bedrooms	06:00–09:00 Living room	09:00–12:00 Living room	12:00–15:00 Living room	15:00–18:00 Living room	18:00–23:00 Living room
1 senior	Mon–Wed	1	1	1	1	1	1
	Thu	1	1	1		1	1
	Fri	1	1				1
	Sat–Sun	1					1
1 adult	Mon–Tues	1	1	1	1	1	1
	Wed	1	1			1	1
	Thu	1	1				1
	Fri–Sat Sun	1					1
2 adults	Mon–Wed	2	2	2	2	2	2
	Thu–Fri	2	2				2
	Sat–Sun	2					2
2 seniors	Mon–Thu	2	2	2	2	2	2
	Fri	2	2				2
	Sat	2	2				2
	Sun	2					2
3 adults	Mon–Wed	1/1/1*	1/1/1*	1/1/1*	1/1/1*	1/1/1*	1/1/1*
	Thu	1/1/1*	1/1/1*			1/1/1*	1/1/1*
	Fri	1/1/1*	1/1/1*				1/1/1*
	Sat–Sun	1/1/1*					1/1/1*
Single parent	Mon–Tues	1/1/1*	3*	3*	3*	3*	3*
	Wed	1/1/1*	3*	3*		3*	3*
	Thu	1/1/1*	3*			3*	3*
	Fri	1/1/1*	3*				3*
	Sat–Sun	1/1/1*					3*
Nuclear	Mon–Wed	2/1*	3*	3*	3*	3*	3*
	Thu	2/1*	3*			3*	3*
	Fri	2/1*	3*				3*
	Sat	2/1*					3*
	Sun	2/1*					3*

Notes: (1/1/1*) one person in each bedroom; (2/1*) two persons in the main bedroom, one in second bedroom; (3*) three or more persons, according to household type.

Black background = lights and appliances on from 23:00 to 24:00 and from 05:00 to 06:00 hours; grey background = lights and appliances on (during the winter period).

living in a two- or three-bedroom dwelling, the rest of the bedrooms were considered to be unoccupied, while for households with more than two adults, the bedrooms were considered occupied during day and night. Table 10 shows the occupancy patterns for each household type for common areas (living room) and bedrooms (0 = absence, 1 = presence).

Internal heat gains

For internal heat gains, the use of lighting and appliances was defined based on the presence of people. In instances in which people are present in the room, the appliances and lighting will be considered to be in use. Two appliances and lighting use patterns per household type were generated: a ‘best-case design’ in which the use of natural light is maximized and thus the artificial lighting demand is determined by the time of the day and presence (artificial light is not used in the absence of people or during daytime); and a ‘poor natural light design’ in which artificial light is

determined only by the presence of people (except in the night-time). The selection of the scenario to be employed would depend on the renovation requirements of the project. Table 10 (background colours) shows the appliances and lighting profiles for each household type in the ‘base-case design’ pattern.

Heating (thermostat setting and radiators use)

Two different target temperatures can be defined in a thermostat: the set-point (or comfort) temperature and the setback temperature. In smart thermostats, the setback can be low enough to allow switching off systems and so save energy but high enough so that the house can be heated again in a reasonable amount of time (Kleiminger, Mattern, & Santini, 2014). However, the setback temperature in houses with manual or programmable thermostats depends on the preferences of occupants.

As previously stated, three profiles for thermostat setting are defined for each household type: living room

Table 11. Heating profiles (C°) for thermostat and radiators.

