3 Effects of occupant behavior on the energy performance of dwellings: a sensitivity analysis

Introductory note

Chapter 3 is a sensitivity analysis conducted using the actual heating behavior data of occupants in the OTB sample. The aim was to model heating behavior and heating energy consumption using Markov chains and Monte Carlo methods. Secondly we wanted to evaluate the robustness of energy consumption of a dwelling to heating behaviors such as thermostat, radiator and ventilation control, as well as presence. The results of this Chapter were compared to Guerra Santin's work (2010), which analyzes the same data using correlation and regression analyses.

This Chapter deals with the Research Question I of this thesis:
"Q I. What is the sensitivity of a dwelling's heating energy consumption to occupant behavior?"

The sub-questions are:
1. *What are the existing models developed for the occupant behavior and energy performance relationship? and how different are the results of these models in terms of calculating the influence of occupant behavior on energy performance?*
2. *How can behavior be modelled in order to assess the robustness of the energy performance in dwellings to occupant behavior?*
3. *What is the weight of each behavioral aspect in terms of its influence on energy consumption?"*

The research reported in this Chapter was a collaborative work between Harputlugil and Bedir. The data was collected by a questionnaire prepared by Guerra Santin and Bedir, using OTB's means of data collection. Data organization and initial statistical analysis was done by Bedir, simulations were conducted by Harputlugil and Bedir together, and finally the evalutation of outputs were done by the same authors. The co-author (G. Harputlugil) has given permission to include this paper in this thesis.

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§ 3.1 Introduction

The amount of energy consumed by a building depends on the characteristics of the building's envelope; the service systems installed for heating and ventilation, electricity, and hot water; the site and climate in which the building is located; and the behavior of its occupants. Occupants interact with a dwelling in order to achieve the indoor comfort conditions they require or to engage in certain activities. These interactions can include regulating the indoor temperature; opening windows or grilles; switching lights on or off; or intermediate actions involving the operation of lighting and devices, such as watching TV, reading, studying, eating, and performing household activities. Research on occupant behavior has increased recently, as newly designed dwellings have not achieved expected energy performance levels, leading to the possibility that occupant behavior is a factor in their underperformance (Guerra Santín and Itard, 2010). Although expected occupant behavior is taken into consideration during the design process for concept buildings, designers do not know exactly how a building and its user(s) will interact before the building is occupied. A more accurate understanding of the effects of occupant behavior on building energy performance is essential to meet the growing demand for more sustainable buildings (Hoes, et al., 2008).

Most of the existing calculation methods- the Dutch energy performance coefficient (EPC), Chartered Institution of Building Services Engineers (CIBSE) certification, and the Building Research Establishment Environmental Assessment Method (BREEAM)- assume a very deterministic modeling approach to occupant behavior. For instance, the EPC assumes schedules for weekdays and weekends for thermostat use, continuous mechanical ventilation, and constant lighting heat gain (6 kWh/m2) (Uitzinger, 2004).

Research on the influence of occupant behavior on the energy performance of dwellings tends to follow one of two methodological approaches: deductive or inductive. The deductive approach deals with the relationship at a macro level, considering household characteristics, income, rent, and energy consumption data garnered through a survey and establishing correlative and regressive statistical models to explain the relationships among these factors. In contrast, the inductive approach is based on actual occupancy patterns, including the operation of heating and ventilation systems, lighting, and appliances, and utilizes a bottom-up model that includes simulations of probabilities and considers presence as a precondition of behavior. The data-collection methods used in the inductive approach are mostly daily records and monitoring, while the data-processing techniques are generally more related to components, such as Monte Carlo (MC), Markov chain, S-curve, and probabilistic methods. These models suggest a greater influence of occupant behavior on the energy performance of dwellings (Figure 1) (for further reading, see Bedir, et al., 2011).

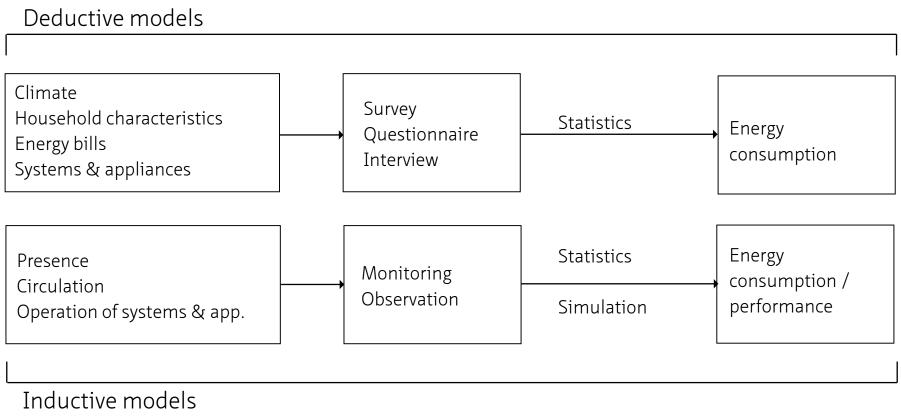

FIGURE 3.1 The inductive and deductive models of occupant behavior-energy performance relationship

The research presented in this article follows the inductive methodological approach, focusing on the heating energy demand of dwellings that originates from occupant behavior, namely the heating energy required to sustain indoor comfort levels and the internal heat gain that results from presence and intermediate activities. The core principle of the inductive approach is the presence of the occupant as the determining element of energy consumption, causing internal heat gain and the probability to act. As Mahdavi (2011) explained, internal heat gain is the passive effect of occupancy, so the model first deals with presence, which generates an indoor resultant temperature. Next, the model addresses the required heating energy demand and the internal heat gain from the occupant's behavioral patterns; this is the active effect of the occupant's presence and is more representative of the occupant's influence on the energy performance of the dwelling. This research evaluates the influence and weight of these patterns on heating energy demand and creates a model of the relationship between occupant behavior and heating energy demand based on this evaluation.

