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Occupant behavior and modeling

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Total energy use in buildings

analysis and evaluation methods

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Contents

II-1

Literature survey
- Driving forces of energy related behavior in residential buildings -

Contents

1. Introduction

In western countries, households account for approximately thirty per cent of the total energy consumption. In order to reduce the energy consumption in buildings, effort has been put in research on and development of more energy efficient technologies and buildings, especially during the last decades. Effort has also been placed on encouraging households to purchase more energy efficient technologies.

The physical aspects related to the energy consumption of buildings, such as the building envelope, building installations and climate, are well understood. However in practice, there is often a significant discrepancy between the designed and the real total energy use in buildings.

Monitoring studies for identical dwellings having the same type of installations have shown great variation in energy use. See for example Figure 1-1, which shows the variation in heating energy for identical dwellings having the same installations.

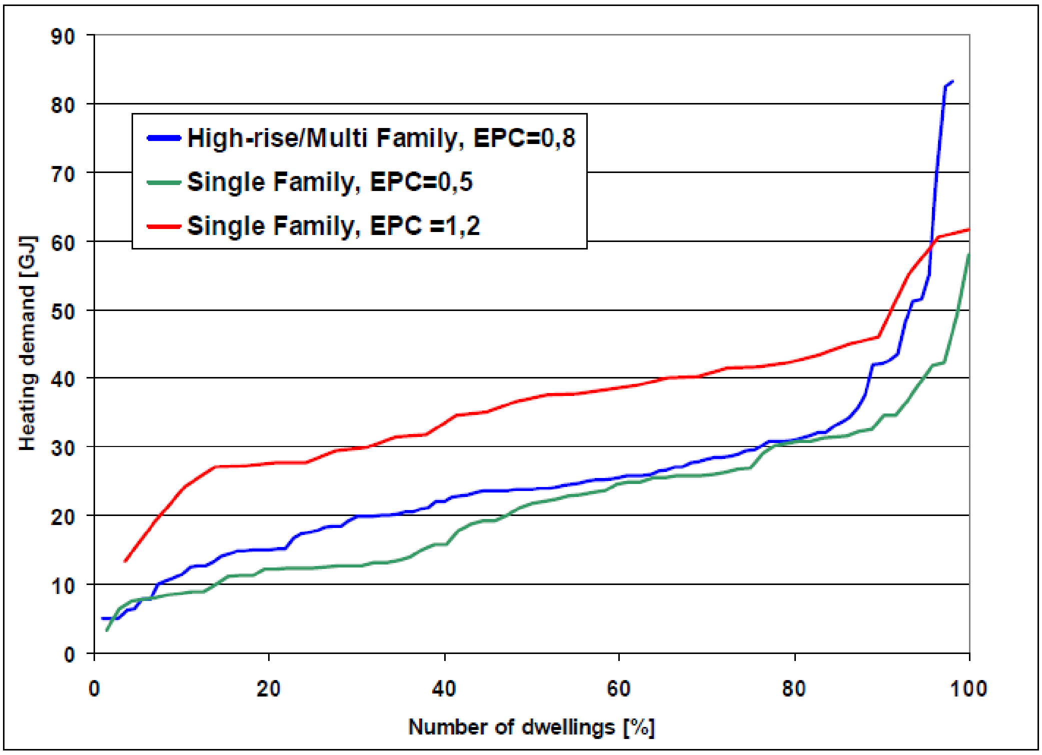

Figure 1-1: Variation in energy use in identical dwellings for three different projects. See Ref. [1].

The three curves in Figure 1-1 represent the heating energy use for three different types of dwellings / installation at three locations in The Netherlands, see Ref. [1]. For example, the single family buildings represented by the red curve display approximately a fourfold difference in heating energy use. The other curves show an even greater variation in heating energy use. This variation in energy use is in this case in a large extent related to the behavior of the occupants of the dwellings, since identical buildings and installations having the same energy efficiency have been considered in this study. Similar findings on the effect of occupant behavior have been reported by other authors in the literature, see e.g. Refs. [2] and [3].

Ref. [3] reports on a study of 1000 quite similar residential buildings in a suburb of Copenhagen, which in spite of their similarity show huge variation in energy consumption. The study has also been reported in Ref. [4]. The comparison of heating energy use for completely identical houses showed that households using the greatest heating energy used a three time more heating energy than the households using the least energy for heating. For electricity use, an even larger variation was found; households using the greatest electricity used five times as much as the households using the least electricity.

Energy-related occupant behavior as meant in this report is related to observable actions or reactions of a person in response to external or internal stimuli, or respectively actions or reactions of a person to adapt to ambient environmental conditions such as temperature, indoor air quality and sunlight. Occupant behavior related to the heating energy use concerns for example the temperature set point, the number of rooms that are heated, the heating duration, and window opening/closing.

Energy use in modern dwellings may show an increased sensitivity to occupant behavior. For example, for very well insulated dwellings the relative increase of heating energy use is quite sensitive to the set point temperature chosen by the occupant, see Figure 1-2.

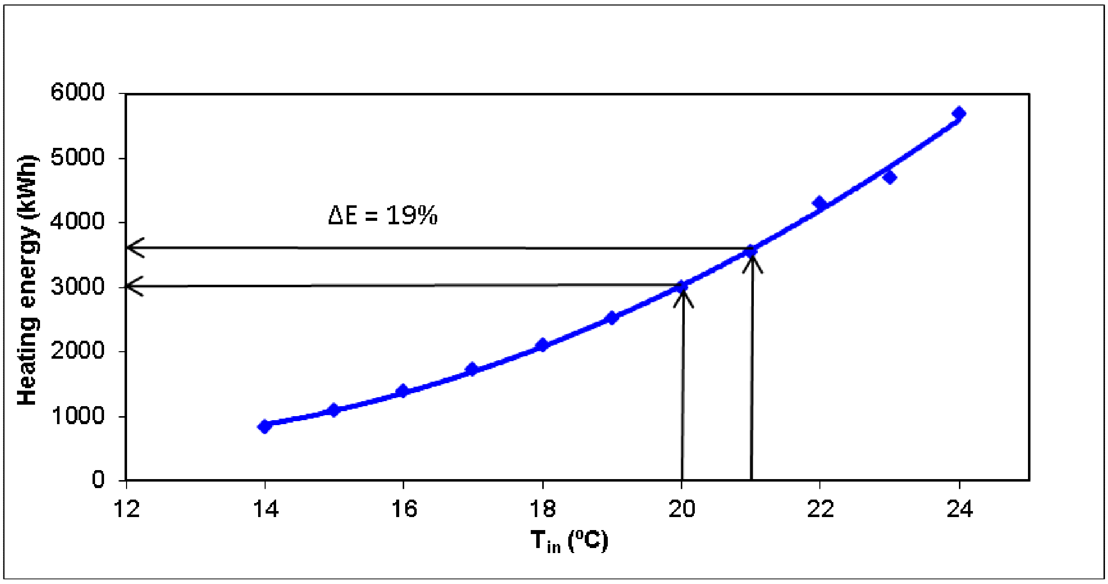

Figure 1-2: Increased sensitivity of heating energy for set point behavior. See Ref [5].

The increase of heating energy of a very well insulated dwelling as a function of the set point temperature is displayed in Figure 1-2. Increasing the set point with one degree, from 20ºC to 21ºC, results in a 19% increase of the heating energy. This example demonstrates the sensitivity of energy use in residential buildings to energy-related occupant behavior.

For modern dwellings with increased air tightness, the occupant behavior can have a larger effect on the air change rate and consequently the energy consumption of the dwelling. As the requirements for energy use in buildings are tightened in national and international regulations, knowledge of physical aspects of energy efficiency is being implemented in new residential and office buildings. In order to fulfill the high expectations for energy savings in buildings in the future, better understanding of how energy-related occupant behavior influences building energy consumption is required. The above examples of the effect of occupant behavior on energy use and the sensitivity to occupant behavior illustrate the importance of acquiring more knowledge on energy-related occupant behavior for understanding and realistically predicting the total energy use in present and future residential buildings and for adapting future building technology to occupant behavior.

In the framework of the IEA ECBCS Annex 53 project, total energy use in buildings and the role of occupant behavior are being investigated. Aspects from natural sciences as well as social sciences are related to the energy use in buildings and are addressed in the project. This chapter contains categorization of the most relevant types of energy-related occupant behavior for residential buildings. In addition, the influencing parameters, referred to as *driving forces*, for the various types of energy-related occupant behavior will be identified in this literature review based chapter.
Quantitative modeling approaches for describing energy-related occupant behavior and energy use in residential buildings are discussed in the second chapter "*Total energy use in residential buildings - the modeling of occupant behaviour*".

2. Driving forces of energy-related behavior

Energy use in residential buildings is influenced by the behavior of occupants in various ways. Energy-related occupant behavior as meant in this report is related to observable actions or reactions of a person in response to external or internal stimuli, or respectively actions or reactions of a person to adapt to ambient environmental conditions (such as temperature, indoor air quality and sunlight), household and other activities. These actions and activities are driven by various factors.

The influence of occupant behavior on the energy use in buildings has been investigated in various domains such as natural sciences, social sciences, and economics. Many investigations in natural science publications focus on (statistical) relations between energy-related behavior and mostly physical parameters influencing this behavior, such as outdoor temperature, indoor temperature and solar radiation. Examples are given in Ref. [6] and Ref. [7].

Various research fields have different foci or requirements for occupant behavior. Determination and regulation of occupant behavior are the foci in social or physiological science. In natural (or building) science, more attention is paid to the quantitative description of occupant behavior based on physical parameters (upper part of Figure 1-3).

However, there is no well-defined relation between physical parameters and control actions such as outdoor temperature and window opening. In reality, an occupant decides to open or close a window and the decision is based on a number of influencing parameters that can be categorized as physical, biological, and psychological, as well as social (the interaction between occupants) to name a few. The lower part of Figure 1-3 illustrates parameters influencing the occupant and his behavior.

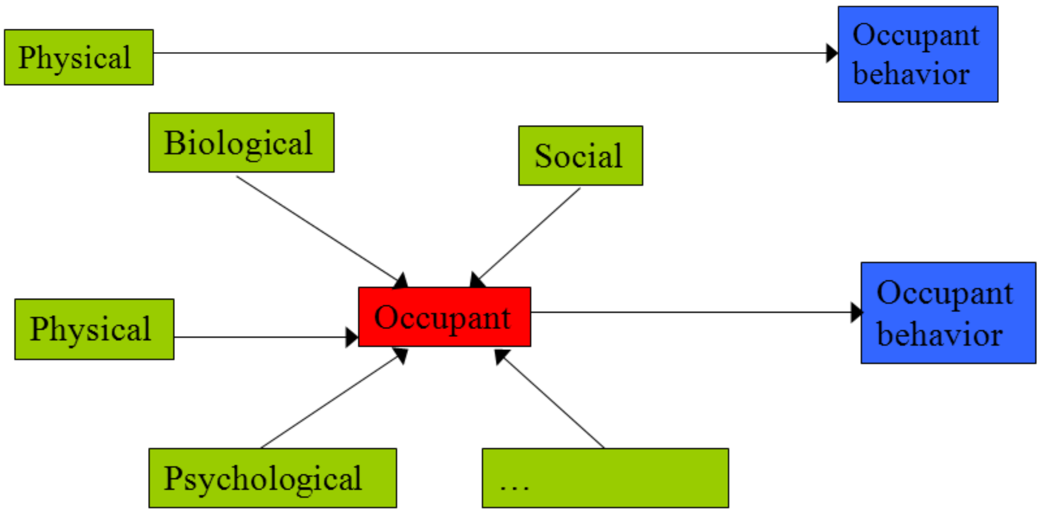

Figure 1-3: Parameters influencing occupant behavior.

This complex relationship between occupants and their environment is elaborated further in Figure 1-4.

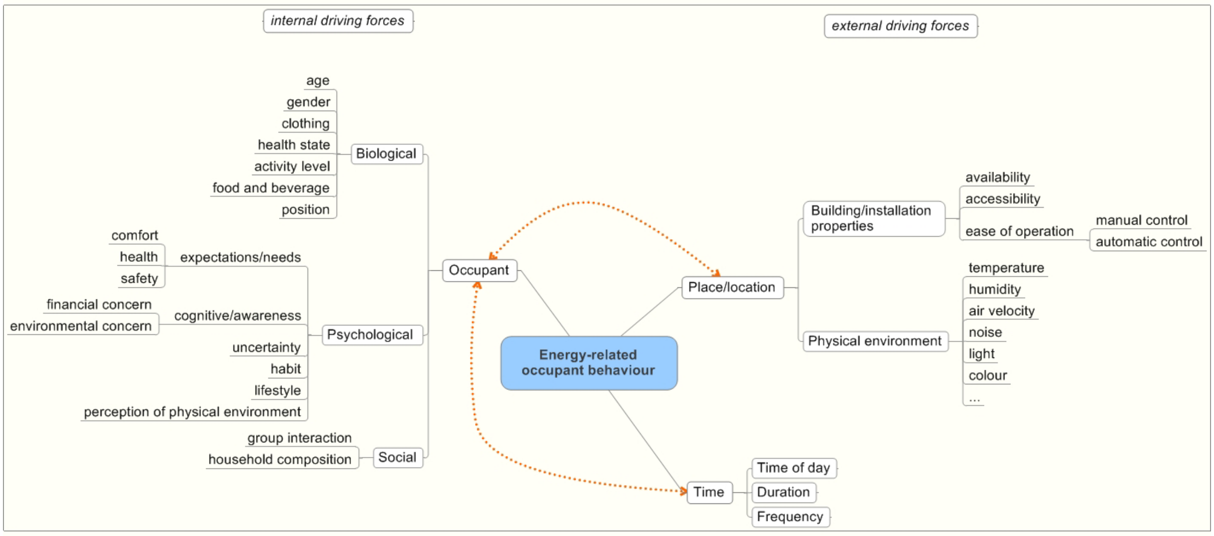

Figure 1-4: Driving forces of energy-related occupant behavior.

This scheme is based on the presence of an occupant at a specific time at a specific location having access to specific building controls. Occupants experience a specific physical environment due to their location, biological, and psychological states, and by the interaction with their environment.

Information about occupant presence and activities may be obtained from time-use surveys and occupancy sensing. The interaction between humans, buildings, and building control systems result from a combination of influencing parameters, from now on referred to as *driving forces*. These driving forces can be regarded as *internal* and *external* driving forces, see Ref. [8] and Ref. [9] for examples. The internal and external driving forces of energy-related occupant behavior as shown in Figure 1-4 are ordered according to the following categories: *biological*, *psychological*, *social*, and *time, building and building equipment properties*, *physical environment (indoor and outdoor)*.

2.1 Internal driving forces

The first three types of driving forces of energy-related behavior are *internal* driving forces of the occupant, *biological, psychological, and social*, and are depicted on the left side of Figure 1-4. These are being investigated in the domain of social sciences, economics, and biology. There is strong interaction between biological and psychological aspects, resulting in disciplines such as biopsychology and psychophysiology. Health can be considered as a biopsychosocial unit combining biological, psychological and social elements. Eating or drinking habits are strongly influenced by cultural aspects. Thus, strict differentiation between these driving forces is difficult to handle. A short section on behavioral thermoregulation representing an interface between biological and psychological driving forces with thermal comfort-related interactions with heating, cooling, ventilating, and window opening is included.

Biological driving forces:
Examples of biological driving forces are age, gender, health condition, activity level, hunger, and thirst. These factors together determine the physiological condition of the occupant.
Psychological driving forces:

Occupants tend to satisfy their needs concerning thermal, visual, and acoustic comfort requirements, along with health and safety, to name a few. Furthermore, occupants may have certain expectations of e.g. the indoor environmental quality (such as temperature). Other examples of psychological driving forces are awareness (e.g. financial and environmental concerns), cognitive resources (e.g. knowledge), habits, lifestyle, perceptions, emotions, and self-efficacy (e.g. environmental control).
Behavioral thermoregulation: Apart from autonomous biological processes, there is a variety of deliberate regulation options which are listed below. Adequate behavioral thermoregulation can be considered result of learning processes, experiences, and/or culturally-driven factors.

1. Clothing: relevant in hot as well as in cold climate conditions, adequate clothing fosters reducing convection;
2. Thirst as the deliberate regulation of hydration is a crucial issue in people being in need for care or old persons drinking too little (this is of special interest regarding demographic change);
3. Use of external sources for convection or thermal heat;
4. Looking for places which, which are more convenient, e.g. shade, areas with more or less natural convection;
5. Sleep (siesta) as an option to reduce metabolic heat production;
6. Acclimatization: the process by which an individual becomes physiologically, behavioral, and psychologically adjusted to the temperature of the environment. This is of importance regarding the degree by which the individual tolerates actual sensitized temperatures especially when it comes to extreme and unfamiliar climates; acclimatization can be a result of repeated exposure to hot climates.

Social driving forces:
Social driving forces refer to the interaction between humans. For example for residential buildings, this depends on household composition which is linked to the primary decision maker in the household, i.e. which household member determines the thermostat set point or the opening/closing of windows.

2.2 **External driving forces**

The *external* driving forces depicted at the right-hand side of Figure 1-4 (*building and building equipment properties, physical environment, and time*), are being investigated in the field of natural (or building) science.

Building and building equipment properties:
Examples of building and building equipment properties are the insulation level of buildings, orientation of façades, heating system type, and thermostat type (e.g. manual or programmable), to name a few.

Physical environment:
Examples of physical environment aspects that drive energy-related occupant behavior are temperature, humidity, air velocity, noise, illumination, and indoor air quality.

Time:
Examples of this type of driving forces that affect energy-relates occupant behavior are season of the year, week or weekend day, time of the day.

2.3 Energy-related occupant behavior

The energy-related occupant behavior block in Figure 1-4 refers to actions and activities related to the categories *heating, cooling, ventilation and window operation, domestic hot water, electric appliances / lighting, and cooking*. These categories are briefly introduced underneath and are discussed in greater detail in the subsequent sections of this chapter.

1) Heating:
The activities of occupants have become more important within energy efficient buildings. Studies have shown that user behavior and lifestyle can affect energy consumption by up to a factor of three. Occupant behavior related to heating concerns temperature set point, number of heated rooms, heating duration, gender, age, expectations, knowledge of control function and meteorological conditions.

2) Cooling:
Depending on the type of system, occupant behavior has a significant influence on the use of cooling. From the general to the detailed, this starts in some cases with the choice of cooling system, the duration and frequency of usage, the choice of set-point temperatures, and the frequency of maintenance.

3) Ventilation and window operation:
Investigations on window opening behavior and natural ventilation have mainly been carried out with two aims: to find whether or not occupants are provided with adequate fresh air and to find the influence on energy consumption. The former category of studies has usually been carried out in dwellings and has a health or a comfort perspective, while the latter category has mostly been studied in offices with a comfort and energy performance perspective. Occupant behavior concerns mechanical ventilation operation, natural ventilation inlet operation, window opening or closing.

4) Domestic hot water:
Occupant behavior can significantly influence the use of hot water in residential buildings. Examples of energy-related occupant behavior related to domestic hot water use are the frequency of taking a shower, duration and intensity of showers; frequency of taking a bath; frequency of sink use; frequency and temperature of washing machines and dishwashers, and efficiency of water usage.

5) Electric appliances / lighting:
The use of electric appliances and lighting in residences is strongly influenced by occupant behavior. When the energy consumptions for appliances and lighting are considered, large variations are found, which partly relates back to socioeconomic parameters such as income, persons per household, age, education etc. The number of appliances and their energy efficiency, as well as the usage frequency and duration determine the energy use.

6) Cooking:

Many different appliances can be used for cooking purposes, such as microwave ovens, ovens, stoves, pressure cookers, kettles, etc. The type of equipment used and their corresponding energy consumption as well as the number of meals prepared will determine energy use for cooking.

Energy-related occupant behavior may be use, purchase, or building maintenance related. The effects of energy-related occupant behavior (e.g. building control actions) on residential energy use and indoor environmental quality may be calculated quantitatively using building simulation software packages.

In this chapter, the driving forces for the above mentioned categories of energy-related occupant behavior will be identified based on a literature review and will be discussed in greater detail in the following sections. Quantitative modeling approaches for describing energy-related occupant behavior and energy use are discussed in the second chapter "*Total energy use in residential buildings - the modeling of occupant behaviour*".

The notation used in the summary tables in the subsequent sections to indicate the importance of these driving forces is explained in . The coding system is based on a range varying form very highly significant to not significant, based on investigations in the literature.

Table 1-1: Notation used for importance of driving forces; the p-value refers to the statistical significance level.

Importance	
Description	*Symbol*
Very highly significant ($p \leq 0.001$)	***
Highly significant ($p \leq 0.01$)	**
Moderately significant ($p \leq 0.05$)	*
Lowly significant ($p \leq 0.1$)	'
Not significant	*n.s.*
Not stated	*x*

3. Heating

The activities of occupants have become more important within buildings when considering heating energy use in energy use predictions. Studies have shown that user behavior and lifestyle can affect energy consumption by up to a factor of three, as stated in Ref. [2, 3]. Firsthand data about user behavior has been collected in various studies. Often, secondary factors combine to affect the set-point temperature and heating schedule of a building.

Low-energy, passive house, and zero energy (including energy autarkic) buildings, are designed to minimize the heating load to supply only the required heat when occupants are present that cannot otherwise be gained through passive solar and internal heat gains. Studies have found that improving the efficiency of the building envelope and building systems significantly reduces overall energy consumption, thus increasing the importance of the role or actions of the occupant, Refs. [10, 11]. How the set-point temperature is determined, the correlating factors for temperature, and the overall operation of the heating system must also be understood to define the driving forces for energy-related behavior for heating.

In well insulated buildings the heating demand is affected by the effect of missing solar gain in case shading devices are a present, Ref [12]. In this reference a part of the occupants lower the blinds before leaving the residential building in the morning. Reviewing the literature on the use of sun shading devices in a residential environment did not reveal a substantial amount of publications regarding the topic of occupant behavior

3.1 Identification of driving forces

The adaptive principle is based upon the assumption that “if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort”, see Ref. [13]. When the goals of thermal comfort and energy savings conflict, it has been found that occupants make decisions regarding their own comfort that may have a negative effect on overall energy consumption.

As low energy houses have higher air tightness and thermal insulation, and use balanced mechanical ventilation with heat recovery, occupant behavior becomes less dependent upon environmental and building/building system factors. Internal factors such as clothing and activity levels, perceived indoor environmental quality (IEQ), and established habits, especially window opening and ventilation, have greater effect on the overall heating energy consumption than set point temperatures.

3.1.1 Biological

Temperature set-point:
Night setback temperatures are shown to have a significant impact on room heating energy consumption partially due to the large variance of preferred sleeping temperatures, see Ref. [14].

Number of occupants:
Household size has been found to be significant in Ref. [14].

Which rooms are heated:

The effect of partial heating in single-family houses on estimating total energy use was studied in Ref. [15], and indicated that estimations were higher than actual consumption due to different heating habits for different rooms. Ref. [14] found that the number of heated bedrooms had a large influence on energy use.

Gender:

In Fanger's experiments using two test groups of university students in Denmark and the USA and a test group of older, retirement-aged people, it was found that men preferred a warmer environment, but the findings were not statistically significant (5%), see Ref. [16]. Fanger compared various literature studies and found that women are more sensitive to changes in temperature, but the results were inconclusive with some studies concluding that women preferred higher temperatures, while other studies showed that men preferred higher temperatures. The effect of gender was also questioned by Ref. [2]; the questionnaire results illustrated a trend that women desired higher set-point temperatures than men. The questionnaire was distributed to a Danish population sample in Copenhagen twice. There were 933and 636 respondents for the first and second groups distributed four months apart in September to October 2006, and then in February to March 2007.

Karjalainen cited in Ref. [2], found that women were more dissatisfied with room temperatures than men, and preferred higher set-point temperatures. In the same study, it was also found that men controlled the set-point temperatures more often than women.

Age:

Ref. [14] has found that heating energy consumption increases with age.

Clothing:

Of the factors that influence behavior, a pattern was found where inhabitants decided their daily clothing level based on the exterior weather conditions at 6 a.m. and made little alterations to the clothing level afterwards. However, exterior weather conditions were not the only influential factors.
As occupants spend more than 90% of the time indoors, climate parameters as defined by Fanger determine their subjective wellbeing. Many studies have been conducted about clothing levels in relation to various activities such as work, shopping, and leisure at home Refs. [17], [18], and [19]. Ref. [19] finds that people actively change their clothing at home corresponding with Andersen's residential questionnaire results finding that clothing adjustment was the main adaptive action, Andersen Ref. [2]. The laboratory tests by Fanger, which used the same clothing ensemble for all experimental groups [5], is disproven in the opinion of Keul et al., as social, cultural, and historic aspects must also be considered, Ref. [19].

3.1.2 **Psychological**

Expectations:

Ref. [20] looked at the perceived winter occupant comfort and indoor air quality in low energy brick residences in Vienna and Salzburg. Amongst the important factors listed, were the occupants' expectations. Previous studies to the type of occupant in low energy residences have shown that they do not have a propensity to high energy conservation behavior, but rather are within the social mainstream of tenants and owners. Ref. [20] has found that training occupants about the new technologies and correction of incorrect heating use soon after moving-in are very important for maintaining high satisfaction with living quality in low energy houses. Media discussions about climate change also influence quality assessments and housing preferences as stated in Ref. [3].

The subjective perceptions of occupants have also been found to be influenced by occupant thermometer and hygrometer readings. The study in Ref. [20] involved 20 Viennese participants divided into three test groups who made diary observations every three hours for 14 days:

7 residents who noted in a diary the subjective temperature and humidity perceptions, assessments, behavior, and measurements from data loggers;
11 residents who noted in a diary the subjective temperature and humidity assessments, behavior, and measurements from their own thermometers and hygrometers (which had an accuracy of ±3°C, and +6% to -28% respectively);
2 residents who noted in a diary the subjective temperature and humidity assessments without any measurement devices.

The questionnaire results by all households in the apartment building (117 households) showed higher dissatisfaction for both winter temperature and room humidity when occupants had their own thermometers and hygrometers.

Table 1-2: Residents' satisfaction with room temperature and room humidity.

	Satisfaction with temperature	Satisfaction with room humidity
Residents with data loggers	94%	68%
Residents with their own thermometers and hygrometers	73%	12%
Residents without any devices	84%	43%

As the winter air supplied in passive houses commonly ranges between 30% and 45% RH, it is understandable that the satisfaction was so low in the test group with their own hygrometers. The humidity would likely show a range hovering below 20% RH.

Refs. [21] and [22] as cited by Refs. [15] and [14] respectively, mention an "economic rebound effect" whereby occupant expectations and heating energy use increases with higher comfort levels achieved by thermal renovations, resulting in achieving only a partial potential of cost and energy savings.

Understanding of how controls function:
Several authors see Refs. [23], [24], [25] and [26], have conducted studies that have determined that many users do not understand how to use thermostats and thermostatic radiator valve (TRV) controls properly. Ref. [26] also found that overheating occurred as a result of misunderstanding the operation of TRV's. Ref. [2] concludes that users' TRV control decisions are habit-based and misconceptions are widespread. The frequency by which occupants control heating coupled with the depth of understanding how the heating functions suggests a correlation with the energy used for heating.

The combination of training and changing habits based on incorrect information can have a widespread positive effect, as misunderstanding heating controls has been shown to exist for different heating control types and in different countries from the works of Refs. [23], [24] and [25] as shown in Ref. [2]. Questionnaire results in Belgium by Ref. [26], also find a large number of occupants who have poor understanding of heating controls, leading to improper use, working against advances in energy efficiencies. The concept of heating over the ventilation system has found to be counterintuitive for laypeople, and training has found to also be important to correct false theories, e.g. only occupants are needed to heat a passive house, Ref. [20].

Interaction frequency with heating controls:
In Ref. [2], many studies into establishing set-point temperature using TRV's have been conducted. The studies of Ref. [27] found that individual households have constant heating set-point temperatures that vary from each other, and Ref. [28] has questionnaire results that indicate that there is large variance in the frequency a user decides to control their environment.

Memory:
Morgan and de Dear state that outdoor exposure from the previous day influences clothing selection upon waking, Ref. [18]. Weather conditions from the previous day also influence the current day's adjustments made to heating; either set-point temperature or degree of heating valve opening.

3.1.3 Social

Ownership (owning/cooperative/renting):
The results of two questionnaire surveys in Austria of 933 and 636 participants showed that solar radiation, type of housing ownership, and perception of indoor environmental values were factors affecting heating use, see Ref. [2]. Ref. [29] and [14] also acknowledge the importance of home ownership on domestic energy use, indicating that more energy is used when energy costs are shared collectively in the rent.

Ref. [20] investigates the differences between owned (condominiums) and cooperative apartments within the same apartment complex. The investigation was carried out in Salzburg, and similarly compared data logger readings, occupants' own thermometers and hygrometers, self-recorded diary entries and interviews. An empty apartment was also logged as a reference point. The results of a satisfaction survey are in Table 1-3.

Table 1-3: Difference in satisfaction levels between owners and renters (cooperative apartments).

	Satisfaction with temperature	Satisfaction with room humidity	Satisfaction with IAQ
Owners	79%	85%	73%
Renters	84%	85%	73%

It was found that the perception of better IEQ was higher with higher humidity, despite the fact that measurements recorded higher CO_2 concentrations with higher humidity levels. The dissatisfaction with occupants' own measurement devices was not repeated in Salzburg. The study by Ref. [20] found that overall satisfaction was very high for temperatures from both owners and renters.

Government Interventions:

Ref. [30] looks at heat demand and heat supply from the year 2000 to 2050 in Austria. Based on simulations, the report indicates that widespread implementation of thermal renovations and new build to the low energy and passive standards will have a significant impact on the energy consumption for heating, and that the heat demand for space and hot water heating has already peaked in the last decade. The study concludes that government intervention is an influential factor for maintaining the trend of thermally renovating residences, especially for buildings built between 1945 and 2000. Encouraging further innovation in heating technologies, especially those that use renewable sources, and thermally activated building systems are further incentives that may be implemented. Suggested forms of regulatory interventions include taxes for CO_2 emissions, financial incentives for installing renewable-based heating systems, and updating building regulations to improve use of renewable and low energy systems. Thermal renovations are seen to become increasingly important for the Austrian building stock in the upcoming decades, see Ref. [30]. Government regulations also play a part in reducing building energy use in the Netherlands, however, the strived for innovations were not reached [31]. Refs. [27, 30, and 31] are within the European framework of the Energy Performance of Buildings Directive (EPBD), Ref. [32]. Regulations for calculating and displaying building energy use are also in countries such as Brazil (RTQ-R, Ref. [33]), the USA (Energy Star), Canada (EnerGuide), and Japan (CASBEE).

The estimated increasing number of thermal renovations of existing buildings will most likely lower the impact of external environmental factors as driving forces, and increase the importance of internal driving forces in the future. Ref. [2] also recognizes the correlation between the greater impact of occupant behavior, with stricter building regulations for energy use, tighter buildings, and higher insulation levels.

3.1.4 **Time**

Time of day:
Time of day is related to both clothing and outdoor conditions. Clothing decisions have been shown to be made upon waking for the day, Ref. [18]. This indirectly influences the selected residential set-point temperature as higher clothing values are generally correlated with lower set-point temperatures. On heating systems without thermostatic controls, it is also possible for occupants to either activate the heating system or increase heating in the evenings when the outdoor temperature is cooler.

3.1.5 **Physical environment**

As stated in Ref. [2], the physical aspects of the building play a greater role than occupant behavior in an approximate ratio of ten to one. In lowest energy buildings, where all building systems have been maximized for energy efficiency, the role of the occupant plays a larger role in determining whether or not the lowest energy targets are achieved. The comparative energy behavior variance can be up to a factor of three, see Ref. [2].

Meteorological conditions:
The most influential factors for conventional residential buildings were found to be outdoor temperature, outdoor air humidity, and wind speed, see Ref. [3]. Climate was also stated as an influential factor on indoor set-point temperature in Ref. [11].

3.1.6 **Building/equipment properties**

Heating System Type:
Reilly and Shankle (1988) as cited in Ref. [29] state that it is common for a combination of heating systems to be used in buildings, and that there is a large variety of types used in different ways by homeowners. Ref. [29], which examines heating system types in German homes, finds a positive correlation between education and gas heating. However, decisions related to socioeconomic factors are secondary to location (urban/rural, East/West Germany) with preference for solid fuels in rural areas, thermal quality of the building envelope, and storage space for solid fuels. The relationships between choice of heating to household income and number of persons in the household are shown in Figure 1-5. Building quality, heating system type, and climate together can influence set-point temperature and thermal comfort perception by occupants [11].

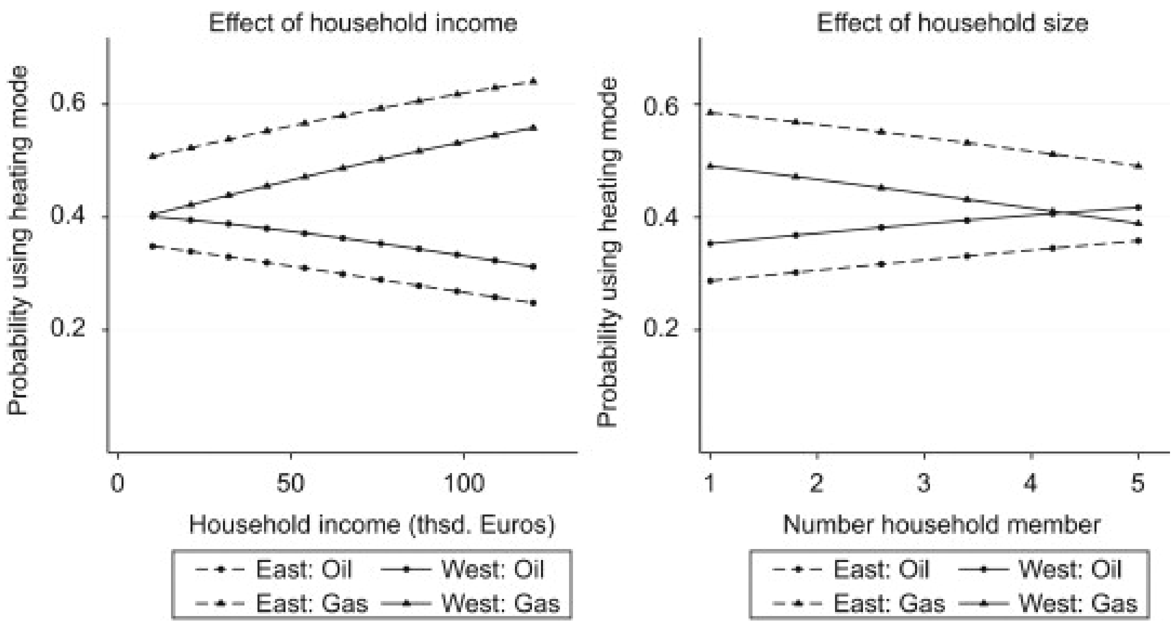

Figure 1-5: Probability of heating type use in the former East Germany and West Germany. Ref. [29].

Level of control:
Studies by Refs [34] , [35], [36] and [37] cited in Ref. [2] have shown that taking control out of the hands of the inhabitant leads to dissatisfaction with the indoor environment, and it can be concluded that control of one’s own indoor environment is very important.

In Ref. [2], window opening and heating behavior within Danish residences is studied. Among the main findings, it was found that there was great variance in the individual behavior patterns, and that the difference in behavior can affect overall energy consumption by up to a factor of three, see Ref. [2].

3.2 **Summary**

In summary the previously identified driving forces for energy-related behavior with respect to heating are grouped and listed in Table 1-4.

Table 1-4: Driving forces for energy-related behavior with respect to space heating. For the explanation of the colors used we refer to the legend underneath, the symbols used in the legend are explained in .

	biological	**psychological**	**social**	**time**	**physical environment**	**building/equipment properties**
Temperature Set Point	Gender [2]	Expectations [20]	Ownership (owning/coop/renting) [20]	Time of day [2]	Exterior air temperature [3]	Building insulation level [30]
	Clothing [2,20]	Interaction frequency with heating controls [2]			Outdoor air humidity [2]	Ventilation type [20]
		Window opening [2]				
Heating Duration	Clothing [2,20]	Understanding how controls function [2, 20,26]	Ownership (owning/coop/renting) [2]		Exterior air temperature [2]	Building insulation level [30]
					Outdoor air humidity [2]	Heating system type [2]
		Window opening [2]	Government interventions [30]		Wind speed [2]	Level of control [2]
# of Rooms Heated		Interaction frequency with heating controls [2]				Level of control [2]
Which Rooms are Heated	Gender [2]					Level of control [2]

Importance	***	**	*	’	n.s.	x

4. Cooling

Depending on the type of system, occupant behavior has a significant influence on the use of cooling. From the general to the detailed, this starts in some cases with the choice of cooling system, the duration and frequency of usage, the choice of set-point temperatures, and the frequency of maintenance.

4.1 Identification of driving forces

Research on the air conditioning unit (AC-unit) usage was first conducted in the frame of studies about the use of electricity in residential buildings. Seligman et al. stated in 1977 that personal comfort and health concerns were the best predictors of electricity demand, Ref. [38]. Up to now, especially in the Japanese research environment, the research on AC-unit usage is set in relation to general behavior patterns, Ref. [39], and the lifestyle of the occupant, Ref. [40]. An exception is the article by Ref. [41], which analyzed the AC-unit usage and window-opening behavior of eight dwellings for three days each in Japan and found large difference in the time and usage pattern between the dwellings.

A questionnaire survey with 554 responses on AC-unit usage during the sleeping hours in Hong Kong revealed that 83% of the occupants use their AC-unit for more than five hours during the sleeping period [42], but did not state any driving forces. Ref. [43] used the 2001 RECS data set to analyze the factors affecting cooling energy and found that "*occupant behavior is the most significant issue related to choices about how often and where air conditioning is used*", which is followed by physical parameters such as the climate and the AC-unit type as well as socioeconomic aspects, such as income, household size and age of the occupant.

Ref. [8] observed the AC-usage and window opening behavior of 39 student rooms in a Japanese dormitory through a continuous six week measurement for one summer. They found varies individual and building related driving forces for the usage of the AC-unit for cooling as included in Table 1-5 and the following sub-sections. Based on the same data from the dormitory building in Tokyo, Japan, Ref. [44], analyzed driving factors for the choice of set-point temperature.

Although cooling energy demand and overheating problems are related to the operation of shading devices during summer, reviewing the literature on the use of sun shading devices in a residential environment did not reveal a substantial amount of publications regarding the topic of occupant behavior

Ref. [45] conducted a worldwide survey with 435 participants of which one third was Japanese, one third German and the other third distributed to more than 40 countries in the summer version.
The 106 participants possessing a cooling device were asked about their reason for the last and hypothetical next start or stop of their cooling device.

There was no literature found related to the frequency of maintenance, assuming it to be another factor influencing the energy demand once the device is switched on.

4.1.1 Biological

Duration and frequency of usage (mainly percentage of usage)
Seligman et al. stated in 1977 that personal comfort and health concerns were the best predictors of electricity demand [46]. Health reasons for not using an AC-unit during the night were stated by 50% of the respondents in Ref. [41]. Ref. [47] observed 13 AC-units in eight apartments of a multi-family building in New Jersey, USA from June through September 1986. They also found that health reasons were claimed for reducing the frequency of usage together with safety reasons (due to a hot extension cord) and a general fear of electrical appliances. The latter two will not be dealt with here in detail, believing that they depend on the period of the survey and the then probably not fully developed technology of residential cooling devices.

Ref. [8] observed the duration and frequency AC-usage for cooling, and found that the way the AC unit was used at home during childhood, gender, and climatic origin have significant influences on AC-usage. Ref. [43] found that the age of occupants influences their usage patterns.

Choice of set-point temperature
Ref. [44] analyzed driving factors for the choice of set-point temperature: the origin from a moderate climate together with the running mean of the outdoor temperature increased the set-point temperature.

4.1.2 Psychological

Duration and frequency of usage (mainly percentage of usage)
Ref. [8] observed a significant influence of the perceived effectiveness of AC and the cultural background on the duration and frequency of the AC-usage for cooling.