		23:00–06:00		06:00–09:00		09:00–12:00		12:00–15:00		15:00–18:00		18:00–23:00	
1 senior		T1	T2/T3	T1	T2/T3	T1	T2/T3	T1	T2/T3	T1	T2/T3	T1	T2/T3
	Mon–Wed	20	20	22	22	23	22	23	22	23	22	24	22
	Thu	20	20	22	22	23	22	21	21	23	22	24	22
	Fri	20	20	22	22	21	21	21	21	21	21	24	22
	Sat–Sun	20	20	21	21	21	21	21	21	21	21	21	21
1 adult		T1	T2	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2
	Mon–Tues	10	10	12	12	14	14	14	14	14	14	17	14
	Wed	10	10	12	12	10	10	10	10	14	14	17	14
	Thu	10	10	12	12	10	10	10	10	10	10	17	14
	Fri–Sun	10	10	10	10	10	10	10	10	10	10	10	10
		*T3–10°C											
2 adults		T1	T2/T3	T1	T2/T3	T1	T2/T3	T1	T2/T3	T1	T2/T3	T1	T2/T3
	Mon–Wed	15	15	17	17	18	18	18	18	19	18	20	18
	Thu–Fri	15	15	17	17	16	16	16	16	16	16	20	18
	Sat–Sun	15	15	16	16	16	16	16	16	16	16	16	16
2 seniors		T1/T3	T2	T1/T3	T2	T1/T3	T2	T1/T3	T2	T1/T3	T2	T1/T3	T2
	Mon–Thu	19	19	21	21	22	21	22	21	22	21	23	21
	Fri	19	19	21	21	20	20	20	20	20	20	23	21
	Sat	19	19	21	21	20	20	20	20	20	20	20	20
	Sun	19	19	20	20	20	20	20	20	20	20	20	20
3 adults		T1/T3	T2	T1/T3	T2	T1/T3	T2	T1/T3	T2	T1/T3	T2	T1/T3	T2
	Mon–Wed	17	16	17	16	18	16	18	16	19	16	20	16
	Thu	17	16	17	16	16	16	16	16	19	16	20	16
	Fri	17	16	17	16	16	16	16	16	16	16	20	16
	Sat–Sun	17	16	16	16	16	16	16	16	16	16	16	16
Single parent		T1/T2	T3	T1/T2	T3	T1/T2	T3	T1/T2	T3	T1/T2	T3	T1/T2	T3
	Mon–Tues	15	15	17	15	19	15	19	15	19	15	20	15
	Wed	15	15	17	15	19	15	16	15	19	15	20	15
	Thu	15	15	17	15	16	15	16	15	19	15	20	15
	Fri	15	15	17	15	16	15	16	15	16	15	20	15
	Sat–Sun	15	15	16	15	16	15	16	15	16	15	16	15
Nuclear		T1/T2	T3	T1/T2	T3	T1/T2	T3	T1/T2	T3	T1/T2	T3	T1/T2	T3
	Mon–Wed	18	18	18	18	19	18	19	18	19	18	20	18
	Thu	18	18	18	18	16	16	16	16	19	18	20	18
	Fri	18	18	18	18	16	16	16	16	16	16	20	18
	Sat	18	18	16	16	16	16	16	16	16	16	20	18
	Sun	18	18	16	16	16	16	16	16	16	16	16	16

Notes: T1 = thermostat 1 (main thermostat, usually in the living room); T2 = thermostat 2 (radiators temperature in bedrooms); T3 = thermostat 3 (radiators temperature in office, bathroom and kitchen).

Black background = night setback temperature;

grey background = day setback temperature.

thermostat (where the actual thermostat would be located), *radiators in bedrooms* thermostat, and *radiators in other rooms* thermostat. These three thermostat settings aim at reflecting the use of radiators in different rooms of the dwelling.

To determine the input value in the simulation programme, descriptive statistics per household were used (Table 8). The results of the ANOVA post-hoc analysis determined the descriptive statistic to use as an input. For the households with middle factor scores (> -0.1 and < 0.1), the thermostat setting was defined as the mean reported thermostat setting; for households with factor higher scores (> 0.1), the thermostat setting was defined as the mean + 1 SD; and for the households with lower factor scores (< -0.1), the thermostat setting was defined as the mean – 1 SD.

The input value for the thermostat setting in the living room thus consists of the statistic defined by the

ANOVA post-hoc test between factor 2 (thermostat setting) and household type. For example, for the *nuclear family*, the thermostat setting for Monday at 10:00 hours is the mean value of all households defined as ‘nuclear family’ in the dataset, for the time slot 09:00–12:00 hours.