In this study, the data on behavioral patterns was derived from a survey of 313 dwellings in the Netherlands conducted by the OTB – Research for the Built Environment Department at Delft University of Technology in autumn 2008. The survey collected data on household and dwelling characteristics, as well as behavioral patterns related to heating and ventilation systems, lighting, and appliances. The raw survey data were refined, and energy simulation models were constructed based on the properties of the Dutch reference row house (tussenwoning) and the derived behavior samples using the MC method.

In order to discuss the methodological approaches (deductive versus inductive) in detail, this study compares its findings with an analysis conducted by Guerra Santín (2010), which applied the deductive method (i.e., correlation and regression) to the same survey sample.

Some of the existing studies discuss realistic methods of modeling occupant behavior patterns in building simulations (see, for example, Baetens and Saelens, 2011; Mahdavi, 2011; Reinhart, 2004; Saelens, et al., 2011), but in this study, simulation-based modeling was used only as a tool for acquiring the energy performance outcomes of each behavioral pattern. Thus, realistic methods of modeling the active and passive behavior of occupants were not included in the scope of this work.

The next section discusses the literature related to the modeling of occupant behavior and its relationship with energy performance. Earlier research has addressed the subject either by modeling each behavioral pattern regarding presence, heating and ventilation systems, lighting, and appliances separately or by developing an umbrella modeling approach that deals with all behavioral patterns. Existing research can also be divided into building functions, namely residential or office. Another aspect worth mentioning here is that, while some research has considered the consequent behavioral probabilities, other studies have begun with the causes of behavior, such as thermal or visual comfort. The third section presents the aims of the research and the research questions, which were derived from the existing literature, and the fourth section explains the research methodology. The fifth section provides the results of the analyses, followed by a discussion of the results in the sixth section. The final section presents the research conclusions.

§ 3.2 Literature Review

In this section, existing research on modelling behavior and energy performance inductively is presented according to the building function, presence, and type of behavioral pattern it addressed. All of the models discussed here deal with modeling occupant behavior, but they do not all relate these behavior models to energy performance calculations; however, they assume the possibility of connecting the models to energy performance calculations. As mentioned in the introduction, the inductive method is built on presence and actual behavioral patterns.

One study that focused on presence in residential buildings is Richardson, et al. (2008), which used a Markov chain approach to consider active presence in a dwelling both during the week and on the weekend. Data were collected through daily diaries, with a data-collection frequency of 10 minutes. Richardson, et al.'s model was based on the hypothesis that presence/activity in a zone at a specific time step is dependent on the presence/activity in that zone in the previous time step, noting that the presence/activity in the latter time step would have a smaller probability of occurring than the presence/activity in the time step preceding it.

Most of the existing research has dealt with office buildings. Like the work on dwellings, rather than focusing on occupants' movements, many of these models are based on occupants' presence in a space. In contrast to Richardson, et al.'s (2008) analysis of an entire dwelling, these studies have dealt with individuals or groups in a single office space. For instance, Page, et al.'s (2008) model included two years of usable data collected on presence in an office space, with the longest period of uninterrupted monitoring being six months. Page, et al.'s Markov chain model was based on Richardson, et al.'s hypothesis on the probability of presence, as well as the hypothesis that presence can be simulated either by multiplying the obtained pattern by the total number of occupants (in the case of collective behavior such as that in a meeting room) or by simulating each occupant's pattern of presence and then adding the produced patterns together.

Tabak et al (2006) developed a model on the presence, use of space and the circulation between spaces (USSU), using actual behavioral information: This model was based on the resource management model (elements: persons, abstract spaces, facilities) combined with an activity scheduler. The resource management model included two different models, one for organization of the people and one for the building. The activity scheduler was made up of 8 different elements: skeleton activities, interaction between activities, intermediate activities, gaps in schedules, overlaps in schedules, joining activities, appropriate location, required movement time. He, then validated the model by observing behavior with Radio Frequency Identification (RFID) (2008).

While all of the work on office spaces has considered presence as an initial input to the model, some of the research has looked at the influence of different behavioral patterns on the energy performance of a building as a following step. Glicksman, et al.'s (1997) work on inductive modeling of occupants' heating behavior at home revealed that analogue control of heating, ventilating, and air conditioning (HVAC) systems resulted in a reduction of energy consumption by 13%. Bourgeois, et al. (2006) confirmed that automatic management of a heating system led to a higher consumption level. Studies on ventilation patterns were first developed by Fritsch, et al. (1990) and Yun, et al. (2008, 2009) based on monitored data on the operation of windows in offices (probabilistic) (assumption: active-passive-medium occupant). Using the MC and Markov chain methods, the main conclusion of these studies was that ventilation use is a function of temperature. Slightly different than Fritsch, et al. and Yun, et al., Humphrey's algorithm on window-opening behavior and energy consumption (used in Rijal, et al., 2007) is based on adaptive thermal comfort theory. Rijal, et al., used data on temperature, season, time of day, and active versus passive occupancy recorded four times per day in offices across the United Kingdom. Their model showed that improved thermal comfort and, accordingly, window operation would lead to a 7% reduction in annual heating energy demand.