Choice of set-point temperature
Preference for air-conditioned rooms was among the main factors to lower the set-point temperature according to Ref. [48]. Origin from an East-Asian country increased the set-point temperature.

4.1.3 Social

Duration and frequency of usage (mainly percentage of usage)
Ref. [43] found that household income has no significant influence on the frequency of AC-unit usage.

Switching on and off the cooling device
Ref. [40] concludes that switching off the cooling device depends more on the schedule, i.e. when leaving a room or going to bed, than the thermal environment.

Number of rooms equipped with a cooling system
Ref. [43] found that socioeconomic factors are significant driving forces related to the number of air conditioned rooms accounting together with climatic and physical factors for 48% of the variation in this parameter.

4.1.4 Time

Duration and frequency of usage (mainly percentage of usage)

Ref. [40] observed the control behavior of air conditioners in living rooms in 79 residential houses in the Osaka region of Japan. They found that usage varies according to the period of the day – the percentage of AC-units being switched on is lower during midday and evening compared to nighttime and morning. Whether this is related to variations in occupancy levels was not reported. Ref. [49] analyzed the AC-unit usage and window-opening behavior of 8 dwellings for three days each in Japan and found large difference in the time and usage patterns between the dwellings. Based on data from four dwellings situated in the Kawasaki area in Japan and a measurement period of four months from June to October, Ref. [39] found that the air conditioning use is mainly influenced by the time of day. Ref. [8] also observed differences in AC-usage for cooling between morning, daytime, evening, and night times.

4.1.5 Physical environment

Duration and frequency of usage (mainly percentage of usage)
Ref. [43] found that the climatic conditions (represented by the cooling degree days (CDD)) and the number of rooms equipped with an AC-unit were the most influential factors. However, only 26% of the variation in usage frequency could be explained by these factors.

Ref. [39] found that air conditioning use is influenced by season and outdoor air temperature. Ref. [40] also recognized outdoor temperature as the main factor. Usage increases with higher outdoor air temperatures. Ref. [50], observing 17 residential and light-commercial AC-systems, found a 6% increase of operation time for every 1°C rise in indoor-outdoor temperature difference. Ref. [8] observed a significant influence of outdoor temperature and humidity on the duration and frequency of AC-usage for cooling.

A one year study observing 8 single-family residences in Austin, USA (Ref. [51]) showed that there was a 6% increase in the hourly fractional operation time for every degree increase in the difference between the indoor and outdoor temperature, and that lower set-point temperatures were related to longer usage periods.

Switching on and of the cooling device
Ref. [52] monitored 24 Korean dwellings (six dwellings for nearly two months and 18 for one week). According to their results, the indoor thermal environment was above the comfort zone according to ASHRAE Standard 55/2010, most of the time the AC-unit was switched on. However, no percentage or further analysis is stated regarding this statement.

With respect to starting the device, 65% stated temperature as the reason, followed by around 15% stating humid conditions according to Ref. [45]. Reasons to stop the device were habit (25%), temperature (22%), and leaving the room (15%).

Ref. [40] concludes that switching off the cooling device depends more on the schedule, i.e. when leaving a room, or going to bed, than the thermal environment.

Choice of set-point temperature
Ref. [40] observed variations in the set-point temperature between 24°C and 29°C, but did not state an explanation. However, they found a positive relationship between the set-point temperature and the

temperature at which the AC-unit was switched on, i.e. when the set-point temperature was 1°C higher, the indoor temperature at the time of switching on the AC-unit was observed to be 1-2°C higher. Ref. [48] analyzed driving factors for the choice of set-point temperature: the running mean of the outdoor temperature increased the set-point temperature.

Existence/Choice of cooling system

Ref. [43] states that there is a close relationship between the ownership of an AC-unit and the climate in which the building is situated.

Number of rooms equipped with a cooling system

Ref. [43] found that climatic factors have a significant influence on the number of air conditioned rooms accounting together with physical and socio-economic factors for 48% of the variation in this parameter.

4.1.6 Building/equipment properties

Duration and frequency of usage (mainly percentage of usage)

Ref. [43] found that the AC-unit type affects the cooling energy. Ref. [8] observed a higher use frequency of the AC-unit for cooling for top floor rooms and rooms having a south-oriented window compared to an east or west facing one. Ref. [43] found that the number of rooms equipped with an AC-unit was the most influential factor together with climatic conditions (represented by the CDD). However, only 26% of the variation of the usage frequency could be explained by these factors.

Choice of set-point temperature

Ref. [48], analyzed driving factors for the choice of set-point temperature; a south-oriented window was among the main factors to lower the set-point temperature.

4.2 Summary

In summary, the previously identified driving forces for energy-related behavior with respect to cooling are grouped and listed in Table 1-5.

Table 1-5: Driving forces for energy-related behavior with respect to cooling. For the explanation of the colors used we refer to the legend underneath, the symbols used in the legend are explained in .

	biological	**psychological**	**social**	**time**	**physical environment**	**Building / equipment properties**
Percentage of usage	*Health* [41], [47]	*Preference for AC on* [2]	*Household income* [43]	*Season* [39]	*Outdoor temperature* [39], [8]	*South orientated window* [8]
	AC unit used at home during childhood [8]	*Perceived effectiveness of AC* [8]		*Time of day* [39], [51], [8]	*Outdoor humidity* [39], [8]	*Top floor* [8]
	Male [8]	Origin from Middle Eastern country [8]			*Wind speed* [39]	*No. of rooms with AC-unit* [43]
	Origin hot&dry country [8]	*Origin from East-Asian country* [8]			*Wind direction* [39]	*Set point temperature of system* [51]
	Origin moderate climate [8]				*CDD* [43]	

					Indoor outdoor temperature difference [51,51]	
Switching on	*Comfort range [52]*		*Guests coming* [45]		*Temperature* [45]	
Switching off			*Leaving room* [45]			
Set point temp.	*Male* [44]	*Preference for AC on* [44]			*Outdoor temperature* [44]	*South orientation of window* [44]
	Origin moderate climate [44]		*Origin East-Asian country* [44]			*Floor (top, middle, ground)* [44]
Existence of AC-unit			*household income* [43]		*Climate* [43]	
No. of rooms with AC-unit					*Climate* [43]	*Type of AC* [43]
						Floor area [43]

Importance	***	**	*	'	n.s.	x

5. Ventilation and window operation

Investigations on window opening behavior and natural ventilation have mainly been carried out with two aims: to find whether or not occupants are provided with adequate fresh air and to find the influence on energy consumption. The former category of studies has usually been carried out in dwellings and has a health or a comfort perspective, while the latter category has mostly been studied in offices with a comfort and energy performance perspective. So far, there are only a few investigations regarding residential buildings and the studies that are aiming at implementing realistic behavior patterns in simulation programs have been based on occupant behavior in offices. Moreover, no investigations regarding the mechanical ventilation driving forces in residential buildings have been found in the literature so far. For this reason, only the topic of natural ventilation and window opening behavior in particular, has been dealt with in this section.

5.1 Identification of driving forces

The use of windows affects ventilation rates in dwellings and consequently influences the amount of energy required in buildings and the indoor climate. Since the air change rate has a big impact on energy consumption, it is evident that different behavior patterns will result in different energy consumptions.

Ref. [53] conducted 358 air change rate measurements in six properties in London using the decay of coal-gas (containing about 50% of hydrogen) liberated into the air. This reference discussed the effects of flues, air gratings, cracks, and leakages on the air change rate in the houses and finally noted that any reasonable amount of ventilation could be obtained if liberal window openings were provided. They obtained as many as 30 air changes per hour by means of cross-ventilation in experimental rooms. Since then, houses have been tightened and sealed, increasing the relative effect of window opening on the air change rate. In fact, when Ref. [54] measured air change rates in a house in Virginia over a year, they found that the window opening behavior had the largest effect on air change rates, causing increases ranging from a few tenths of an air change per hour to approximately two air changes per hour. Another paper describing the same measurements, Ref. [48], stated that opening a single window increased the air change rate by an amount roughly proportional to the width of the opening, reaching increments as high as 1.3 h^{-1}. Multiple window openings increased the air change rate by amounts ranging from 0.10 to 2.8 h^{-1}.

While Ref. [53] found an average air change rate of 0.8 h^{-1} and with only 11% of the measurements under 0.4 h^{-1} in London, Ref. [55] found that 75% of dwellings without mechanical ventilation had air change rates lower than 0.35 h^{-1}, suggesting that these dwellings had been tightened to such an extent that occupants needed to actively adjust building controls to obtain adequate supply of fresh air. Ref. [56] also found that, depending on the season, between 50% and 90% of the Californian dwellings in the study had air change rates lower than 0.35 h^{-1}.

According to Keiding et al., Ref. [57], who conducted a questionnaire survey in Danish dwellings, 53.1% of the occupants slept with an open window during autumn while 25.2% had a window open during the night in winter, which in most situations should ensure an air change rate of more than 0.35 h^{-1}. They found that 91.5% of the respondents vented by opening one or more windows each day throughout the year. The results showed that a large proportion of Danish occupants use windows to adjust the supply of fresh air to the dwelling. The effects of this behavior on the energy consumption might be substantial. Ref. [58] measured the air change rate and temperature in 16 Danish dwellings and found an average air change rate of 0.68 h^{-1}.

In a study, Ref. [59], it was noted that there was a considerable difference in the total air change between the individual dwellings. As the basic air change was fairly similar in the dwellings, it was concluded that the user influenced air change (i.e. the behavior of the occupants) caused these large differences. This conclusion was confirmed by Ref. [60], who concluded that a substantial variation in ventilation behavior found among seven households, reflected different occupant functions and management strategies.

The authors of Ref. [41] were able to quantify the effect of occupant behavior on air change rate. They investigated the relationship between occupant behavior and the energy consumption used for air conditioning, by means of tracer gas measurements and questionnaire surveys in Japan, and concluded that 87% of the total air change rate was caused by the behavior of the occupants.

One aspect that affects the air change rate is how often and for how long the windows are opened but also the degree of opening will have an impact.

Window opening and closing
The window opening and closing behavior in dwellings is strictly connected to the building characteristics since the effectiveness of natural ventilation is strongly dependent on the characteristics of ventilation openings and their controllability (aspects which are closely related to the type and size of the windows and its placement within the facade). The type of dwelling (single house or apartment), orientation, and type of the room (bedroom, living room or kitchen) are the main parameters found to have an influence on occupant behavior related to window opening and closing.

5.1.1 Biological

The interaction between the occupant's gender and perceived illumination had a statistical impact on the window opening behavior, Ref. [64].

The investigation in Ref. [14] on households in the Netherlands that took place in autumn 2008 showed that the behavior of elderly people significantly differed from that of younger people, and the results fit with the Annex 8 results, Ref. [66]. A chi-squared test showed that presence was associated with fewer hours per day of open windows in living rooms and bedrooms, while the presence of children at home was associated with keeping windows closed in the living room.

5.1.2 Psychological

Ref. [66] highlighted that indoor climate preferences in terms of temperature are one key driver of the behavior of the occupants, but this driver is strongly connected to the occupant's perception of comfort.

5.1.3 Social

The Annex 8 project, Ref. [66], highlighted a clear correlation between smoking behavior and the airing and ventilation of living rooms: in smoking households, the living room is ventilated twice as long on average than non-smoking households. Moreover, the longer the dwelling is occupied the longer the windows were kept open, especially the bedroom windows, and in this way the Annex 8 project concluded that the presence of occupants in a dwelling and the use of windows were related.

5.1.4 **Time**

Investigations have shown different daily patterns for the different types of rooms, see Figure 1-6. Typically, the maximum number of open windows occurs during the morning, but during early afternoon (when cooking) the number of open windows is still relatively high but gradually decreases during the afternoon until the return of working inhabitants to the home (at about 5 p.m.). The time of day was found to determine window transition probabilities (closed to open and open to closed) in the aforementioned study in Ref. [67].

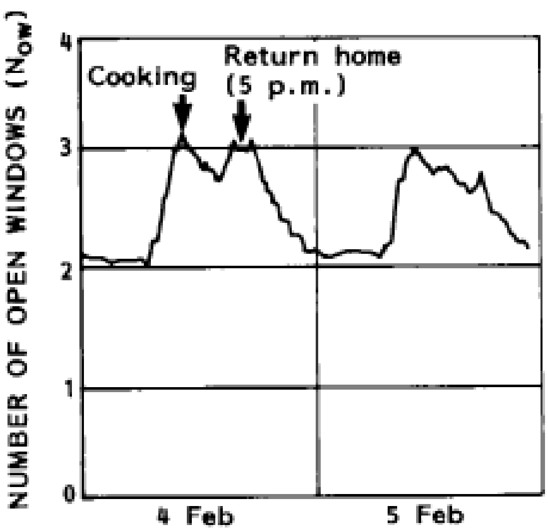

Figure 1-6: Daily profile of window opening, Ref. [66].

Season has been found to be correlated with window opening behavior in Ref. [68], i.e. windows are open longest in summer and shortest in winter. While in August the overall opening period for all windows amounts to about 25% on average, it decreases to about 5% in winter. This finding is supported by a successive study conducted in office buildings in 2008, Ref. [61], where the percentages of open windows are highest in summer, lowest in winter, and intermediate in autumn and spring.

5.1.5 **Physical environment**

Window opening behavior is strongly related to the perception of comfort and the microclimate in dwellings. Due to this correlation, the most important environmental parameters have been investigated in many studies.

Not surprisingly, the outdoor temperature had a considerable impact on window opening behavior. An earlier study, Ref. [62], found that the outdoor temperature was the single most important explanatory variable when investigating the number of open windows in 15 dwellings. The investigation in the

Annex 8 project, Ref. [66], has shown that in the temperature range between -10˚C to 25˚C, a direct linear correlation exists between window use and outdoor temperature, see Figure 1-7.

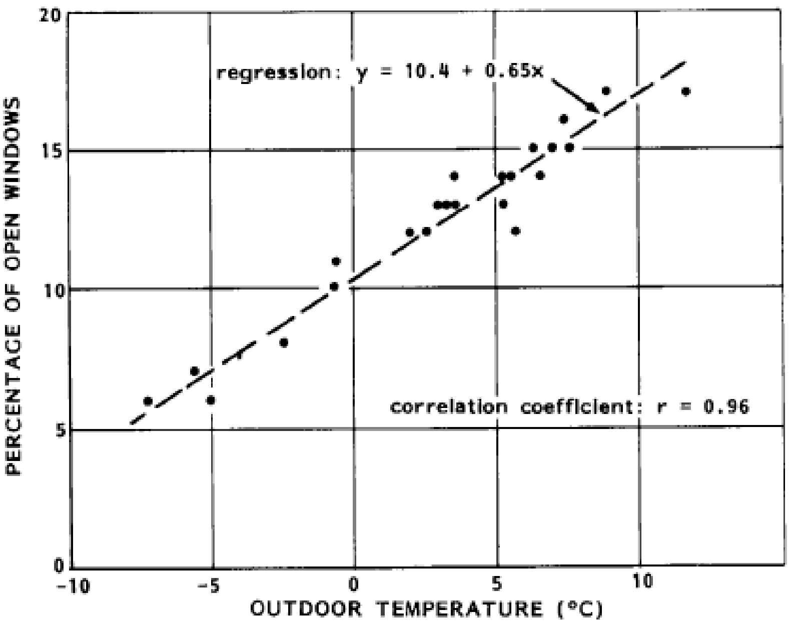

Figure 1-7: Relationship between the average use of windows and doors and the average outdoor temperature, Ref. [66].

Ref. [63] found that temperature (mean monthly temperature and average temperature swing) is an important explanatory factor for window opening. Ref. [68] found a change in ventilation behavior around 12˚C: generally, below 12˚C, daytime ventilation increases by approximately 75% per degree temperature difference, above 12˚C, ventilation increases by about 1.1% per degree. In terms of ventilating frequency, this represents an increase of about 50%. The results of Ref. [64] are consistent with the findings in Ref. [68]. The statistical analysis related to the questionnaire survey carried out in 2006 and 2007 in Danish dwellings has shown that window opening behavior is strongly linked to outdoor temperature. Recently, the results of the logistic regression model based on long-term monitoring of behavior and environmental variables in 15 dwellings confirm that outdoor temperature, indoor temperature, solar radiation, and indoor CO_2 concentration were the most influential variables to determining window opening/closing probability.

The Annex 8 project, Ref. [66], showed that windows are open more often and for longer periods during sunny weather, the findings of Ref. [65] fit with these earlier studies. In Ref. [68], a distinct dependence on solar radiation could not be confirmed, as the influences of outdoor air temperature and global irradiance are superimposed.

The influence of wind speed was investigated in all the aforementioned studies, and the results are coherent in finding a significant decrease in the prevalence of open windows at high wind speeds: above a wind speed of about 8 m/s, nearly all windows were closed.

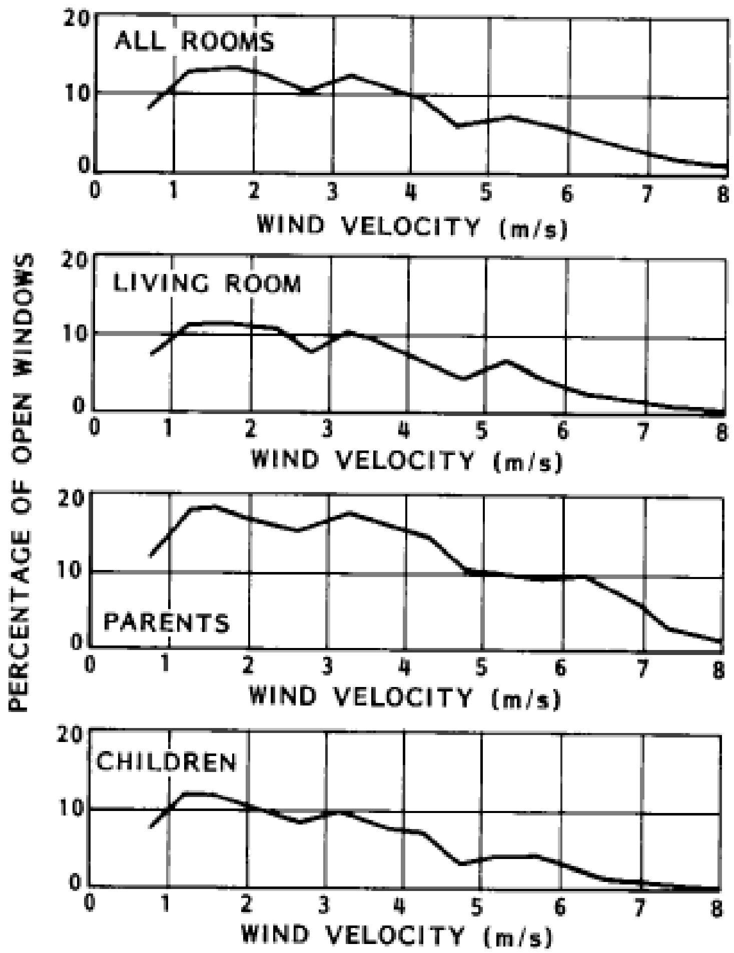

Figure 1-8: Percentage of open windows as a function of wind speed, Ref. [66].

Based on an average wind velocity of 3 m/s, Ref. [68] proposed to introduce the wind influence as a correction term for temperature-related window ventilation periods with the following equation:

$$t_{open\,(w)} = \frac{10 - W}{7} \times t_{open\,(3\,m/s)} \quad (\%) \qquad (1)$$

5.1.6 Building/equipment properties

As early as 1988, the study of Annex 8 on occupant behavior with respect to Ref. [66] focused on a combination of questionnaires and observations to determine which action is taken by occupants to ventilate their homes and to evaluate the reasons for their actions. The study has shown that the type of dwelling (house or apartment) influences the length of time windows are open and also has an effect on the degree of window opening. In the same investigation, it appeared that windows in living rooms and kitchens were open on average for shorter periods, whereas windows in bedrooms were open for longer periods in houses compared to apartments. The type of the dwelling (detached one-story residence) was found to affect the degree of window opening in residences in the pilot study conducted by the authors of Ref. [67] in North Carolina between October 2001 and March 2003.

shows the room type ranked according to window use for each of the investigated dwellings. These results could be summarized as follows: according to the study of Annex 8, Ref. [66], the main ventilation zones are bedrooms, while the greatest percentages of windows which are never opened are in living rooms, kitchens, and bathrooms.

This finding is consistent with a study for 24 identical flats in Germany, Ref. [68]. Even in the extreme winter weather, bedrooms are ventilated more frequently than all rooms on average: during the entire measuring period the window opening time in bedrooms exceeded the average for all rooms by approximately 50%. The room orientation is also important. The Annex 8 project, Ref. [66], found that when the sun was shining, south facing living rooms and bedrooms were more likely to be ventilated for longer periods than similar rooms orientated in other directions.

Table 1-6: Rank order of window use per type of room, Ref. [66].

Project / Rank Order	La Chaumière (CH)	Empa/ Bus (CH)	Worms (D)	Namur (n=40) (B)	Namur (n=3000) (B)	B.B.R.I. (B)	Schiedam (NL)	Surrey (UK)
1	Parents bed. + 2nd bed. (0.26)	Parents bed. (0.66)	Parents bed. (0.58)	Parents bed. (0.193)	Parents bed. (0.109)	Mean bedroom (.13)	Parents bed. (1.3)	Mean bedroom (.27)
2	Kitchen (0.04)	2nd bedroom (0.53)	Small bedroom (0.42)	2nd bedroom (0.106)	2nd bedroom (0.074)	Kitchen (.05)	2nd bedroom (0.63)	Kitchen (.03)
3	Living (0.02)	Living (0.37)	2nd bed. (0.35)	Kitchen (0.43)	Kitchen (0.46)	Living (.02)	Small bed. (0.51)	Living (.02)
4	—	Kitchen (0.1)	Living (0.13)	Bathroom (0.039)	Bathroom (0.038)		Kitchen (0.38)	
5	—		Kitchen (0.10)	Living (0.035)	Living (0.028)		Living (0.29)	

N.B. Values in brackets are the number of open windows per dwelling (N_{ow})

The investigations have shown different daily patterns for different room types. Typically, the maximum number of open windows takes place during the morning, but during early afternoon (when cooking) the number of open windows is still relatively high but gradually decreases during the afternoon until the working inhabitants return home at about 5 p.m. The time of the day is found to determine the window transition probabilities (closed to open and open to closed) in the aforementioned study in Ref. [67].

Degree of opening

In the various projects conducted for the Annex 8 project, Ref. [66], three levels of window opening were examined (closed, slightly open, and wide open). Large variations among the degree of window opening were found. The Dutch research findings showed a tendency towards a larger percentage of wide open windows, while the Belgian research findings based on interviews with the occupants in 2400 social houses, showed a trend towards slightly open windows.

Weather also influences the degree of window opening. The studies conducted for the Annex 8 project showed that when the outside temperature was 5˚C and -8˚C, fanlights were left open for more than eight hours in 17% and 8% of living rooms respectively. Moreover, an outside temperature change from 15˚C to -5˚C produced changes in the percentage of open or slightly open windows from 41% to 34% in the mornings and from 32% to 24% in the afternoons. For the main bedrooms, these figures are 70% to 64% and 55% to 44% respectively.

Ventilation type

The study in Ref. [68], compared the duration of window ventilation with naturally ventilated flats. Ref. [63] concluded that windows in flats without mechanical ventilation systems are open about four times longer than in flats with mechanical ventilation. Actually, this result is inconsistent with the Annex 8 project, Ref. [66], where only small differences are found between dwellings without mechanical ventilation and dwellings with various types of ventilation systems. However, the interviews showed that the occupants had no understanding of how to use their mechanical ventilation systems.

The IEA Contributed Report 08, Ref. [69], examined the influence of specific ventilation systems on the active ventilation behavior. From the report it is concluded that ventilation by behavior is only partly related to the type of ventilation device installed in the dwellings; the mechanical ventilation system in living rooms tends to influence the ventilation by behavior; in bedrooms, behavior tends to be independent of the installed system.

Moreover, the Annex 8 project, Ref. [66], found that windows in centrally heated dwellings were less likely to be opened for long periods than those in non-centrally heated dwellings, and that dwellings with warm-air central heating were ventilated less than dwellings with radiator systems.

Clothing

Ref. [70] carried out a field study in a 17 story office building. The author found that the anticipated outdoor environmental conditions influenced the choice of clothing worn on a specific day more than the anticipated indoor office temperature. These two studies suggest that the outdoor temperature has a very high impact on the choice of clothing. This was further investigated by the authors of Ref. [71] who analyzed the relationship between clothing behavior and the indoor and outdoor temperatures based on field investigations in 28 cities all over the world. They found that the outdoor temperature at 6 o'clock in the morning influenced the clothing insulation the most. The influence of outdoor temperature was larger in naturally ventilated buildings than in mechanically ventilated buildings.

Since thermal comfort is thought to be one of the main determinants of temperature set-point and may have a significant impact on window opening behavior, clothing behavior will also influence these parameters. Consequently, the occupants' clothing choice will affect the energy performance of a building. However, clothing behavior is an occupant's adaptation means to the indoor environment and as such does not affect energy consumption directly.

5.2 **Summary**

In summary, the previously identified driving forces for energy-related behavior with respect to ventilation/window operation are grouped and listed in Table 1-7. Unfortunately, studies regarding driving forces related to mechanical ventilation usage in residential buildings were not found in the literature. For this reason, only window opening behavior has been dealt with in this section on ventilation.

Table 1-7: Driving forces for energy-related behavior with respect to ventilation/window operation. For the explanation of the colors used we refer to the legend underneath, the symbols used in the legend are explained in .

	biological	**psychological**	**social**	**time**	**physical environment**	**building/equipment properties**
Windows opening and closing	Age [14,66]	Perceived illumination [64]	Smoking behavior [66]	Season [68]	Outdoor temperature [62, 63, 64, 66, 68]	Dwelling type [66,67]
	Gender [64]	Preference in terms of temperature [66]	Presence at home [66]	Time of day [66,67]	Indoor temperature [62]	Room type [66,68]
					Solar radiation [65,66]	Room orientation [66]
					Wind speed [66,68]	Ventilation type [63, 66, 68, 69]
					CO_2 concentrations [64]	Heating system [66]
Degree of opening					Outdoor temperature [66]	

Importance	***	**	*	'	n.s.	x

6. Domestic hot water

Occupant behavior can significantly influence the use of hot water in residential buildings. Showering frequency, duration and intensity of showering, bathing frequency, sink use frequency, washing machine and dishwasher use frequency and running temperatures, and appliances' water use efficiency are examples of domestic hot water energy-related occupant behavior. Domestic hot water use patterns vary on different time scales: time of day, time of the week, month, and year. In the literature, several detailed modeling approaches for domestic hot water use can be found, see e.g. Refs. [72], [73], [74], and [75]. Domestic hot water modeling approaches will be discussed in more detail in the second chapter on modeling.

A typical example of the (measured and modeled) variation of domestic water use during the time of day is displayed in Figure 1-9.

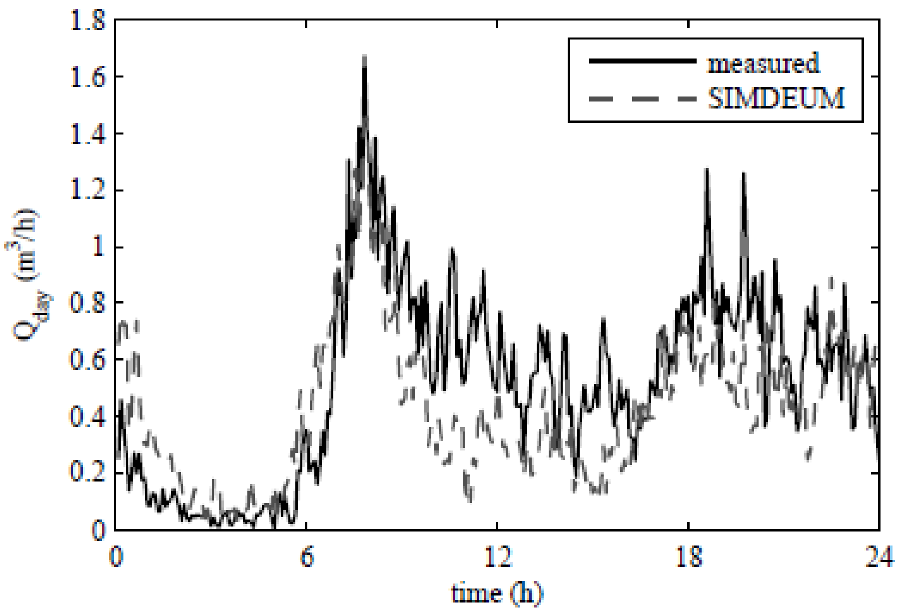

Figure 1-9: Residential water flow rate during the course of a day showing modeled and measured values based on 43 dwellings, Ref. [74].

6.1 Identification of driving forces

A study of domestic hot water use has been reported in Ref. [76] based on data from seven dwellings in the United States. The findings of this study show that bathing accounts for the largest use, while the kitchen accounts for the second largest use. The variation in energy use per person is primarily attributed to behavioral differences among the occupants. In this study, the variation in individual water use behavior is greater than the variation in the total domestic hot water use in all houses.

The authors of Ref. [77] reported the largest daily hot water use was for bathing and showering (43%) and the second largest use was by washing machines (30%). This study is based on American data. Various household characteristics have been analyzed in this study, such as *age*, *education*, *number of children*, *satisfaction with hot water temperature, and hot water conservation index*. In this study, *education* was found to be the only significant variable explaining hot water use. The higher the education level, the more hot water was used. Since education is usually correlated with *income*, it is likely that these households owned more water-using appliances. A positive correlation between *income* and domestic hot water use was also found in [78]. However, in Ref. [79] it was found that people having a higher education, higher income, and a higher status job were more likely to apply water saving strategies.

The model in Ref. [78] suggests that renter-occupied dwellings consume less domestic hot water than owner-occupied dwellings. However, research in Ref. [80] suggests that homeowners are more likely to save energy than renters.

Residential water use monitoring by water companies often provides interesting statistics of water use behavior. For example, research by the Dutch association of drinking water companies, Ref. [81], showed that showering accounts for the greatest water use. The increase in water use observed in the last few years in the Netherlands is primarily due to changing showering habits: shower *duration* is increasing and the showers with higher water *intensities* are increasingly used. Water use for showering depends on the occupant's *gender*: shower frequency and duration are higher for women than for men. The lower the occupant's *education level* and *job status*, the more water is used for showering.

Average per-capita domestic hot water use may be quite different for different countries, Ref. [82]. Important aspects of energy-related behavior for domestic hot water use are the *duration* and *intensity* (water flow rate) of a shower and the *frequencies* of showering and bathing. These will be discussed below.

6.1.1 Biological

A Dutch study, Ref. [83], showed that shower duration is strongly related to *age*, see Figure 1-10. The shower duration is relatively long for people around 20 years old and for people older than 65 years.

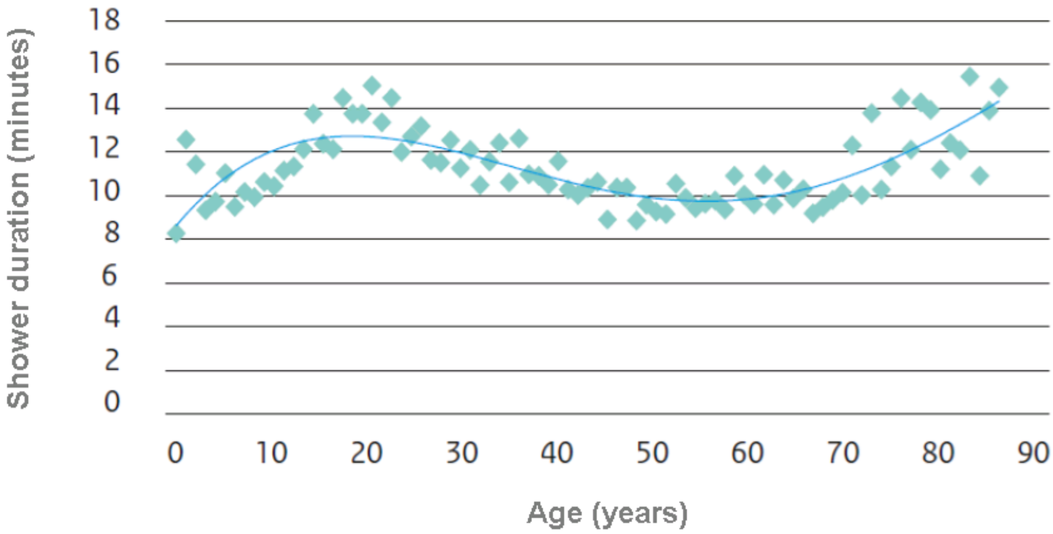

Figure 1-10: Shower duration in minutes as a function of the age of occupants in years in the Netherlands. See Ref. [83].

Shower frequency is also strongly related to *age*, as can be found in the report of a Dutch study, Ref. [83]. The reported shower frequencies are shown in Figure 1-11. The shower frequency is highest for ages between 20 and 45 years; the corresponding average shower frequency is six to seven times per week. Lower frequencies are found for younger and older people.

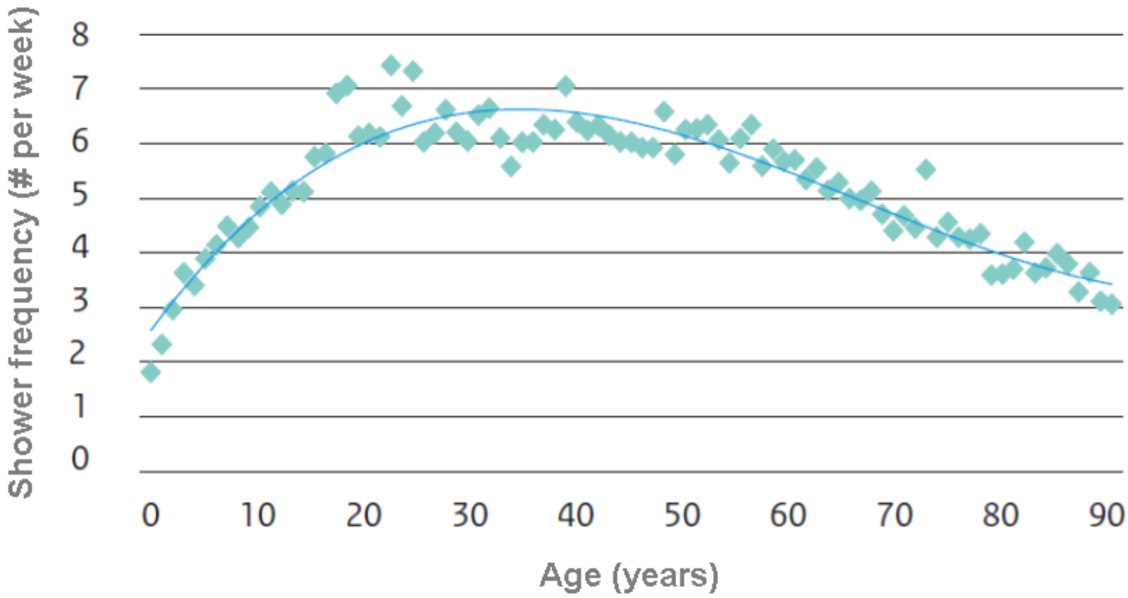

Figure 1-11: Shower frequency per week as a function of the age of occupants in years in the Netherlands. See Ref. [83].

6.1.2 Psychological

A negative correlation was found between shower duration and *income* in the study of Ref. [83]. A possible explanation is that people with a high income may have less time for taking a shower.

People with a higher education, higher income, and a higher status job are more likely to engage in water conservation practices according to Ref. [79].

The lower the *education level* and *job status*, the more water is used for showering according to Ref. [81].

Contrary to the previous paragraph, Ref. [78], finds a positive correlation between *income* and domestic hot water use. According to Ref. [83], the frequency of using a bath depends upon *income*. Households that frequently use their bath are mainly families with children and a relatively high income.

6.1.3 Social

The frequency of using the bath also depends on *household composition* and *household size*, Ref. [83]. Households that frequently use their bath are mainly families with children.

6.1.4 Time

Shower duration is different for weekdays and weekend days, Ref. [82].

6.1.5 Physical environment

The authors of Ref. [84] found seasonal differences in hot water consumption up to a factor of three based on data from 10 families in Japan, which could be related to changes in outdoor weather conditions. In winter, daily consumption was around 30 MJ/day, while in summer hot water consumption was below 10 MJ/day.

6.1.6 Building/equipment properties

Intensity of water use events can be influenced by specific properties of the applied equipment (water saving devices). For example, the use of *low-flow showerheads* can reduce energy use for domestic hot water. However, off-setting behavior such as an increase in shower length after installing a low-flow showerhead may undo the positive effects of water saving technologies, Ref. [85].

6.2 Summary

In summary, the driving forces for energy-related behavior with respect to domestic hot water use are categorized according to Figure 1-4 and listed in .

Table 1-8: Driving forces for energy-related behavior with respect to domestic hot water use. For the explanation of the colors used we refer to the legend underneath, the symbols used in the legend are explained in .

	biological	**psychological**	**social**	**time**	**physical environment**	**building/equipment properties**
Shower duration	*Age* [83]	*Income* [83]	*household size* [83]	*Weekday or weekend* [82]	Outdoor conditions [*84*]	*low-flow showerhead* [85], [83]
	Gender[1)] [81]	*Origin Turkey, Morocco, Suriname* [81]		time of day[1]		*Boiler* [83]
	health[2]	comfort[2]				
Frequency bath/shower	*Age* [83]	comfort[2]	household composition: [83]			ease of operation[2]
	Gender[1)] [81]	*Origin Turkey, Morocco, Suriname* [81]				
		hygiene[2]				
Intensity shower						*low-flow showerhead* [85]
Other appliances		*Education* [77]	Household size [86]			

1) Duration and frequency is higher for women than for men.

Importance	***	**	*	’	n.s.	x

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[1] Not based on references, yet.

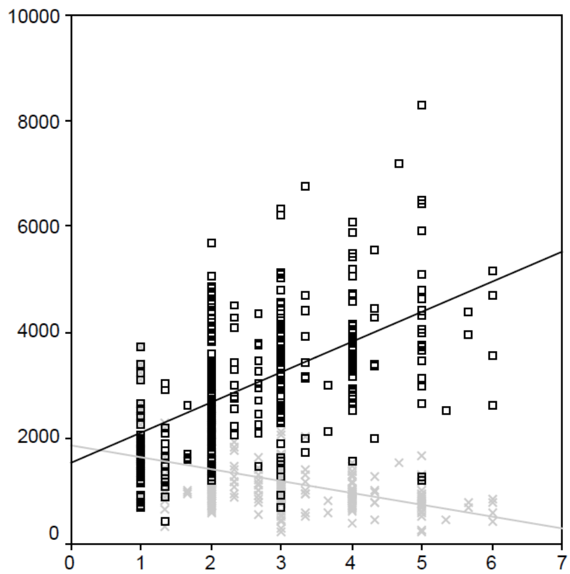
7. Electric appliances / lighting

The use of electric appliances and lighting in residences is strongly influenced by occupant behavior. In the literature, investigations of energy-related behavior and its driving forces are very rarely separated between appliances and lighting, but information from studies in office buildings can be used to some extent.

7.1 Identification of driving forces

When the energy consumptions for appliances and lighting are considered, large variations are found, partially relating to socioeconomic parameters such as income, persons per household, age, and education, etc. 30-40% of the variation in electricity consumption can be explained by these parameters, see Ref. [87]. Research to find other ways to describe the occupant behavior related to energy consumption is ongoing, although a final and perfect model is way ahead of us at the moment.
Another suggestion for understanding occupants comes from social sciences, where the practices of the occupants are used as indicators for their energy consumption. This model is suggested by Ref. [88]. It is based on practice theory where the routines, ways of thinking and acting of the occupants form the basis for different energy related behaviors varying from high energy consumption families to low energy consumption families who effectively implement energy conserving strategies. In Ref. [89], it is concluded that routines are influenced by norms and ethics learned in childhood, conscious reasoning about economic or ecological aspects, design of new technologies, and changes in social relations. Figure 1-12 shows the electricity use in 1068 residences in a suburb of Copenhagen.