The setback temperature was determined with the ANOVA analysis of the households in relation to factor 3: *thermostat setback*. A setback temperature was considered for hours of occupant absence, and for the night-time (based on Table 10, presence in the dwelling). The setback temperature was obtained using the mean reported value for thermostat setback for household types reporting a low thermostat setback setting, while for households with high setback thermostat settings the same input used for the thermostat setpoint setting was used (*i.e.* the thermostat is always the same). Table 11 shows the three

thermostat settings in the living room (T1) for each household type.

To define the temperature settings in the bedrooms and in the other rooms, the results from the ANOVA analysis were used to define households likely to turn on the radiators in bedrooms and service rooms (factors 4–6). The temperature for radiators open was considered as equal to the main thermostat settings; the temperature for radiators closed was equal to the setback setting or (in case of households with no thermostat setback) the lowest temperature in the main thermostat schedule. The

temperature for radiators half open was defined as equal to the average between the highest and the lowest temperature setting per household type. The heating profiles for bedrooms and service rooms are shown in Table 11 (T2 and T3 respectively).

Ventilation profile

Differences in ventilation while heating patterns were not found to be statistically significant for the different types of households. Table 12 shows the descriptive statistics for the natural ventilation frequency during the winter period in the dataset. Nearly 50% of the respondents for each household type reported always using natural ventilation during the winter. The percentage of household in each frequency category was very similar. Thus, for the occupancy profiles developed, it is assumed that all household profiles have the same ventilation behaviour at all times.

Figure 5 shows the complete profile for a ‘single senior’ household. The profile consists of a profile for the presence, artificial lighting use and thermostat setting for the living room (or the place where the thermostat is located), bedrooms and other rooms. The profiles show the thermostat settings in degrees Celsius, and the presence (1) and absence (0) of people and artificial light per hour and day of the week.

Table 12. Reported natural ventilation during the winter in Dutch households

	Only mechanical (%)	Mechanical ventilation and daily (%)	Always ventilation (%)	10 minutes to 1 hour (%)
1 senior	4	7	52	36
1 adult	6	9	50	35
2 adults	5	10	50	34
2 seniors	6	9	44	40
3 adults	6	11	50	33
Single parent	3	7	52	38
Nuclear family	7	10	49	34
All	6	9	49	36