Andersen (2009) made a theoretical study on a single room with a single occupant in Copenhagen, focusing on different comfort levels (3 PMV factors) and behavioral modes (naïve and rational) and their impact on primary energy consumption. The occupant behavior in the study referred to the use of table fan, window opening, blinds, and heating, in reaction to the perception of comfort. In this respect naïve behavior means to turn on the table fan at 0,03 PMV, to open the window at 0,06 PMV, to drawn the blinds at 0,09 PMV, to remove clothing garment at 0,11 PMV, and finally the to turn off the heating beyond 0,17 PMV. Rational behavior, on the other hand, is assumed as more considerate reaction to the perception of comfort, such as turning off the heat in the first step, rather than turning on the table fan. The result is that the naïve behavior results in 3 times more energy use than the rational (3948 kWh/year-1198kWh/year).

Tanimoto et al's (2008) research on single dwellings in Tokyo proposed a method to predict the peak energy requirement for cooling, that combines an algorithm that generates short-term events that are likely to occur in residences, and the stochastic variations in these short-term events. Research about simulating behavior either by statistics or by simulation programs, deal with office spaces, on a single zone model, or more zones with less details on use, more articulation on movement. This underlines the gap in the research field of modelling occupant behavior in residences, in a manner that involves both use of space and circulation patterns, and in relation to the dwelling energy performance.

Lighting control is another aspect of modeling occupant behavior and energy performance that appears in the literature, though most of the studies are in their initial phase. Widen, et al. (2009) asked the occupants of 167 dwellings to keep a diary for one weekday and one weekend to record their presence and lighting control; the authors then developed a Markov chain model to predict lighting behaviors. Lindelöf, et al. (2006) studied 14 offices, taking measurements of lighting control, inside and outside temperatures, solar radiation, luminance, wind speed and direction, window opening, and presence for three years. The authors used a Poisson process to set up their model and concluded that different users behaved quite differently from one

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another, so both active and passive lighting patterns needed to be generated. Reinhart (2004) developed a lighting control algorithm in which he used data related to lighting control, presence, electric lighting and blinds garnered from existing literature.
The algorithm was to be used in energy demand calculations, and validation of the algorithm through stochastic processes was needed. This algorithm. was inserted in Esp-r by Bourgeois (2006).

Research by Ioannou and Itard (2015) on the influence of building characteristics and occupant behavior on heating energy consumption utilize a Monte Carlo sensitivity analysis based on the results of energy performance simulation. A single residential housing unit in the Netherlands was selected for this. The analyses were conducted using the technical and physical properties of the building, which are the thermal conductivity of the walls, floor and roof, window U and g values, orientation, window frame conductivity and indoor openings. The simulations were carried out with the variations of: multi-zone and single-zone versions of the building, two different grades of insulation, three different types of HVAC services, and the occupant behavioral characteristics focusing on the heating period in the Netherlands (thermostat level, ventilation behavior, metabolic rate, clothing and presence which in simulation terms is the heat emitted by people). The predictor parameters were chosen in such a way that they cover all of the parameters mentioned above. The thermally efficient and thermally inefficient reference building were first simulated with predictor variables: walls, roof and floor conductivity, window glazing U and g values, window frame thickness, building orientation, and then with the additional occupant behavior related parameters of ventilation, thermostatic level and the heat emitted due to the presence of the occupant.

The technique of sensitivity analysis was used to assess the thermal response of buildings and their energy consumption (Lomas and Eppel, 1992). The findings were articulated on the basis of the simulation results of physical characteristics alone and when combined with occupant behavior; compared the themally efficient building with the thermally inefficient one; the different heating systems; and the comfort index. This research revealed that when behavioral parameters were not taken into account, the most critical parameters were the window U-value, window g value and wall conductivity in the thermally efficient building, and in the thermally inefficient building the orientation of the building replaced the window U-value.

Ioannou and Itard (2015) found the predominance of behavioral parameters on energy performance (thermostat setting and ventilation flowrate), meaning they reduce the explanatory power of the physical parameters considerably. For both the thermally efficient and inefficient model, specifically the thermostat setting was the parameter that dominated the effect on the heating consumption, and the physical parameters had a very small impact. For most of the simulation model configurations and different heating systems, the proportion of variance in the heating that was explained by the parameters used in the study (higher than 70%, and in some cases reached 98%, except the thermally inefficient building with behavioral parameters and floor heating as the heating system).

The literature reviewed thus far has dealt with presence and/or specialized behavioral patterns, such as those related to heating and ventilation systems and lighting. Using an inductive, holistic approach to behavior, Herkel, et al. (2008) studied user behavior in 21 offices, monitoring presence, outdoor temperature, window control, and internal heat gain for one month. They found that the MC method is an appropriate tool for calculating thermal building performance, with a true mean value and standard deviation (SD).

Finally, in order to make a methodological comparison between the findings of the present research and an earlier analysis conducted on the same survey sample, it is important to briefly explain Guerra Santín's (2010) study. Her analysis of the relationship between occupant behavior and energy consumption in dwellings revealed that the most important factor in energy use was the number of hours that the thermostat was at the highest chosen setting. She also found correlations with the number of hours the radiators were turned on, the number of bedrooms that were used as living areas, and the presence of a programmable thermostat (which was associated with more hours with the radiator on). These results confirmed the findings of Haas, et al. (1998); Hirst and Goeltz (1985); Jeeninga, et al. (2001); and Linden, et al. (2006). Guerra Santín found that (1) there were statistically significant differences in energy consumption depending on whether the windows in the living room were sometimes open or always closed; (2) the effect of open grilles on energy consumption was independent of the effect of open windows, though both played an important role in energy consumption; and (3) households tended to use natural ventilation (windows and grilles) more than mechanical ventilation.