Electricity use
kWh/year



Number of persons in a household

Figure 1-12: Electricity use per year per person in the household (grey); electricity use per year per household (black), Ref [4].

Figure 1-12 illustrates both the large variation in electricity use between households of equal size, and that electricity use per person decreases as household size increases as not all electricity use in a household is dependent on household size.

In the following tables the households are divided into three different categories – low use, average use, and high use households – to find explanations for the differences in electricity use. Generally, energy efficiency of appliances and lighting (Table 1-9 and Table 1-10) could not explain the differences in electricity use; however, the number and use of appliances could (Table 1-11 – Table 1-14).

Table 1-9: Relation between electricity use per household and the energy efficiency of refrigerators/freezers, Ref. [4].

	Low use	Average use	High use	Total
No low energy refrigerator/freezer	38%	26%	37%	100%
Low energy refrigerator/freezer	26%	35%	29%	100%

Table 1-10: Relation between electricity use per household and the energy efficiency of light bulbs, Ref. [4].

	Low use	Average use	High use	Total
Less than 25% high efficiency light bulbs	32%	35%	33%	100%
25-50% high efficiency light bulbs	35%	28%	37%	100%
More than 50% high efficiency light bulbs	36%	23%	41%	100%

Table 1-11: Relation between electricity use per household and the number of refrigerators/freezers, Ref. [4].

	Low use	Average use	High use	Total
1 Refrigerator/freezer unit	41%	31%	28%	100%
2 Refrigerator/freezer units	21%	37%	42%	100%
3 Refrigerator/freezer units	17%	35%	48%	100%

Table 1-12: Relation between electricity use per household and possession of a tumble dryer, Ref. [4].

	Low use	Average use	High use	Total
Do not have tumble dryer	45%	36%	19%	100%
Have tumble dryer	16%	30%	55%	100%

Table 1-13: Relation between electricity use per household and use of the tumble dryer, Ref. [4].

Use of tumble dryer	Low use	Average use	High use	Total
1 time per week	28%	33%	38%	100%
2 times per week	13%	39%	48%	100%
3 times per week	14%	28%	58%	100%
4 times per week	8%	28%	64%	100%
5 times or more per week	9%	21%	70%	100%

Table 1-14: Relation between electricity use per household and number of TV/video units, Ref. [4].

	Low use	Average use	High use	Total
1 TV/Video unit	50%	30%	20%	100%
2 TV/Video units	31%	40%	29%	100%
3 TV/Video units	22%	32%	46%	100%
4 TV/Video units	16%	36%	48%	100%
5 or more TV/Video units	7%	13%	80%	100%

To get an idea of how electricity is used per household, an analysis of end use was made in Ref. [87] in 100 different households. The results are displayed in Figure 1-13. The group for "other" consumptions also includes electricity for cooking, which according to Ref. [87] typically amounts to 10% of total electricity consumption.

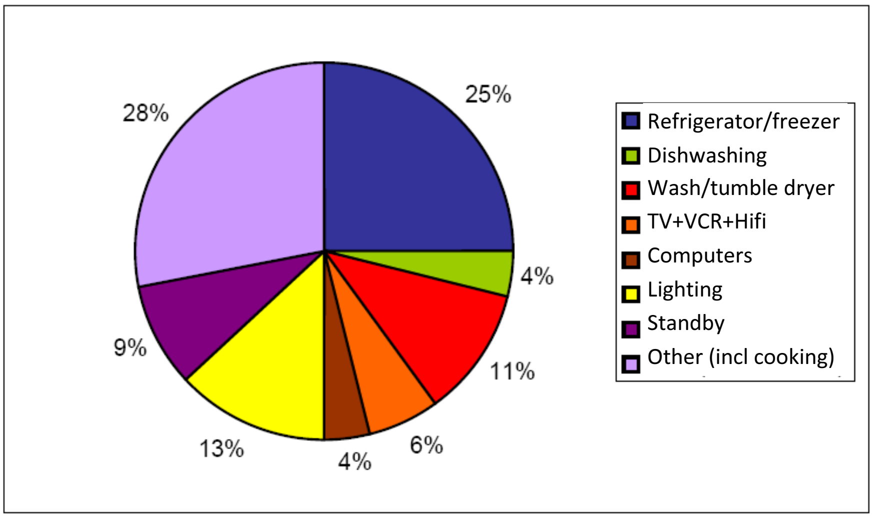


Figure 1-13: Distribution of household electricity consumption based on measurements in 100 dwellings, Ref. [87].

Different electrical appliances uses have different routines and driving forces. Lighting practices (number and type of lamps and operation) are strongly influenced by cultural norms of comfort and interior decoration style, see Ref. [90], and also habits from childhood seem to influence electricity use routines, see Ref. [89]. Interviews in Ref. [89] showed that occupants reflected much more about lighting energy use than on all other aspects of electricity consumption, which was not very rational as it typically accounted for less than 15% of total electricity use. The use of electric lighting in the domestic sector also depends on the level of natural light coming in from outdoors coupled with the activity of the household residents. The number of people who are at home and awake (active occupancy) is the other key factor for domestic lighting use.

Energy use for clothes washing is not questioned and few consider the environmental cost, see Ref. [89]. However, tumble dryer use differs greatly from family to family ranging from non-use to constant use for every wash load, as illustrated in Table 1-12 and Table 1-13.

Routines and energy use for cooking including the use of freezers and microwaves differs greatly from household to household, as does the use of information and communication technologies (ICT) (computers, television, hi-fi, etc.). Investigations have shown that up to 90% of electricity use for ICT is used in standby mode and only a minor percentage is derived from actual use , see Ref. [91].

7.1.1 **Biological**

A Danish investigation of 100 families showed that gender had no significantly influence on electric energy use, Ref. [87]. However, an age influence was found, reflecting the different stages in life and consequent changes in energy use. It was shown that people above 60 years had relatively larger energy use for refrigerators/freezers and for lighting, while energy use for ICT was at an average level, and the energy use for washing, dishwashing and clothes drying was considerably lower.

Small children below the age of six have slightly lower electricity use than adults, while teenagers used 20-30% more.

7.1.2 **Psychological**

No documentation on the influence of these driving forces has been found in the literature.

7.1.3 **Social**

In the following, some of the most important socioeconomic parameters are described.

Persons per household

One of the very important parameters influencing the electricity consumption is the number of persons per household. It is found that electricity consumption increases with the number of people in the household, which is documented by Refs. [92] and [87].

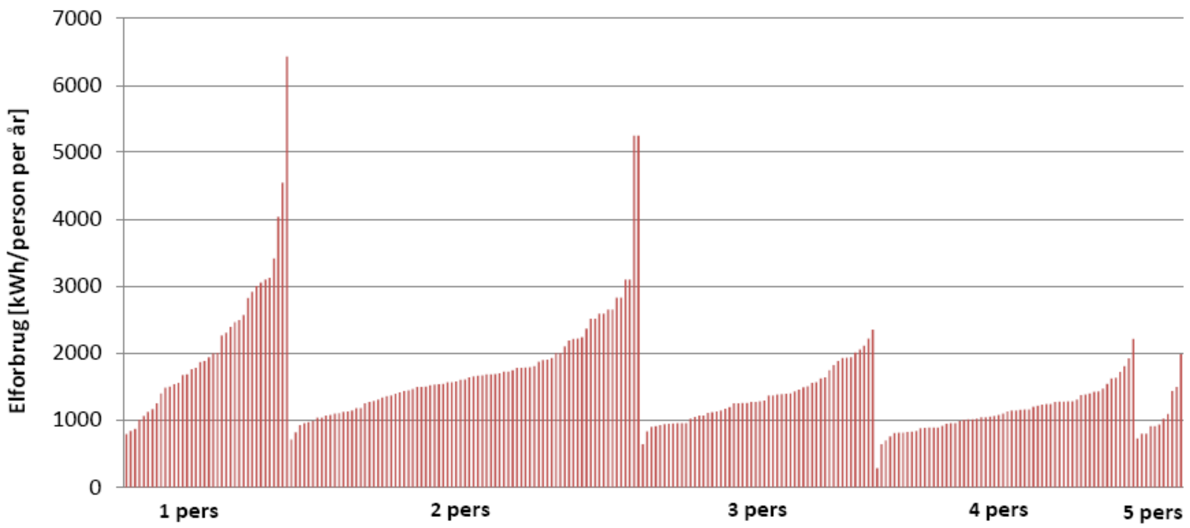


Figure 1-14: Electricity consumption in kWh/person per year as a function of the number of persons per household in a larger area with dwellings in Århus, Denmark, Ref. [92].

As seen in Figure 1-14, there is large consumption variation for different household sizes. Common for the largest and smallest consumption for each household size is a decreasing tendency with a greater number of persons. If the electricity consumption per person is calculated, it is decreasing with the number of persons per household, which is illustrated in Figure 1-15.

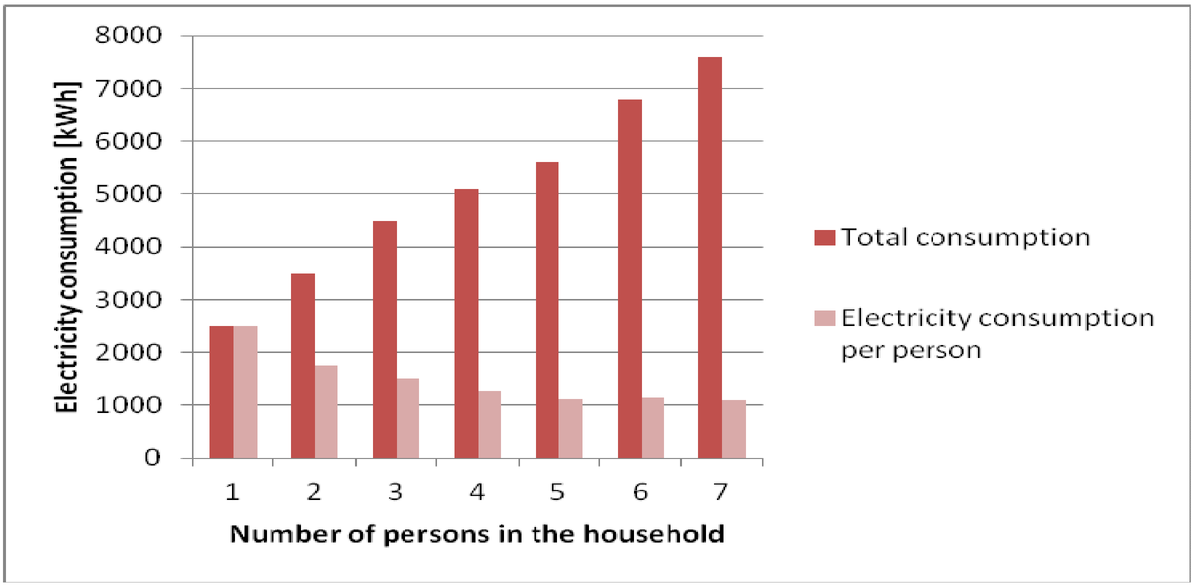


Figure 1-15: Electricity consumption as a function of persons in the household based on Ref. [87].

The decreasing consumption per person can be explained by the basic electricity consumption which is common for all households despite household size. Included is electricity use by the refrigerator, freezer, and partly by cooking, and lighting.

Ref. [93] showed that the energy use for artificial lighting was also strongly dependent on household size, see .

Table 1-15: Electricity consumption by lighting; annual average for different household sizes. The data are seasonally and geographically standardized, Ref. [93].

Household size	Number of households	Lighting, kWh	Lighting/person, kWh
1	20	405	405
2	27	586	293
3	7	735	245
4	11	941	235
⩾5	4	1113	223
All	69	636	

Income and dwelling area

The importance of income and area changes according to Ref. [87] whether one looks at apartments or detached single family houses. Income has a larger impact than area on energy consumption of detached single family houses. The opposite is found for apartments, where the area has the largest influence. The analysis is based on data from more than 50,000 Danish dwellings.

Figure 1-16 and Figure 1-17 show the clear dependency between income and electricity consumption. The income is in Danish Kroner (€1 is approximately 7.5 DKr) and is before taxes (tax approximately 40%).

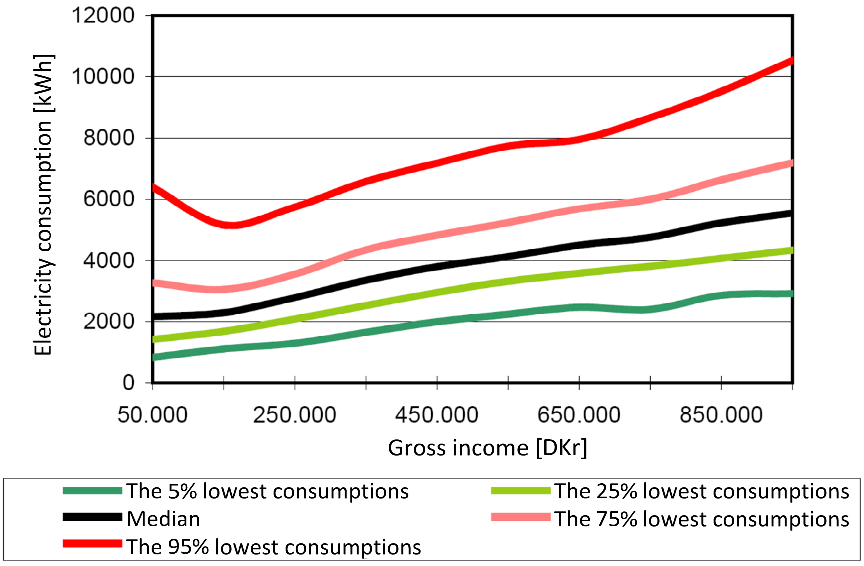


Figure 1-16: Electricity consumption as a function of income for detached single-family houses, Ref. [87].

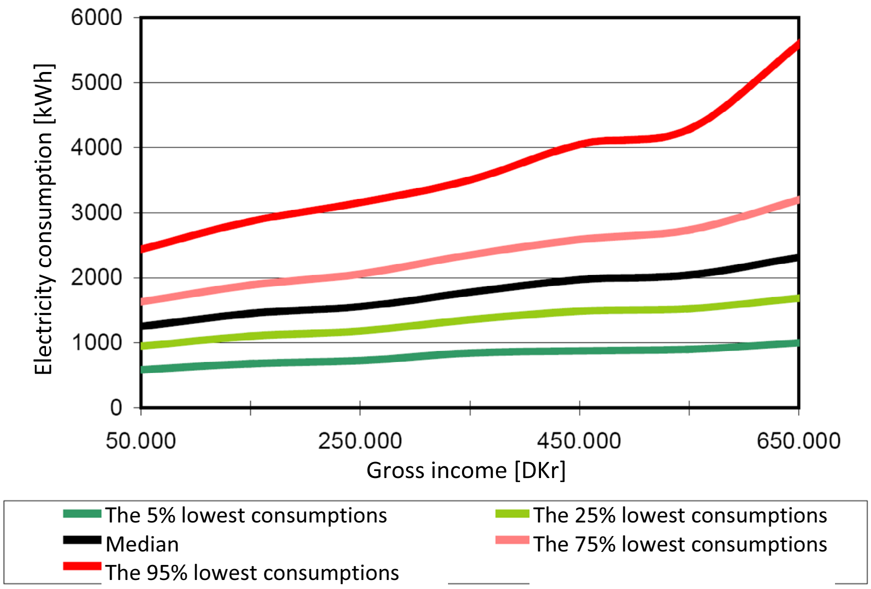


Figure 1-17: Analysis of electricity consumption as a function of income for apartments, Ref. [87].

The same electricity consumption analysis is made as a function of the dwelling area. The results from this analysis are shown in Figure 1-18 and Figure 1-19.

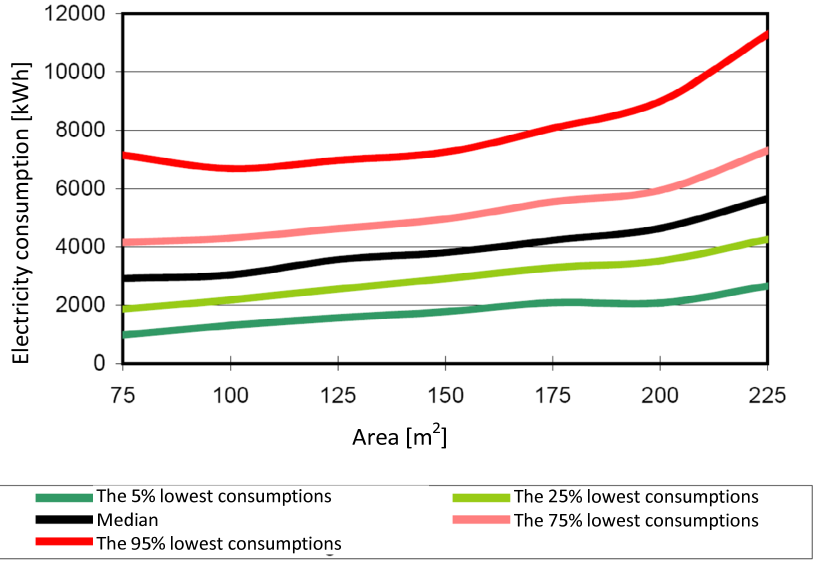


Figure 1-18: Electricity consumption as a function of area for single-family detached houses, Ref. [87].

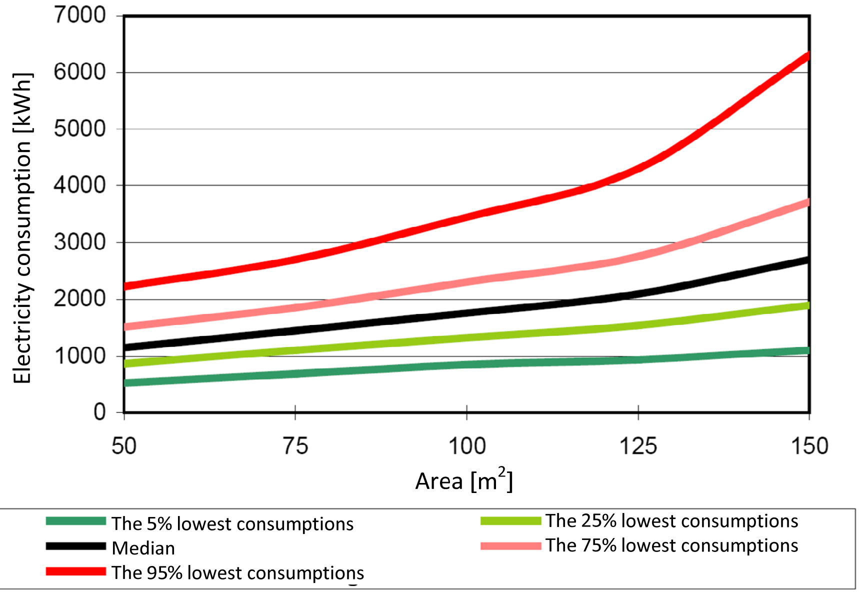


Figure 1-19: Electricity consumption analysis as a function of apartment area, Ref. [87].

7.1.4 **Time**

In office and school buildings, occupants switch on artificial lighting upon arrival and while present in a room as a function of the natural *illumination*, and rarely switched off artificial lighting until departing a room if the room was completely empty, see Ref [94].Figure 1-20 shows the probability of switching on artificial lighting as a function of work plane illuminance. Similar results have been found by other authors, see e.g. Ref. [7].

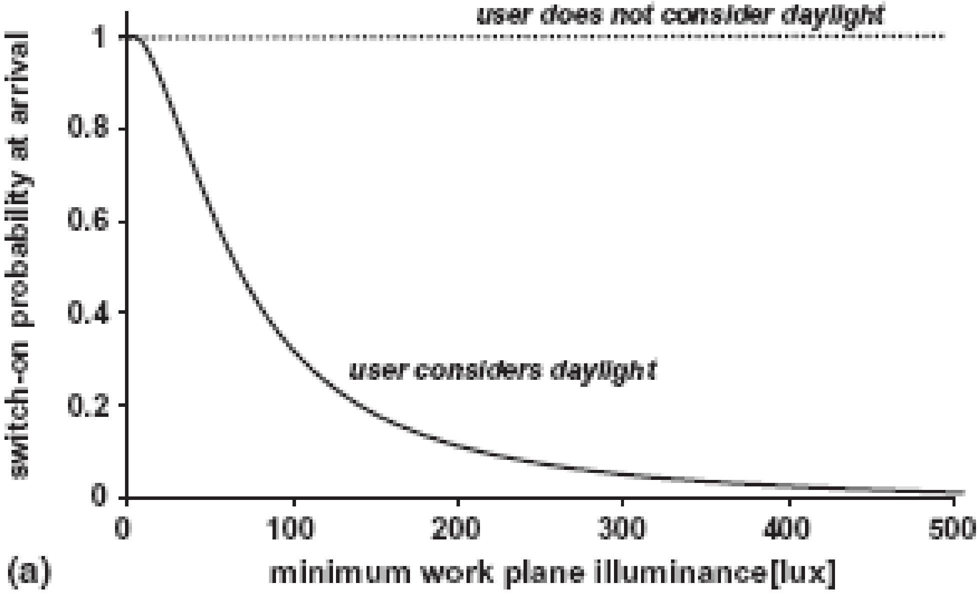


Figure 1-20: Measured switch-on probability function upon arrival in office buildings. Hunt's original function (solid line) describes the average switching behavior of a group of users, see Ref. [94].

Ref. [95] obtained similar results through measurements in five different office buildings. Figure 1-21 shows the probability of switching the lights on upon arrival in two of the offices as a function of the prevailing task illuminance level, while Figure 1-22 shows the probability of switching the lights off as a function of the duration of absence in minutes. Similar results have also been found by Ref. [96].

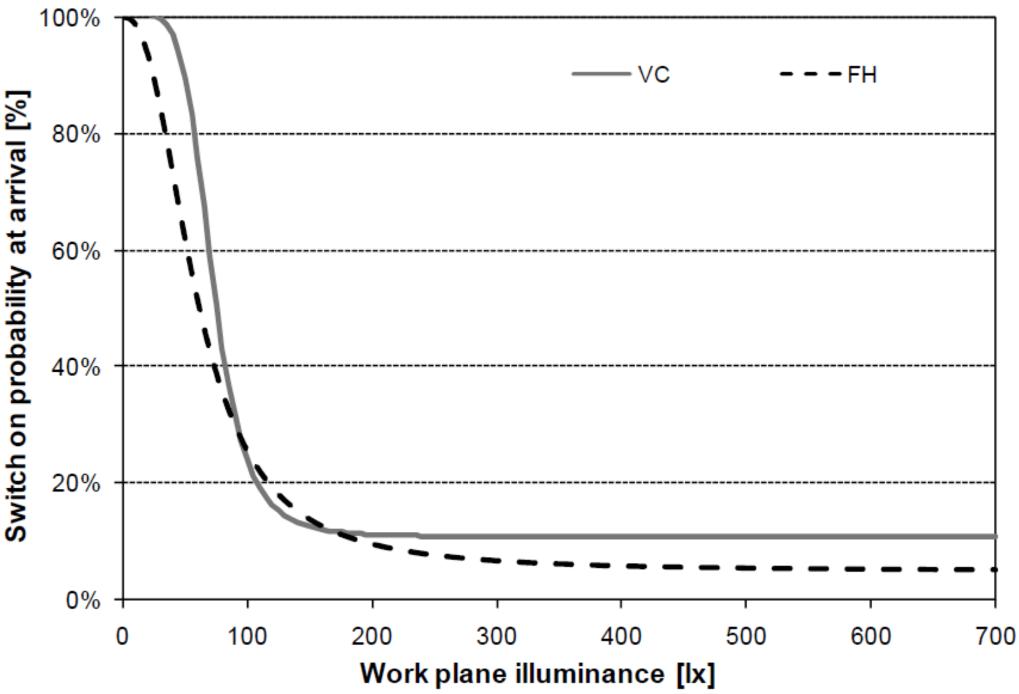


Figure 1-21: Probability of switching the lights on upon arrival in the office in VC and FH as a function of the prevailing task illuminance level, Ref [95].

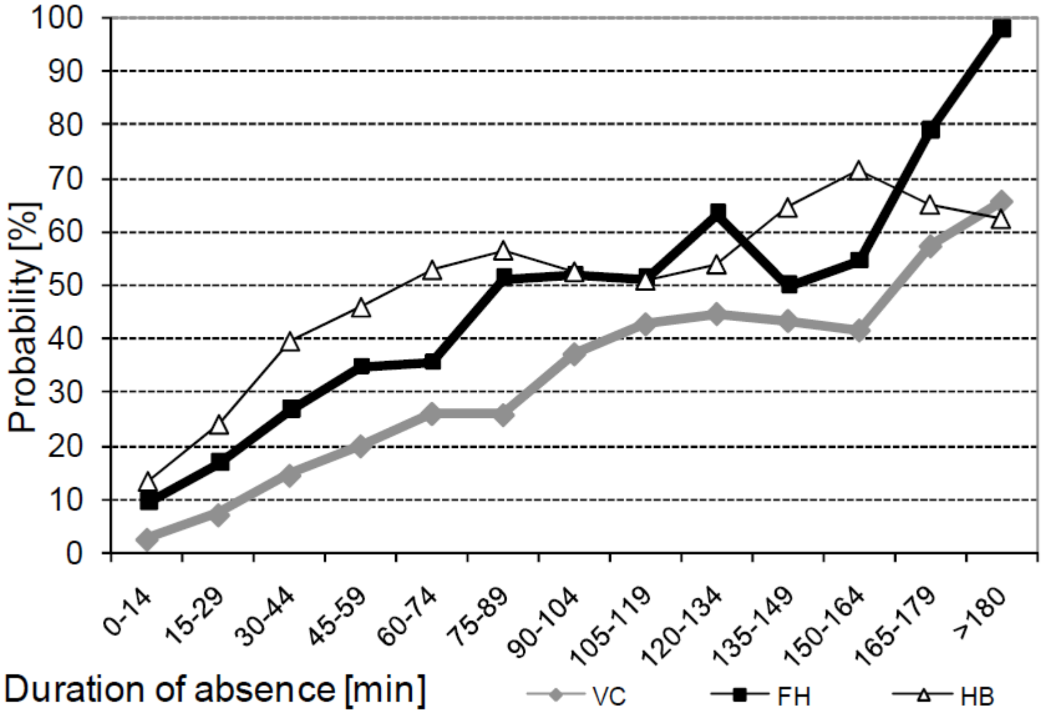


Figure 1-22: Probability of switching the lights off as a function of the duration of absence (in minutes) from the offices in VC, FH, and HB, Ref. [95].

Similar results could be expected to be valid for residences, although the relationships might be quite different. Moreover, the number of people who are at home and awake (active occupancy) is the other key factor for domestic lighting use. This is supported by results obtained from a lighting demand survey taken in 100 UK residences, which shows how the lighting demand during a typical weekday changes with season, Ref. [97].

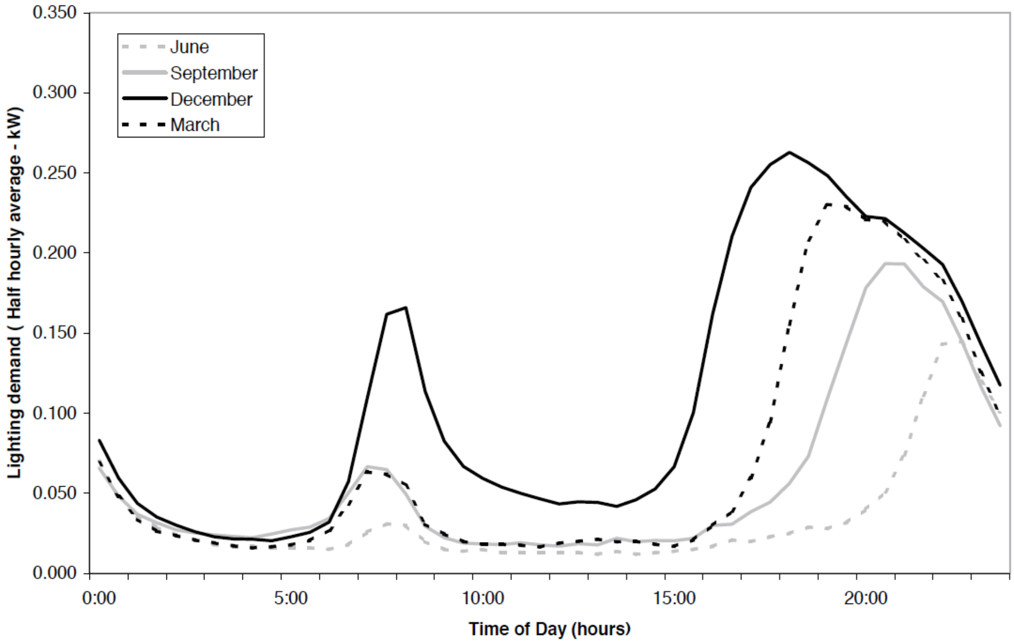


Figure 1-23: Daily lighting profile (monthly averages, weekdays) at different times of the year averaged over 100 homes showing demand in June (dashed grey line), September (solid grey line), December (solid black line) and March (dashed black line), Ref. [97].

7.1.5 Physical Environment

In a residential study, Ref. [64], the operation of lighting is found to correlate strongly with solar radiation, perceived illumination, and outdoor temperature. The age, gender, and thermal sensation of occupants also had an influence on the lighting use probability in residential buildings.

No documentation has been found in the literature on the influence of the physical environment on other electricity uses in residences.

7.1.6 Building/equipment properties

No significant relationship has been found in the literature on the influence of building/equipment properties on electricity use for appliances and lighting. Actually, the opposite was found regarding equipment properties; see Table 1-9 and Table 1-10.

7.2 Summary

In summary the previously identified driving forces for energy-related behavior with respect to electricity/lighting use are grouped and listed in Table 1-16.

Table 1-16: Driving forces for energy-related behavior with respect to electricity use. For the explanation of the colors used we refer to the legend underneath, the symbols used in the legend are explained in .

	biological	**psychological**	**social**	**time**	**physical environment**	**building/equipment properties**

Level of electricity consumption	Age [87]		Income [87]			*Area of the dwelling* [87]
	Gender [87]		Persons per dwelling [92], [87]			Efficiency of equipment
			Teenagers in the household [87]			Use of high efficient light bulbs
				Extent of the use of appliances		Number of appliances
Number of appliances			Income [87]			

Importance	***	**	*	'	n.s.	x

8. Cooking

For cooking purposes, many different appliances can be used such as microwave ovens, ovens, stoves, pressure cookers, kettles, etc. The type of equipment used, their corresponding energy consumption, and the number of meals prepared will determine energy use for cooking.

Cooking activities are usually performed around meal times. Based on time-use data, cooking patterns have been modeled in the literature, see e.g. Ref. [98]. In this investigation, it is shown that the measured and modeled curves for cooking correspond quite well, despite the simple modeling schemes that have been applied.

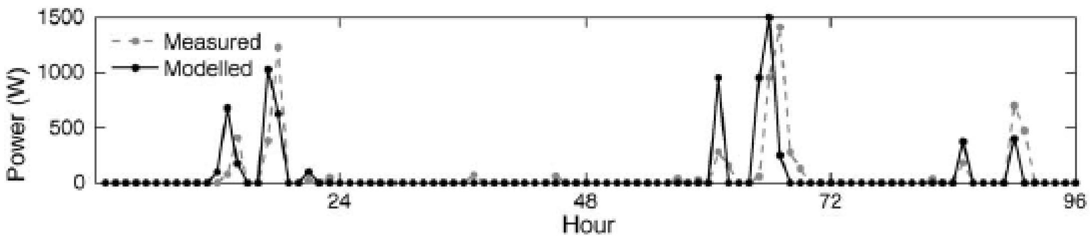


Figure 1-24: Example of modeled and measured cooking demand during four successive days for one household, see Ref. [98].

8.1 Identification of driving forces

Only very limited information on driving forces for occupant behavior related to cooking has been found in the literature.

A recent study on electricity use by European households, Ref. [99], showed the following: Pressure cookers, which are very *energy efficient*, are not widely used in Europe. The use of a lid on the pan while cooking can have a significant impact on the energy used for cooking. The best behavior of always using a lid while cooking varies from 8% in Denmark to 71% in Belgium and Portugal.

The presence of an open kitchen leads to a reduction of energy use compared to the absence of an open kitchen, probably due to the heat gain by cooking and the use of kitchen appliances. An energy reduction of 1.7 GJ per year is possible. See Ref. [14].

9. Interaction between behavior and other issues

Information in the literature on the relationship between different types of energy-related occupant behavior is limited. Some aspects found on the relationship between different types of behavior are discussed in this section as well as other issues not mentioned in previous sections.

Occupant behavior related to heating is not an isolated phenomenon, but rather a combination of driving forces that must be analyzed in relation to each other. Ref. [2] finds that heating behavior is typically influenced by the combination of set-point temperature combined with window opening in Danish homes without mechanical ventilation.

The homes used in the measurement portion of Ref. [2] were mostly naturally ventilated and used thermostatic radiator valves as heating controls. A strong correlation was also found between window opening behavior and indoor temperature set-point during the cold season, making it difficult to ascertain which influences which behavior: indoor set-point temperature or degree of window opening. Homes have become increasingly airtight since post-WW2 construction making it increasingly important for occupants to open windows for sufficient fresh air supply. However, as the indoor temperature is affected by the extent and duration of window operation and vice versa, it is difficult to study these two parameters in isolation from one another.

Similar to the findings in Ref. [2] that occupants have established behavioral patterns that are not coupled with environmental factors, some interviewed occupants in the Viennese low energy cooperative also opened windows due to established morning and evening routines, as opposed to opening windows as a reaction to microclimate conditions. The time of day then becomes a driving factor, see Ref. [20].

In Ref. [100], multivariate regression models have been developed for window opening, fan usage and interactions with the sun shading device based on data from a semi-controlled climate chamber experiment in an office environment. They found that for the window opening behavior, the fan state has a significant influence as well as vice versa (i.e. the window state influences the fan state). The usage of the sun shading device was influenced by the state of the window, but not by that of the fan. The state of the sun shading device did not have a statistically significant influence on the other two interactions.

There are several studies dealing with the use of shading systems in office environments, see e.g. Refs. [101], [102], [103], [104], and [105]. Nevertheless, a literature review on the use of sun shading devices in a residential environment did not reveal a substantial amount of publications regarding the topic of occupant behavior. A variety of literature could be found dealing with simulation, advices, effects on energy consumption, or experimental studies on automatic sun shades.

According to those studies related to the office environment, the devices are not often used. In Ref. [102] it has been found that 60% of blinds are not being used during their investigation. The authors of Ref. [101] observed 1.5 actions a day on average, with remotely controlled systems leading to higher usage (2.1 times a day vs. 0.7 times). When used, venetian blinds were found to be either totally raised or lowered – an intermediate stage was chosen for only 6.5% of time. Once a shading device is lowered, a drastic change of external luminous conditions is needed to raise the system, see Ref. [103]. In Ref. [105] it has been observed that 45% of the changes made by an automated system were rejected by the occupant. The authors of Ref. [101] extracted the influence of the type of control system (manual, remotely controlled, or automated) on usage.

Whether and to what extent these findings are true for the residential environment cannot be concluded. The significant influence of sun shading on the energy demand (e.g. 32% cooling energy savings according to Ref. [106]), suggests that more research dedicated to this type of energy-related occupant behavior should be performed.

10. Summary and conclusions

A better understanding of how energy-related occupant behavior influences residential building energy consumption is required for a realistic prediction of total energy use in buildings. Energy-related occupant behavior is related to building control actions (i.e. in order to control the indoor environmental quality) as well as household or other activities.

In this chapter, a literature review of relevant driving forces of energy-related occupant behavior is given. Quantitative modeling approaches for describing energy-related occupant behavior and energy use are discussed in in the second chapter.

The energy use of occupants in residential buildings has been classified in the following categories: heating, cooling, ventilation and window operation, domestic hot water, electrical appliances and lighting, and cooking. For these residential energy use categories, the relevant types of occupant behavior (i.e. building control actions) have been discussed.

Furthermore, the various types of driving forces of energy-related occupant behavior in residential buildings that have been found in the literature have been reviewed. The categories for driving forces of energy-related occupant behavior that are distinguished are the following: biological, psychological, and social contexts, time, physical environment, and building/installation properties.

The identified driving forces for the various types of energy-related occupant behavior that have been discussed are summarized in various tables throughout this chapter. These summary tables also give a clear overview of the references in the literature in which the specific types of energy-related occupant behavior and their driving forces have been investigated.

In general, multiple driving forces may (simultaneously) affect a specific type of energy-related occupant behavior. For example the frequency of taking a shower depends of biological, psychological, and social driving forces such as age, gender, country of origin, and household composition as discussed in the section on domestic hot water. This example illustrates the complexity of accurately modeling and predicting the relationship of shower frequency to domestic hot water energy use.

The identified driving forces can or are being used in a quantitative understanding and modeling of energy-related occupant behavior and energy use.

Besides many different driving forces having been identified for various types of energy-related occupant behavior, this chapter has also shown that knowledge on some types of energy-related behavior and their corresponding driving forces is missing. For example, no literature has been found on driving forces of occupant behavior related to mechanical ventilation. In addition, very limited information has been found in the literature on energy use for cooking and the related driving forces.

As mentioned before, the various types of energy-related occupant behavior are not isolated phenomena, but rather a combination that should be investigated in relation to each other. Information in the literature on the relationships between different types of energy-related occupant behavior is however limited; more research is needed for a better understanding of the relationships.

Furthermore, several studies deal with the use of shading devices in office environments; Whereas, a literature review on the use of sun shading devices in residential buildings did not reveal many publications regarding the topic of user behavior. To what extent the findings for office buildings are applicable to residential buildings cannot be said. More research dedicated to this type of energy-related occupant behavior should be performed.

Automatic control system are very promising for reducing energy use in buildings. However, possible discomfort experienced by occupants due to the lack of control in the case of automatic control systems may result in unforeseen re-actions of occupants leading to improper use of installations and an increase in energy use. This should be investigated further, and should be considered during the design of new buildings and installations and their control systems.

On conclusion, occupant behavior was found as a complex phenomenon very different from the way it is currently implemented into most energy performance simulations. This should be taken into consideration during the design phase of a new building in such a way, that there is a high probability that the system is used as designed. One idea would be to include, a thorough check of the buildings robustness towards occupants actions in order to understand how the buildings energy use is affected by unforeseen behaviors.

11. References

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II-2

Literature survey
- Total energy use in residential buildings -
the modeling of occupant behavior

Contents

1. Introduction

As pointed out in the final report of Sub-Task C and in the report “Driving forces of energy-related behavior in residential buildings”, occupant behavior does affect building energy usage. Studies presented in the mentioned report found that this affect can be in the magnitude of 3 and above. This second report of the Task-Force of Occupant-Behavior focuses on the modeling of occupant behavior related to the energy use in residential buildings.

A wide range of driving forces of energy-related behavior was shown to have a significant influence – these were grouped into biological, psychological, social, time, and physical parameters of the environment and buildings. Thus, the manifold issue of behavior demands interdisciplinary work between engineering and social sciences.

But what is meant by behavior? When it comes to interaction between buildings and human beings, a variety of disciplines is occupied by research on energy-related comfort parameters, such as room temperature and indoor air quality (IAQ). So it is worthwhile to explain how behavior is defined within the topic of this report.

With respect to the energy-related issues of this report, the term ‘behavior’ is predominantly meant by the following: observable actions or reactions of a person in response to external or internal stimuli, or respectively actions or reactions of a person to adapt to ambient environmental conditions such as temperature, indoor air quality or sunlight. In this definition of behavior, attitudes and motives of an individual which lead to a specific action are not included. Data concerning behavior often stem from sensors (e.g. for window opening) in terms of indicators for observed behavior. Another approach is asking the occupants to rate their degree of satisfaction with the ambient environment or to ask them to give information on their behavior, e.g. how often a person opens the window or for how long a person closes the sun shading during a given time period. Both methodological approaches – technically measured data as well as self-reported information from the occupants - are helpful for a better understanding of energy-related behavior. Both approaches have their advantages and their margin of error.