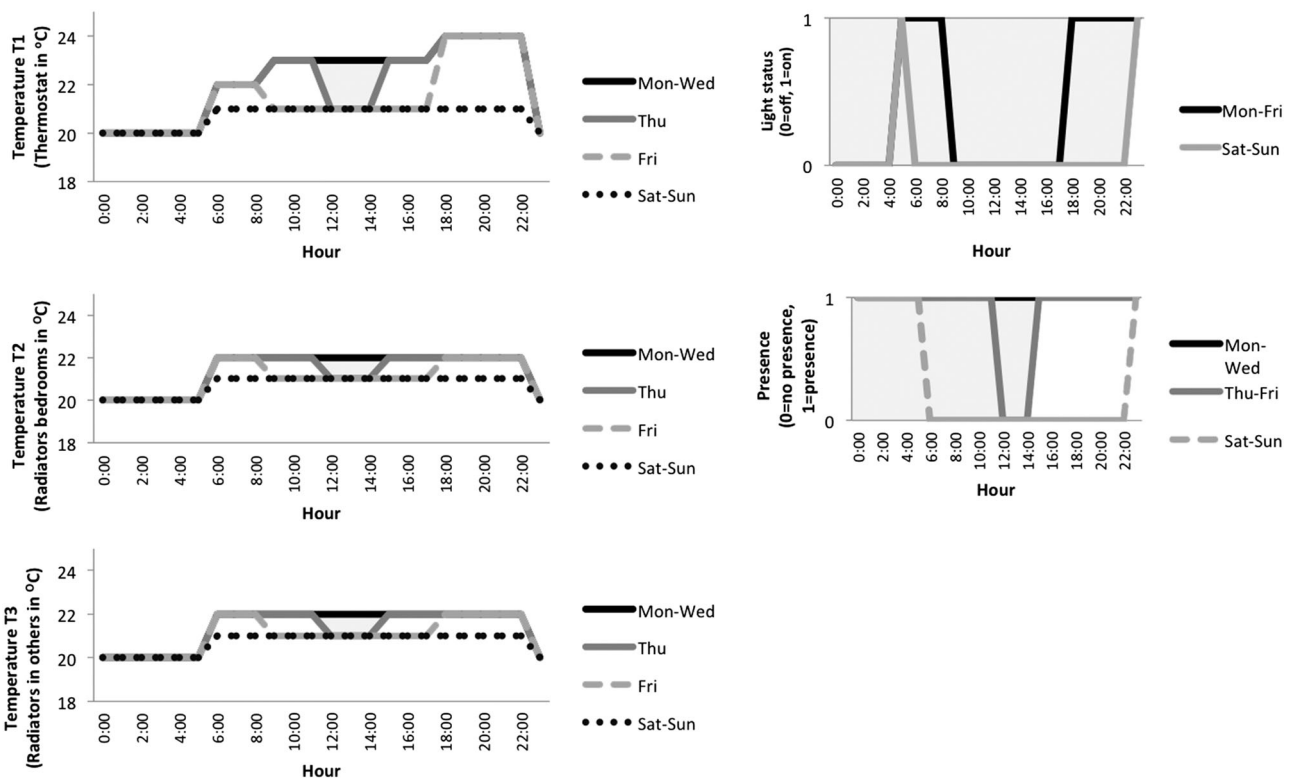


Figure 5. Graphical representation of household profile: 1 Senior household.

Table 13. Pearson correlations between occupancy factors and gas consumption.

Occupancy factors	Number of cases	Correlation
1. Presence home factor score	4790	.069**
2. Temperature day factor score	4790	.063**
3. Temperature setback factor score	4790	.096**
4. Bedroom radiators factor score	4790	n.s.
5. Ventilation factor score	4790	-.030*
6. Other rooms' radiators factor score	4790	-.219**

Note: * $p < .01$; ** $p < .001$.

n.a. = Not significant.