To conclude the literature review, it is important to highlight a few points: first, in the existing literature, presence is assumed to be a precondition of occupant behavior in buildings. Second, the inductive methodological approach to occupant behavior and energy performance follows a bottom-up, probabilistic modeling method, driven by the presence and actual behavior of occupants. The most common tools for data processing in these models are the MC and Markov chain methods. The inductive approach predicts a much greater influence of occupant behavior on energy performance than the deductive methodological approach. Third, research into window opening behaviors correlates to one or more of these aspects: the daily schedules of occupants, indoor thermal comfort, indoor air quality, and/or outdoor weather conditions. Finally, the use of lighting has been modeled to an advanced detail level. It has been inserted into building performance simulation programs and seems to work correctly, though how much lighting behaviors influence energy performance has not been fully explored.

In spite of advances in the modeling of presence and the operation of windows and lighting devices, some aspects of the field merit further research:

- Existing research has tended to focus on behavior in offices, while analyses of residential properties are rare.
- Occupant behavior has been scrutinized in several models, but few studies have conducted a sensitivity analysis (SA).
- Studies on the use of heating systems, namely the thermostat and radiator controls, are conspicuously absent from the literature.
- Time of day and seasonal differences in natural ventilation patterns should be investigated in detail.
- Most of the existing research has taken window position into account in a very simple way, being either open or closed. However, windows are operated in several different ways, such as always closed, closed, open, ajar, and always open. This level of detail has yet to be covered in the literature.

§ 3.3 Aims and Research Questions

This paper presents a SA of the influence of occupant behavior on the energy performance of dwellings. The aims of the study were to determine occupant behavior patterns quantitatively and reveal the robustness level of energy consumption in dwellings with respect to occupant behavior. Unlike in the existing research, in this study, presence is not assumed to be a precondition for behavior; instead, the occupant is assumed to have both an active and a passive influence on energy consumption. The passive influence results from the default settings of control mechanisms, which affect energy consumption even when the occupant is not present; active influence results from the occupant being present in a space, changing the systems and devices according to his or her needs, and the internal heat gain resulting from his or her presence.

This research addresses certain aspects of the literature that have not yet been studied to any great extent, namely, the use of heating systems and the control of natural ventilation in residences. Considering previous literature related to occupant behavior and energy performance in dwellings, the authors derived the following research questions:

- How can behavior be modeled in order to assess the robustness of the energy performance of dwellings with respect to occupant behavior?
- What is the weight of each behavior in terms of its influence on energy performance? Which occupant behaviors are more robust than others?
- How do the results of inductive models differ from those of deductive models in terms of calculating the influence of occupant behavior on energy performance?

It is hypothesized that, by using an SA method and building performance simulation tools, the behavioral patterns obtained from a dataset on presence, heating, and ventilation can be modeled, allowing the effects of behaviors on the energy consumption of a dwelling to be investigated free of the original dataset.

§ 3.4 Methodology

The literature review presented a number of methods for modeling and analyzing the influence of occupant behavior on the energy performance of dwellings. Since the objective of this research considers the robustness of behavior, the research methodology is based on an SA (see Hamby, 1994; Helton, et al., 2006; Saltelli, et al., 2000).

Sensitivity analysis (SA) is the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variation. A mathematical model is defined by a series of equations, input factors, parameters, and variables aimed to characterize the process being investigated. Input is subject to many sources of uncertainty including errors of measurement, absence of information and poor or partial understanding of the driving forces and mechanisms. This imposes a limit on our confidence in the response or output of the model. SA is used to increase the confidence in the model and its predictions, by providing an understanding of how the model response variables respond to changes in the inputs (Saltelli, 2000)

There are several ways of carrying out SAs, the most common of which is based on sampling. "A sampling-based SA is one in which the model is executed repeatedly for combinations of values sampled from the distribution (assumed known) of the input factors" (Saltelli, 2000). A number of sampling-based strategies are available, including random, importance, and Latin hypercube sampling. This study uses the latter.

There are many examples of the use of SA in building thermal modeling (Bedir, et al., 2011; Corson, 1992; Fürbringer and Roulet, 1999; Harputlugil, et al., 2011; Lam and Hui, 1996; Macdonald, 2004; Spitler, et al., 1989; Westphal and Lamberts, 2005). For energy-sensitivity simulation models, a set of input parameters and their values are defined and applied to a building model, and the simulated energy consumption of the model is used as a base for comparison to determine the extent to which output (here measured in terms of heating energy demand per year) changes as a result of particular increments of input values (Corson, 1992; Harputlugil, et al., 2011). The results show which parameters can be classified as "sensitive" or "robust." Sensitive parameters are those that cause effective changes in the outputs when changes are made to their values; in contrast, a change to robust parameters causes a negligible change in the outputs (Harputlugil, et al., 2011).

Hamby (1994); Hansen (2007); and Saltelli, et al. (2000) discussed the various classifications of SAs, including local SAs and global SAs. According to the definitions put forward by Hansen (2007), a local analysis follows a one-at-a-time approach, is less complex, has a sensitivity ranking that is dependent on the reference building, and has parameters that are assumed to be independent. In contrast, a global analysis requires random sampling, has a large degree of complexity, has a sensitivity ranking that is less dependent on the reference building, and provides information about possible correlations (interdependencies) between parameters. The present study uses a global SA.