With respect to the complexity of this issue, aside from the models dealing with simulation of energy performance, some psychological models are presented, showing different approaches to explain behavior as a result of decisions, attitudes, and habits. Different energy-related behavior patterns based on different environmental attitudes may play a role in the context of counseling, decision making concerning technical building systems, or intervention strategies for households.

Although there are no general differences in scientific principles between natural sciences and human sciences, the integration of different perspectives and vocabulary is not trivial. Nevertheless, the goals are ambitious with respect to models at the interface between formalistic parameters and real life processes, especially when human behavior is taken into account.

Models are always a reduction of complexity and abstraction, at the same time it has to be guaranteed that all relevant parameters are considered, namely objective physical (environmental) parameters, personal variables, and the interaction between these two sides. The models are translated into computer simulation as a connection of theory and experiment. This includes mathematical logic processing, by which there may be the risk of overestimating the degree of precision, respectively the explanatory power of the results: "A computer simulation does not necessarily guarantee that a theory is more consistent or comprehensible. Nor does a program's successful performance guarantee that the theory is generalizable, or even that the causes for the success are those predicted by the theory" [58].

From the perspective of environmental psychology, computer simulation is considered as a helpful method to look at complex systems and to handle practical problems, but the method is seldom applied [92]. Computer simulation in the field of occupant behavior and energy use can serve as an approach to practical problems in different energy-related settings. The models can be used as basis for calculation of expected energy consumptions as well as verification of theoretical assumptions about driving factors for energy-related behavior.

Beyond the calculation of energy consumption, the models could show the potential to face practical implications such as:

- the fit between building operation and user behavior (match or mismatch)
- behavior as a basis for building optimization (under which conditions behavior turns into counterproductive behavior?)
- behavior as a basis for interventions (e.g. information about the building concept, handling of controls, as well as training for energy-related behavior).

This reports starts with a discussion of the purposes of modeling occupant behavior when looking at the total energy use of buildings and the categorization of model types. In the following chapters general (psychological) models as well as models applicable to the prediction of total energy use are described. In the last section, summarizing prospects for further research are discussed.

2. Purpose of modeling and model types

This chapter first discusses purposes of modeling occupant behavior with respect to total energy use in buildings. Based on this discussion, model types usable for the various purposes are defined.

2.1 Purposes of modeling occupant behavior

On the most general level, two purposes of modeling occupant behavior can be distinguished:

1) modeling occupant behavior in order to understand the driving forces for the behavior itself, and
2) modeling the occupant behavior in order to reveal its relationship to energy demand and usage and the driving forces for variations.

Within the framework of this Annex, the second is the major concern, while the first may be necessary to gain deeper insights into the factors leading to variations in the relationship.

An important question is the degree of detail required to reach the set purpose. This is strongly dependent on the number of buildings, the user profile, and the time scale. With respect to the number of buildings, a single building needs to be dealt with differently compared to multiple buildings. The user profile can be made for a known user or unknown users, and the time scale considered can be short-term (daily, hourly, or down to fractions of a second) or long-term (season or year). The occupant behavior can be modeled through schedules or diversity profiles (Type A), stochastic models (Type B), or agent-based models (Type C).

Table 2-1 gives an overview of possible objectives for the simulation of occupant behavior, together with typical time scales and time steps for a single building, and Table 2-2 gives the same objectives for a group of buildings.

Table 2-1.Objectives for the simulation of occupant behavior, and time scales for a single building.

	Design			**Commissioning**		**Operation**
	Conceptual	Preliminary	Final	Initial	On-going	Control
Aim:	design concept comparison	design optimization	system sizing/ building code compliance	initial commissioning	fault detection	model predictive control
Typical time scale:	season, year	season, year	season, year	?	continuous	1 or 2 days ahead
Typical time step:	1 hour	1 hour	1 hour	1 min, 1 hour	1 min, 1 hour	1 min, 1 hour

Table 2-2. Objectives for the simulation of occupant behavior and time scales for a group of buildings.

	Design	**Commissioning**	**Operation**

	Conceptual	Preliminary	Final	Initial	On-going	Control
Aim:	policy making/ solar/shading analysis	solar/shading analysis	design of electricity grid/ design of district storage	?	fault detection of district storage	district energy storage
Typical time scale:	season, year, 30-years	week, season, year	week, season, year		continuous	1 day ahead, 1 season ahead
Typical time step:	1 hour	1 min, 1 hour	1 min, 1 hour		1 hour	1 hour

Figure 2-1 gives an overview of additional factors influencing the choice of a model.

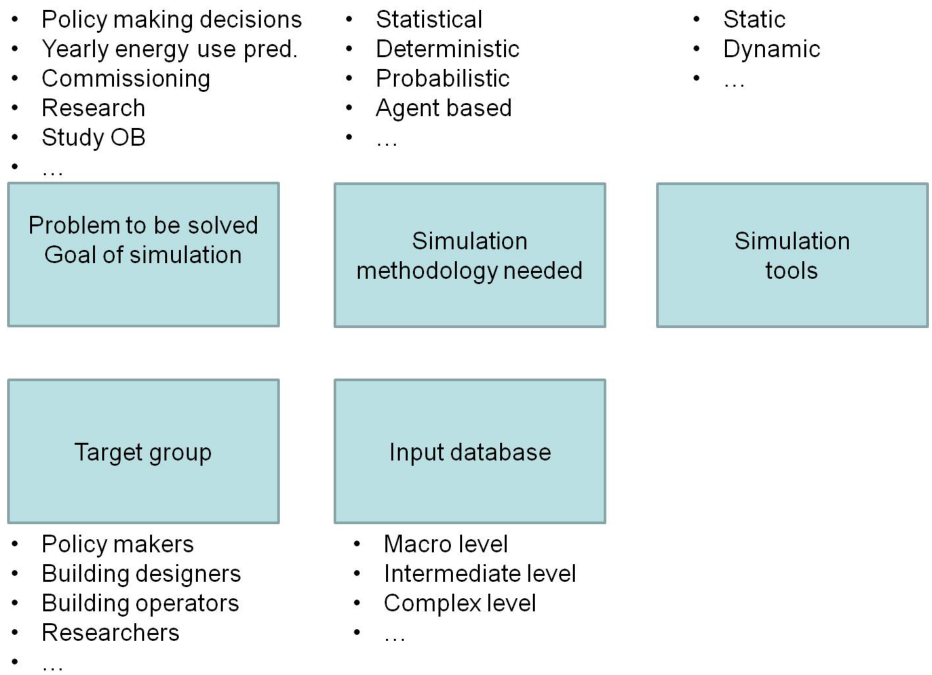


Figure 2-1. Overview of factors influencing model choice

2.2 Definition of model types

In order to clarify the approach used for the following work, six basic types of models shall be defined here.

<u>Psychological models</u> of occupant behavior can be grouped into those explaining the behavior itself and those related to the energy use in buildings.

<u>Average value models</u> use the important parameters for occupant behavior which influences the total energy use of a building for a selected period (e.g. daily, weekly, or monthly basis).

Deterministic models use predefined typologies of families, which give deterministic input values for computer simulations.

Probabilistic models use parameters and equations to evaluate the probability of an action or state.

Agent based models model occupants as individuals, with autonomous decisions based on rules and experiences (e.g. memory, self-learning).

Action based models define “occupant behaviors’’ as actions — *movement* and *control action* — that change the state of occupant location, the operation state of windows, lights, air-conditioners (AC), etc., and propose a uniform description for occupant movement and control actions respectively.

3. Psychological behavioral models

A few behavioral models proposed in the literature are discussed below. This is not a comprehensive review, but rather an indication of the type of model that could be used to understand the relation between occupant behavior and energy use.

3.1 General psychological behavioral models

The theory of planned behavior

The theory of planned behavior (see [2] and Figure 2-2) has been one of the most widely used theories in environmental behavioral research as well as in other areas of research including building energy use.

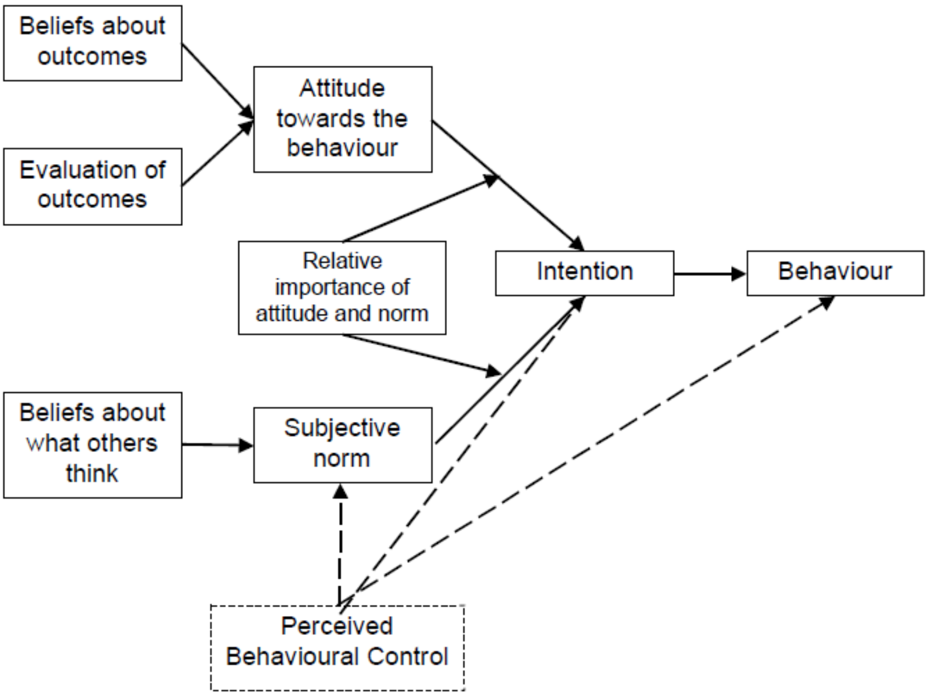


Figure 2-2. Theory of planned behavior.

The theory of planned behavior is an extension of the theory of reasoned action, which has been developed in the field of social psychology. The model tries to predict behavior as result of a variety of predictors which determine a person's intention for a specific behavior. As predictors a person's beliefs and cognitive processes as well as the subjective norm have an impact on the intention. The subjective norm represents the social pressure: if a person is convinced that people in the social environment would appreciate the behavior, this behavior is more likely to be shown by the person. This model has been extended by including the variable 'perceived behavioral control' which is based on the principle that one's belief about how difficult or easy a behavior is influences their decision to conduct that behavior [37].

The MODE model of attitude-behavior processes

According to Fazio et al. [24], behavior is not exclusively rationally based and consciously reflected. The link between attitude and behavior comprises emotional aspects and irrational decision making processes. Fazio and colleagues developed the MODE model (Motivation and Opportunity as Determinants) of attitude-behavior processes [24] arguing that attitudes can be accessed spontaneously or deliberately; they are mostly a mix of combined automatic and controlled processes [24]. Most of the activities of daily living are less elaborated and consciously reflected: “The ease with which we all engage in normal social discourse in itself suggests that much of our behavior is spontaneous rather than the planned outcome of some reflective process.”[24]. In situations where persons are unmotivated or under time pressure, automatically accessible attitudes relevant for the specific situation are more likely to be activated. The motivation for a specific activity has to be balanced against competing motivations. More effort for a specific behavior is more likely to lead to avoidance or denial instead of approximation to a certain behavior. In this process, attention is focused more upon negative aspects of an object or situation.

The “modified norm activation” model

Figure 2-3 shows a model which was developed to explain altruistic/moral decision making. It takes into account the activation and influence of personal norms on behavior, and also addresses moral motivation which must be balanced against other competing motivations [57][43]. Competing motivations could possibly be saving monetary or behavioral costs, such as changing clothes instead of just altering the heating set point. Often behavioral costs lead people to not behave in accordance with their personal norms regarding the environment. The model integrates external influences, e.g. comfort, price of behavior, and social expectations, as well as internal influences. Especially in contexts with highly repeated activities of daily living, persons develop stable patterns of behavior; therefore habits play an important role in this model. An important aspect of this model is the assumption that the decision to not behave in accordance with one’s normal activities may lead to defense mechanisms like denial of responsibility or redefinition of a situation (e.g. negating a problem or abilities). Thus, the model is applicable to identify constraints and possible risks of implementing soft measures [43][57].

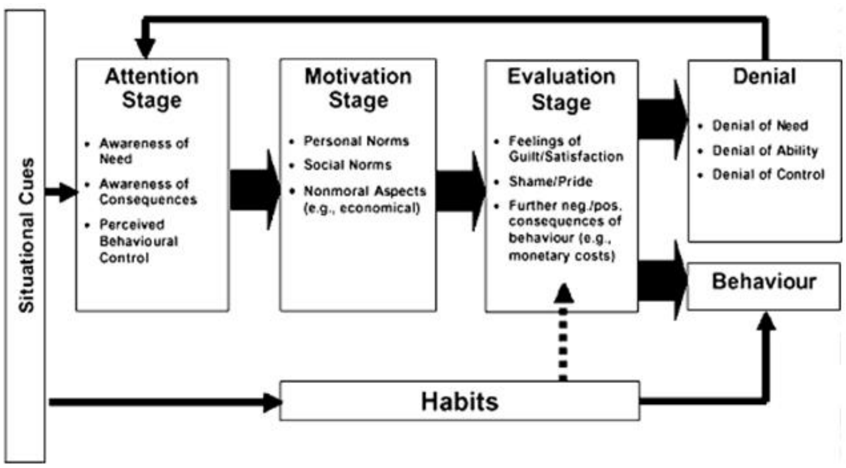


Figure 2-3. Modified norm activation model [57].

The “knowledge-desire-ability-action” model

The social-psychological knowledge-desire-ability-action model, Ref. [21], is based on the awareness-interest-desire-action funnel model by E. St. Elmo Lewis (see Ref. [88]). In this framework, various stages leading to certain behaviors can be distinguished, see Figure 2-4.

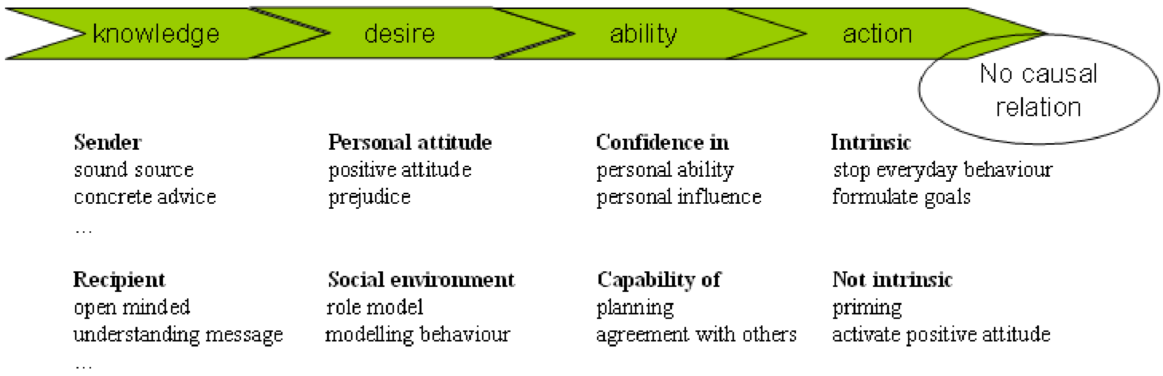


Figure 2-4. The “knowledge-desire-ability-action” framework, translated from Ref. [21].

This framework can be used to investigate behavioral change. In this framework, not all stages are required in order for certain behavior to emerge. For example, consciousness (knowledge) not necessarily precedes a positive attitude (desire), whereas a positive attitude not always results in a certain behavior.

3.2 Theoretical behavioral models and frameworks with respect to energy use in residential buildings

The behavioral model for residential energy use

Van Raaij et al. [68], propose a behavioral model for residential energy use. In this model, they relate personal, environmental, and behavioral factors to energy use, see Figure 2-5. Furthermore, Van Raaij et al. discuss the determinants of household energy use in detail; they distinguish between socio-demographic factors, family lifestyle, energy prices, energy-related behavior, cost-benefit tradeoffs, effectiveness and responsibility, feedback, information, and home characteristics.

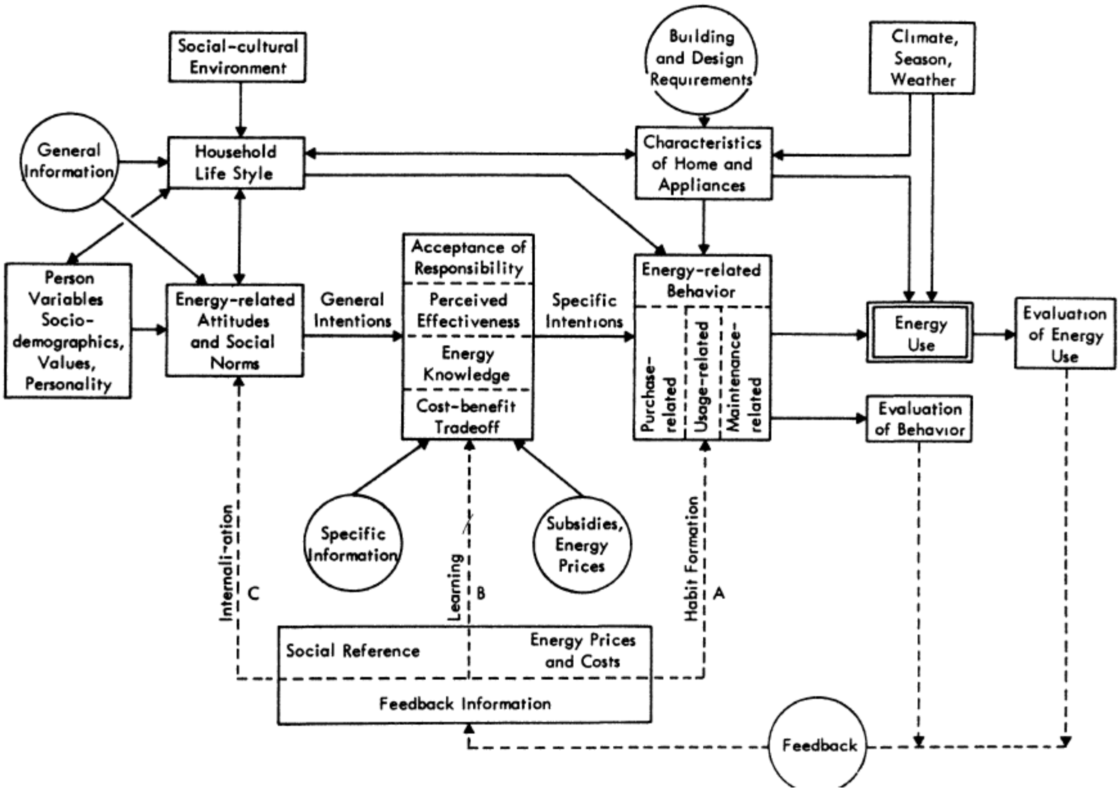


Figure 2-5: A behavioral model of residential energy use, by Van Raaij et al. [68].

The central parts of the model are energy use and energy-related behavior where purchase, usage, and maintenance-related behaviors are distinguished. In this model, home characteristics directly affect energy use, and also influence behavior. Feedback loops are present for the evaluation of energy use and behavior. The content of feedback information may be the amount or costs of energy used, or a comparison with earlier periods or other households. The shorter the feedback period or the better the correlation to a specific activity, the more effective the feedback will be.

The five factors in the circles in Figure 2-5 can be applied in an energy-conservation campaign. Feedback information on energy costs is more effective for reducing energy use than general information on energy savings. General information will probably be the least effective since it has the longest path to energy use compared to the other factors.

The “needs-opportunities-ability” model

Another useful conceptual framework for understanding the role of occupant behavior in relation to energy use is the “needs-opportunities-ability” model (NOA) of consumer behavior; see Ref. [25] and Figure 2-6. This model can be used for explaining behavior.

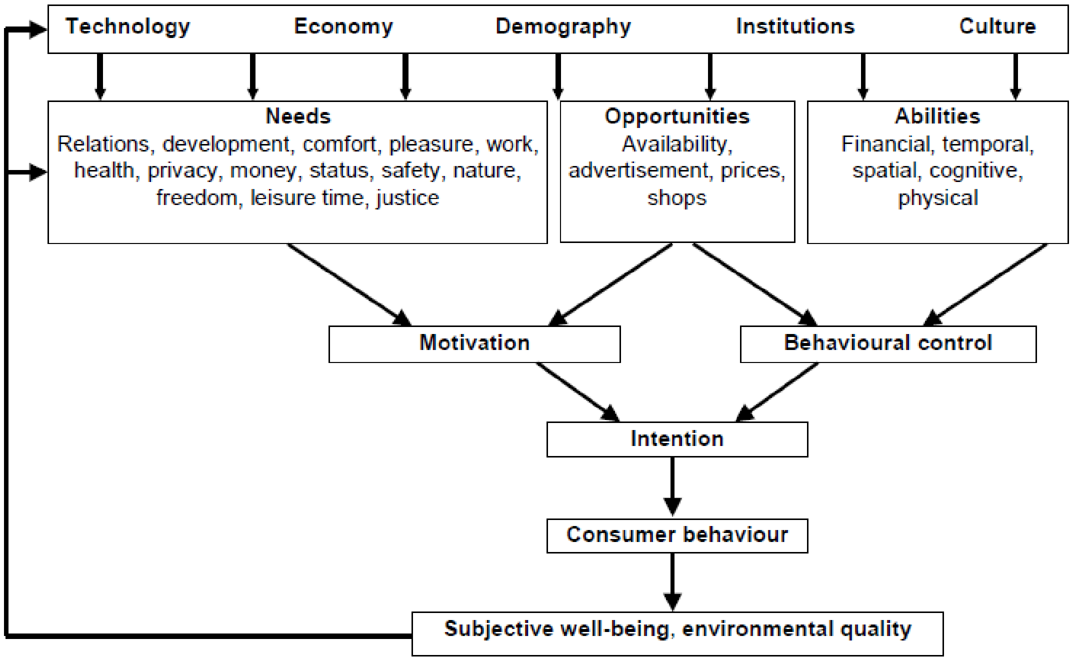


Figure 2-6: The Needs-Opportunity-Ability model for consumer behavior, Ref. [25].

In this framework, the consumption of energy use is driven by five kinds of driving forces: technological, economical, demographical, institutional, and cultural developments (TEDIC complex). From left to right, these driving forces vary from “easy-to-change” to “hard-to-change”.

Needs and opportunities determine the motivation to consume. Opportunities and abilities determine the degree of behavioral control people have in order for a certain kind of consumer behavior to emerge, whereas people need to have both behavioral control and motivation to do so. Opportunities are external conditions, such as availability and accessibility of goods, available information, and prices. Abilities are internal capacities of individuals or households to obtain equipment and services: financial (income), spatial (space at home to store goods, distance to shops and services), temporal (time spent on holidays), cognitive and physical means, and skills (health and fitness).

4. Modeling of occupant behavior for energy demand prediction

Occupant interactions with building systems lead to the impact of the occupant on building system performance (e.g. indoor environment, energy consumption, etc.). These interactions can generally be broken down into two aspects: one is the metabolic heat gain produced by occupants (the so-called passive effect); the other is the usage or operation of building device objects (windows, blinds, lights, air-conditioners, appliances, etc.) that satisfy all sorts of occupant's needs (the so-called active effect). The ways occupants interact are illustrated by Figure 2-7.

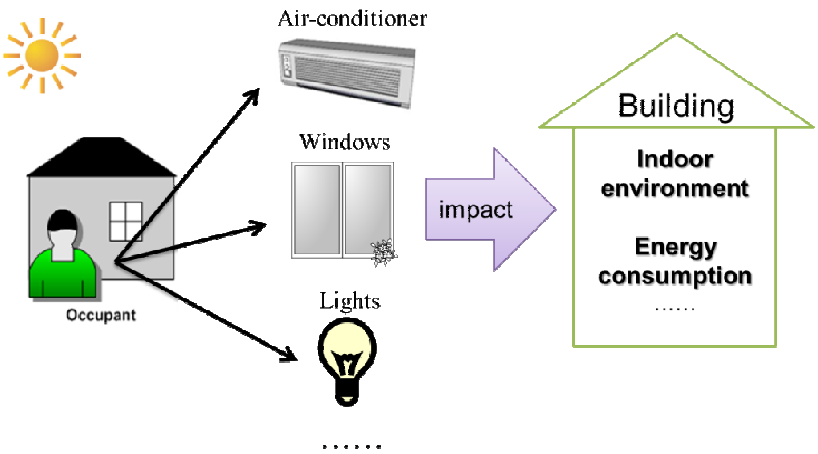


Figure 2-7. Interactions between occupant and building system.

To evaluate these impacts, the occupant heat gain and the states of device objects are needed in the building energy simulation.

For one room in a building, the amount of occupant heat gain is determined by the metabolic heat production per occupant, the number of occupants in the room, and the uses of devices that usually happen when the room is occupied. Both aspects of occupant interactions with the building system are related to occupancy (i.e. whether the room is occupied and how many people are in it). On the other hand, the state of each device object is regarded as the result of occupant control actions that change the device object's state. Once one action of this kind happens, and the device state at a previous moment is known, its state at the current moment is determined.

This chapter presents the theory and background regarding the modeling of occupant behavior and the implementation of the derived models into computer simulation. This chapter is divided into the three modeling approaches defined above: average values, deterministic, and probabilistic together with the agent-based and action-based modeling approaches.

4.1 Average values models

In a review of building energy use models, Zhao and Magoules identify four models which use average values [104]. The work by Yao and Steemers uses cluster analysis to create five occupancy-based domestic load categories for predicting daily end energy consumption to size residential renewable energy systems [101]. Rice et al. uses a database of actual user inputs based on crowd-source inventory data to model the end energy use. The heat emitted by electrical appliances is included in the calculated indoor set point temperature. Heating and cooling loads are estimated as the movement of heat through the building envelope in relation to a single indoor set point temperature and outdoor temperature. The building model is reduced to a single U-Value for all envelope components [74]. Wang and Zu also consider internal heat gains from electrical appliances in their model, as a thermal network of lumped thermal mass [94]. The Wang and Zu model simplifies the building envelope using average values based on readily available physical data based on a frequency character analysis. Genetic algorithms are used to identify key model parameters. The final model reviewed by Zhao and Magoules is the model proposed by Yik et al., wherein a simplified model for predicting the cooling load for different building types results from the combined results using detailed simulation tools. This model predicts the simultaneous cooling load for different buildings types [102]. Table 2-3 below summarizes a few examples of average value models used to represent occupant behavior in building energy use analyses.

Table 2-3. Examples of occupant behavior average value models.

Author(s)	Analysis methodology	Simplified occupant behavior model	Purpose of simulation
Yao and Steemers[101]	cluster analysis	end energy, heating, cooling, and DHW use daily profiles	domestic renewable energy systems sizing (Final design)
Rice et al. [74]	crowd-source inventory database	internal heat gain from people and appliances	building total energy use prediction in operating phase (Operation)
Wang and Zu[94]	genetic algorithm	internal gains as thermal network of lumped thermal mass	determining key parameters for thermal performance prediction (Conceptual design)
Yik et al. [102]	combination of detailed simulation results	hourly-based profile of presence, lighting, appliances, and ventilation rate	cooling load prediction (Preliminary design)
Seif et al. [84]	random numbers	end energy, heating, cooling, and DHW use hourly profiles	heating load prediction (Preliminary design)

Although the studies by Rice et al., Wang and Zu, and Yik et al. focus on office buildings, the grouping of energy-related user actions and passive effects to build average value models can be similarly applied when considering large scale residences with a large number of similar or identical dwellings, e.g. high-rise apartment buildings, collections of low-rise buildings, or student residences. Predicting total energy use for individual single family homes has shown to be more challenging as the statistical sample is one, and the energy use profile for single houses can show great variance from the current estimations based on average values [44]. Thus, the energy use profile has been analyzed in greater detail in single family homes to consider more variables and to improve the accuracy of average values models [74][101].

Data collection

Models based on average values use data inputs in four categories: climate, building envelope, building systems, and occupant behavior. As the means to obtain the average values for the models can be quite complex, the level of required detail in each category depends upon the type of information that is available, the factors considered in the model, and the purpose of the model.

The purpose of the model will define the data structure to be collected. Mahdavi presents an example of a structure to organize monitoring data to apply to occupant model development. He groups the effects of occupants as passive and active, and defines passive effects as the "effects of people on the hygrothermal conditions in buildings" which are "caused by the 'mere' presence of people in the building [55]." Active effects are further defined as the actions taken by people to manipulate their environment to create their desired indoor conditions. Using this terminology, the passive functions of people such as the release of heat, moisture and carbon dioxide can be considered as constant rates in average value models.

Mahdavi further categorizes the relationship of active effects as "states" (S) and "events" (E) where states relate to a steady or slowly changing condition, and an event involves a change of state. Table 2-4 presents an overview of the proposed organization.

Table 2-4.Proposed observational data organization of occupancy, presence, and actions in buildings [49].

Data	Type	Illustrative instances
Events (E)	System-related (E_s)	Switching lights on/off
	Occupancy-related (E_o)	Occupant entering into (or leaving) an office
States (S)	System-related (S_s)	Position of shades/windows
	Indoor environ. (S_i)	Illuminance level
	Outdoor environ. (S_e)	Outdoor temperature
	Occupancy-related (S_o)	Room occupied/vacant

Various sources of data are used for the models such as national statistical databases [101], time-use surveys, monitoring data of case study buildings [11], questionnaires and surveys [22], crowd-source inventory data [74], personal observations, and building simulation default values to name a few.

As an example, Seif et al. [84] constructs an occupant behavior model using data from various sources. The questionnaire results from Einfalt et al. [22] forms the basis for household electricity use, national population censuses determines the range of household populations, and desired a set point temperature is taken from literature research. Data from various sources is similarly collected for other models using average values.

Model development

Each model considers the criteria listed in 0 to varying degrees, taking different approaches to construct the specific model. Top-down models assess energy from a supply perspective; bottom-up models consider individual end energy uses to construct a holistic summative profile for individual, categorical, or large scale applications.

Probable passive and active occupant effects were composed according to the following criteria:

- the number of people in the household, categorized according to the number of adults and small children
- the presence probabilities in different rooms
- the ventilation habits per room according to personal profile type for one window type and two opening positions [46]
- the room type, room use, and adjacencies
- set point temperature of each room
- internal load profiles based on radiated heat from people and appliances, and the energy used by appliances [22]

Individual energy-use profiles are created using random numbers to stochastically generate a set of different behaviors representing a population. In this case, a set of 500 user profiles were generated and used as the input parameters for whole building simulations of a single detached family home. The quality of the house construction was also varied between three building standards: existing – to represent houses built to 1970’s housing regulations (over 60 kWh/m²a); low energy standard (between 15 to 60 kWh/m²·a), and lowest energy standard (below 15 kWh/m²·a). The whole building simulations thus generated a set of 1500 outputs for the abovementioned user profile set.

Figure 2-8 illustrates the process by which the average values are determined and validated. The boxes represent calculations and the symbols represent outputs. HED (500) is the set of 500 heating energy demand outputs from the building simulation, $HED_{ave,sim}$ is the averaged heating energy demand calculated using the monthly balance method, $HED_{ave,mb}$ is the averaged heating energy demand calculated from the whole building simulation, $T_{i, ave}$ is the average interior set-point temperature, $q_{i, ave}$ is the average value for internal heat gains, n_{ave} is the average air change rate.

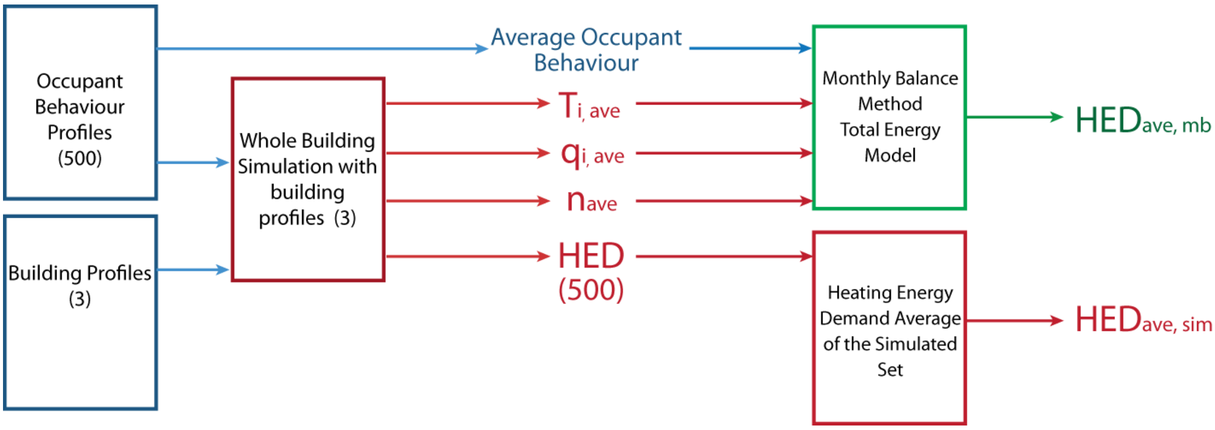


Figure 2-8: Process diagram of determining and verifying average values for the heating energy demand.

Figure 2-9 shows the probability distributions for the three building standards for the 500 user profile set. As can be seen, the positive skew increases with increasing building quality. The sensitivity to the overall impact of user behavior has a tendency to become greater with better insulated buildings. The average total heating energy demand is estimated to be greater in the poorer insulated single family homes. However, there are also cases which show the opposite, i.e. higher energy use in better insulated homes and less energy use in less insulated single family houses.

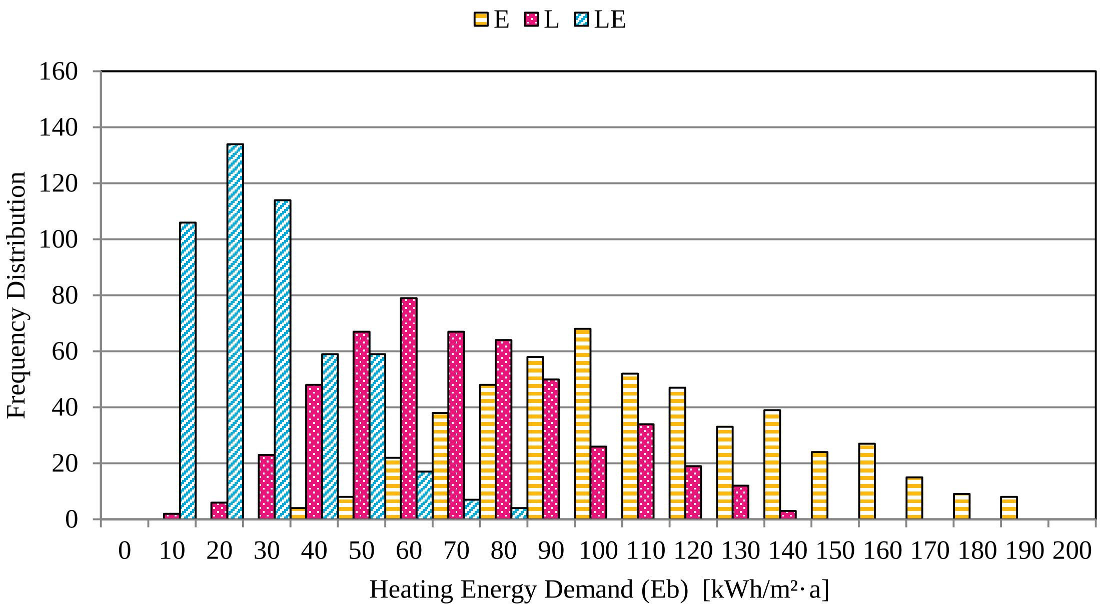


Figure 2-9: Probability distributions for the impact of user behavior on heating energy need for a house built to three building standards: existing (E), low energy (L), and lowest energy (LE).

The outputs from the whole building simulation sets are averaged to generate new, more accurate values representing the occupant behavior in single family homes:

- weighted monthly and annual mean air change rate (ACH) using the net air volume of each zone within the conditioned area
- mean monthly and annual room temperatures
- mean internal loads due to equipment and occupants
- mean electricity consumption due to equipment

The input parameters for average value models of the total energy use in residential buildings are the mean values for ACH, room temperature, internal loads, and electricity consumption. In addition, the energy need is averaged for each of the investigated houses which results in the monthly and annual heating energy need for room heating presented in Figure 2-9.

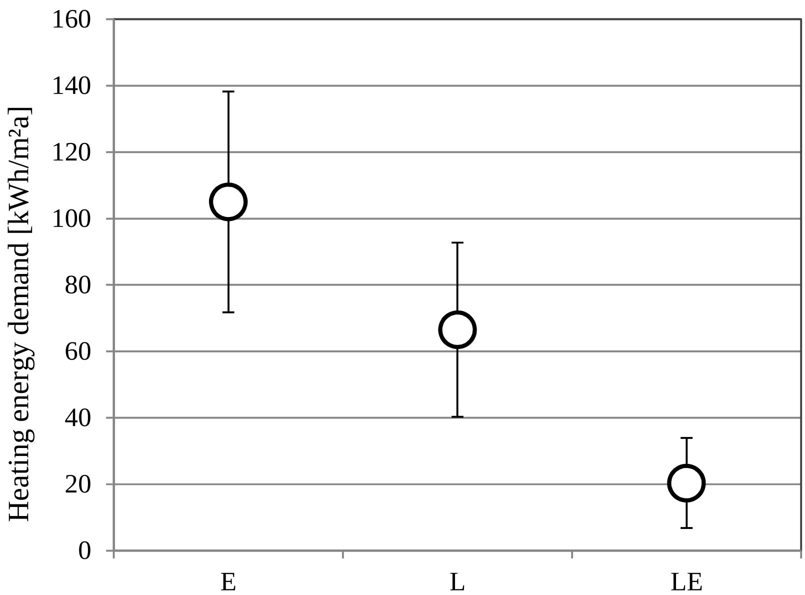


Figure 2-10: Average values with max and min ranges for the impact of user behavior on heating energy need for a house built to three building standards: Existing (E), Low Energy (L), and Lowest Energy (LE).

As expected, the heating energy demand decreases in relation with the building standard, the LE building standard consuming the least energy. The diagram also shows that the range of values decreases with higher building standards.

Implementation

The application of average value modeling is appropriate for estimating total energy use in single buildings [74][104], single family homes for large or very large sample sizes such as a building stock or national level residential energy use analyses [84], or also to predefined building categories [74].

Model validation

Figure 2-11 shows a comparison of the average energy demand calculated using building simulation for a population of 500 single family households using the above described average values and the monthly balance method. The results showed good correlation, especially for the LE standard.

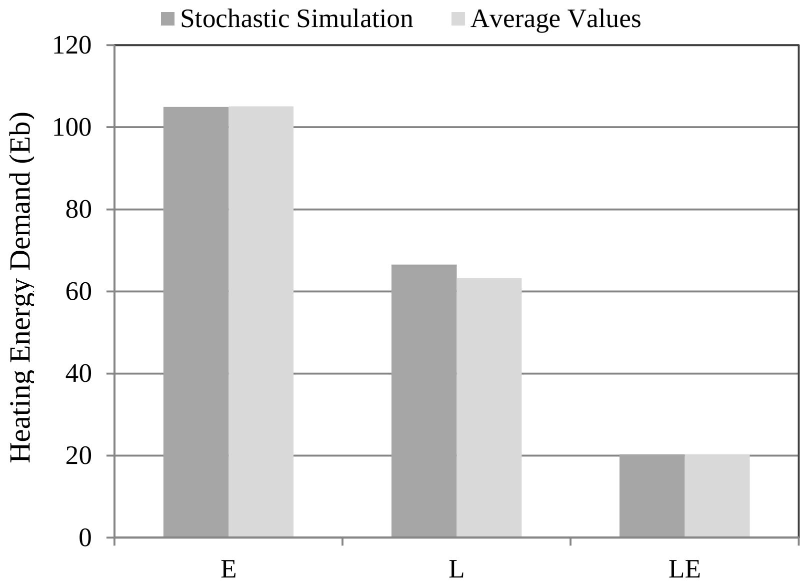


Figure 2-11: Comparison of whole building simulation results with the monthly balance method average values.