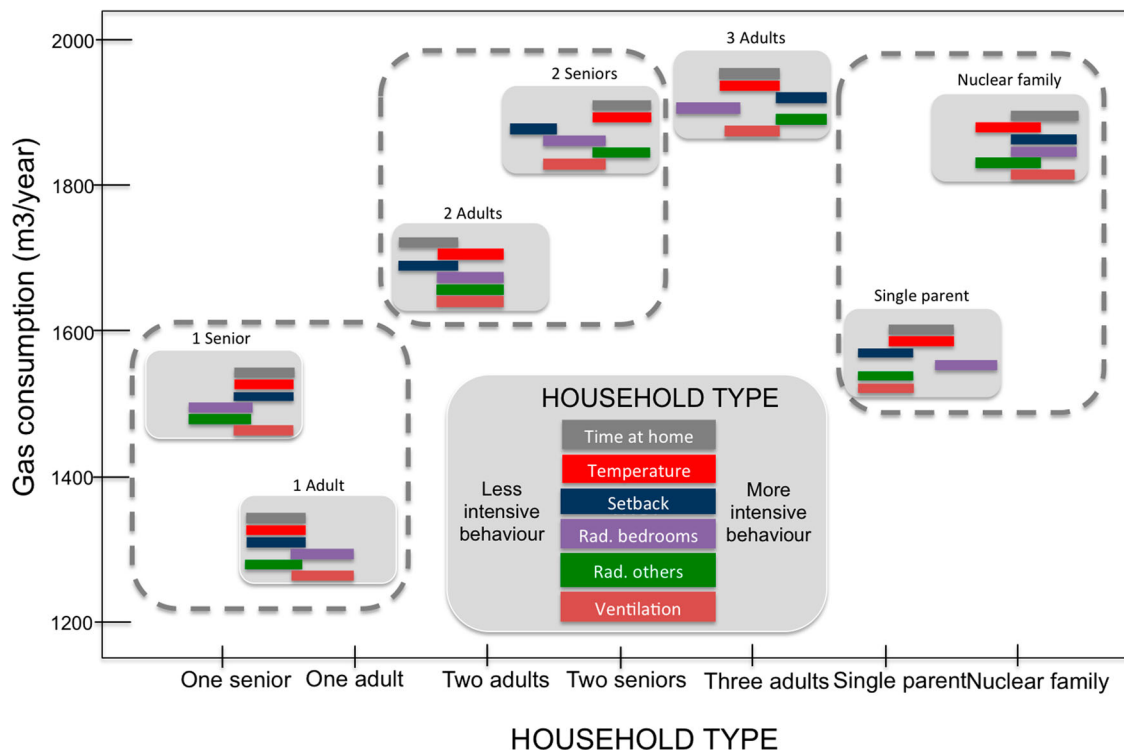
Validation of household profiles

The profiles developed in this study aim at discerning the differences in behaviour between household types on a national sample. Although the household profiles are not completely related to energy consumption due to the effect of building characteristics, a certain level of correlation is expected between the profiles and gas consumption. Therefore, in a first attempt to validate the profiles created, Pearson correlation tests between the factors (occupancy patterns) and gas consumption were carried out (Table 13). The results show small but statistically significant correlations between gas consumption and all factors except *Radiators in bedrooms*. The lack of correlation between *Radiators in bedrooms* and gas consumption seems to be originated by little variance on this behaviour within the sample.

More important than the absolute energy consumption per household is the relative difference in the intensity of behaviours between household types, thus looking at behaviour and not to the influence of building characteristics (such as dwelling size). Figure 6 shows the relationship between gas consumption per household type and the household profiles developed in this study. It shows that households with more intensive heating behaviours (*i.e.* bars towards the right): one senior, two seniors and a nuclear family show higher gas consumption than their household size counterparts (*i.e.* one adult, two adults, a single parent). The higher gas consumption of larger households (three adults and households with children) will be evident in the results of building simulations, when the number of spaces heated are considered.

Given that the household profiles in this investigation are generated using statistical analysis of self-reported data (*i.e.* the respondents reported on their own behaviour), it would be necessary to validate the results with data from building monitoring campaigns in terms of measured behaviours per household type. A companion paper will deal with the development of household profiles based on monitoring data, and their comparison with the profiles developed in this study.

It is important to add that the development of occupancy and heating profiles in this paper aimed at determining household-specific profiles, and not with the intention of predicting occupancy patterns or energy

**Figure 6.** Relationship between household profiles and gas consumption per household type.

consumption (*i.e.* stochastic models). The approach followed is deterministic and descriptive in nature, and thus the use of statistical data allows generalizations to be made to the population of study.

Discussion

Seven household profiles were developed based on statistical analysis with the aim of providing nationwide occupancy input data for building simulation. The use of national statistical data allows the results to be generalized. The profiles developed are made up of information known to have an effect on energy consumption, and of information needed for input in the building simulation program Bink, although similar information is required in most simulation programs.

The household profiles developed aim to reflect the lifestyle and preferences of seven representative household types in the Netherlands, with the objective being to determine the effect of different household characteristics during the design phase of buildings. It is important to add, however, that these profiles could slightly change if a specific sector of the population is under consideration, for example in projects directed to social rental properties, where households with lower incomes are the target group. Future research should aim at defining these differences.

The advantage of the household profiles developed in this study is related to the practicality of using deterministic occupancy data as input in building simulation programs. The relative simplicity of the method would allow its use in practice, especially in the design phases of construction or renovation processes, when fast iterations of calculations are required. Software libraries can be easily implemented to be employed in different projects and by different energy modellers.

The main disadvantage of this method is related to the reliability on self-reported questionnaire survey data. Previous research has found that self-reported behavioural data are not always accurate. However, the large sample sizes provided by these methods (which would be prohibitive in other methods) makes it possible to create generalizations for the Dutch population. Further phases of this study aim to use monitoring datasets to validate the profiles. Therefore, the limitation of this study is related to the validation of the developed profiles with actual occupancy data, which could only be obtained through numerous and extensive monitoring campaigns. However, given that the profiles were determined based on a large dataset and with a random sampling in the population, they provide a much improved alternative to 'standard' occupancy profiles based on rules of thumb.