In this study, the sensitivity of occupant behavior is analyzed using the MC method, which is a popular means of analyzing the approximate distribution of possible results on the basis of probabilistic inputs (Hopfe, et al., 2007; Lomas and Eppel, 1992). Moreover, it permits the application of a global SA in order to gather information about possible correlations between parameters. Here, the input parameters are presence and occupant behaviors that affect energy consumption in the dwelling (use of the heating and ventilation systems). Figure 2 illustrates the five steps followed in the analysis:

1. The raw survey data are preprocessed in a statistical analysis program. The mean and SD per hour value of each input parameter is determined.

2 The SimLab 2.2 (https://ec.europa.eu/jrc/en/samo/simlab) pre-processor is used to create 250 Latin hypercube samples, which represent behavioral patterns for each 24-hour period. The sampling method produces data points around the mean value, using a normal distribution pattern based on mean and SD values. This way it provides a realistic representation of the distribution of the studied parameters' actual values.
3 Each behavioral sample is tested in terms of the energy use of the reference dwelling, simulated in ESP-r.
4 Inputs and outputs are combined in the SimLab post-processor to conduct MC analysis.
5 The results are interpreted using graphical outputs.

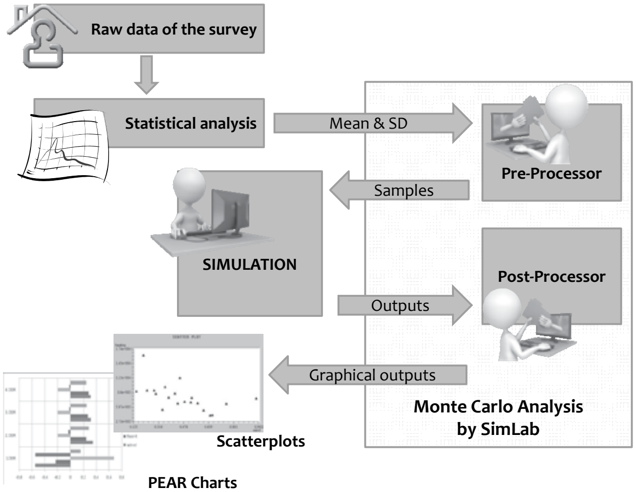

FIGURE 3.2 Flow chart of the study methodology

Data

Data on occupant behavior was collected from two neighborhoods developed after 1995 in Utrecht and the Hague, the Netherlands. A survey conducted in these two neighborhoods in autumn 2008 resulted in a response sample of 313 dwellings, 117 (37%) of which were row houses. The survey was developed in the form of a questionnaire by researchers in the OTB – Research for the Built Environment Department at Delft University of Technology to obtain information on dwelling and household characteristics, energy consumption, and actual household behavior patterns related to heating and ventilation. Respondents were asked a wide variety of questions about their dwelling's characteristics and their actual behavior related to their use of heating and ventilation systems, lighting, and appliances, including their hourly presence at home generally and in each room during the week and on weekends in the summer and winter, their hourly control of heating and ventilation devices in each room during the week and on weekends in the summer and winter, and their total hours of use of lighting in the living room and electrical appliances in the house (Bedir, et al., 2011; Guerra Santín, 2010). Table 1 lists the types of data collected in the OTB survey.

Individual (user) level				Dwelling and household level	
Heating behavior	Ventilation behavior	Lighting behavior	Appliances behavior	Household characteristics	Dwelling characteristics
- Heating system type	- Ventilation system type	- Nu. of low energy light bulbs in the living room	- Appliances in the house	- Presence in the house	- Dwelling type
- Radiator use (hours, set point)	- Window use (room, hours, opening)	- Number of normal or halogen light bulbs in the living room	- Hours appliances are used (daily and weekly)	- Presence in specific rooms	- Nu. of rooms
- Thermostat use (hours, set point)	- Grilles use (room, hours, opening)		- Nu. of appliances on stand by mode in the living room	- Duration of presence	- Function of rooms
	- Mechanical ven-tilation use (hours, set points)			- Household size	
				- Age	

TABLE 3.1 Types of data collected in the OTB survey (based on Bedir, et al., 2011; Guerra Santín, 2010). Data highlighted in blue are used in the MC analysis.

For this study, the authors used the specific survey data related to actual household behavior in row houses in winter (the heating season). These included (1) presence at home (number of people at home); (2) hourly data on heating behaviors, including thermostat settings, radiator use in each room, and set points; and (3) hourly data on ventilation behaviors, including use of windows and grilles in each room and position of windows. Building simulations were conducted for heating energy demand using the heating-season data from the questionnaires.

The consumption values of the dwellings were used to calibrate the initial heating energy demand models. In 1995, the Netherlands introduced a set of energy performance regulations that focused on the overall energy performance of buildings. In 1999, the Dutch Organisation for Energy and Environment (SenterNovem) responded by developing six reference houses using the regulations. The reference houses are used for calculating the impact of energy-saving measures on energy performance in dwellings, as well as for determining whether a dwelling meets the health and safety requirements outlined in the Dutch building standards and regulations.