The monitoring results from three lowest energy Austrian apartment buildings also support the average value model for estimating the total energy use in cases of residential buildings with many inhabitants [11]. The various energy use patterns by the inhabitants result in average energy consumptions that equal the energy use for heating, hot water, and household equipment for different large buildings [11]. The larger the building, the larger the sample set, and the deviation from the average becomes less with greater numbers of living units.

4.2 Deterministic models

If an occupant is exposed to the exact same conditions a number of times, (s)he will not react in the exact same manner every time. As a consequence, the behavior of occupants will by nature include elements of randomness. Building simulation tools on the other hand, are based on heat transfer and thermodynamic equations, which are deterministic. Typically human actions (operation of lights, blinds, and windows) are modeled based on predefined fixed schedules or predefined rules (e.g. the window is always open if the indoor temperature exceeds a certain limit). These tools often reproduce building dynamics using numerical approximations of equations modeling only deterministic (fully predictable and repeatable) behaviors. In such a way, an “occupant behavior simulation” could refer to a computer simulation generating “fixed occupant schedules”, representing a fictional behavior of a building occupant over the course of a single day [27]. Often, the occupant behavior is not specifically addressed in the simulation programs, but only modeled by means of its effect e.g. the infiltration rate may be modeled as a fixed value that does not vary over time, with the assumption that occupants will manipulate windows in order to reach this infiltration rate.

Data collection

The internal environment of buildings is determined by different energy sources and methods that evolve at different rates. The main sources can be identified as:

1) Outdoor climate, the main variables of which (in this context) are: air temperature, radiant temperature, humidity, solar radiation, wind speed and direction
2) Occupants that cause an unpredictable building energy performance because of their metabolism, and their behavior related to the energy use (use of electrical equipment or building systems to control the building indoor environment)
3) Auxiliary systems

Input data in current simulation tools "hide" behaviors or preferences of the occupants and users; the schedule for air temperature for example covers the users' preferences in terms of indoor temperatures. The common procedure for integrating the opening and closing of windows uses fixed schedules of airflow based on assumed occupancy patterns or uses its possible effect (through hourly air change rate variation) as inputs.

Model development

A common approach to model occupant behavior consists of assumptions based on scientists' thoughts or literature reviews [27]. The findings are based on and depend upon the assumptions made.

The literature shows that a variety of assumptions have been made by modelers about the window-opening behavior of occupants:

1) A schedule of open windows is assumed based on occupancy, with or without field evidence.
2) Window opening is assumed to be controlled by temperature, humidity, wind, and/or rain based on assumptions about behavior. Again field evidence is often absent.
3) Windows are controlled to produce a given air flow rate or air exchange rate, and may be more related to indoor air quality or minimum ventilation rather than thermal comfort. This approach assumes the occupant will utilize the window openings to achieve the design ventilation rates.

Implementation

Currently, the most common means used to consider occupant presence and behavior within simulation tools is the so-called "diversity profile". This is used in order to estimate the impact of internal heat gains from people, office equipment, and lighting on energy and cooling load calculations of a single building. The profiles depend on the type of building (typical categories being "residential" and "commercial") and sometimes on the type of occupants (size and composition of a household, for example). Weekdays and weekends are usually handled differently, especially in the case of commercial buildings. A daily profile (either for a weekday or a weekend) is composed of 24 hourly values between 0 and 1, each corresponding to a fraction of the maximum peak value. The weekday and weekend profiles and the peak are related to a particular type of heat gain such as metabolic heat gain, receptacle load, lighting load; they may be based on data collected from a large number of monitored buildings or simply based on common sense or national guidelines. Alternatively, the users of the simulation tool can also enter profiles that they deem appropriate for the building in question. An annual load profile for each type of heat gain is constructed by repeating the weekday and weekend daily profiles and multiplying them by the peak load. To add greater variety to these profiles, Abushakra et al. [1] have proposed not only to make available the average diversity profile but also those of the 10th, 25th, 75th and 90th percentiles. While they suggest the use of the average profile to determine the internal heat gains, they propose to use the 90th percentile for sizing of the building's cooling system.

Model validation

The deterministic approach to modeling the behavior of occupants is widely used. Actually their predictive accuracy can only be assessed by comparing its output with results from real measured data. Often, the results of the simulations are not compared to the performance indicators of the actual building due to the difficulties associated with data acquisition and shortcomings inherent in even the most sophisticated program. Empirical validation is therefore expensive and time consuming and only pursued within well resourced projects (like EPSRC Validation project [103] or BRE/EdF Validation Project [104]).

Inter-program comparison allows program to be tested. This is a particular useful device where the input models can be established to stress a particular aspect known well to be handled by one of the programs, like occupancy schedules. Sensitivity analysis allows the influence of input parameters on output to be determined. This information can then be used to refine the program.

As a result, publications including these sorts of comparisons are very few. This puts a limit to how well the deterministic models can be validated.

Kristensen and Jensen [45] is an example that shows the inadequacy of the deterministic (and in this case, unrealistic) modeling of the occupants' behavior in predicting the energy consumption of nine residential houses.

4.3 Probabilistic models

The first issue to examine is human behavior related to energy usage.

The traditional approaches look at human behavior as if they would behave in a fully deterministic way: that is to say in a fully repeatable manner. Moreover, in a design stage some "design conditions" are simulated, meaning that when the building is realized, the occupants' interactions with the indoor environment will exactly coincide with the design values during the entire operational time.

However, if we analyze more carefully what happens in the real world, it is easy to discover that actually, many parameters influencing environmental conditions and human behavior vary significantly and unpredictably during the entire building life. This implies that, for smaller or larger amounts of time, not all the interactions of the building occupants to control the indoor environmental parameters would satisfy the assumed requirements in all rooms.

In order to set up such an evaluation procedure for modeling the occupants' interactions with the indoor environment, some concepts which have been long used in mechanical engineering may be adopted. In particular, a technique which seems to be suitable to this task is the so-called "reliability-based design procedure" of mechanical components.

The philosophy behind this method accounts for stochastic factors, and the result of the design process will be no more a “single value” for the system performance, but a probability to fulfill a certain performance over time.

In this way, the evaluation of the occupant behavior will be not only based on fixed action typologies (e.g. opening windows if indoor temperature exceeds a certain limit), but also on coupling these repeatable interactions with the building control systems, with a probability of performing an action.

From a practical point of view, the proposed approach means to start with continuous measurements of both indoor environmental parameters and external climate conditions along with the behavior of the building occupants (such as window opening, thermostat radiator valve (TRV) set point temperatures, occupancy sensors, etc.), performed in a sufficient number of areas and rooms representing different interaction zones in the building. The monitoring period may be different lengths, ranging from medium (i.e. one week – or better if repeated for different seasons) to long-term time spans (i.e. a yearly basis).

The simple measurement of physical quantity time profiles (such as relative humidity, temperature, pollutant concentrations, luminance, etc.) generates huge amounts of information which is difficult to “translate” into behavior.

In order to overcome these barriers, different suitable user behavioral patterns (models) were defined by means of statistical analysis (logistic regression, Markov chains, etc.) and can now be implemented in many of the actual simulation tools (such as Esp-r, IDA Ice).

When in the probabilistic approach, models of user behavior are implemented, the energy simulations show improved accuracy and validity of the results. Moreover, a probabilistic distribution instead of a single value is preferred as a representation of energy consumptions.

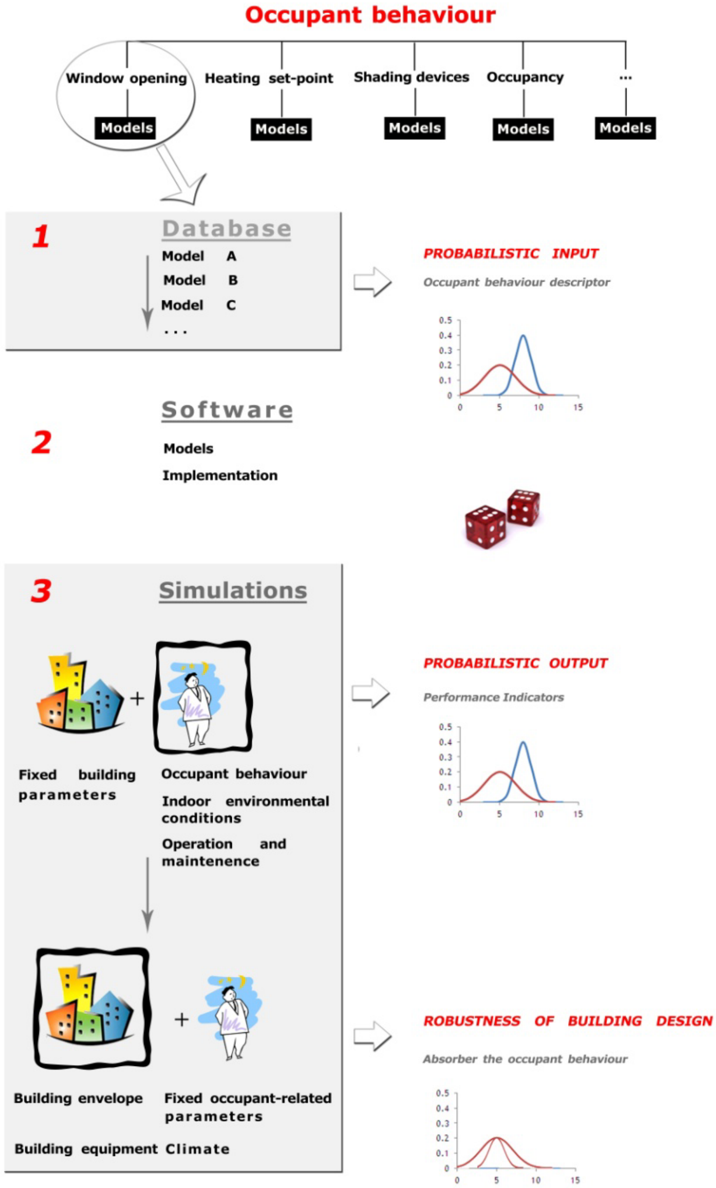


Figure 2-12. The probabilistic approach to model the human behavior related to the control of indoor environment.

The procedure to simulate realistically the human behavior is based on a probabilistic approach for the evaluation of both input and output parameters. This probabilistic approach is related to variability and unpredictability during whole building operation in many of the actual simulation tools (such as Esp-r, IDA Ice).Figure 2-11 shows the different steps representing the proposed approach and is described in the following sections.

Data collection

A complete database should include all the parameters regarding the possible occupant behavior driving forces. In particular, as explained in Fabi et al. [22], both external parameters (physical environmental and contextual variables) and internal parameters (social, psychological and physiological variables) should be collected as outlined below:

- physical parameters (air temperature, outdoor temperature, CO2, etc.)
- subjective feelings (thermal comfort, perceived IAQ, etc.) which may be predicted from physical parameters
- personal factors (lifestyle, hearsay)
- a combination of the above factors

Typically, the data to assess the behavior of the building occupants can be obtained by setting up a measurement campaign along with questionnaires given to and answered by the occupants.

The measurement campaign can be addressed to evaluate the external factors and could be applied only to one parameter (for example, room operative temperature), but may include measurements of many other quantities (related to the thermal and IAQ environment).

Monitoring indoor and outdoor climate variables and occupants' control actions is to be conducted preferably on a yearly basis (offices or dwellings) with identical or similar characteristics to limit the variability due to different envelope typologies or installed plant systems. A series of variables concerning indoor environmental conditions (temperature, relative humidity, CO_2 concentrations, etc.) are to be monitored and meteorological data (wind velocity, global solar radiation, rainfall precipitations, etc.) should be obtained from national meteorological stations in the building's proximity. Occupant interactions with controls, as heating set-point temperatures or window positions, should be gathered by measurements of the most representative zones and rooms of the building, for example, one TRV in the bedroom and one in the living room of each dwelling.

Internal driving forces should be collected by means of surveys and questionnaires, aimed at investigating the factors strictly connected to individual and subjective data. In particular, users' preferences, thermal backgrounds, behavioral backgrounds, attitudes, lifestyles, activities, ages and genders should be included in the database.

Moreover, as reported in [22], there are some specific "drivers" having the greatest influence on the occupant to make an action. These "pre-eminent" drivers are crossing a different field of study, highlighting the complexity of the research regarding occupants, but they should be gathered in order to characterize as much as possible the behavior of the building occupants.

Even if the majority of the existing studies mainly focused on monitoring activities through measurements, it is important to point out again that surveys and questionnaires addressed to occupants are also an important tool to properly characterize users' behavior. Both objective and subjective evaluations are always sought.

All the data collected by means of both objective and subjective procedures should be analyzed in a statistical way.

As a result of the monitoring data analyses by means of the statistical analysis, the probability of doing a certain action (such as opening or closing the window, turning up or down the heating system) was inferred for defined behavioral models. User control actions are deduced by means of logistic regression with interaction between variables, Markov chains, or other typologies of statistical analysis. The results are “occupant behavior descriptors” used as “probabilistic inputs” to integrate within building energy simulation software.

Model development

In general, the existing probabilistic models are expressing the probability with which actions will be performed on windows, valves, lights, etc. There are several statistical approaches applicable for the development of such models, which will be introduced in the following paragraphs.

Logistic regression analysis

In the literature, examples can be found of regression analyses that directly relate energy use in dwellings to the factors influencing energy use and energy-related behavior (e.g. thermostat set point) [28], [79].

Another approach can be found in natural sciences literature; here several investigations focus on relations between energy-related behavior and (mainly physical) drivers of this behavior [61], [70], [78] and Figure 2-13.

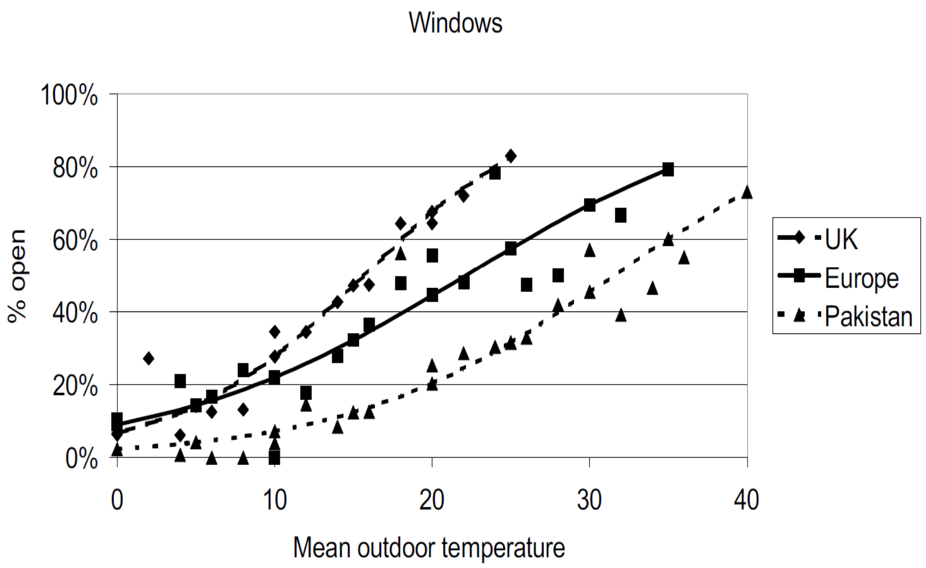


Figure 2-13: Probability function relating window opening behavior to outdoor temperature, Ref. [61].

According to Ref. [61], energy-related behavior is clearly affected by physical parameters, but the relationship tends to be stochastic. For example, there is no exact temperature at which every occupant would open a window, but for increasing temperatures, the probability that an occupant will open a window increases.

In order to obtain a logistic regression model, at each time step, the probability of observing a window to be open is independently determined by a logistic equation including “p” explanatory variables x_1, …,x_p, see also [81].

Depending on the model to be derived, for each variable the coefficients for the logistical regression are identified for different times of day, and day of the week. The model predicts the probability of an action with a number of variables (temperature, CO_2 concentration etc.) and their possible interactions. For more details see ref. [7], [31], [82].

State transition analysis using Markov chains
A Markov chain is collection of random variables (where the index runs through 0, 1, ...) having the property that, given the present, the future is conditionally independent of the past. At each time step, actions are modeled by transition probabilities P_{ij} from state i (e.g. window open) to state j (e.g. window closed) (i,j = 0, 1) also formulated as logistic models (Equation (1)), with P_{01} e.g. being the probability of a transition from closed to open, and vice-versa for P_{10}.

Monte Carlo modeling
A description of the Monte Carlo approach applied to building simulation is seen in Ref. [54], [65].

Monte Carlo methods are mathematical procedures based on the use of random numbers which are uniformly distributed over the interval [0,1] and observing what fraction of the numbers obey a given property. Conceptually the method is based on the possibility to perform, using random numbers for the generation of stochastic variables from various probability distributions, F(X), i.e. on the possibility of resulting a sequence of events, X1, X2, ..., Xn, ..., distributed according to F (X).

The Monte Carlo method can be traced back many simulation methods, which aim at the determination of the parameters typical of complex phenomena in random nature.

Monte Carlo method consists of building models of possible results by substituting the probability distributions. It works by calculating results over and over, changing each time the random values from the probability functions. Depending upon the number of uncertainties and the ranges specified for them, a Monte Carlo simulation could involve many recalculations before it is complete. Monte Carlo simulation produces distributions of possible outcome values. By using probability distributions, variables can have different probabilities of different outcomes occurring. In this way, it is possible to have more reliable results describing uncertainty in variables of the occupant behavior analysis.

In literature, some Markov-Chain Monte Carlo (MCMC) models have been developed for simulating occupancy in dwellings; see e.g. Refs. [74][97]

Neural network
Artificial neural networks (ANN) are inductive models that represent an alternative approach with respect to deductive models. In building energy modeling, ANNs are used as a surrogate for analytic computer codes to evaluate energy flow and system performance; i.e. they are useful for forecasting and modeling.

The ANNs learn from key information patterns allowing discovery of complex relationships between the variables. The ANNs allow robust processing even from noisy data. On the other hand, they provide a limited knowledge of process mechanisms.

It is well-known from literature that one of the most interesting features of neural models is their ability to handle incomplete data. Several studies have shown in some cases forecasting models for energy consumption based on neural networks are more accurate, even if more complex than those based on multiple linear regression.

An artificial neural network is a massively parallel distributed processor that has a large number of artificial neurons interconnected through weighted synaptic connections. Connections can be "adjusted" through a network training process based on a given pattern rather than on predefined rules. In other words, this process allows the “rule” to be learnt which is based on the application of physical phenomena starting from known situations and applications to new situations. This feature, and the relative simplicity of implementation and programming, encourages the application in prediction tasks. In addition, the use of a nonlinear model allows the identification of interactions between independent variables without exploiting complex models. A commonly used neural network architecture is the Multi-Layer Perceptions. Its basic structure consists of a set of units organized in layers; each element produces its output applying an activation function to a weighted linear combination of input signals. The weights of this linear combination are those associated with connections that affect the neuron. The activation function determines a relationship between the activation of the neuron and its output. More details could be found in [105]: the authors used neural network techniques to estimate different end-uses, in particular space heating and cooling, appliances and lighting and domestic hot water.

Implementation

One of the main objectives in developing models for occupant behavior is the implementation in computer simulation programs. With probabilistic models, this task demands either dynamic simulation programs suitable to handle probabilistic functions or the consideration of a group of people in a steady state calculation.

For the latter, e.g. a group of 100 occupants is considered, and the probability of the state of an open window is translated into the ratio of people having the window open and closed based on the probabilistic model under certain conditions. This rather simplified implementation was applied e.g. by Schweiker and Shukuya [83].

Relations for energy-related behavior (e.g. thermostat set point, window opening) found by any type of regression analysis can be applied in building simulation software to predict energy-use and indoor climate. The factors directly affecting energy use can also be correctly physically accounted for by building simulation software in such an approach as seen in Figure 2-14.

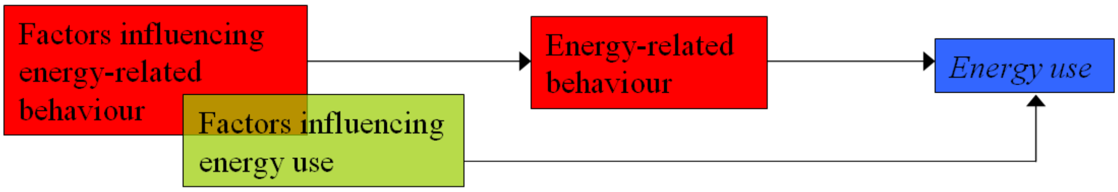


Figure 2-14: Energy use and factors influencing energy use and energy-related behavior.

The idea is to change from a deterministic approach of building energy simulation toward a probabilistic one taking into account the occupants' presence and interactions with the building and systems.

Results of the statistical analysis show the possibility of defining occupants' behavioral models building uses and building systems to control the indoor environment to be implemented in simulation tools for building energy analyses.
In order to investigate the effect of occupant behaviors both on energy consumption and indoor environmental quality, simulations should be run in thermal zones maintaining location, weather file, and building construction of the monitored buildings. In the occupancy schedule, the occupant could be still considered as always present, but the control of a building's indoor environment is now probabilistic in nature; it does not follow predefined controllers or fixed rules. The probability of adjusting the temperature set-point or opening a window is calculated in the simulation software on the basis of the equations previously used to describe the behavior statistically. Most simulation programs are deterministic in nature, so there is a need to translate the probability of an event into a deterministic signal. One way of doing this is to compare the probability to a random number to determine if the event takes place. As the given probability is the probability of doing a certain action in a certain time period, the comparison is to be made with a random number that changes with the same interval. The action occurs when comparing the random number with the calculated probability; the former was smaller than the latter. In this way it is possible to calculate the energy performance through a performance indicator.

A probabilistic distribution of energy consumptions depending on user type is obtained by switching the random number lists in the simulation program.

Fixing all the parameters related to the energy performance of the building (i.e. climate, building envelope, and building equipment), the simulations are aimed at verifying the influence of the characterized user behaviors on energy consumptions. It is possible to have a curve of building energy performance in different situations and for different occupant typologies by running a large number of simulations and substituting a random number list for the probability of an occurring action. It is preferable to have a probabilistic distribution (or a "probabilistic output") instead of a single value representing different energy consumptions.

Inarguably, an infinite number of scenarios could have been simulated using different comfort categories representing different user profiles and therefore more outcomes could have been found.

Indeed, this approach aims to represent a procedure that could be extended to all users' interactions with indoor environmental controls systems such as window operations, heating set point adjustments, and solar shading operations.

A further step is represented by the application of user models in simulation programs to verify the "robustness" of the building from the users' perspective. Once the user behavior has been characterized by a model and its impact on energy performance verified with a number of simulations, it is interesting to check what happens when the building properties and equipment are changed but maintaining the same behavioral user pattern.

Ferguson et al. [25] and Hoes et al. [33] defined performance robustness as the ability of a building to handle changes (or disturbances) in the building's environment and its ability to maintain required performance. Therefore, it is important to take performance robustness into account during the design process [52].

The procedure is then extended to the verification of thermal mass, percentage of transparency in the facade, and shading devices, amongst others. Nevertheless, factors involved in the implementation of energy programs can be extended to thermal mass, percentage of facade transparency, shading devices, or window opening with the aim to understand which of these have the most influence on energy use and thus, constitute recommendations for improved building design with regard to energy reduction. This allows the designer (e.g. engineers, architects, or technicians) to select the most robust solution for the building design.

Model validation

One way to validate probabilistic models is to compare the output of the calculation (a probability) with a random number. In such a procedure, the model can be validated using a sufficiently high number of simulation runs.

The following criteria as introduced by Ref. [31] and already applied by Ref. [81] can be used for the comparison of simulation outcomes and measured data.

Discrimination models

Discrimination criteria are deduced by comparison between observed and simulated outcomes. Simulation results may be classified in four groups: a positive predicted outcome (window open, P) is either (i) truly positive (TP) or (ii) falsely positive (FP); a predicted negative outcome (window closed, N) is either (iii) truly negative (TN) or (iv) falsely negative (FN). We may then aggregate these results to define:

- The true positive rate (proportion of actual positives which are correctly predicted positive): TPR = TP/(TP + FN),
- The false positive rate (proportion of actual negatives which are wrongly predicted negative): FPR = FP/(FP + TN),
- The accuracy (proportion of correct classifications): ACC = (TP + TN)/(P + N).

These criteria allow for a good understanding of the ability of a model to correctly discriminate between periods where windows are open and closed. It is however not possible to faithfully summarize this ability in a single figure, so that these indicators should be considered in combination.
Overall proportion open

Based on the total survey duration, $T_{meas,tot}$, and the total window opening time, $T_{open,tot}$, we define the overall window opening ratio for each office as $r_{open} = T_{open,tot} / T_{meas,tot}$. This criterion allows the general coherence of the total predicted opening duration to be checked.

Number of actions
In order to check the coherence and the dynamics of occupants' actions, the observed number of actions, $N_{act,obs}$ per day is compared with the simulated actions, $N_{act,sim}$.
Median opening and closing durations

The delays between actions, or alternatively the durations windows are left open and closed, is another indicator related to the dynamics of occupants' behavior. In order to reduce the influence of extreme values, the medians of these durations rather than the mean values are considered for evaluation.

4.4 Agent-based models

Agent-based simulation models are being used to quantitatively study multi-agent systems in which agents are autonomous, and interact with each other and their environments. The behavior of agents and the interaction between agents are responsible for the global development in a multi-agent system. The agents may be very different objects varying from individual human beings to components of energy networks. The agents are in a specific state at a specific time during the simulation. Due to interactions with other agents the state may change over time.

An agent-based model for simulating domestic user behavior can be used in a co-simulation with, e.g. a building model.

Agent based modeling is based on a bottom up approach. It focuses on individual behavior and local interactions. Simple behaviors at a micro-level will result in complex behaviors at a macro-level.

Data collection

The agent-based modeling approach requires a database that should include information concerning the driving forces of energy-related occupant behavior including social, psychological and biological driving forces, as well as driving forces related to the physical environment, building/installation properties, and time. See also the report "Driving forces of energy-related behavior in residential buildings".

This data could be gathered with questionnaires to be filled in by occupants and could possibly be obtained by means of measurements.

Model development

A bottom-up approach is used in the model development for agent-based models. Individual behavior and local interactions are accounted for. Behaviors of agents and interactions between agents at a micro-level will result in more complex behavior at a macro-level. Agent-based simulation models generally consist of the following main elements:

- generation of a physical environment
- generation of an agent population in a specific state and located at specific places in the environment
- definition of agent needs, beliefs, and behavior, and rules for interaction
- simulation: agents are allowed to behave and interact with each other and with the environment
- observation of what happens during the simulation

These main elements for an agent-based model to simulate user behavior and domestic energy use can be made more concrete, see e.g. Ref. [51].
The physical environment involves time (e.g. minute/hour/day/month), space (e.g. kitchen, living room, bathroom, etc.), and objects (e.g. heating system, windows, blinds, lighting), physical parameters (e.g. temperature, humidity, lighting, noise).

The population of agents may refer to e.g. family (father, mother, son(s), daughter(s)) or visitors (friends, neighbors, relatives).

User behavior in dwellings is considered to correspond with user activities in order to satisfy their needs depending on the physical environment. The term behavior refers to the actions of an object. Some needs have to be met in order to survive, whereas other needs make people more comfortable. (e.g. a person enters a room having a temperature of 18 degrees; the person believes he is feeling cold and wants to increase the set point of the heating system. If other people are present in the room, other behaviors then increasing set point could result, such as putting on other clothes. An example for a causal model for user behavior at home is given in Ref. [51], see also Figure 2-15. In this figure a person's psychological state and contextual elements (e.g. environmental factors, time of day, other people) are denoted respectively by "inside cause" and "outside cause" of a person's need. The abbreviation "CC" stands for causal condition. In case a causal condition is satisfied, an effect is created.

In order to perform agent-based simulations, the model has to be implemented in an appropriate software environment; see next subsection. In practical applications, the simulations may also be co-simulations: the (agent-based) behavior simulator will exchange data with, e.g. a building performance simulator.

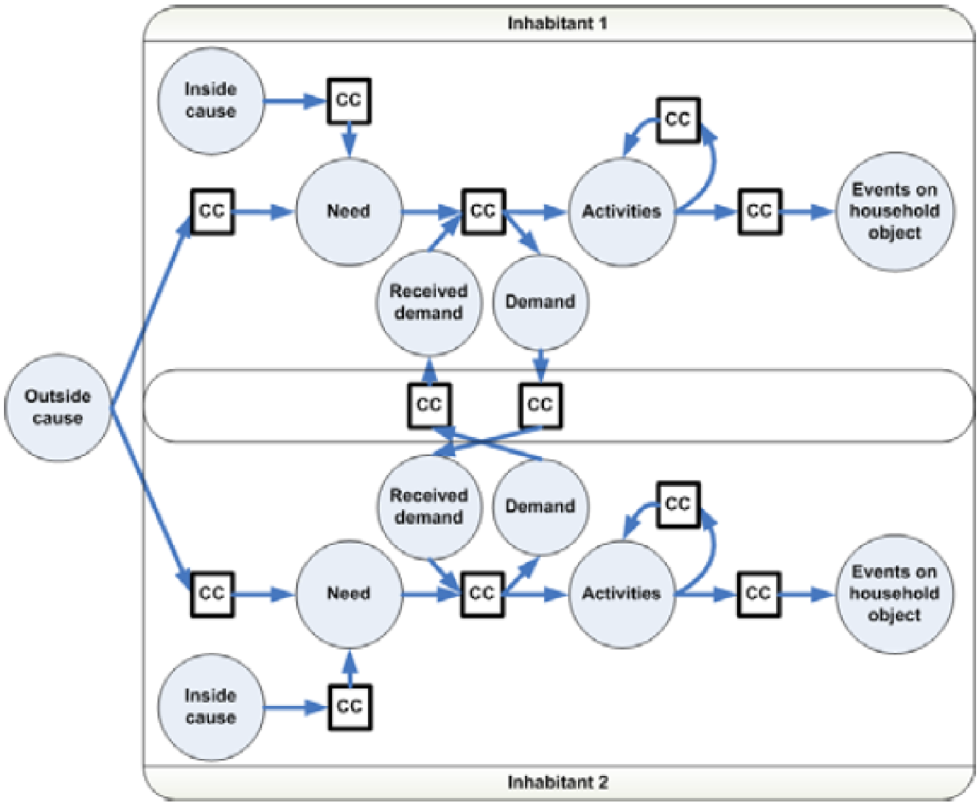


Figure 2-15: Causal model for residential user behavior [51].

Implementation

With the implementation of agent-based models in computer simulation programs, it is possible to quantitatively analyze the global behavior in a multi-agent system. Several computer programs may be used for agent-based modeling of occupant behavior and energy use, e.g. Repast [73], Mason [55], and Brahms [84].

The Repast Suite is a family of advanced, free, and open source agent-based modeling and simulation platforms that have collectively been under continuous development since 2003. MASON is a fast discrete-event multi-agent simulation library core written in Java. MASON contains both a model library and an optional suite of visualization tools in 2D and 3D. Brahms is a data driven (forward chaining) discrete-event environment usable for simulation purposes as well as for agent-based software solutions requiring the use of intelligent agents.
Such programs have been used for simulating energy-related occupant behavior and energy use in buildings [42], [51], [80], [84], [101].

In the following, the Brahms environment will be discussed in more detail. Brahms, acronym for business redesign agent-based holistic modeling system, is a simulation environment that can be applied to simulate and analyze the behavior of people over time. It has been applied in Ref. [42] for simulating domestic energy-related occupant behavior.

Brahms focuses on communication between people to support social behavior. Social and behavioral elements are required for a dynamic behavior. In Brahms, the following concepts are key elements:

a) Facts which represent the physical state of the environment; they are global and can be seen by any agent of an object in the environment;
b) Beliefs that differ from agent to agent; agents can reason about their beliefs and they can also communicate their beliefs;
c) Activities as an abstraction of real-life actions that help to accomplish a task;
d) Work frames are condition-action-consequence rules. If a condition is true, then the corresponding activities are performed. Consequences are the facts of beliefs that may be asserted when a work frame is executed;
e) Thought frames define deductions referred to as production rules. Thought frames are similar to work frames, but are actually inferences an agent makes without executing any activities
f) Communication are activities transferring beliefs from one agent/object to the other
g) Detectables are mechanisms by which an agent or object may notice a particular fact that occurs in the environment. The noticing of a fact may cause an agent or object to stop or finish a framework.

A screenshot of the graphical interface of the Brahms environment containing results of a simulation is displayed in Figure 2-16.

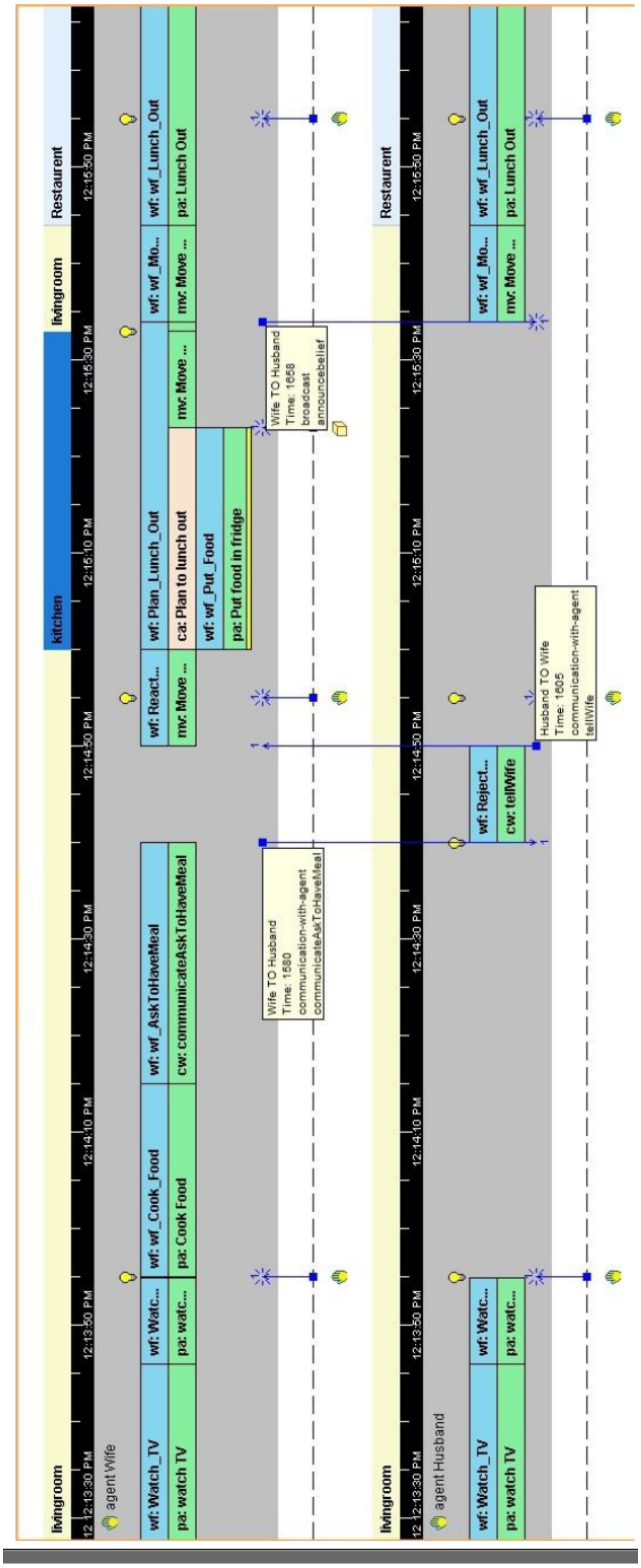


Figure 2-16. Brahms graphical interface. Simulation results showing social agreement between agents to go out for lunch.

In this example, the top horizontal bar represents agents movements to different locations (e.g. from the living room to the kitchen). The black horizontal bar displays the time in the agents' environment. The blue horizontal bar shows work frames containing composite (represented by "ca") or primitive (represented by "pa") activities. The yellow horizontal bar below the primitive activity shows that the agent is interacting with objects in the environment.

Yellow hands broadcast the beliefs from objects and the clock to agents. Yellow bulbs represent the thought frames of agents' beliefs.

Blue vertical bars are used to represent the communication between agents and the transfer of beliefs. The vertical bar coming down from agent "Wife" to agent "Husband" at the moment when agent "Wife" moves from the kitchen to the living room, represents the wife's belief to go to the restaurant which is transferred to the husband.

Inhabitants' perceptions, cognitions, and group behavior are simulated using Brahms in e.g. Ref. [42]. An agent model that represents agents including a group hierarchy and a communication model to exchange beliefs are included in Brahms. It can also be used to model human beings interacting with a domestic environment as active and intelligent agents rather than passive participants. See Figure 2-17.

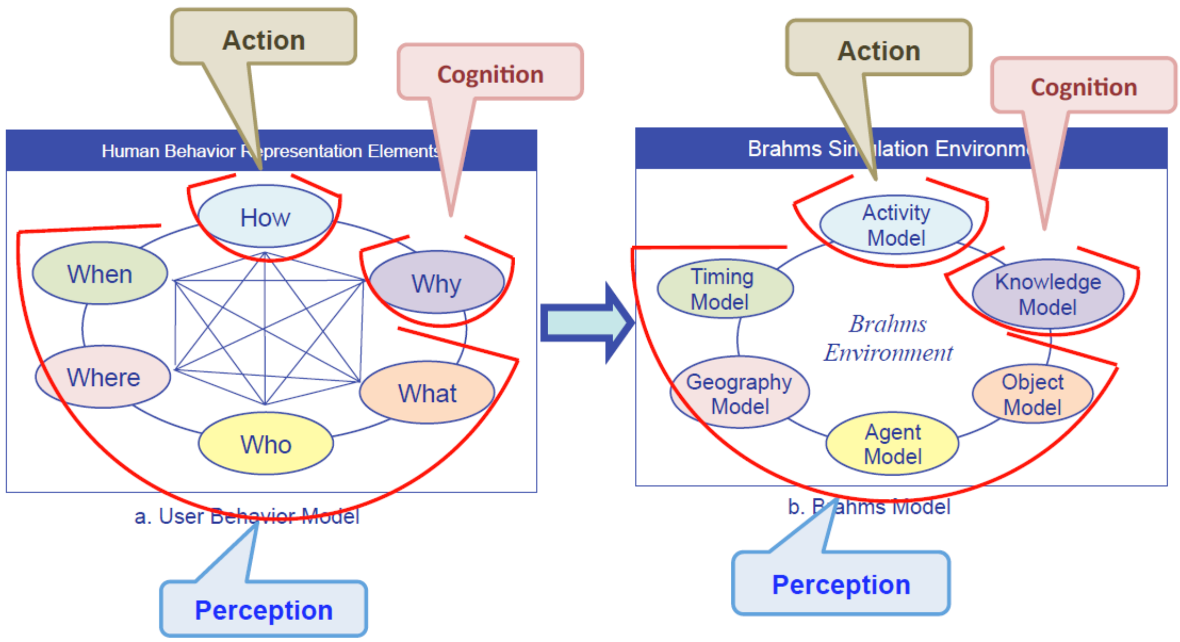


Figure 2-17: Brahms' approach to map domestic user behavior, see Ref.[41].

Model validation

Data collection from actual inhabited dwellings is needed to validate the final model results to assess the agreement between the model and the real world, and to assess the assumptions that have been made in the model about the agents' behavior and interaction with other agents and the environment. For a validation study, sufficient and detailed data are required.

4.5 Action-based models

Action based models exist for occupancy as well as for the occupants' actions. In the action-based model, occupancy is determined by occupant locations which can be regarded as the straightforward result of occupant movement among building spaces, while the occupant movement process is simulated by the Markov chain method.

From the action-based viewpoint, the uses of all sorts of device objects can be expressed by a few control actions, including opening windows, closing windows, turning lights on, turning lights off, turning on air conditioning, turning off air conditioning, adjusting the air conditioning set point, turning on a computer, turning off a computer, etc. Control actions of this kind are further expressed as a uniform function of purely physical parameters, including occupancy, time, environmental parameters, the device state, and the states of other devices.