The results shown in this investigation are in line with trends found in other studies. For example, Kane et al. (2015) found that heating patterns vary depending on the age of households and employment status. Households over 60 years old or unable to work turn the heating on earlier in the year, heat longer each day and heat to higher temperatures in comparison with younger households and those in employment. Yohanis, Mondol, Wright, & Norton (2008) found that households over 65 years old are usually at home during daytime hours; young householders (less than 40 years) tend to have active evenings but low daytime consumption; and middle-age households (50–65 years) usually with children at home have higher electricity consumption in the evenings. This paper goes further by offering complete heating patterns per household type, integrating presence and heating-related behaviour.

The approach presented in this paper is intended for implementation (with some adaptations) in other countries in which datasets as the one employed in this analysis might not be available. Therefore, to determine the patterns in a country without statistical information, or to validate the statistical patterns, building monitoring campaigns could be used. In addition, more information is needed regarding ventilation patterns. In the WoON dataset, around 50% of the households responded to make use of natural ventilation during the winter; however, it is unclear whether the users completely open the windows or only use vents (the latter is a common ventilation practice in the Netherlands). Monitoring data could provide more information about these patterns.

Conclusions

Energy refurbishment approaches are attractive, not only from a CO₂ mitigation perspective but also from a financial point of view. For the acceptance by the end user and the feasibility of the business cases of these refurbishment approaches it is important that uncertainty about the actual energy consumption is minimized. Will the energy use be zero in practice? Today the differences in energy use between the households are huge. It is unhelpful to speak of an average household in this perspective. Therefore, it is important to understand the relation between occupancy and energy consumption.

In this research, occupancy patterns for energy consumption in the Netherlands were defined. Seven statistically defined household types were linked to occupancy patterns (building operation). Factor analysis and ANOVAs were used to define the relationship between the household types and the occupancy patterns.

The results showed that households with seniors and nuclear families have more energy-intensive heating

practices than households with single adults or single-parent households. Households with two adults could be considered to be close to an average household. The differences in heating behavioural patterns seem to be caused by differences in lifestyle between households (e.g. hours present at home), by comfort preferences (e.g. senior households keep higher indoor temperatures) and household composition (e.g. presence of children). However, the less energy-intensive heating practices of the single-parent household might indicate that other household conditions could also be affecting the occupancy patterns for heating.

The use of statistics to determine the occupancy patterns proved useful to define the occupancy of a building when real information about the occupants is not available due to the building renovation schedule, a sensitive processes or when the building is unoccupied. This method can be applied to any type of building renovation projects in the Netherlands, or even in new housing projects. The approach could also be used in other countries provided that datasets containing information about household demographics, building characteristics and occupant behaviour are available.

The household profiles developed in this study aim at providing energy modellers with reliable, detailed and ready-to-use occupancy data for building simulation input. Household type-specific occupancy information can be used in projects that are highly sensitive to the uncertainty related to payback periods and return of investments. By calculating the energy requirements per household type, the designers can make sound data-based decisions leading to energy targets that are true for all users, and not only for an average household.

The calculation of energy requirements taking into account the effect of household typology aims at reducing the gap between the expected and actual energy performance of buildings and at tacking and minimizing the consequences of the rebound effect in renovation projects.