The reference houses illustrate a schematic view of reality to allow builders and designers to assess real houses as accurately as possible, and using the reference houses at an early stage in the design process is strongly encouraged to make the process of obtaining building permits more successful. In this study, the reference row house (tussenwoning) was modeled using simulation software (SenterNovem, 2006). Figure 3 presents the plan/section/elevation of the reference row house, and Table 2 presents the envelope characteristics and energy use of the reference row house based on the Netherlands Standardization Institute (NEN) standards 5128 and 5129 (NEN, 2006, 2010). The Dutch standard values for ventilation (NEN 1087) were assumed for calculating the total ventilation rates (NEN, 2001) (Table 2)

Survey respondents were asked to fill in tables recording whether they opened windows or grilles in each room for each hour and whether and how they adjusted their mechanical ventilation each hour. A value was recorded for both weekdays and the weekend. The data recorded in the survey tables were converted into values to permit further mathematical calculations (for example, 1 = open window/grille, mechanical ventilation on; 0 = closed window/grille, mechanical ventilation off), which were then used to calculate the air change per hour (AC/h) values for each room with or without natural and/or mechanical ventilation. All 117 row houses from the survey dataset featured open kitchens, so the reported data on ventilation behaviors in the living room and kitchen were combined. The natural ventilation patterns for the entrance, bathroom, and circulation zones reported in the survey were not simulated because the reference row house did not propose natural ventilation through windows in these areas.

The air-change rates for each room during the day were calculated using the AC/h value assumptions calculated from the NEN standards, the reference row house, and the converted ventilation-behavior data from the survey dataset. The AC/h values for each room were determined using the following formula and the physical description of the reference row house:

Supply Air Rate (AC/h) = Volume Flow Rate (m3/h) / Room Volume (m3)
Living room = 1.25 AC/h
Bathroom, Bedroom 1, Bedroom 2, Entrance, and Circulation = 1.26 AC/h for each
Attic = 1.47 AC/h
Bedroom 3 = 1.15 AC/h

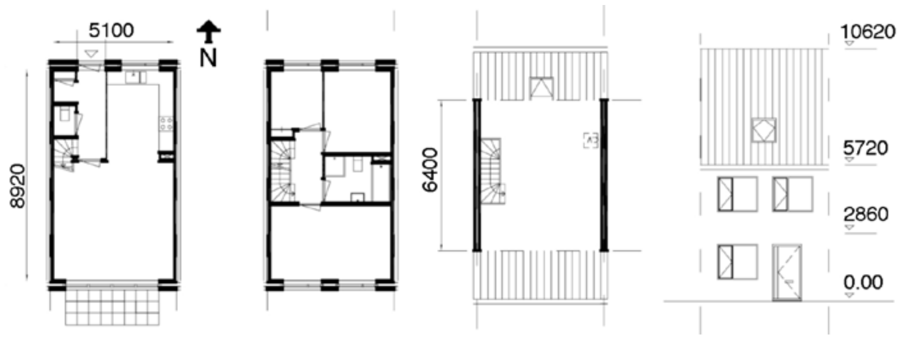

FIGURE 3.3 Plans and sections of the Dutch reference row house

Characteristics	
Measure	**Dimension**
Width (m.)	5.1
Depth (m.)	8.9
Floor height (m.)	2.6
Floor area (m2)	45.4
Volume (m3)	118.0
Rc for Façade (m2K/W)	3.0
Rc for Roof (m2K/W)	4.0
Rc for Ground floor slab (m2K/W)	3.0
U for Window (W/m2K)	1.8
U for Front door (W/m2K)	2.0
EPC value	0.78
Yearly energy consumption (MJ/m2)	359.0

TABLE 3.2 Envelope characteristics and energy use of the Dutch reference row house (NEN, 2006, 2010; SenterNovem, 2006)

To calculate internal heat gain, the authors used data from CIBSE Guide A, which suggested that each person is responsible for 95W of sensible heat and 45W of latent heat (CIBSE, 2006). These Figures were required for the energy performance simulation. One limitation of using an energy simulation program is that the program allowed only one air-flow value for ventilation, meaning that it was only possible to use the combined effect of natural and mechanical ventilation in the simulations.

Characteristics	
Room	Value
Living room	1 dm3/s/m2 floor area
Bedroom	1 dm3/s/m2 floor area
Kitchen	21 dm3/s
Bathroom + water closet	14 dm3/s
Water closet only	7 dm3/s

TABLE 3.3 Dutch standards for ventilation (NEN, 2001)

§ 3.5 Results

In this section, the results of the MC analysis are explained to provide an understanding of the variance of inputs and the outputs of heating energy demand and minimum indoor resultant temperature. The Pearson product-moment correlation coefficient (PCC) values are also discussed. To derive the energy simulation results, all input data (each parameter for each of the 250 Latin hypercube samples) were inserted into the model in ESP-r, one parameter at a time.

	Weekday				Weekend			
Input	Min	Max	Mean	SD	Min	Max	Mean	SD
Presence (number of people at home)	0.00	4.00	1.06	0.87	0.00	5.00	1.58	1.32
Heating (thermostat set point)	0.00	22.20	13.33	8.27	0.00	23.00	14.19	8.73
Heating (radiator setting)	7.00	27.00	10.54	5.93	7.00	27.00	10.54	5.93
Ventilation (air change rate including window, grilles, mechanical ventilation)	0.20	2.17	1.53	0.58	0.20	2.17	1.53	0.58

TABLE 3.4 Minimum, maximum, mean and SD values for presence, heating, and ventilation for weekdays and the weekend.