In one word, the movement and control actions of the occupant become the objective occupant behaviors that we are concerned with in building energy simulation.

The real behaviors (movement and control actions) of any occupant usually show a complex nature (uncertainty, variability, and randomness). To solve this issue, the classification method is recommended, which is commonly used in biology. In this way, based on the uniform formalization of the description of occupant behaviors, a "pattern" (or mode) is further defined. For each kind of action, it can be classified into a few typical patterns (patterns A, B, C, D, E, etc.). Each pattern has a logical expression with specific quantitative parameters required to represent the main characteristic of real occupant behavior. For example, movement patterns A, B, and C are defined for buildings of different types and people of different professions while control action patterns A, B, and C are defined for opening windows, closing windows, etc. As a result, occupant behavior could be quite simple and clear. A database of typical patterns can be obtained through measurements or questionnaire surveys.

The action based model makes a personalized description of the occupant. If all respects of behavior patterns related to different devices are combined, a "typical occupant" is defined. For example, typical occupant 1 may be a combination of turn-on- air-conditioner (AC) mode A, turn-off-AC mode B, turn-on-light mode C, turn-off-light mode D, etc. The difference of occupants from different regions or countries can be represented in the aspect of building usage behavior.

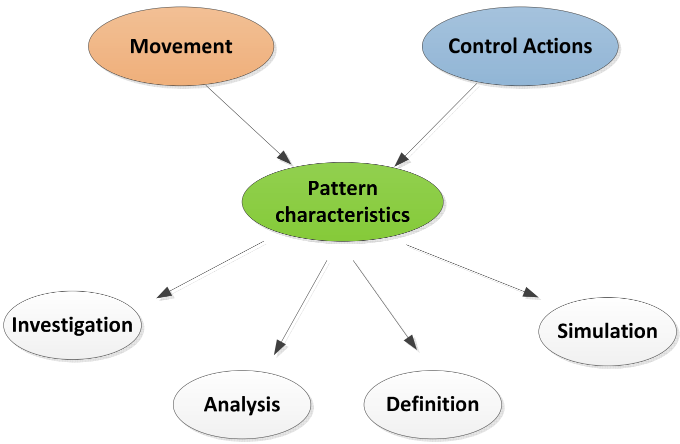


Figure 2-18.Framework of the action-based model.

With the pattern characteristics, we can quantify occupant behaviors in investigation, analysis, definition and simulation. Figure 2-18 shows the framework of the action-based model. Compared to other models of occupant behavior, the action based model has many advantages:

It provides a uniformly defined formulation of occupant behaviors (movement and control actions), which is easy to understand, use, and extend;

1) all model parameters are physical, explicit, and finite, handling the time-related, environment-related, and random characteristics of occupant behaviors;
2) both the Markov process of occupant movement and the description of occupant control actions are very easy to implement in dynamic simulations;
3) an individual model of occupant behaviors is provided, which can represent the difference between occupants and leads to an approach from an individual scale to an overall scale for building energy analysis;
4) the user interface style of all kinds of devices can be regarded as an independent factor that impacts occupant behaviors and building performance. The constraints of device user interfaces to occupant behaviors (control rights, operability) can thus be analyzed in a simulation.

Data collection

The inputs of the movement model, which could be collected or calibrated by measurement or questionnaire surveys, include:

1) Building typology as the number of spaces,
2) Occupant information such as the number of occupants for each internal space and the accessible spaces for each occupant,
3) Time step (5min, 10min, etc.) and initial location of occupants,
4) Movement parameters such as events and related statistical indices, and movement patterns for each occupant.

The investigation of the above information is similar to that of the traditional method named "fixed schedule" (or fixed profile). Some additional information like the average morning arrival time, the average nightly departure time, the time proportion, and the mean sojourn time staying in each zone, needs to be provided. If necessary, the inputs can be simpler based on the need of the real problem. For example, in some cases only the transition from the outside to the inside of a building is significant while the movement within the indoor spaces can be ignored.

The input of each control action model, which can be collected or calibrated by measurements or questionnaire surveys, includes three parts:

Pattern: choose a suitable pattern representing occupant behavior;

2) System status: a set of parameters to describe the situation at every moment, the input of control action model, including:

a) device state: the operation state of device (before executing any control action);
b) zone occupancy: location of occupant, occupancy status (on arrival or at departure or during occupancy);
c) indoor environment conditions: temperature, humidity, luminance, etc.;
d) outdoor environment conditions: temperature, humidity, luminance, rain, wind speed, solar radiation density, etc.;
e) other devices' states (before any action takes place) and state changes (after an action if it takes place)

3) Behavioral characteristics: the numerical characteristics of a control action, which are fixed at every moment and the configuration parameters of control action model including:

a) time: i.e. when the action takes place;
b) environmental conditions: indoor temperature, outdoor temperature, etc.;
c) statistical parameters: frequency and average duration of action, etc.;

Model development

Occupant movement occurs in the spaces inside and outside a building. It can be defined by the change of occupant location. Here, the location of the occupant refers to the space the occupant is in. Firstly, the scenario of single occupant movement is investigated. Secondly, the single-occupant model is extended to multi-occupant scenarios.

$\text{movement} = F(\text{location, movement characteristics})$ (1)

Consider a building with n zones, where a zone (indexed by 1,2,…,n) is an internal space in the building, and the outside of the building is regarded as a specific space (indexed by 0). Assume an occupant moves within all the spaces inside and outside of a building. The building spaces can be regarded as a topology network (closed graph) with $n + 1$ nodes, where a node is a space. The location of the occupant is then expressed by the index of nodes.

The occupant movement from any node to the next can be determined by the following matrix of transition probabilities (denoted by the P matrix in the sequel):

$$P = (p_{ij})_{(n+1)\times(n+1)} = \begin{pmatrix} p_{00} & p_{01} & \cdots & p_{0n} \\ p_{10} & p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n0} & p_{n1} & \cdots & p_{nn} \end{pmatrix} \tag{2}$$

The fixed value p_{ij} represents the probability that the occupant will next make a transition into space j from space i. If the previous location of the occupant and the transition probabilities held in the P matrix are known, the current location of the occupant can be determined by a random simulation.

Here, the following assumptions have been made: (i) the location of the occupant due to movement has a Markov property; (ii) any location change of the occupant due to movement can be finished in one time step.

An event mechanism is proposed to represent the movement occurring in certain periods of time; for example, going to the office in the morning and leaving in the evening. In addition, the event mechanism is used to treat the relevance of the movements of occupants (e.g. a joint movement such as attending a meeting).

An event in the model is an object representing the occupant movement for a specific location change. Each event has a valid period (with a start and an end time) during which it takes place. A range of actions can affect the occupants; however it only influences specific occupants. Thus, each occupant can be specified with different events for his own movement pattern. The event drives occupant movement through the P matrix exactly by specifying the corresponding elements in the P matrix during its valid period. The probability elements associated with the event can be determined from some statistical indicators of the event. Each event also has a priority that determines the order of the event taking effect on the P matrix in case the valid periods of events have intersections, and these events have common elements in the P matrix. In this situation, the elements of the P matrix would be specified with the event with highest priority.

In summary, an event object usually has six attributes: starting time, ending time, locations (from one space to another), participants (taking part in the event), statistical indicators (driving the movement of participants), and priority (to resolve conflicts).

The key issue of the movement model is to determine the transition probabilities in the P matrix. Since the probabilities in the model are event-dependent, it has greatly reduced the complexity in the time dimension compared to the pre-existing models. However, it still seems difficult to directly specify all the entries of the P matrix due to P's high order (corresponding to the number of spaces), especially in multi-zone scenarios.

An important feature of the model is that a simplified method is found to solve this problem. The P matrix can be specified by some statistical indicators defined for events, which capture the specific statistical characteristics of occupant movement and have explicit understandable meanings. The related indicators in occupant movement are the time of day, duration of stay, and time proportion of day. The mathematical relationship between event indicators and transition probabilities are established. Accordingly, the transition probabilities can be calculated from the corresponding event indicators. This method greatly reduces the number of inputs of the movement model.

A set of events can be made in chronological order to represent the movement process of an occupant in a building. However, a compromise should be made to limit the number of events in order to reduce model complexity while capturing the major changes in the occupant movement process.

Using a white-collar office worker as an example, a typical movement pattern in an office building includes the events: go to the office, eat lunch, finish work, attend a meeting, and a random walk; while a typical movement pattern in a residential building includes the events: wake-up, go to the office, return home, eat dinner, go to bed, and a random walk. In contrast with office building, the movement model for residential building would provide not only the location of occupant but also the active state (awake or asleep) of occupant.

A movement pattern involving major events and characteristic parameters can be easily obtained through measurements or questionnaire surveys. A database of typical movement patterns can be established to apply in an engineering analysis.

The above discussion focuses on the single-occupant scenario. However, it is actually easy to extend the model to multi-occupant scenarios. Only two assumptions are needed: (i) the movements of each occupant are independent, thus each occupant has his own transition probability matrix; (ii) occupants are allowed to participate in the same event (i.e. movements of these occupants are driven by the same event). In this way, both the independence and interactivity between the movements of occupants are considered. In the model, events for typical movement patterns are first defined, then the set of events representing an occupant movement pattern are specified for each occupant while some events can be shared by different occupants.

The outputs of the movement model include the time series of:

a) The location of each occupant
b) The occupancy of each zone (occupied status, number of occupants).

Since the simulation of the occupant movement process uses a small time step, the outputs should be converted into hourly values in building energy simulations.

<u>Control action model</u>

Control actions are used to describe the interactions between occupants and building devices (windows, lights, air conditioners, etc.). These actions can be defined by the operation state change of device objects, and further expressed by a unified function form with the input of physical parameters. Firstly, the single occupant scenario is investigated. Secondly, the single-occupant model is extended to multi-occupant scenarios.

Consider an occupant staying in a room who can fully control all devices including windows, air-conditioning (AC), lights, curtains (or blinds), computer, etc.

In this model, a control action is defined by the operation state change of a device. Here are three points: (i) each control action is connected to a specific device; (ii) a device's operation state (denoted by state in the sequel) refers to the device state (on or off, open or closed, and the status of additional control variables like the set point and fan speed of AC) which are usually directly operated by an occupant via the human-machine interface (HMI) of the device; the number of states a device has depends on the complexity of its HMI and can be simplified for actual needs; (iii) any device state change leads to an (independent) control action; a device with n states corresponds to P_2^n control actions where $P_2^n = n(n-1)$.Accordingly, three steps are needed to apply the defined method of control action: (1) choose a device; (2) select the states of the device; (3) define the related control actions. Take the light for example. The light has only two operation states (usually)—on and off. Two related control actions can be defined: “turn on light” (i.e. the state change from off to on) and “turn off light” (i.e. the state change from on to off).

When quantitatively modeling occupant control actions, it is of interest to predict whether an action has taken place given a set of independent variables. Thus, the model to describe occupant control actions should be expressed as a function of which the output is a control action, and the input is a set of physical factors that can be calculated, investigated, and compared.

As occupant behaviors are random, uncertain, and variable, so are control actions. It is difficult to make a comprehensive description of them. In practice, we can use some numerical characteristics to reflect their main features. The numerical characteristics are generally related to time of day (or week), environment conditions, or statistical characteristics of random variables. They can also be regarded as behavioral characteristics in daily life. The function body, F, is just an illustration of how the numerical characteristics shape occupant behavior. In this model, a unified function form is proposed to describe every control action.

$$\text{Control action} = F(\text{system status}, \text{behavioral characteristics}) \quad (3)$$

The control action model can be illustrated by Figure 2-19. With the fixed behavioral characteristics as controlling parameters, the model determines whether the occupant would perform a control action on a device at every moment according to the system status.

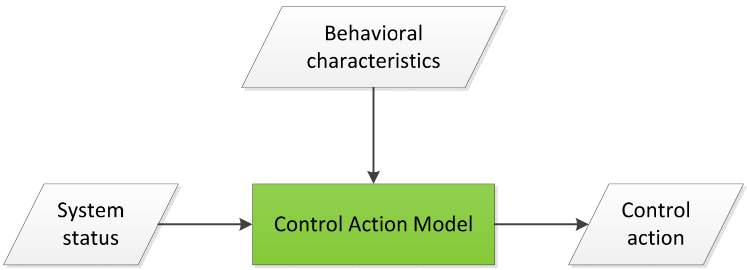


Figure 2-19. Schematic of control action model

Control actions for different kinds of devices (open window/close window, turn lights on/turn lights off, etc.) can be described based on the unified form. The specific form, inputs, and configurations of each control action model depend on the type of device and the type of control action.

From literature research and our everyday experience, there are three basic forms for actual control actions corresponding to the above three types of numerical behavioral characteristics: time-related actions, environment-related actions, and random actions.

It can be observed that many actions usually take place at a certain moment, e.g. opening a window upon arrival (entering a room) or closing window at departure (leaving a room) concerning the occupancy status of the occupant themselves; or taking place during a certain period or time of day concerning the schedule of daily life, e.g. cooking appliances used before meals. These are time-related actions.

The time factor is used as the numerical characteristic to describe the actions. This kind of time-triggered action can be expressed by a simple rule in the form of an *if*-statement. An example of a window opening pattern description on arrival is as follows:

if on arrival the light is off, *then* turn on the light. (*else* no action take place.)

Boolean variables are used to replace the judgment following ‘if’ to check the momentary condition and assignment, following ‘then’ to determine whether an action has taken place in the if-statement for computer programming.

The time-triggered action would be repeated periodically in the whole year dynamic simulation (daily, weekly, etc.).

The control actions related to the use of windows, air conditioners, blinds, lights, etc. are clearly influenced by the indoor and outdoor environmental conditions and called environment-related actions. These actions are usually driven by some environmental stimuli that depart from the comfort zone based on the transient demand of people. Through actions, people are able to suit the indoor environment to satisfy their thermal, visual, acoustic, olfactory comfort, and indoor air quality.

The key numerical characteristic for actions of this kind is the “threshold” value. When indoor or outdoor environmental conditions exceed the threshold, an action would take place to adjust the (indoor) environment.

The kind of environment-triggered action can be also expressed by a simple rule. An example of a pattern description for opening windows when the indoor temperature is higher than 30℃ (without air conditioning) and closing windows when the indoor temperature is lower than 16℃ is as follows:

if indoor t > 30℃, window is closed, and	*if* indoor t < 16℃, window is open, and

The environment-triggered action would be repeated as the environmental conditions change in the whole year dynamic simulation.

Another kind of action is simply regarded as purely random behavior without any significant trigger of time of day or environmental condition, probably because the actions happen less frequently. For example, while watching TV during the weekends, infrequently (once every few weeks) the times to start and finishing watching television may start anytime (turn on TV) and end any time (turn off TV). The numerical characteristics for those actions used in this model are frequency and average duration.

These kinds of random actions can be directly described by a two-state transition probability matrix where the frequency and average duration are used to determine the matrix entries.

Control actions usually express a compound pattern of basic forms, i.e. an action can be driven by time, environmental conditions, and random factors. According to the three basic forms, control actions can be classified into two groups: i) with trigger conditions, ii) without trigger conditions (fully random).

This kind of action, e.g. opening a window, is evidently triggered by time and (or) environmental factors, and is also influenced by other uncertain factors. To describe both the features of action triggers and randomness of this kind, a practical form can be used as illustrated in Figure 2-20.

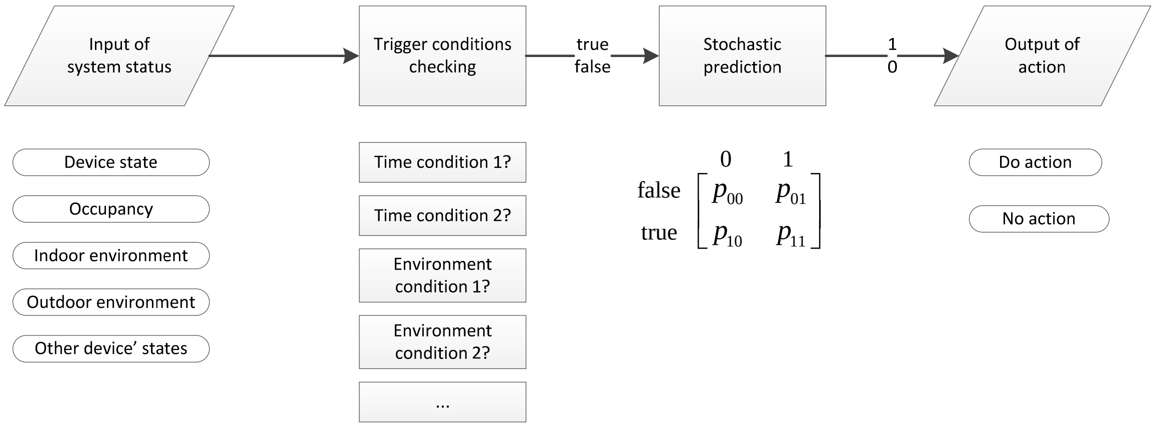


Figure 2-20. Schematic diagram of actions with trigger conditions

Compared to the basic trigger forms, an additional stochastic link to represent the randomness of action led by other uncertain factors is added to the practical form. The form first checks if the trigger conditions are satisfied, then predicts if the action would take place with the transition probability matrix,(P), where p_{01} represents the probability that the action will take place even if the trigger conditions are not satisfied (false), p_{10} represents the probability that the action does not take place even if the trigger conditions are satisfied (true),

$$p_{00}=1-p_{01},\ p_{11}=1-p_{10}. \quad (4)$$

$$P = \begin{array}{c c} & \begin{array}{cc} 0 & 1 \end{array} \\ \begin{array}{c} \text{false} \\ \text{true} \end{array} & \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \end{array} \quad (5)$$

In the deterministic case,

$$p_{01}=p_{10}=0,\ p_{00}=p_{11}=1. \quad (6)$$

Actions without trigger conditions (See Figure 2-21) are fully influenced by uncertain factors, e.g. watching TV. The actions can be directly described by a two-state transition probability matrix, (P), where 0 represents off-state while 1 represents on-state,

$p_{00}+p_{01}=1,\ p_{10}+p_{11}=1.$ (7)

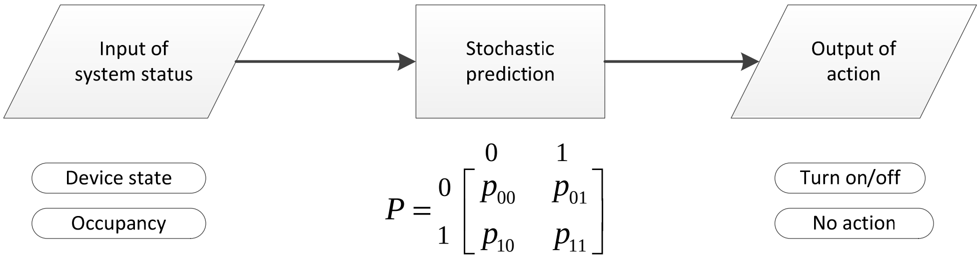


Figure 2-21: Schematic diagram of action without trigger condition

Given the use frequency, α (e.g. once a week, which would be shown as 1/7), and the average duration per time β (measured in the number of time steps, e.g. 1h per time, i.e. 12 given a time step of 5 minutes), the entries of the P matrix can be determined by the following equations:

$$p_{00} = 1 - \frac{\alpha}{\beta(1-\alpha)} \quad p_{11} = 1 - \frac{1}{\beta} \qquad (8)$$

Note that both α and β are dimensionless numbers.

There are two common rules for both kinds of actions: (i) any action happens only when the occupant is in the room (except when using remote controls, which is rare in practice); (ii) the off-state results in an opening/turning-on action, while on-state results in closing/turning-off action.

Although occupant behaviors show great variation, the hypothesis that occupant behaviors follow some specific rules is widely used and verified in the humanities. On this basis, behaviors are abstracted to several ‘behavioral patterns’ used to represent the main recognizable feature of individuals’ behaviors. In spite of this idealization, the approach is simple, easy, and effective for understanding occupant behavior and utilizing it in practice. Inspired by this approach, ‘patterns’ to describe the control actions are used.

Patterns can be defined in the above practical form of control actions. Using patterns, we can discuss the following cases when describing control actions.

If a control action is triggered by multiple factors, to form trigger conditions it should consider the interrelation of factors in an order of parallel, combination, and priority, involving: (i) each factor makes up of one trigger condition (parallel, ‘or’); (ii) several factors make up of one trigger condition (combined, ‘and’); (iii) some of the factors have priority while others have not.

In this case, we need patterns to finalize the trigger conditions and distinguish behavior habits of different individuals.

If two or more control actions can adjust the same environmental status, it should consider the interrelation of these actions in the order of parallel, combination, exclusion, and priority actions involving (i) no interaction, where each action takes place independently, or one would not influence another (parallel); (ii) all the actions take place in the meanwhile, or one would lead to another (combined); (iii) one action takes place while others do not (exclusive); (iv) some of the actions have priority while others have not.

In this case, patterns are required to finalize the order of actions and distinguish behavior habits of different individuals.

In practice, we predefine several (i.e. 3~5) typical action patterns which can be extended into future work. All the patterns should be verified by real daily life use habits.

A set of action patterns mounted on a device (two for light) makes up a complete description of usage behaviors of the device. Note that an opening/turning-on action and a closing/turning-off action are two different things due to different trigger conditions.

Nevertheless, occupant behaviors are not static but have a long-term evolution. Using static patterns to describe behaviors is suitable in the short term due to the stability of occupant behaviors. However, patterns from a different phase can be used for the study of behavior change in the long-term through comparison and analysis.

The constraints from device operability or control limit can be represented directly in the action-based model in a probabilistic way: (i) for actions with trigger conditions, adjust the values of p_{10} and p_{11} (a higher p_{10} value represents higher operation difficulty); (ii) actions without trigger conditions, adjust the values of α and β (a lower level of difficulty).

To deal with multi-occupant scenarios, two assumptions are made: (i) the control action of each occupant is independent, thus each occupant has his own behavioral pattern for any control action; (ii) occupants have different 'weights' (preference or sensitivity) for different control device actions, e.g. some people are more sensitive to their thermal environment and they will adjust windows or air-conditioners more frequently, while others are more sensitive to their visual environment and they will adjust blinds or lights more frequently. Of course, more investigations should be carried out to verify this assumption and to obtain the 'weights' of occupants. At present, we assume the weights are equal for all control actions of occupants.

The output of each control action model is the state change of a device at every moment (return a pair of states to represent the change 'from state1 to state2' if the action happens. Otherwise, return 'from state1 to state1', i.e. no action takes place and the device state will not change).

The individual-based model provides an integral description of occupant behaviors on all devices and also provides a simple approach to study the multi-occupant scenarios and explain what would happen if many people stay in one room or in one building.

Implementation

Implementation of the occupant movement model

The proposed model has a two-level hierarchical structure consisting of a basic module named "movement process" and a high-level module named "events" as shown in Figure 2-22. The "movement process" module essentially implements a simulation of the Markov chain process and generates the locations of occupants step by step, which can then be used to calculate the occupancy for each zone in a building. The "events" module is used to specify the transition probabilities of a Markov chain in specific periods of time, in order to represent the occurrences associated with time.

Figure 2-23 shows how the algorithm works: (0) initialize the locations of all occupants at time step 0.For each time step, (1) update the set of active events at present according to the input set of events and their valid periods. (2) Update the P matrices of all occupants according to the set of active events, the corresponding elements of P matrix are specified by the active events, and note that the sum of elements in each row of P matrix should equal 1. (3) For each occupant, determine the current state of the occupant according to the previous state and the updated P matrix. The MATLAB function rand generates a pseudorandom value drawn from the standard uniform distribution. The same is to be repeated for all occupants. (4) Calculate the current occupancy for all zones according to the locations of all occupants. By repeating this procedure step by step, the time series of the location of each occupant and the occupancy of each zone in the building can be generated.

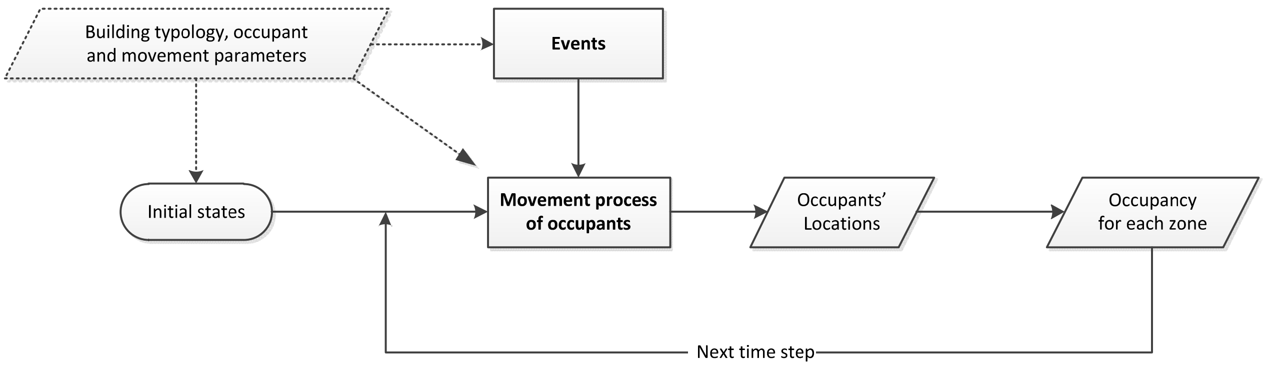


Figure 2-22. Schematic of the movement model

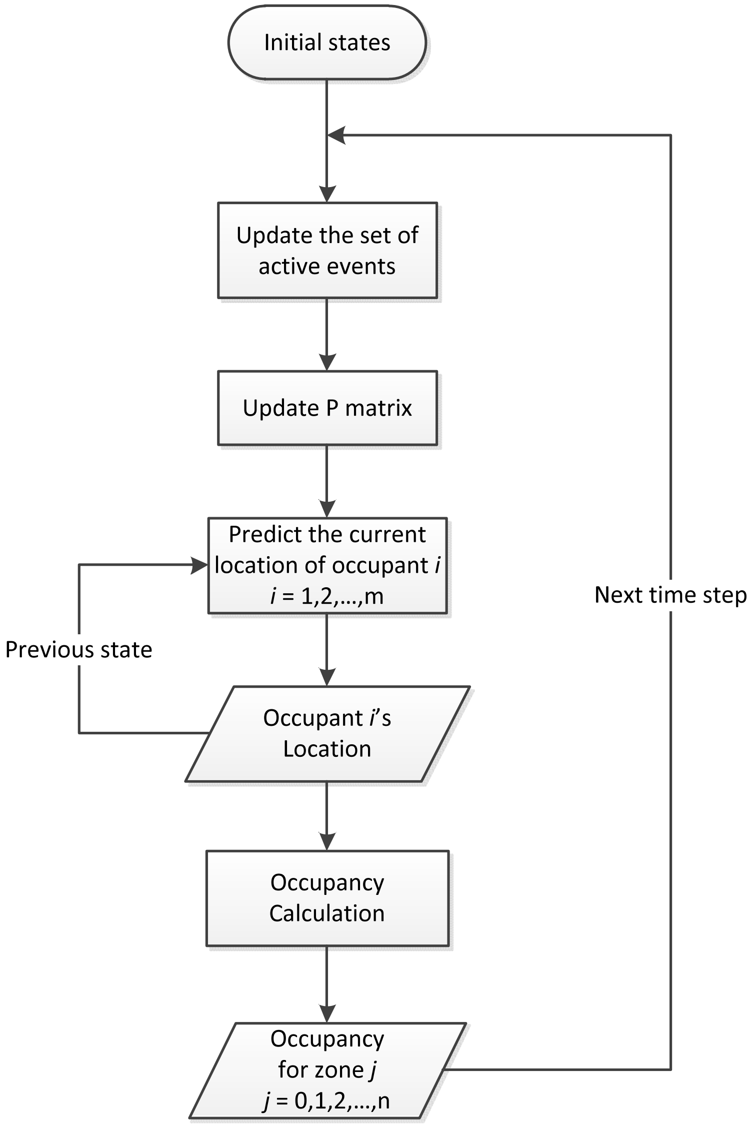


Figure 2-23. Algorithm workflow

Implementation of control action models

Given a pattern for a control action on a device with numerical characteristics, the implementation of the control action is illustrated in Figure 2-24.

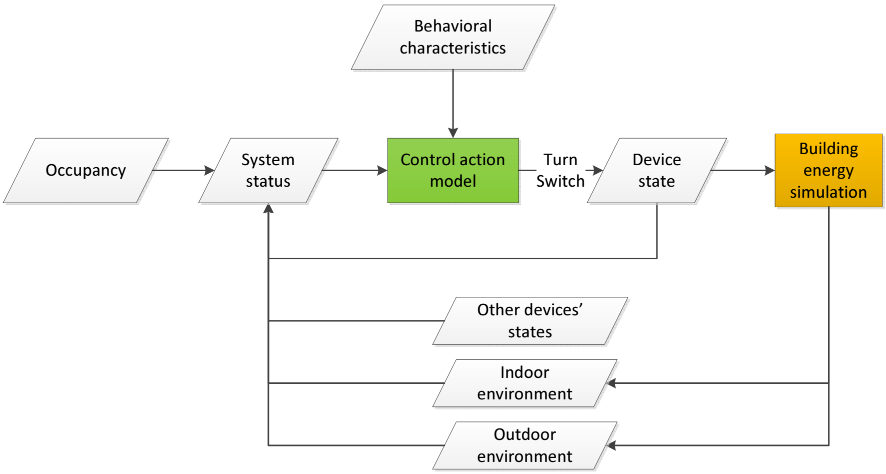


Figure 2-24.Schematic of each control action

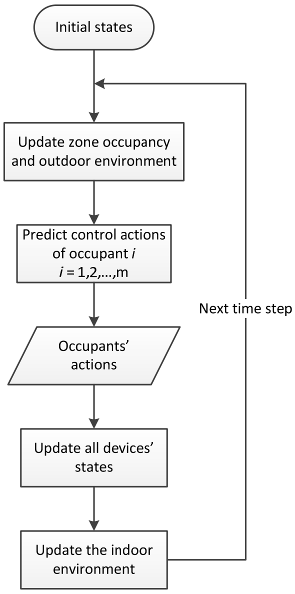


Figure 2-25.Workflow of control action models

An integral scheme is necessary to deal with the interrelationship of control actions, representing how an occupant controls everything in a room. Figure 2-25 shows how the scheme works: (0) initialize the system status (zone occupancy, all devices' states, indoor environment, outdoor environment) at time step 0; for each time step, (1) update zone occupancy and outdoor environment; (2) for each occupant, predict all his control actions on devices according to the system status; (3) update all devices' states; (4) update the indoor environment. By repeating this procedure step by step, the time series of the occupant control actions and the states of devices in the building can thus be generated.

The occupant behavior model made up of movement and control actions can be easily integrated with building energy simulation tools. Figure 2-26 illustrates the integral workflow: (0) run the module of occupant movement process and output the zone occupancy data (pre-process); for each time step, (1) run the control action module, predict occupants' control actions on devices according to the system status, and update all devices' states; (2) run the module of building thermal process and update the indoor environment. By repeating this procedure step by step, the time series of the occupant actions and the indoor environment in the building can thus be generated.

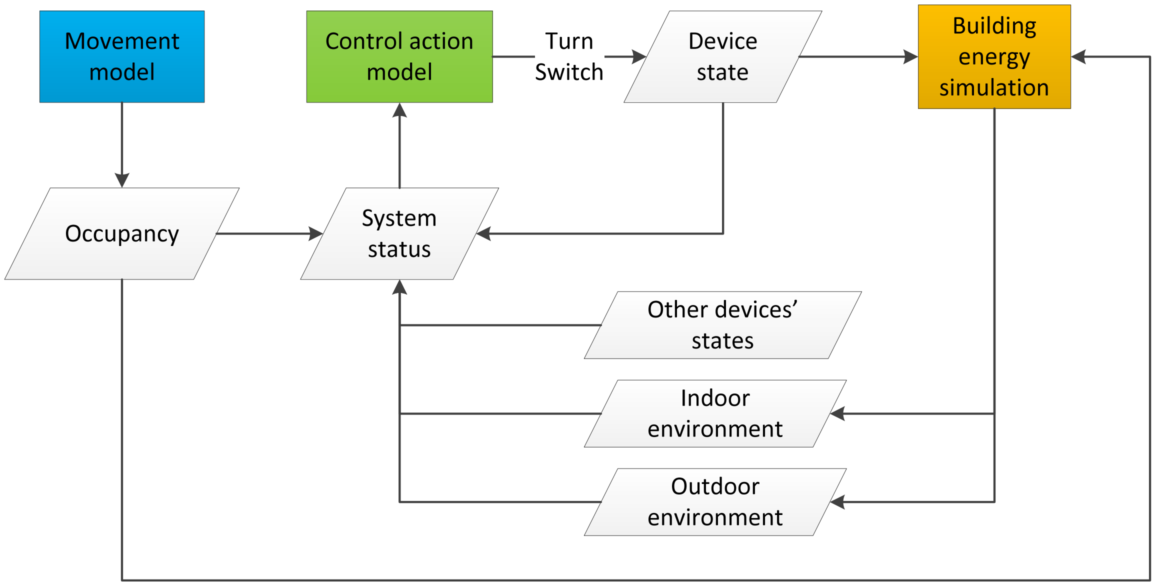


Figure 2-26. Integral workflow of occupant behavior model and existing building simulation tool.

Based on the integral framework, the impact of occupant behaviors on building system performance can be quantitatively evaluated.

Validation

Movement model

Due to the random simulation, the criteria for model validation should be whether the simulated movement curve of the occupant (i.e. the curve of occupant location) is "equal" to the actual statistical movement curve. The curve depends on which statistical indicators are chosen.

For the movement model, the inputs are already the statistical indicators (i.e. events with statistical attributes) representing the characteristics of actual movement processes that the model tries to achieve. Thus, these inputs should be chosen as the statistical variables in the validation criteria. The validation criteria would be satisfied if (and only if) the outputs of the model—the simulated movement curve—can keep the same statistical indices involved in the inputs.

In fact, our model is based on the mathematical relationships between event attributes and transition probabilities in the P matrix. Thus, if the random simulation technique and the execution codes are correct, the statistical indices of inputs would be naturally kept in the outputs .This has been verified in the above example.

In addition, the zone occupancy generated by our model keeps the time and space relevance in a way. To further approximate the actual movement curve, more statistical indices can be proposed if necessary.

Control model

The validation criteria of control action model are similar to movement model. For the control action model, the inputs are already the statistical indicators .i.e. the F-pattern and behavioral characteristics represent the characteristics of actual action process that the model tries to achieve. Thus, if the random simulation technique and the execution codes are correct, the statistical indices of inputs would be kept naturally in the outputs.

More generally, the validation criteria of an occupant behavior model should include: (i) how much the model represents the real process of occupant behavior (suitability); (ii) how much the model meets the requirements of practical application (practicability). Compared to other existing models, our model is a direct quantitative description of occupant behavior in a real sense, which has a few significant advantages (easy to understand, simulate, and investigate) and shows its great potential. Of course it needs more investigation and validation to check the capability of this model, like the example of air-conditioning behavior from a Chinese family.

Summary

The occupant movement model provides a new approach for building occupancy simulation and the use of building devices. Compared to the "fixed schedule" method, this model considers the randomness that results in the uneven and non-synchronous change of occupancy in space and time. Compared to other random process methods, this model keeps the time and space relevance of occupancy and is more practical due to the great reduction of inputs. This model can provide a relatively realistic and equitable condition for the evaluation of HVAC systems, especially for decentralized systems [150]. The model can provide a more realistic and equitable condition of occupant factors for the evaluation of building system design, especially for natural ventilation, daylighting, and decentralized HVAC systems [150]. It is a direct description of occupant behavior in a real sense. Using patterns, the interrelationship of multiple driving factors, the interrelationship of multiple control actions, and the quantification of uncertainty are solved. In such a way, the model is simple to understand and simulate. Through the model, occupant behaviors are easy to define and investigate.

Furthermore, via the patterns and behavioral characteristics as occupant behavior descriptions, the action-based model establishes a clear link (see Figure 2-27) between building engineering and social, economic, psychological, physiological, and human-factor engineering sciences. Although human behavior is usually in the research fields of the latter and is explained as a deep mechanism, the pattern description is first needed and the building simulation technique can evaluate the influence degree of occupant behavior patterns on building system performance, which would lead the latter to become the focus of the most important behavior pattern.

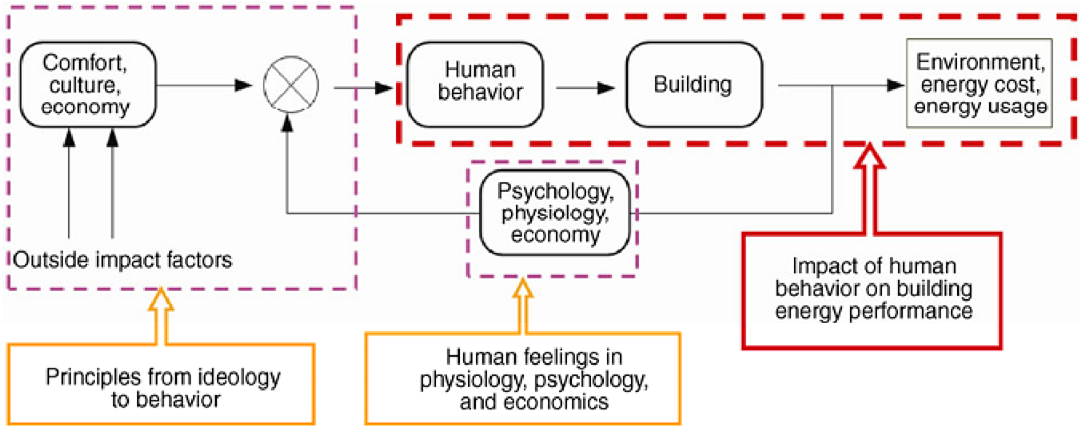


Figure 2-27. Relationship between different research fields.

5. Examples of occupant behavior modeling

In the following, several examples are given for occupant behavioral modeling and the implementation into computer simulation. Each example is introduced and evaluated.

5.1 **Occupancy**

Markov Models of Occupancy

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Occupancy office	Probabilistic	Markov, Poisson models	Yes/ No	Yes/ No	[60],[64],[89],[93]
Occupancy dwelling	Probabilistic	Markov model	No	Yes	[74]
Occupancy dwelling	Probabilistic	Markov model	No	Yes	[97]
Occupancy dwelling	Probabilistic	Markov model Monte Carlo	No	No	

Stochastic models capable of simulating occupancy patterns for office buildings have been presented in various investigations; see e.g. Ref. [60], [64], [89],[93].

The occupancy model of the Light switch model (Ref. [60]) is a Markov model consisting of three occupancy probability functions as a function of time of day; five minute bins have been used. The three functions for arrival, temporary absence, and departure have been derived from observed data. Ref. [89] proposes a Poisson process model with two different exponential distributions to simulate occupancy and vacancy: the occupancy behavior is a random process. The vacancy intervals were found to be distributed exponentially, but the occupancy intervals were not. Ref. [64] considers occupancy as a Markov chain interrupted by occasional periods of long absence. This Markov model has been calibrated with data measured in twenty zones of an office building over a period of two years. The model is capable of realistically reproducing the main properties of occupancy such as times of arrival, periods of intermediate absence and presence, times of departure, as well as long periods of absence.

The remaining part of this section will deal with occupancy modeling in domestic buildings. In recent literature, some Markov-Chain Monte Carlo (MCMC) models have been developed for simulating occupancy in dwellings; see e.g. Refs. [74][97]. The stochastically-generated occupancy patterns in Ref. [74] have been used to predict the proportion of dwellings with at least one non-sleeping inhabitant, see Figure 2-28. This figure shows very good agreement between time-use data (points) and the results based on the stochastic model (solid line).