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References

- AEDS. (2013). AEDS- Vereniging van woningcorporaties. Retrieved May 20, 2014, from <http://www.aedes.nl/content/feiten-en-cijfers/feiten-en-cijfers.xml-corporation-system>
- AgentschapNL. (2011). KOMPAS Energiecijfers. Retrieved October 3, 2011, from <http://senternovem.databank.nl/>
- Al-Mumin, A., Khattab, O., & Sridhar, G. (2003). Occupant's behaviour and activity patterns influencing the energy consumption in the Kuwaiti residences. *Energy and Buildings*, 35, 549–559. doi:10.1016/S0378-7788(02)00167-6
- Ampatzi, E., & Knight, I. (2012). Modelling the effect of realistic domestic energy demand profiles and internal gain on the predicted performance of solar thermal systems. *Energy and Buildings*, 55, 285–298. doi:10.1016/j.enbuild.2012.08.031
- ASHRAE 90.1.2004. (2004). Energy standard for buildings except low-rise residential buildings.
- Azar, E., & Menassa, C. C. (2012). A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. *Energy and Buildings*, 55, 841–853. doi:10.1016/j.enbuild.2012.10.002
- Bink software from <http://binksoftware.nl>
- Capasso, A., Grattieri, W., Lamedica, R., & Prudenzi, A. (1994). A bottom-up approach to residential load modelling. *IEEE Transactions on Power Systems* 9.
- CBS. (2014). Centraal Bureau voor de Statistiek. Retrieved February 20, 2011, from <http://www.cbs.nl/nl-L/menu/home/default.htm>
- Davis, J. A. III, & Nutter, D. W. (2010). Occupancy diversity factors for common university building types. *Energy and Buildings*, 42, 1543–1551. doi:10.1016/j.enbuild.2010.03.025
- D'Oca, S., & Hong, T. (2015). Occupancy schedules learning process through a data mining framework. *Energy and Buildings*, 88, 395–408. doi:10.1016/j.enbuild.2014.11.065
- Duarte, C., van den Wymelenberg, K., & Rieger, C. (2013). Revealing occupancy patterns in an office building through the use of occupancy sensor data. *Energy and Buildings*, 67, 587–595. doi:10.1016/j.enbuild.2013.08.062
- Field A. (2005). *Discovering statistics using PSS: And sex, drugs and rock'n'roll*, 2nd ed. London: Sage.
- Flores Larsen, S., Filippin, C., Beascochea, A., & Lesino, G. (2008). An experience on integrating monitoring simulation tools in the design of energy-saving buildings. *Energy and Buildings*, 40, 987–997. doi:10.1016/j.enbuild.2007.08.004