§ 3.5.1 Variance of Inputs

Table 4 shows the minimum, maximum, mean, and SD values for presence, heating, and ventilation behavior pattern inputs gathered from the survey. The greatest number of people at home during the week was four, occurring between 12:00 pm and 7:00 pm; on the weekend, the maximum number was five, occurring between 9:00 am and 7:00 pm. The variance of presence was quite high for both weekdays and the weekend. During the week, the highest value recorded for the thermostat setting was 22°C, while the mean was 13°C. On the weekend, the highest chosen thermostat setting was 23°C, and the mean was 14°C. The SD of the thermostat setting was high for both weekdays and the weekend. These values indicate that more people were at home for longer periods on the weekend, when the chosen maximum thermostat setting was almost 1°C higher.

Figures 4-7 present the average presence and behavior patterns obtained from the 250 samples. (For ventilation and radiator use, the weekday and weekend data were combined into a single average value.) Figure 4 shows there were higher numbers for presence during the weekend, while people stayed at home for shorter durations during the week. As Figure 5 shows, the highest value for ventilation was recorded in the afternoon (3:00-4:00 pm); the lowest values occurred at night. During the day, ventilation was kept at a constant value that was higher than the night values. Figure 5 shows that radiator use varied considerably throughout the day, peaking in the early evening and lowest at night (midnight to early morning). As might be expected, the

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thermostat use patterns generally followed the presence patterns. The patterns for Saturday and Sunday were very similar, both in terms of schedule and set point, and the weekend set points were a little higher overall than the weekday set points (Figure 7).

§ 3.5.2 Heating energy demand and minimum indoor resultant temperature

The heating energy demand and minimum indoor resultant temperature values were garnered from the 250 samples using the dynamic simulation program ESP-r. For the heating energy demand values, the authors chose the winter seasonal values (heating season), which started at midnight on October 1 and ended at midnight on March 31. The authors chose the minimum indoor resultant temperature output to reveal the effects of occupant behavior on the indoor temperature as a trigger of heating demand. Figure 8 presents the output data for the entire sample. Most of the minimum indoor resultant temperature values ranged from 9°C to 11°C; the lowest value was 7°C, and the resulting heating energy demand was 347.18 kWh.

§ 3.5.3 PCC values

As a simple measure of sensitivity, the PCC value was used as the linear correlation coefficient based on a regression analysis. PCC values reveal the correlations between input and output data; positive values represent a direct correlation, while negative values represent an indirect correlation. A comparison of the PCC values for different behavioral patterns for weekdays and the weekend showed that heating energy demand was most sensitive to presence between 6:00 pm and 5:00 am on weekends ($r = -.14$), to the thermostat setting between 7:00 am and 2:00 pm on weekdays ($r = .34$), to the radiator setting between 5:00 am and 8:00 am (average of weekend and weekday values) ($r = -.11$), and to the ventilation rate between 11:00 pm and 6:00 am (average of weekend and weekday values) ($r = .20$) (Figure 9).

The minimum indoor resultant temperature was most sensitive to presence between 12:00 pm and 7:00 pm on weekdays ($r = .17$), to the thermostat setting between 7:00 am and 2:00 pm on weekdays ($r = .32$), to the radiator setting between 8:00 am and

2:00 pm (average of weekend and weekday values) (r = .15), and to the ventilation rate between 11:00 pm and 6:00 am (average of weekend and weekday values) (r = -.21) (Figure 10).

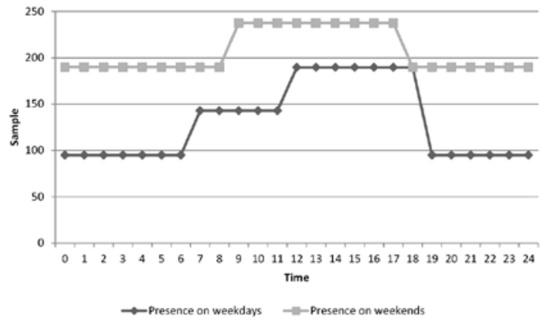

FIGURE 3.4 Average hourly presence at home pattern

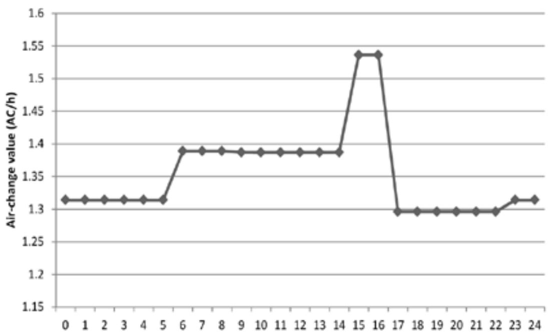

FIGURE 3.5 Average air change rate (per hour) during the day

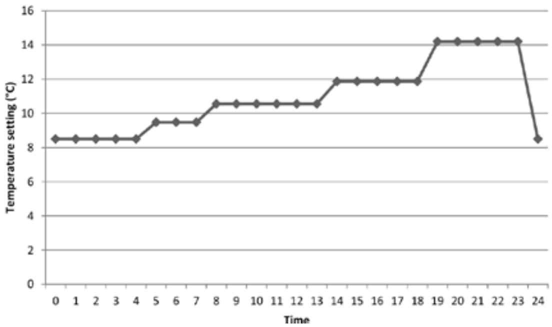

FIGURE 3.6 Average hourly radiator-thermostat setpoint preference during the day

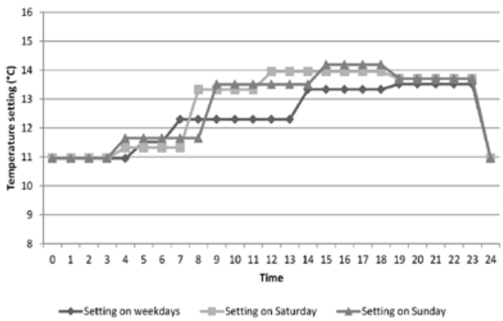

FIGURE 3.7 Average hourly thermostat-set point preference during the day

§ 3.6 Discussion

Research on energy performance of dwellings covers thorough investigation of the aspects that are involved in the design and building processes, as well as the behavioral performance in the post occupancy process. There has been extensive progress on the building physics aspects of energy performance; concerning methods and practices for specification of building geometry, material properties, and external conditions. However, the resolution of input information regarding occupancy is still rather low.