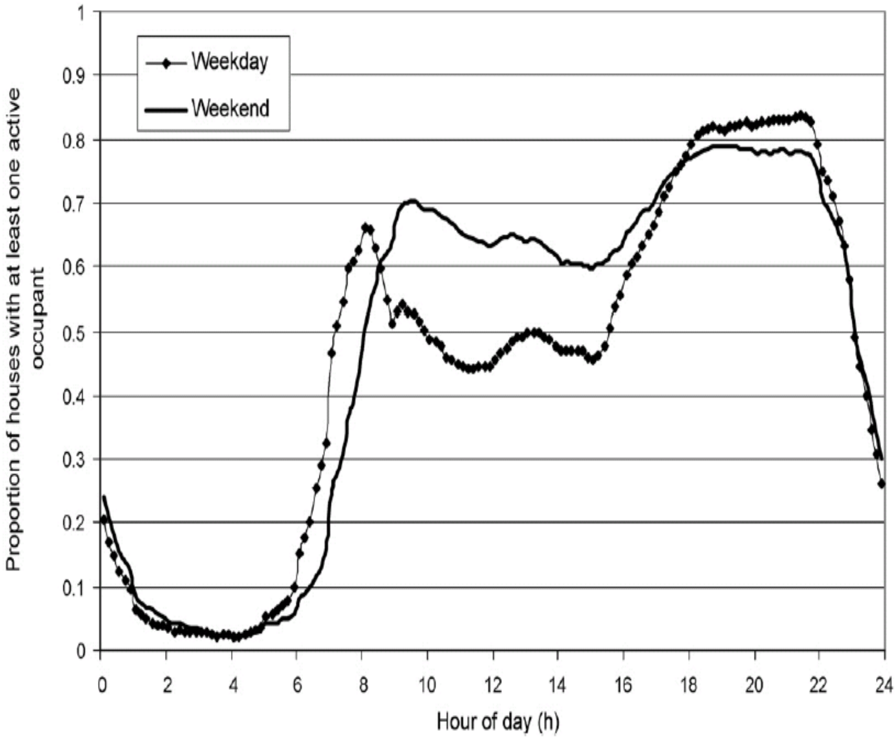


Figure 2-28: Aggregated active occupancy for all survey participants by weekday and weekend days taken from Ref.[74].

Analogous to developments in the recent literature ([74], [97]),a MCMC model has been developed for simulating residential occupancy and on-demand space heating (i.e. during occupancy). This MCMC model can stochastically generate occupancy in dwellings over time as described below.

For the simulation of occupancy, we have used time-use data collected by the "The Netherlands Institute for Social Research", see Ref.[91]. Based on this data, we have selected three types of households:
Two elderly families

1) Two working families
2) A family with two adults and two children.

Respondents of the time-use survey indicated the number of people in their household. Only one person filled in the survey per household. Therefore correlations between occupancy of different people in the same household cannot be derived from the time-use data and are not taken into account in the model. The different types of time-use (activities) are translated into occupancy for specific rooms in the dwelling. In this translation of time-use to occupancy, we distinguished between six different occupancy types:

1) bedroom
2) bathroom
3) kitchen

4) living room
5) other
6) not at home

For these six states, 6x6 transition matrices have been derived for the cumulative transition probabilities describing the transition from one state to another during a time period, see e.g. Figure 2-29.

BE-BE	BE-BA	BE-KI	BE-LR	BE-OT	BE-NH
BA-BE	BA-BA	BA-KI	BA-LR	BA-OT	BA-NH
KI-BE	KI-BA	KI-KI	KI-LR	KI-OT	KI-NH
LR-BE	LR-BA	LR-KI	LR-LR	LR-OT	LR-NH
OT-BE	OT-BA	OT-KI	OT-LR	OT-OT	OT-NH
NH-BE	NH-BA	NH-KI	NH-LR	NH-OT	NH-NH

Figure 2-29: Cumulative transition probability matrix. The codes BE, BA, KI, LR, OT, NH, correspond with bedroom, bathroom, kitchen, living room, other, and not at home.

For these six states, 6x6 transition matrices have been derived for the cumulative transition probabilities describing the transition from one state to the other during a time period. The values of the cumulative transition probabilities have been derived from the data for 7x24x4 quarters of an hour (one week).

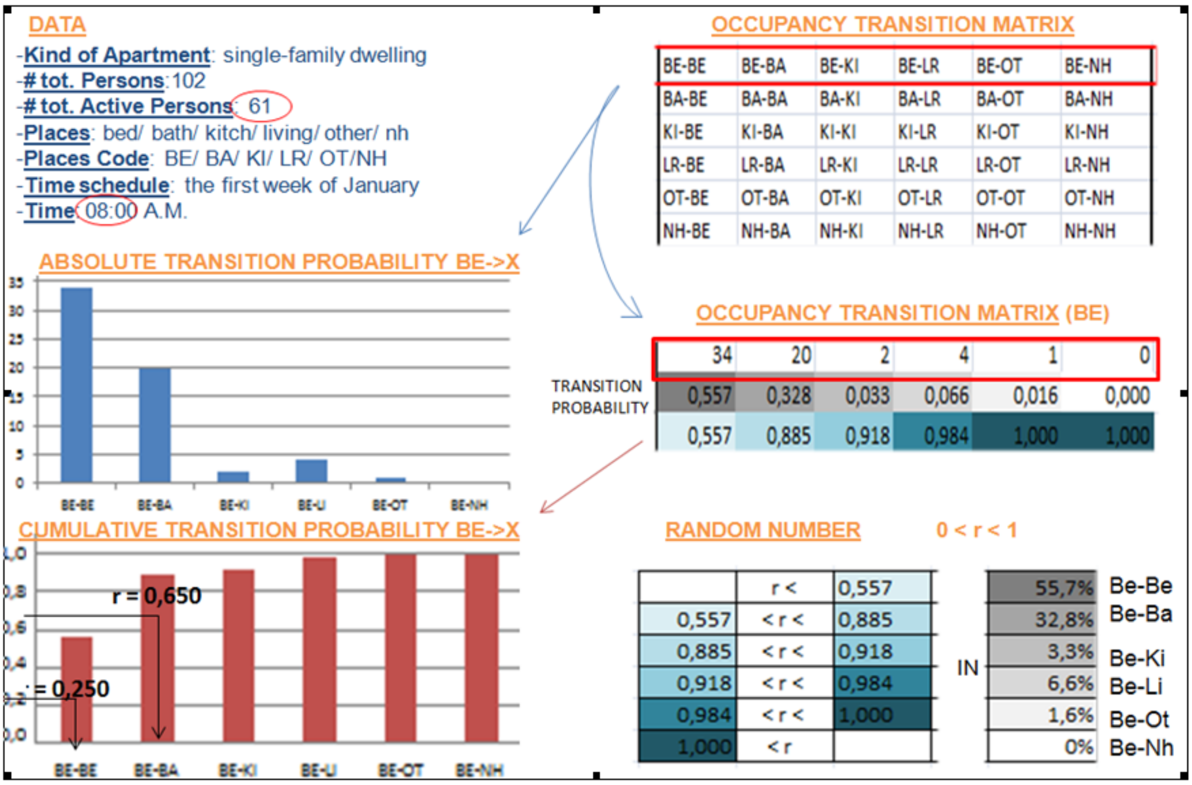


Figure 2-30: Schematic view of the Markov Chain Monte Carlo method for stochastically generating occupancy.

A schematic view of the Markov Chain Monte Carlo method is shown in Figure 2-30. The following steps are followed for each inhabitant for each time step in the simulation

the present occupancy state of each inhabitant is determined;

1) cumulative transition probabilities are calculated based on time-use data;
2) the transition probability matrix is calculated;
3) a random number between 1 and 0 is generated;
4) the new occupancy state is determined based on the old occupancy state, the random number, and the cumulative transition probabilities.

Following the above described procedure, occupancy and on-demand space heating can be simulated for a complete year. Repeating this simulation will result in a variation in the energy use for space heating. An example resulting from this MCMC approach is given in Figure 2-31.

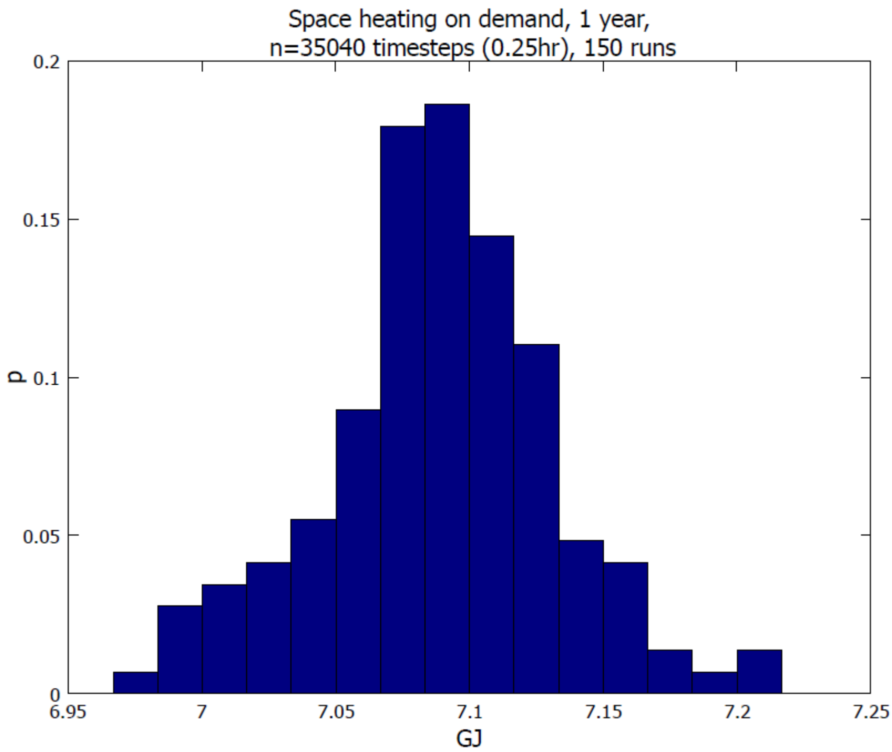


Figure 2-31: Histogram of the yearly energy use for on-demand space heating for a two working person household resulting from the Markov Chain Monte Carlo method described above.

Figure 2-31 shows the variation in yearly energy use for on-demand space heating for a two working person household. The variation in energy use is much smaller than expected from the variation in occupancy in the time-use data for two working person households.

The MCMC method for simulating occupancy also applied in the literature does not seem to be appropriate for simulating the variation in occupancy in dwellings and on-demand space heating, Refs. [64], [74], [97]. On the one hand, it is very unlikely to generate extreme occupancy patterns by applying this method (almost always present or absent). On the other hand, the transition probabilities for moving from one room to the other are based on the time-use data of many different respondents. These transition probabilities are used to generate the occupancy of an individual inhabitant in an individual dwelling. Therefore, the generated occupancy will resemble an average occupancy as contained in the time-use data.

An alternative Monte Carlo procedure for simulating the variation in occupancy and on-demand space heating is proposed as follows:

Random sampling of individual deterministic occupancy profiles of all inhabitants, derived from time-use data;

1) **Calculating the yearly energy use for space heating on demand based on these profiles.**
Repeating this simulation will result in a variation in the energy use for space heating. An example is given in Figure 2-32.

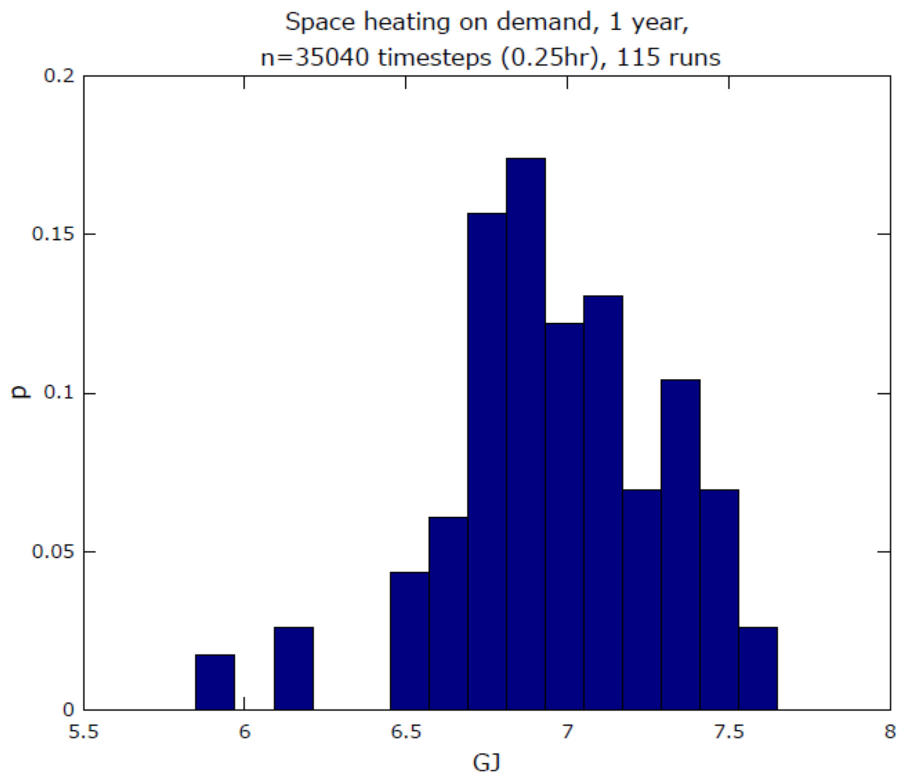


Figure 2-32: Histogram of the yearly energy us for on-demand space heating for a two working person household following from the alternative Monte Carlo procedure based on sampling the above described deterministic occupancy profiles.

Figure 2-32 shows the variation in yearly energy use for on-demand space heating for a two working person household based on the alternative Monte Carlo procedure described above. In this case, a larger and more realistic variation in energy use for on-demand space heating has been predicted.

Action Based Models of Occupancy

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Occupancy	Action based	Markov chain	Yes	Yes	

A family apartment in a residential building is used as an example to demonstrate the procedure to apply the occupant movement model to a specific type of building. This example is illustrative and the input data are taken from experience.

Inputs

2) **Determine the building topology.**
The 2D plan of the apartment building is shown in Figure 2-33. There are 4 bedrooms, 1 living room, 1 kitchen and 2 restroom, indexed from 1 to 8; the outside is indexed by 0. There are 9 spaces in total.

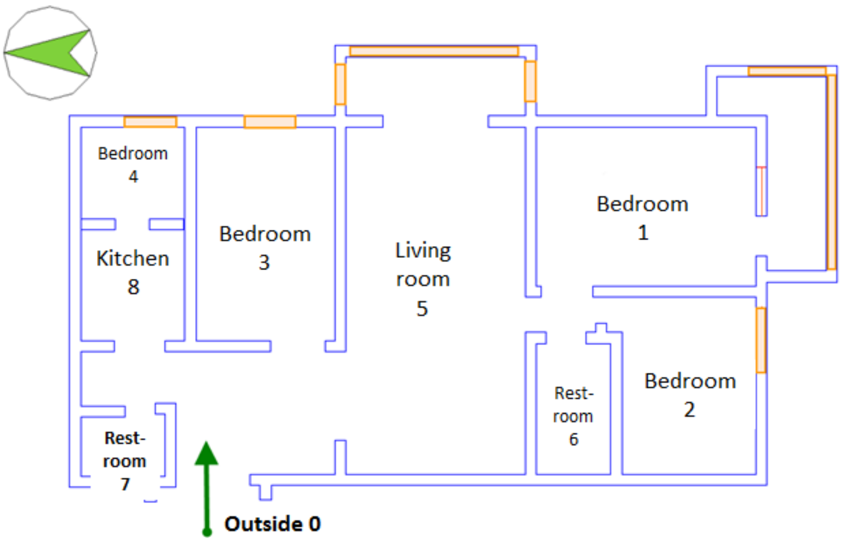


Figure 2-33.Plan of the residential building.

3) **Determine the occupant information.**
There are 5 occupants in the apartment: a couple of office workers living in the bedroom 1, a grandma (retired at home) in bedroom 2, a son (middle school student) in bedroom 3 and a nanny in bedroom 4. They move among the 9 spaces (i.e. all spaces are accessible for each occupant). The number of occupants for each bedroom is shown in Table 2-5.

Table 2-5. Number of occupants in each bedroom

Room No.	Number of occupants	Room No.	Number of occupants
Bedroom 1	2	Bedroom 2	1
Bedroom 3	1	Bedroom 4	1

1) Determine the time step and initial locations.

The time step used in the case is 5 min; an occupancy time series of one day is comprised of 288 points. All occupants are in the outside space, 0, at the initial time step.

2) Determine the movement parameters.

The daily schedule and events for the five occupants are different except that they have lunch and supper together at home. Here take the husband as example, his schedule and events in the workday are shown in Table 2-6.

Table 2-6. Schedule and events in a working day

Event	Valid period	Statistical index	Expected value	
Get up	6:30~7:30	Morning awake time	7:00	
Go to office	7:30~8:30	Morning leaving time	8:00	
Go back home	18:00~20:00	Night return time	19:00	
Go to bed	23:00~1:00	Night asleep time	0:00	
		Long-run proportion of time and mean sojourn time in each room	Proportion of time	Mean sojourn time
Walk around	17:00~7:00.	In own bedroom	0.88	24 (2 hrs)
		In other rooms	0.1	2 (10 min)
		In outside	0.02	2 (10 min)

Run simulation

Run the simulation of movement process. The simulation for a workday runs 1000 times consecutively, with different random seeds for each simulation.

Outputs

Both the locations and active state of occupants for every time step are generated. The location and active state of occupant is respectively marked by the space index (from 0 to 8) and a Boolean value (0- asleep, 1-awake). Accordingly, the hourly occupancy of the building and zone can be calculated.

1) Location of occupants

Figure 2-34 shows the generated time series of the locations and active states of the husband and grandma in one workday. As expected, the husband 1) get up in the morning, and then go to work, 2) stays outside for the daytime, 3) go back home in the evening and stays at home until going to bed. During the period of staying home, he stops in several spaces (bedroom 1, living room 5, restroom 6, bedroom 3 and outdoor) and stays in his own bedroom for most of the time. The grandma gets up later and goes to bed earlier than the husband. She stays at home during the day. However, she takes a walk outside in the morning and has a siesta after lunch (lunch is located in the living room 5).

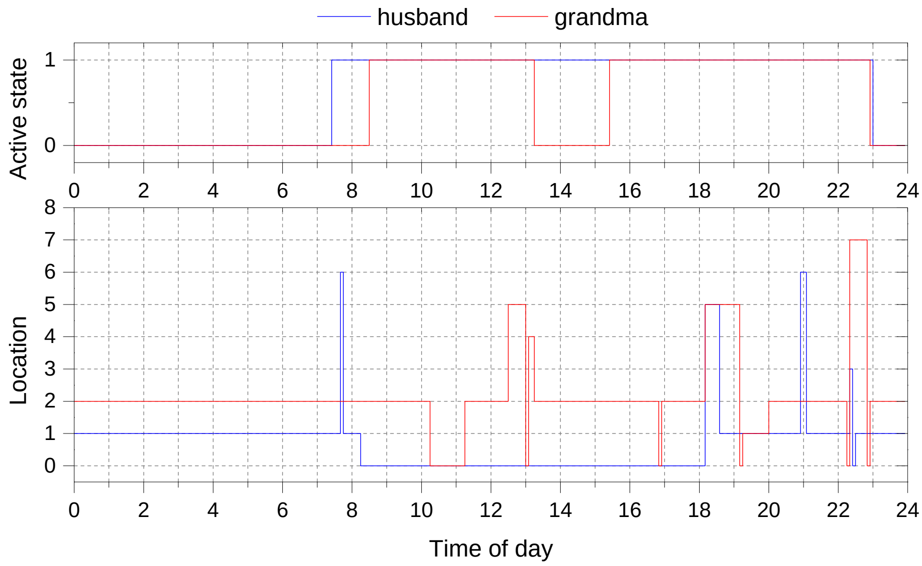
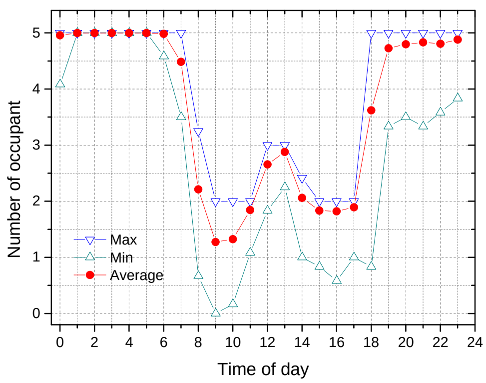


Figure 2-34.The locations and active states of husband and grandma.

4) **Occupancy of building and zone**

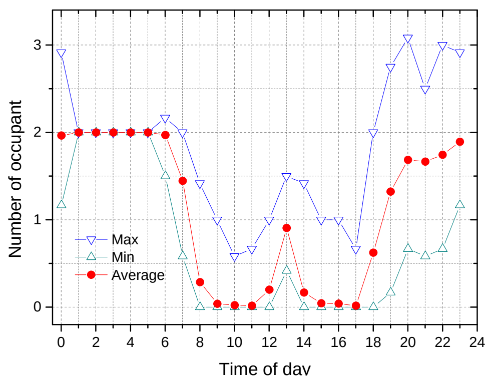
Figure 2-35 and Figure 2-36shows the change of occupant number in the whole apartment and bedroom 1 over a workday, where the hourly occupancy takes the mean of five-minute results. It can be seen that (1) the trend of “going to the office/school - working - lunch - working – getting off work” in a typical workday for the couple and son is reproduced; (2) the total building occupancy reaches a maximum or minimum gradually, rather than sharply under a fixed schedule; (3) during the period of staying home, total apartment occupancy keeps nearly conserved while varies due to the movement of occupants (to outside), which means, the relationships of stochastic occupancy in multiple zones are taken into account and make the occupancy distribution in zones is closer to the reality.

Besides, such a movement process changes for every simulation. Figure 2-37 shows the first three runs’ results of bedroom 1’s occupancy. It can be seen that the occupancy of bedroom 1 changed and differed for each day, which is understood as random in everyday life.



Hourly occupancy in the whole building

Figure 2-35. Hourly building occupancy over a



(c) Hourly occupancy in office 1

Figure 2-36. Hourly occupancy in bedroom 1 *workday* *over a workday*

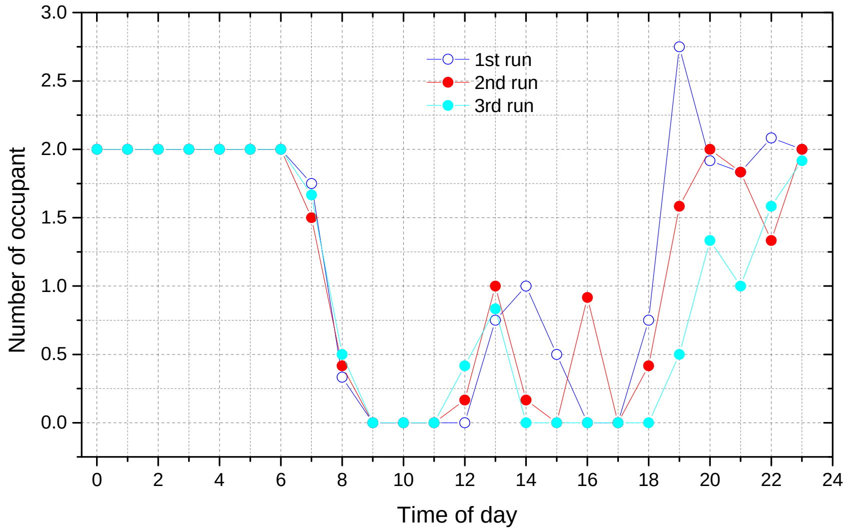


Figure 2-37.Bedroom 1's occupancy for the first three runs

In general, the stochastic occupancy over a typical workday in a residential building can be realistically produced by using the proposed model.

5.2 Heating

Average values model for heating

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Heating	Average values		Yes	Yes	

By simulating possible daily routines of occupants, a data set of heating-related behaviors was generated randomly. As heating behavior is influenced by and related to secondary behaviors such as window opening, internal heat gains, DHW use, and presence, these factors were also considered. The average values from the occupant behavior data set were input into a computer simulation to generate the HED. The same average values were input into the monthly balance method to obtain a HED to validate the HED from the building simulation. A comparison of the results is seen in Figure 2-10 above [11].

Probabilistic models for the state of AC-unit for heating

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Heating	Probabilistic	Akaike	No	No	[82]

		Information Criterion Nagelkerkes R2 Logistic regression analysis			

Ref. [82] uses the Akaike Information Criterion (AIC) and Nagelkerkes R^2-index in order to develop a multivariate regression model for the probability of AC-unit usage for heating. By consequently adding variables, which lead to a higher R^2-index and a lower AIC-value, they improved the model fit to the data from an R^2-index of 0.04 for the univariate model including outdoor temperature alone up to 0.48 for the multivariate model. The final model includes in total 19 variables related to physical parameters of the surrounding as well as individual parameters such as the preference.

Deterministic models for the set-point temperature for cooling and heating with AC-unit

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Heating	Deterministic	Linear regression analysis	No	No	[83]

Ref. [83] applied the same procedure and presents a multivariate regression model for the choice of set-point temperature for heating in wintertime.

5.3 Cooling

Probabilistic models for the state of AC-unit for cooling

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Cooling	Probabilistic	Regression analysis	No	No	[32]
Cooling	Probabilistic	Akaike Information Criterion Nagelkerkes R2 Logistic regression analysis	No	No	[82]

Ref [32] calculated the probability of switching on the AC-units as a function of mean hourly outdoor temperature.

Ref. [82] uses the Akaike Information Criterion (AIC) and Nagelkerkes R^2-index in order to develop a multivariate regression model for the probability of AC-unit usage for cooling. By consequently adding variables, which lead to a higher R^2-index and a lower AIC-value, they improved the model fit to the data from an R^2-index of 0.04 for the univariate model including outdoor temperature alone up to 0.48 for the multivariate model.

Deterministic models for the set-point temperature for cooling and heating with AC-unit

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Cooling	Deterministic	Linear regression analysis	No	No	[83]

Ref. [83] applied the same procedure and presents a multivariate regression model for the choice of set-point temperature for cooling in summertime.

Probabilistic models for the state transition of AC-units

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	References
AC-usage	Probabilistic	Markov model	No	No	[48]

Ref. [90] applied the Markov model to relate AC usage to different time intervals of the day based on the data from eight observed dwellings in Fukuoka, Japan. Ref. [63] presented a logit line for cooling in mixed mode office buildings, but not for residential buildings.

Action based models for the state transition of AC-units

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Cooling	Action based	Markov chain	Yes	Yes	

Air conditioning control behavior is used as an example to demonstrate how to apply the procedure to the present control action model for a specific type of device. The behavioral patterns of turning-on the AC and turning-off the AC are investigated for a Chinese family with a split AC unit. This is a ‘part-space part-time’ air conditioning mode (see Figure 2-38): (1) Turning-on the AC pattern is defined as "turn on AC if an occupant is in a room and feels hot"; the threshold value is 28.5℃. (2) The turning-off AC pattern is defined as "turn off AC if an occupant is out of the room".(3) Adjusting-set-point pattern is defined as "using fixed set point"; the set point temperature is 26.5℃.

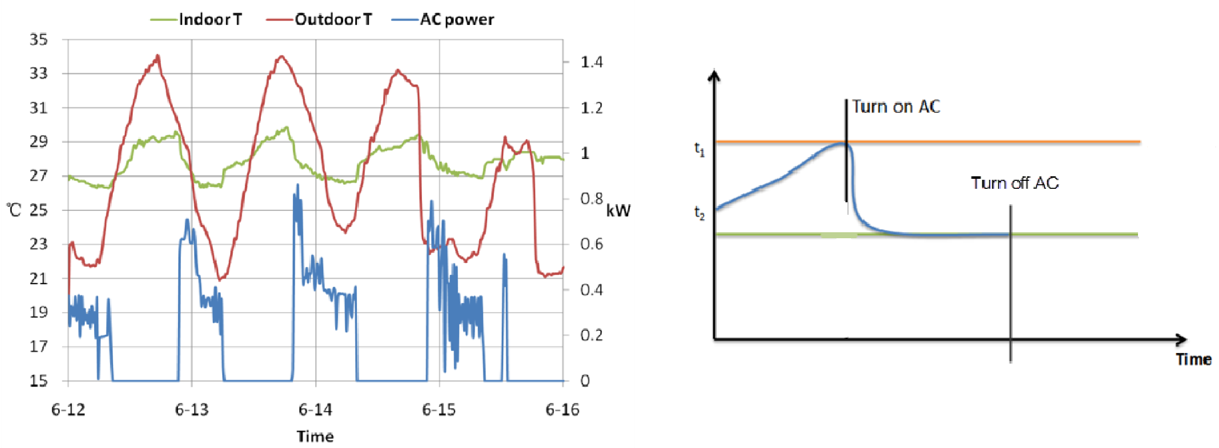


Figure 2-38. Air conditioner operation: (a) indoor and outdoor temperature, and AC power; (b) turn-on and turn-off patterns

The system status inputs are zone occupancy and indoor temperature; the outputs are turn-on/turn-off actions and the states of the air conditioner. Figure 2-39 shows the simulation results of air conditioning actions. It can be seen that (1) the air conditioner is turned off when the occupant leaves the room; (2) it is turned on when the occupant enters the room and the indoor temperature is higher than 28.5℃; (3) the set-point temperature is 26.5℃. The simulation results reproduce the characteristics of the real operation of air conditioner.

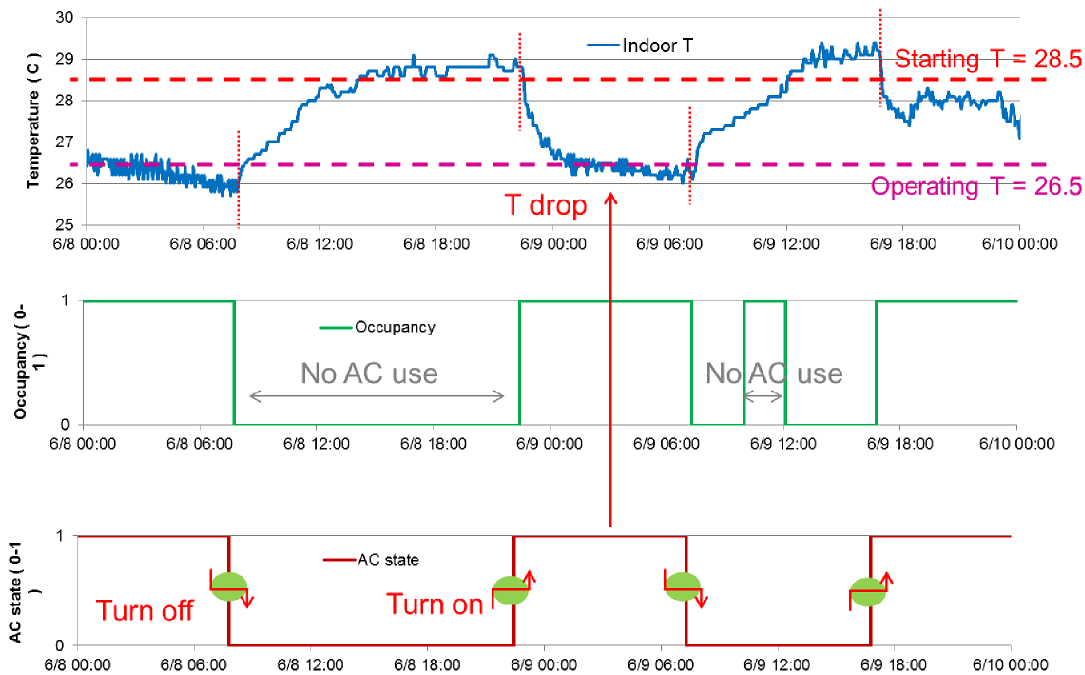


Figure 2-39.Simulation of air-conditioning behavior.

5.4 Ventilation and window opening

Probabilistic model for the window state

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Window opening	Probabilistic	Stepwise linear regression	Yes/ No	Yes/ No	[39]
Window opening	Probabilistic	Regression Markov model	Yes (R)	Yes	[81]
Window opening	Probabilistic	Regression	Yes (ESP-r)	Yes	Humphreys Algorithm

So far, there are only two published models regarding the window opening behavior in dwellings. In 2005, the authors of Ref. [39] developed a linear regression model: a series of stepwise linear regression analysis were performed on the data to identify factors associated with open windows and doors. The statistical analysis is focused on identifying the variables that can be used to predict when a residence will have one or more open windows or doors.

The authors of Ref. [81] have recently developed models for window opening in a residential setting. Their study uses the analysis of data from two distinct measurement campaigns in residential indoor environments in Japan and Switzerland. Calibration and the verification were conducted for several modeling approaches of varying complexity with respect to the number of variables included in the models. The previously developed models for occupants' office window uses are related to the study of Ref. [31] and Ref. [82]. In particular, they tested the Bernoulli process based on a single probability (an indefinite repetition of an experiment that can give two alternative outcomes, 0 or 1) and a Markov Chain model: , each model included a set of variables retained on the basis of forward selection. The combination of these distinct approaches results in nine types of models for the prediction of actions on windows.

In the case of the Swiss dataset, the analysis demonstrates the ability of carefully formulated behavioral models developed from office environment data to reliably predict window usage in a residential context and vice-versa. The same models perform less satisfactorily in the Japanese residential database. From these results, it seems that such models require specific calibration in the case of buildings equipped with an air-conditioning unit as was the case of the Japanese database.

Adaptive comfort temperatures are now well-established concepts in which comfortable indoor temperatures vary with the running mean outdoor temperature. Adaptive behavior applies to free running naturally ventilated buildings where the occupants have opportunities for adapting; i.e. adjusting clothing, posture, windows, blinds, fans etc. Even though Humphreys' algorithm [57] is for window opening in office buildings, it is worthwhile to highlight it in this review of existing models. It was derived from analyzing extensive survey and the relationship between the likelihood that a window is open and the indoor global temperature (T_g) and outdoor air temperature (T_{ao_i}) was quantified by means of logistic regression. The windows open algorithm has been implemented in the building energy simulation software ESP-r to allow window control within the airflow network of a building model. The implementation of the algorithm in ESP-r is named the "Humphreys adaptive algorithm" [57]. The window open behavior as represented by the algorithm is shown to be more sensitive to changes in building design parameters than a non-adaptive approach. It is suggested that an adaptive algorithm will better represent human control of windows and will allow a more accurate assessment of human thermal comfort conditions and building performance including summer overheating and annual energy use. Once again, the algorithm embedded in simulation software will assist in the design of more comfortable and energy efficient buildings.

Probabilistic models for the state transition of windows

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	References
Window opening	Probabilistic	Markov model	Yes/ No	Yes/ No	[7]

In Ref. [7], the authors developed a logistic model inferring the probability of opening and closing a window (a change from one state to another) separately to determine the most dominating drivers for each action.

5.5 Domestic hot water

Models for hot water usage based on average values

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Hot water usage	Average values	Stepwise linear regression	Yes/ No	Yes/ No	[40]
Hot water usage	Average values	Poisson arrival processes	Yes/ No	Yes/ No	[16], [17]

Realistic load profiles for domestic hot water use with a time step of one minute for a one year period have been generated stochastically in Ref. [40]. In this approach, four types of loads were used: short load (e.g. washing hands), medium loads (e.g. dish washer), bath, and shower. Probability distributions have been defined for each type of load during the year, weekday, and day based on domestic hot water use data from various studies. The distributions were used to stochastically generate the load profiles.

A Poisson Rectangular Pulse (PRP) model for residential water demand has been developed in the 1990s, Refs. [16] and [17]. In this model, the residential water demand is composed of rectangular pulses having a specific intensity and duration arriving various times a day. The frequency of water use follows a Poisson arrival process with a time dependent rate parameter. The residential water use times are distributed exponentially. The parameters and probability distributions of the PRP model are determined from many flow measurements for various households; the parameters are specific for the network used for measurements. It is difficult to relate the parameters obtained via these measurements to data such as household size, age, or type of end-use. Consequently, the model is more descriptive than predictive. Analogous to the PRP model, Ref. [4] describes a model based on the (stochastic) Neyman-Scott clustered point process.

Probabilistic model to determine the hot water usage

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Hot water usage	Probabilistic	Multiple regression	Yes/ No	Yes/ No	[47]
Hot water usage	Probabilistic	Multiple regression			[53]
Hot water usage	Probabilistic	Fitted probability distribution Monte Carlo	Yes/ No	Yes/ No	[11], [13]

In the eighties, Ladd et al. [47] presented the EPRI (Electric Power Research Institute) model: a behavioral model containing a set of multiple regression equations predicting the behavioral structure of hot water use during the day; weekdays and weekend days are considered separately. In this model, hot water use is regarded as a function of various variables, such as number of household members, age, unemployment of household members, and water heater description. In this study, only electric water heaters have been considered (gas-fired water heaters have not been considered). The study is based on a sample of 110 households (all of them owning washing machines and dishwashers).

Lutz et al. [53] presented an expansion of the EPRI model in the nineties. In this study, not all households owned washing machines and dishwashers. In addition, “households consisting of seniors only” and “households not paying for hot water” were considered. Due to a lack of data on hot water use for households with gas-fired water heaters, possible differences in hot water uses associated with water heating equipment type were not addressed.

Recently, a more detailed stochastic end-use water demand model has been developed for predicting water use patterns having a short time scale (1 second) and small spatial scale (residence level), see Refs.[11] and [13]. The model is based on statistical data of users and water end uses, such as the number of people per household, age, frequency of use, duration/intensity of a water use event, and occurrence over the day. Eight types of water end uses have been used: shower, bath, washing machine, dishwasher, kitchen tap, bathroom tap, outside tap, and WC. Fitted and assumed probability distributions for the frequency, duration, intensity, and time of the event for each type of water end use are used to stochastically generate water use patterns (Monte Carlo). This approach is based on statistical data on occupants and water using equipment in the dwelling; this data will be different for different countries. An example of measured and fitted probability distributions for shower duration is shown in Figure 2-40. A complete list of probability distribution functions for frequency, duration, and intensity for various residential water end uses is shown in Figure 2-41. The simulated residential water use patterns compared well with measured water use patterns.

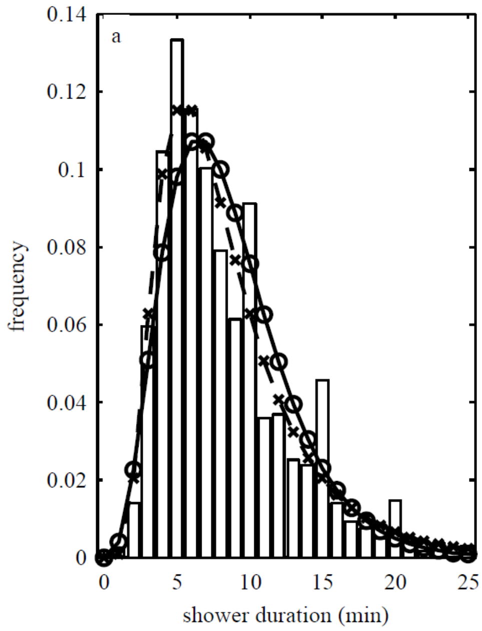


Figure 2-40: Probability distribution for shower duration in the Netherlands: measured data (bars), fitted distributions, χ^2 (circles), and lognormal (crosses). See Ref. [11].

End-use type / subtype		Frequency (day^{-1})		Duration		Intensity (L/s)	
		μ	pdf	μ	pdf	μ	pdf
Bathtub	120 litres	0.044	Poisson	10 min	N.A. (fixed)	0.200	N.A. (fixed)
Bathroom tap	Washing and shaving	4.1	Poisson	40 s	Log-normal	0.042	Uniform
	Brushing teeth			15 s			
Dish washer	Brand and type	0.3	Poisson	Specific dishwashing pattern (4 cycles of water entering, total 84 seconds, 0.167 L/sec = 14 L)			
Kitchen tap	Consumption	12.6*	Negative binomial (r = 3, p = 0.192)	16 s	Log-normal	0.083	Uniform
	Doing dishes			48 s		0.125	
	Washing hands			15 s		0.083	
	Other			37 s		0.083	
Outside tap	Garden	0.44	Poisson	300 s	Log-normal	0.1	Uniform
	Other			15 s			
Shower	Normal	0.7	Binomial	8.5 min†	χ^2	0.142‡	N.A. (fixed)
	Water saving type					0.123	
Washing machine	Brand and type	0.3	Poisson	Specific washing pattern (4 cycles of water entering, total 5 minutes, 0.167 L/sec = 50 L)			
WC	6-litre cistern	6.0	Poisson	2.4 min§	N.A. (fixed)	0.042	N.A. (fixed)
	9-litre cistern			3.6 min			

Figure 2-41: Probability distributions and averages of frequency, duration, and intensity for various types of residential water end uses in the Netherlands. See Ref. [11].