- Guerra Santin, O. (2010). *Actual energy consumption in dwellings. The effect of energy performance regulations and occupant behaviour*. Sustainable Urban Areas series. Delft: IOS Press.
- Guerra Santin, O., Itard, I., & Visscher, H. (2009). The effect of occupancy and building characteristics on energy consumption for space and water heating in Dutch residential stock. *Energy and Buildings*, 41, 1223–1232. doi:10.1016/j.enbuild.2009.07.002
- Guerra-Santin, O., & Itard, L. C. M. (2010). Occupants' behaviour: Determinants and effects on residential heating consumption. *Building Research and Information*, 38(3), 318–338. doi:10.1080/09613211003661074
- Hopfe, C. J., & Hensen, J. L. M. (2011). Uncertainty analysis in building performance simulation for design support. *Energy and Buildings*, 43(10), 2798–2805. doi:10.1016/j.enbuild.2011.06.034
- Itard, L. C. M., & Meijer, F. (2008). *Towards a sustainable Northern European housing stock* (Vol. 22). Amsterdam: IOS.
- Jeeninga, H., Uytterlinde, M., & Uitzinger, J. (2001). Energy consumption of energy-efficient residences. Report ECN & IVAM.
- Johansson, D., Bagge, H., & Lindström, L. (2011). Measurements of occupancy levels in multi-family dwellings – Application to demand controlled ventilation. *Energy and Building*, 43, 2449–2455. doi:10.1016/j.enbuild.2011.05.031
- Jovanovic, R. Z., Sretenovic, A. A., & Zivkovic, B. D. (2015). Ensemble of various natural networks for prediction of heating consumption. *Energy and Buildings*, 94, 189–199. doi:10.1016/j.enbuild.2015.02.052
- Kane, T., Firth, S. K., & Lomas, K. J. (2015). How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling. *Energy and Buildings*, 86, 817–832. doi:10.1016/j.enbuild.2014.10.011
- Kleiminger, W., Matter, F., & Santini, S. (2014). Predicting household occupancy for smart heating control: A comparative performance analysis of state-of-the-art approaches. *Energy and Buildings*, 85, 493–505. doi:10.1016/j.enbuild.2014.09.046
- Lee, Y. S., & Malkawi, A. M. (2014). Simulating multiple occupant behaviour in buildings: An agent-based modelling approach. *Energy and Buildings*, 69, 407–416. doi:10.1016/j.enbuild.2013.11.020
- Mahdavi, A., & Tahmasebi, F. (2015). Predicting people's presence in buildings: An empirically based model performance analysis. *Energy and Buildings*, 86, 349–355. doi:10.1016/j.enbuild.2014.10.027
- Martinaitis, V., Zavadskas, E. K., & Motuziene, V. (2015). Importance of occupancy information when simulating energy demand of energy efficient house: A case study. *Energy and Buildings*, 101, 64–75. doi:10.1016/j.enbuild.2015.04.031
- McLoughlin, F., Duffy, A., & Conlon, M. (2012). Characteristic domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study. *Energy and Buildings*, 48, 240–248. doi:10.1016/j.enbuild.2012.01.037
- Monetti, V., Fabrizio, E., & Filippi, M. (2015). Impact of low investment strategies for space heating control: Application of thermostatic radiator valves to an old residential building. *Energy and Buildings*, 95, 202–210. doi:10.1016/j.enbuild.2015.01.001
- Richardson, I., Thomson, M., & Infield, D. (2008). A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings*, 40, 1560–1566. doi:10.1016/j.enbuild.2008.02.006
- RVO, Rijksdienst voor Ondernemend Nederland. (2015). Nul op de meter. Ervaringen van vernieuwers in de woningbouw. RVO-059-1501/BR-DUZA, Utrecht. Retrieved January, 2016, from www.rijksoverheid.nl
- Ryan, E. M., & Sanquist, T. F. (2014). Validation of building energy modelling tools under idealized and realistic conditions. *Energy and Building*, 47, 375–382. doi:10.1016/j.enbuild.2011.12.020
- Santos Silva, A., & Ghisi, E. (2014). Uncertainty analysis of user behaviour and physical parameters in residential building performance simulation. *Energy and Buildings*, 76, 381–391. doi:10.1016/j.enbuild.2014.03.001
- Sunikka-Blank, M., & Galvin, R. (2012). Introducing the pre-bound effect: The gap between performance and actual energy consumption. *Building Research & Information*, 40(3), 260–273. doi:10.1080/09613218.2012.690952
- Tigchelaar, C., & Leidelmeijer, K. (2013). Energiebesparing: Een samenspel van woning en bewoner – Analyse van de module Energie WoON 2012. ECN-E-13-037.
- Virote, J., & Neves-Silva, R. (2012). Stochastic models for building energy prediction based on occupant behaviour assessment. *Energy and Buildings*, 53, 183–193. doi:10.1016/j.enbuild.2012.06.001
- Wei, S., Jones, R., & de Wilde, P. (2014). Driving factors for occupant-controlled space heating in residential buildings. *Energy and Buildings*, 70, 36–44. doi:10.1016/j.enbuild.2013.11.001
- Wilden, J., & Wackelgard, E. (2010). A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*, 87, 1880–1892. doi:10.1016/j.apenergy.2009.11.006
- Yao, R., & Steemers, K. (2005). A method of formulating energy load profile for domestic buildings in the UK. *Energy and Buildings*, 37(6), 663–671.
- Yohanis Y.G., Mondol J.D., Wright A., & Norton B. (2008). Real-life energy use in the UK: How occupancy and dwellings characteristics affect domestic electricity use. *Energy and Buildings*, 40, 1053–1059.
- Yu, Z., Fung, B.C.M., Haghghat, F., Yoshino, H., & Morofsky, E. (2011). A systematic procedure to study the influence of occupancy behavior in building energy consumption. *Energy and Buildings*, 43, 1409–17.