Agent-based models of hot water usage

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Hot water usage	Probabilistic (?)	Stepwise linear regression	Yes/ No	Yes/ No	[9]

Agent-based models can simulate the influence that people with different water use behavior have on each other. This influence will result in a change of water use behavior and energy use as a function of time. See e.g. Ref. [9]. In this reference, three types of occupants are defined: High Energy Consumers, Medium Energy Consumers, and Low Energy Consumers. Due to the lack of literature on actual rates of influence, the authors assumed values for these rates (a sensitivity analysis is to be performed in future work). Presently, it is assumed that Low Energy Consumers have the most effective influence through promoting green principles; the High Energy Consumers' have an effective, however lower, influence; and the Medium Energy Consumers have the lowest influence. The initial number of occupants has to be defined for each category. The model then calculates the time evolution of the number of occupants for each category. After a long time, all occupants became low energy users (due to the largest influence rate for the category Low Energy Consumers).

Agent-based models are also able to evaluate the effect of market penetration rates of water-saving techniques, economic developments, and policy scenarios about water use as a function of time, see e.g. Ref. [19].

5.6 Electrical appliances / lighting

Deterministic models for electricity consumption

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Electrical appliances (including lighting)	Deterministic	Linear regression analysis	Yes	(Yes)	[49], [38]
Lighting	Deterministic		Yes	(Yes)	[49]

Models of residential electricity consumption have been developed at Aalborg University in 2010, where data from two Danish cities, an island, and two measurement projects (the Comfort Houses in Vejle, see Ref. [49], and Energiparcel in Tilst, see Ref. [50]) are used to create profiles for relative consumptions (sum of all months equals 100) and to determine if specific seasons are present, Ref. [38]. The models can be used as the basis for calculating expected electricity use profiles.

In Figure 2-42, the derived seasonal distribution is shown. It is seen that the number of seasons necessary to describe the pattern turned out to be four, as indicated by different colored bars. It is visible that consumption is relatively high in the winter and becomes gradually lower as the days become longer and warmer. The months where the lowest electricity consumptions are observed are June and July.

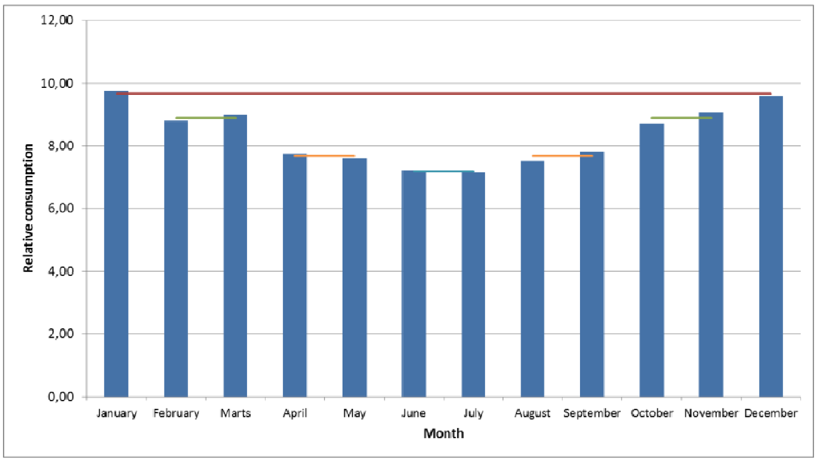


Figure 2-42: Seasonal investigation of electrical energy consumption in Denmark. See Ref. [38].

The electricity consumption profiles are shown in Figure 2-43 and Figure 2-44, where groupings of "workdays" and "not workdays" are conducted. This was a result of an investigation made on 4 houses from Energiparcel in Tilst (energy renovated houses) and 3 houses in Skibet in Vejle (passive houses).

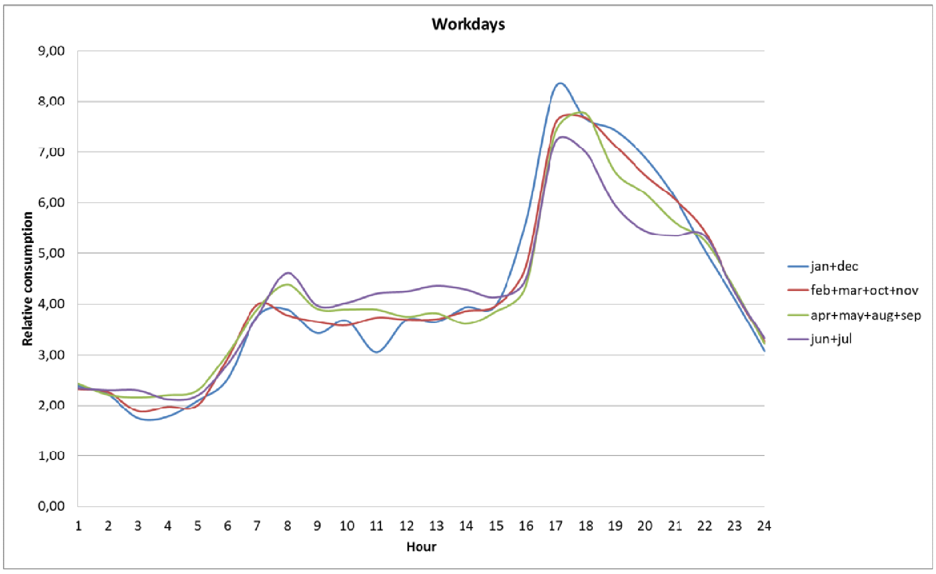


Figure 2-43: Relative electrical energy consumption day-profiles for "workdays" divided into four seasons. See Ref. [38].

The profiles show that electricity is used the least from 0 to 6 and use is somewhat stable from 8 to 16 (working hours). From hours 16 to 18, a significant increase in consumption is visible, which is believed to be a result of people coming home from work and starting to make dinner. The daily pattern does not seem to deviate much between seasons, as actual electrical energy consumption does, (see Figure 2-42).

For the "not workdays", the same tendencies are observed. From around hour 6, an increase in consumption is visible and is again visible at hour 16. During midday, the level of consumption is higher, which results in a lower peak value at dinner time in the evening.

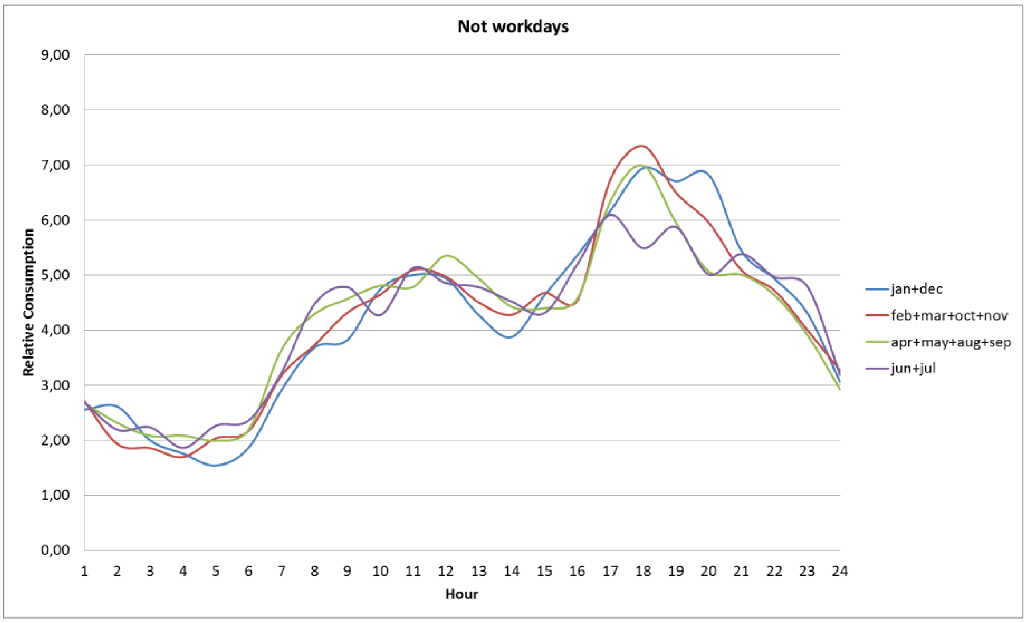


Figure 2-44: Relative electricity consumption day profiles for "not workdays" divided into four seasons. See Ref. [38].

Similar energy use profiles have been developed for artificial lighting, [86]. Figure 2-45 shows results obtained from measured lighting energy use in 100 UK residences in half-hour intervals. It shows how the lighting demand profile during a typical weekday changes with season.

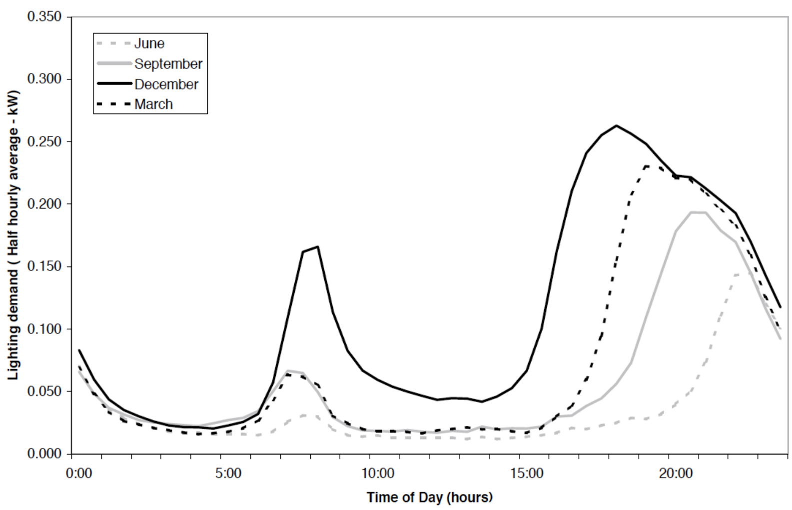


Figure 2-45. Daily lighting profiles (monthly averages, weekdays) at different times of the year (averaged over 100 homes)—showing demand in June (dashed grey line), September (solid grey line), December (solid black line) and March (dashed black line), Ref. [86].

The profile in Figure 2-45 falls into four discrete periods during which occupant behavior remains relatively similar for each half-hour – nighttime, morning peak, daytime, and evening peak. By assuming an underlying function for each period, annual trends may be stored for the parameters that describe each of these functions. The morning peak, for example, was modeled by a Gaussian function in terms of peak height, width, and peak time. The evening peak was modeled by a more intricate function, which included the description of leading and falling edges. Further relationships were investigated to model the annual trends for each of these parameters. For example, the leading edge parameter for the evening lighting peak was found to be a sine wave, whilst the trailing edge parameter was constant throughout the year. The developed model was implemented in a software tool that also allowed representation of diversity by employing scaling factors for differences in occupancy, income, lifestyle, etc.

Probabilistic models for the electrical energy consumption

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Electric appliances	Stochastic		Yes	Yes	[94][97][98]
Lighting	Probabilistic	Markov model	Yes	No	[60]

A high-resolution stochastic model of multiple electricity-dependent activities in households (including lighting) and the associated electricity demand has been developed in Ref. [94]- [98]. This model produces activity patterns for individual occupants as well as the domestic electricity demand based on these patterns. The activity patterns are based on a nine-state Markov chain (absence, sleeping, cooking, dishwashing, washing, TV, computer, audio, and other). The Markov chain transition probabilities are based on extensive Swedish measurements between 2005 and 2007 in monthly or annual periods in 14 households, and time-use data for five of these households. Based on these transition probabilities, at each time step in the calculation a stochastic process determines which activity will take place. Using a relatively simple conversion model, generalized load patterns for various electricity end-uses are related to the activities to calculate the power demand for the end-uses.

The occupancy model of the Lightswitch model (Ref. [60]), is a Markov model consisting of three occupancy probability functions as a function of time of day; five-minute bins have been used.

It uses a simulation algorithm that predicts the lighting energy performance of manually and automatically controlled artificial lighting and blind systems in private and two-person offices. Inputs are annual profiles of user occupancy and work plane illuminances. These two inputs are combined with probabilistic switching patterns developed for three different situations: arrival, temporary absence, and departure. Switching patterns have been derived from observed data.

Figure 2-46 illustrates the Lightswitch-2002 algorithm for artificial lighting and blinds. Figure 2-47 shows the measured switch-on probability functions.

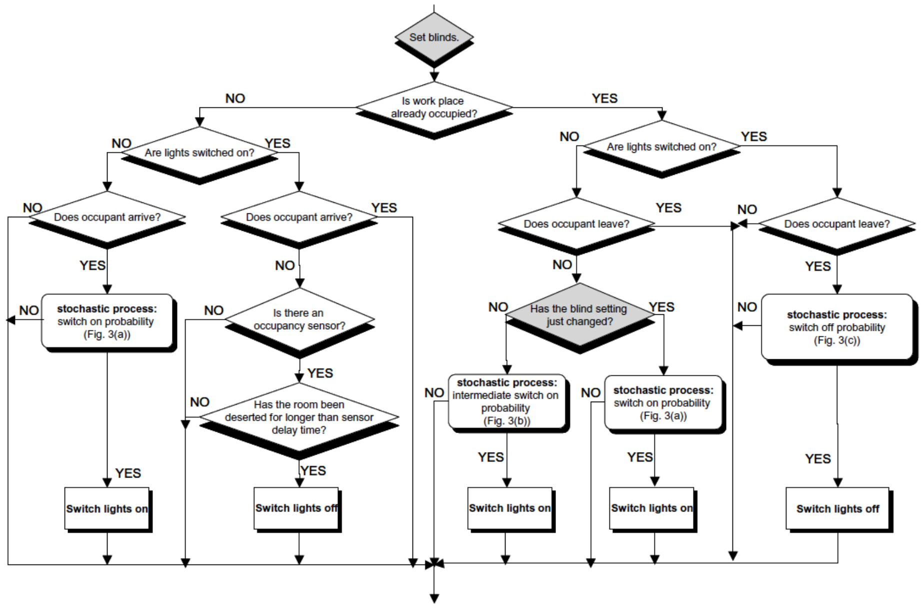


Figure 2-46. The Lightswitch-2002 algorithm for electric lighting and blinds.

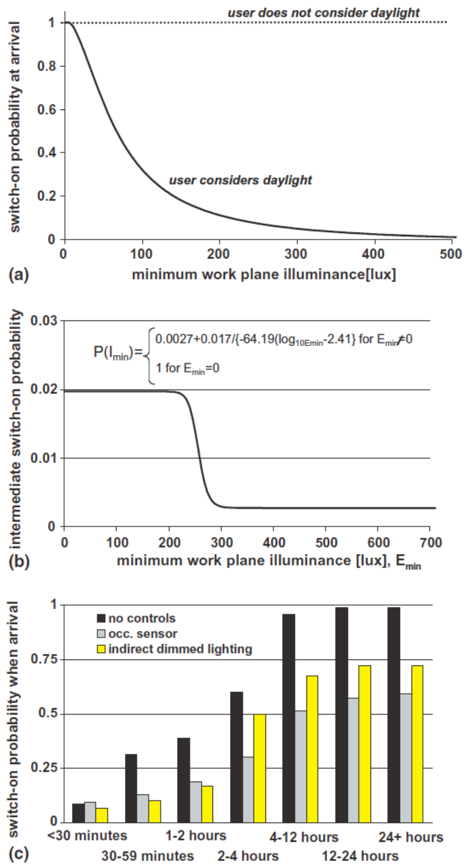


Figure 2-47. (a) Measured switch-on probability function upon arrival [35]. (b) Intermediate or within-day switch-on probability for electric lighting [71]. (c) Measured switch-off probabilities for different times of user absence for a lighting system without controls, with an occupancy sensor [67], and for an indirectly dimmed lighting system [71].

5.7 Cooking

Cooking activity and energy use models

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Cooking	Probabilistic	Markov model	No	Yes	[76]
Cooking	Average values		No	Yes	[94]

Cooking activity profiles (probability as a function of time-of-day) have been derived [76] based on data derived from the UK 2000 time-use survey (Ref. [36]). This database is based on thousands of single day diaries recorded at a ten minute resolution. The profiles show that expected peaks in cooking activity occur around meal times, but cooking can occur at any time of the day.

Cooking power demand profiles have been derived in Ref. [94] based on the Swedish time-use data set TU-SCB-1996. This data set contains data from 431 persons in 169 households recorded during an autumn period of five months at a five minute resolution. The modeled cooking power demand profile corresponds well to the measurements, but the evening peak for the cooking demand, which corresponds well in magnitude, is predicted one hour too early.

5.8 Sun shading

Literature research reports regarding sun shading with respect to housing and energy could not be found. Therefore, the following descriptions are based on a model which was developed in the context of office buildings. As an example for an approach which considers the usage of blinds, a manual lighting control model is described below in which the usage of external venetian blinds is integrated. Reinhart [69] developed this model based on gathered data during a pilot field study in 10 rooms in an office building in Germany. The investigation of the manual control of venetian blinds was a small part of his thesis focusing on simulation studies and analyses concerning daylight and lighting control to predict artificial lighting usage in offices.

Reinhart explored the correlation between solar penetration depth and the mean blind occlusion for the time periods when employees were present in their offices. The tendency to close blinds increased when direct sunlight was above 50 Wm^{-2} (see *Figure 2-48*). Bülow-Hübe [18] found in her research that employees are more likely to operate blinds when there are sun patches in the room.

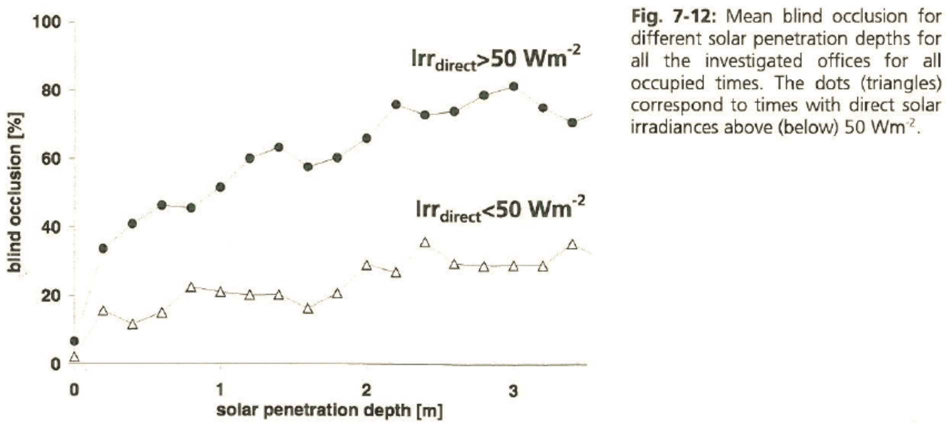


Figure 2-48: Correlation of blind occlusion and solar penetration, [69], p. 82].

Model for sun shading

Type of behavior	Type of model	Statistics used	Implemented into computer simulation (software)	Validated	Reference
Blind usage	probabilistic,	logistic regression	Yes	No	[69][76]
Blind usage	deterministic; probabilistic	Stochastic (decision outcome); algorithm inputs of annual profiles of user occupancy and work plane illuminances (5 minute time steps throughout the year)	Yes	No	[70]

Observed patterns of user behavior in an office building in Germany provided information for the model. The adjustment of blinds is incorporated in the extended version of the LIGHTSWITCH 2001 Model, (see *Figure 2-49*).

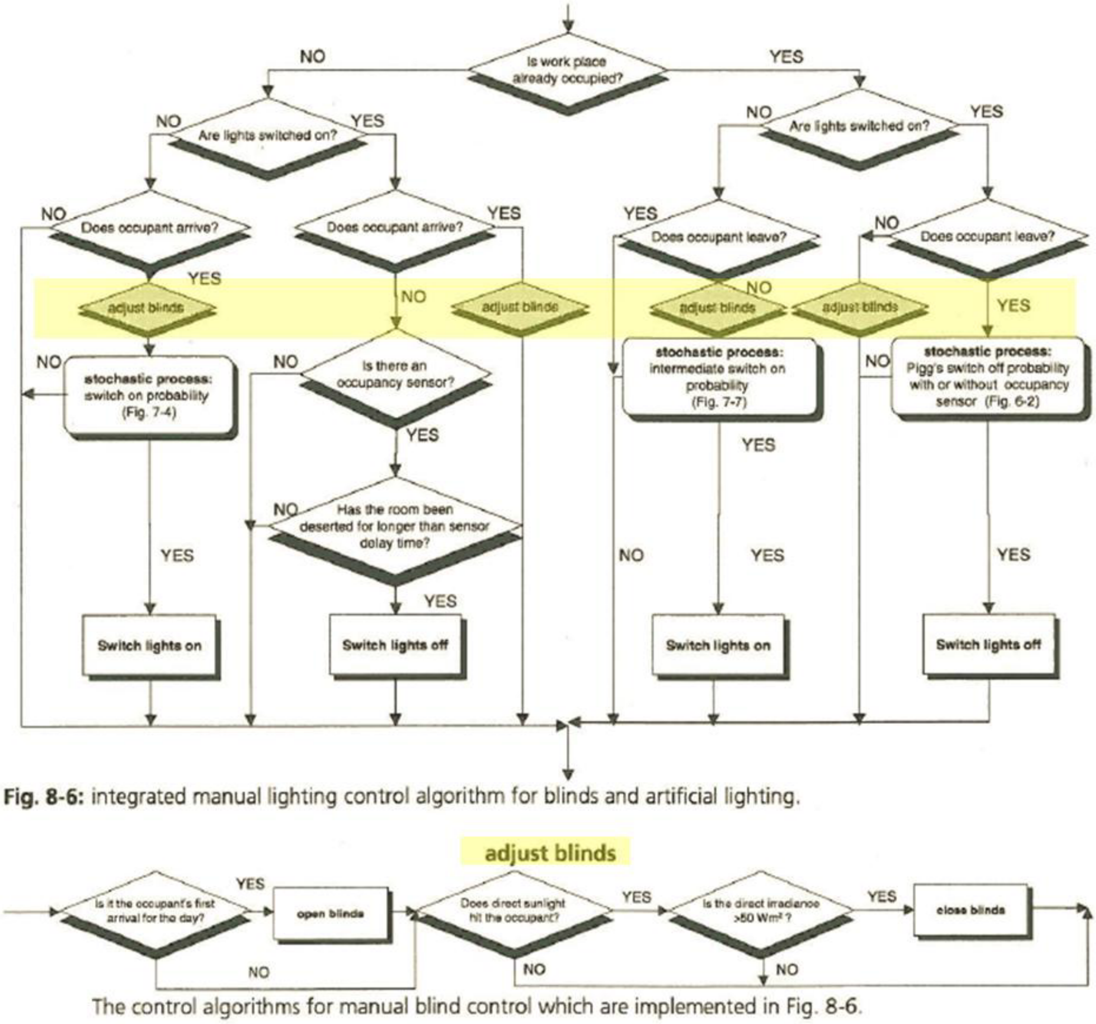


Figure 2-49: LIGHTSWITCH 2001 Model with integrated control algorithm for blinds, [[69], p. 26].

Figure 2-50 shows a part of the LIGHTSWITCH 2002 Model for manual lighting and blind control which is based on a stochastic and a dynamic control algorithm [70]. One of the benefits is to support lighting designers for energy saving analysis concerning electric lighting and blind control concepts. It is applicable for private or two-person offices. Other advantages are:

1) the algorithm imitates the individual control decisions and is assumed to be closer to real behavior,
2) the algorithm simulates variations in individual control behavior (observations from field studies).

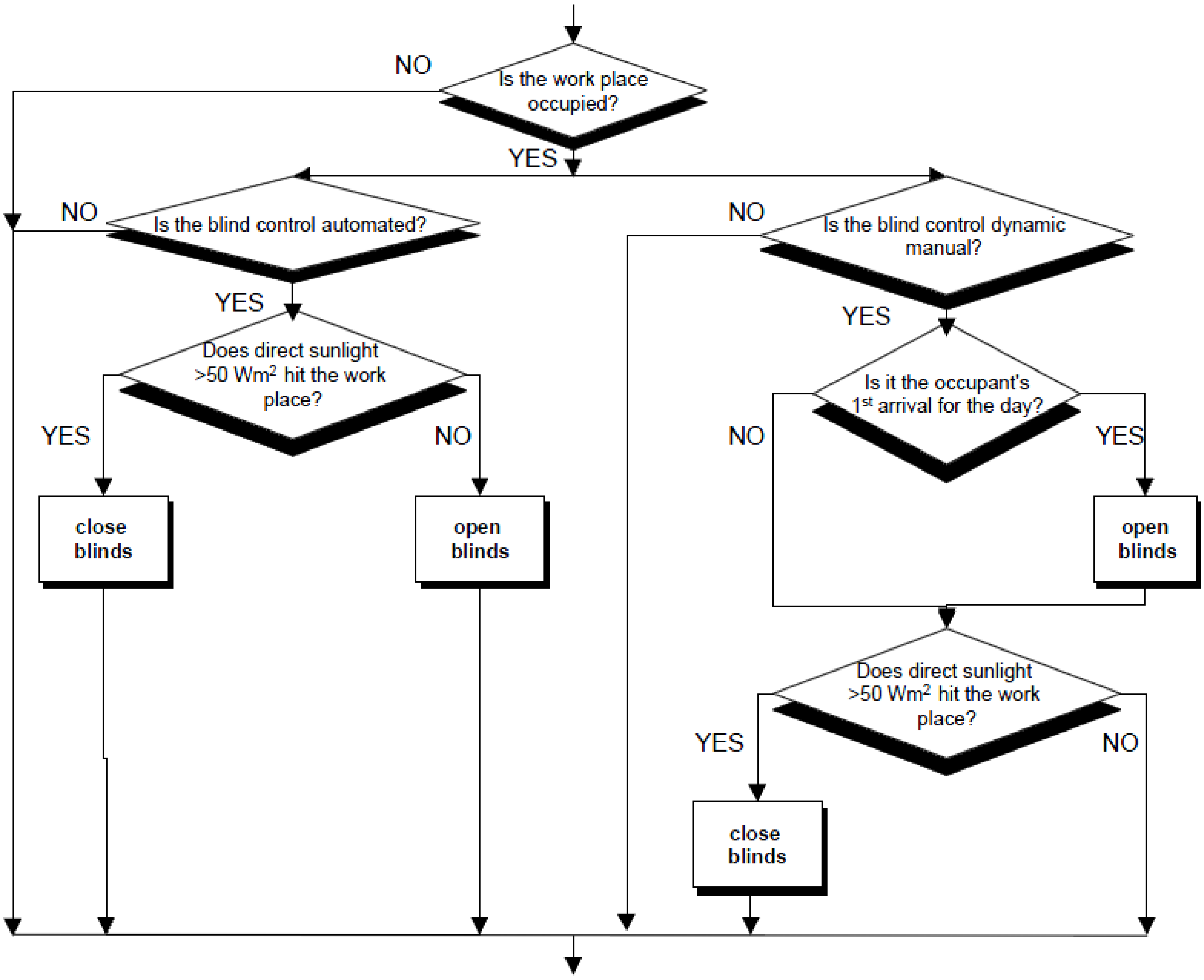


Figure 2-50: Control algorithms for manually controlled and automated blinds. Close blinds comes along with fully lowered blinds; the smallest slat angles are 0o, 45o and 75o is chosen under which direct sunlight is fully blocked, [70], p. 28].

The author stresses the limitations as aspects which are not covered by the model, e.g. thermal considerations or privacy needs in dense settings.

Reinhart and Wienold [72] investigated occupant behavior patterns with respect to energy issues. They presented an analysis simultaneously considering annual daylight availability, visual comfort, and energy use, combining annual daylight glare probability profiles with an “occupant behavior model in order to determine annual shading profiles and visual comfort conditions” [[72], p. 410].
Calculations are based on two extreme opposite user profiles:

1) type passive user = preference of daylight while avoiding glare; closes blinds once the index DGP (Daylight Glare Probability, see [99]) at the workplace is more than 40%,
2) type active user = avoids direct sunlight; closes the blinds once the sunlight is above 50Wh/m2.

“The ‘true occupant behavior is likely to lie somewhere in between these two extremes” [See [72], p. 414).

Based on five scenarios for blind usage and user type, calculations of energy loads and greenhouse gas emissions based on hourly schedules were carried out focusing on the electric and external blinds statuses (see *Figure 2-51*). The findings show that besides comfort, usage of sun shading is energy-related. Results showed that external blinds are applicable to reduce cooling use but, on the other hand, increases the heating load. The integration of external venetian blinds lowers energy costs by 6% and carbon emissions by 10% for passive users. For the active user, "yes or no" changes with respect to external blinds could not be found.

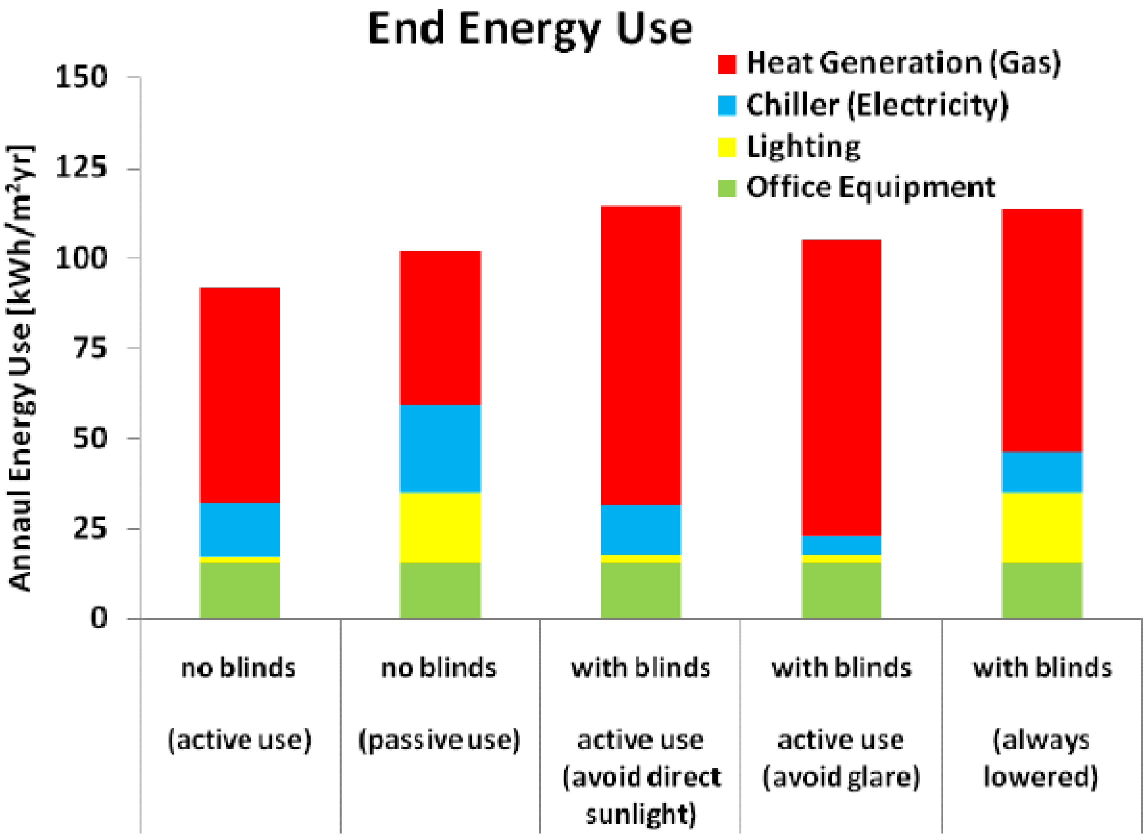


Figure 2-51: Analyses for annual energy use in a space for different blind control strategies and occupant behavior patterns, [72], p. 392].

The above described models which focus on the usage of blind control give examples for interesting approaches. A worthwhile topic for further research would be to determine if these approaches can be applied to behavior patterns in private housing. A fundamental characteristic of the office environment is a predominantly extraneous operation of devices such as sun shading; automation is mostly done by the maintenance personal.

Besides the avoidance of internal heat gains, another aspect is the problem of glare with respect to comfort issues at the workplace. This is especially important for employees working at desks near windows. The issue of glare may not play a major role in housing. Besides a variety of restrictions in comparisons of working and private settings, it can be argued that some behavior patterns might be similar up to a certain degree. Behavior, like handling shades and blinds, are often learned and trained and become habits, in terms of preferences like having a view to the outside. Nevertheless, in the context of residential buildings, behavior patterns might show greater variation than in the office context due to a bundle of factors such as lifestyle, environmental consciousness, or the linkage between behavior and private energy costs. Yet, blind usage models are based on small numbers of human subjects, thus, further validation of the models is needed as well as further investigation into the relationship of blind usage and energy in residential buildings.

6. Conclusions

Average and deterministic models are often based on assumptions, not on data, but could be based on data as well. At best, they represent e.g. the average for window opening frequency. Implementing such values into simulation algorithms, the outcome is a single value for each assumed/ derived type of behavior. In order to show variety (of behaviors, types of occupants, …) various simulations have to be run once each for each model.

Probabilistic models could be based on assumptions as well, but in practice, they are mainly based on data. They are representing probabilities of a behavior. Various types of occupants can be represented either by different models or by variables related to the aspects modeled within one model. The outcome is a distribution of behaviors/ energy demands and the variety is shown by results of different models or the distribution of one model.

Agent-based simulation models are used to quantitatively study multi-agent systems in which agents are autonomous, and interact with each other and their environments. The agents may be very different objects varying from individual human beings to components of energy networks. The agents are in a specific state at a specific time during the simulation. Due to interactions with other agents the state may change over time. An agent-based model for simulating domestic user behavior can be used in a co-simulation with, e.g. a building model.

Action based models provide a new approach for building occupancy simulation. Compared to the “fixed schedule” method, this model considers the randomness that result in the uneven and non-synchronous change of occupancy in space and time. Compared to other random process methods, this model keeps the time and space relevance of occupancy and is more practical due to the great reduction of inputs.

Following the description of the modeling approaches, examples for energy-related behaviors found in the literature were presented together with those developed within the framework of this Annex. A broad range of models are shown, however, only few have been implemented into simulation software for energy demand prediction. Furthermore, all those models were – if at all – validated only internally and not on external data (see Ref. [81] for such an approach to window opening behavior). Therefore no conclusion can be drawn on the quality of the developed models.

6.1 Recommendations for the choice of models

The choice of model depends strongly on the objective of the simulation, but also on the software chosen or available.

As presented in Chapter 3, the occupant behavior can be modeled through schedules or diversity profiles (Type A), stochastic models (Type B), or agent-/action based models (Type C). The recommended choice of a certain model type depends on various factors as described in Chapter 2. Table 2-7 and Table 2-8 summarize the preferred behavior models for a single building and a group of buildings with respect to the objective of the simulation, following the objectives of Table 2-1 and Table 2-2.

Table 2-7.Preferred behavior models for a single building.

	Design			**Commissioning**		**Operation**
	Conceptual	Preliminary	Final	Initial	On-going	Control
Preferred behavior model:	A	A, B or C*	A (B or C*)	A, B or C*	A, B or C*	A, B or C*

* The required model depends on the sensitivity of the investigated building performance indicator to occupant behavior. This sensitivity depends on the performance indicator itself (e.g. compare comfort indicators to energy load indicators) and on various building related aspects, among others, building function and user type (e.g. compare schools to offices), building/system concept (e.g. slow responding to fast responding systems) and the degree of which the occupants are able to interact with the building (e.g. operable windows or no operable windows) [34].

Table 2-8.Preferred behavior models for a group of buildings.

	Design			**Commissioning**		**Operation**
	Conceptual	Preliminary	Final	Initial	On-going	Control
Preferred behavior model:	A	A	A		A	A

The possibility to use a certain model also depends on the software used. Table 2-9 gives an overview, which software is capable of handling probabilistic functions. Furthermore, not all simulation tools generate all necessary variables needed for some of the models presented in Chapter 4, e.g. Energy Plus does not calculate CO_2 concentrations needed for some window opening models.

Table 2-9.Simulation software characteristics.

Software	**Handling probabilistic functions**	**Random number generation**	**Limitations/ comments**
Energy-Plus	No	No	Only fixed schedules possible, engine to combine with MatLab in progress
IDA-ICE	Yes	Yes	
ESP-r	Yes	Yes	
TRNSYS	Yes	Yes	

6.2 Proposed methodologies for future model developments

Future model developments are meaningful just in case they are accompanied by their validation on external data. This necessitates case studies available to perform such validation. The final report of Sub-Task C presents the outlines of existing studies analyzing the total energy use in buildings. All of them indicate whether occupant behavioral variables are included in the database and whether the database can be used by others.

In the following a list of recommended variables found to be relevant is given for researchers who are planning new case studies.

Action modeled	Type of model/ Application	Recommended variables
General	All	Electricity consumption Energy use (gas, oil, wood, …)
Heating-/Cooling control, window opening	Average values	Family size, dwelling properties, climatic data
Heating-/Cooling control, window opening	Stochastic	Indoor and outdoor data (at least temperature) (IAQ) Personal characteristics/ preferences

Data acquisition using citizen science & crowd sourcing

Collecting data for energy-related behavior is time consuming, as both a large sample set and a large number of parameters are used in energy use analyses. The time required to collect energy-related occupant data may be decreased by directly involving the occupants who are residing in the study homes through citizen science.

Citizen science is defined as “scientific activities in which non-professional scientists volunteer to participate in data collection, analysis and dissemination of a scientific project” [30]. According to Cohn, citizen science as a means of data collection has been in use for over a century [30]. There is some debate about the definition of citizen science, as more recent definitions include interaction and use of the internet together with information and communication technologies as the primary interface and data collection platform, and thus represent a scientific application of crowd sourcing [100]. To date, citizen science has been an approach not only for gathering data for various research projects, but also to involve those who may directly benefit from the results of the study at hand. The amount of data that can potentially be collected is very large, as the number of involved parties can also grow exponentially. Newman et al. even propose a web-based data management structure to handle large data volumes [59].

6.3 Suggestions for future work

Whole building simulation model outputs are currently often singular values, often leading to false confidence that estimated building energy consumption will match simulated results. A range of estimated energy consumptions integrating high, typical, and low energy consuming behaviors can be determined by integrating the results of various two-step models such as average, agent-based, or action-based models in order to represent occupant behavior in greater detail in building energy simulations. The range of values can be applied to provide various building energy use scenarios such as those needed for energy certificates, large scale energy models, or long-term energy predictions. When used for the energy certificates for individual buildings, the energy use scenarios may be used to predict the impact of their own energy use decisions to the home and building owners and building occupants.

Building users adapt their energy-related behavior to changes in their local environment including changes in building technologies. Based on collected field data from longitudinal studies, energy use models can be built representing the adaptation of occupants at different stages to changes in building services and building quality resulting from thermal renovations. This behavior may also be referred to as “learning behavior”.

Current energy use models mainly concentrate on “business as usual” scenarios. Dynamic occupant behavior models may also be applied in energy use estimations for unstable energy supplies or energy disruptions caused by natural disasters to predict the range and impact of individual conservation measures over short and long time periods.

The introduction of new construction methodologies and building technologies may incur a higher probability of error in the design, construction, and commissioning phases of a building than following traditional building practices until the technologies become common practice. Errors in the phases prior to occupancy can potentially affect the overall thermal comfort in the buildings and effectiveness of occupants to modify their surroundings to meet their comfort criteria while meeting a building’s energy use targets. Thus, risk assessments may be conducted considering various scenarios of construction and installation defects and the relative remedial, maintenance, and operation costs in conjunction with the range of occupant responses to meet both comfort and energy criteria.
Although studies have been conducted for occupant satisfaction/dissatisfaction and occupant behavior in residential settings, further research into the combined impact of design decisions, commissioning settings, and operation/maintenance decisions on thermal comfort and occupants’ wellbeing may provide further insight into the actions occupants take to adapt to their surroundings.

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