Mahdavi and Pröglhöf (2009) claimed that recent and ongoing research attempts to construct models for the effects of passive and active occupancy on building energy performance, require physical and psychological descriptions of occupancy, and empirically based observational data and inductive models require extensive observational data (Mahdavi, 2011). This leads us to our hypothesis: By using an SA method and building performance simulation tools, the behavioral patterns obtained from a dataset on presence, heating, and ventilation can be modeled, allowing the effect of behaviors on the energy consumption of a dwelling to be investigated free of the original dataset.

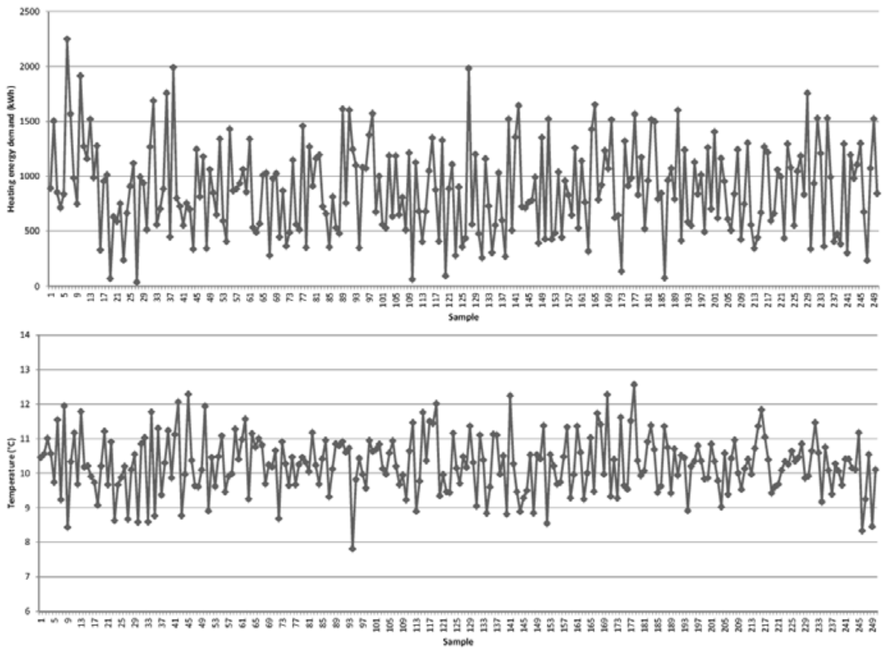

FIGURE 3.8 (Top) Heating energy demand and (bottom) minimum indoor resultant temperature values for the entire dataset

Figures 4-7 present the average presence and behavior patterns obtained from the 250 samples. The presence values for both weekdays and weekends were as expected, setting the background for the heating and ventilation behaviors. For ventilation, the highest values were achieved in the afternoon, and the lowest values were seen at night. During the day, ventilation tended to be kept at a constant value that was higher than the night values. This variance indicates that people tended to ventilate their houses when they got up in the morning (around 6:00 am), maintained ventilation at a constant level during the day, and increased ventilation in the late afternoon and early evening when they came home and possibly cooked or showered. They then decreased the ventilation as they relaxed in the evening and went to bed. Radiator use varied considerably, reaching a peak in the early evening and falling to its lowest levels at night. This was rather unexpected, as heating is generally regulated via thermostats. Finally, the patterns for thermostat use generally followed the presence patterns. The thermostat settings on Saturday and Sunday were very similar, both in terms of schedule and set point, and the weekend set points were a little higher overall than those during the week. Thus, one part of the hypothesis is confirmed: SA can be used as a method of evaluating the impact of occupant behavior on the energy consumption of a dwelling.

One important difference in our modeling approach is that it does not assume presence is an initiator of behavior or a precondition for behavior. Behavior can indirectly influence energy consumption in a space because heating and ventilation systems and lighting may be set to certain control points without the occupants even being present in a space. This is fundamentally in contrast to the existing research, which has carried out the inductive modeling of occupant behavior considering presence as a preliminary factor for occupant behavior. Nevertheless, presence can influence energy performance through indoor heat gain.

In this paper, an attempt has been made to address how occupants control their thermostat and radiator settings in dwellings. Previously, this aspect had not been considered in the research. The times and values of ventilation use during winter were carefully modeled. Existing research has covered window positions in a very simple way, defining them as only open or closed; however, this research incorporated a number of different window positions — always closed, closed, open, ajar, and always open — as well as the positions of grilles in terms of air flow. Research into window-opening behaviors correlates to one or more of these aspects: the daily schedules of occupants, indoor thermal comfort, indoor air quality, and/or outdoor weather conditions.

The survey did not address thermal comfort, so the assumption in the literature that thermal comfort has a large influence on window-opening behavior still needs to be validated with the current model. The sensitivity of energy performance to the use of appliances was not analyzed in this study because the model made an assumption based on the Dutch regulations, which was then used as a constant value for each sample. The influence of thermal comfort and the use of appliances on occupant behavior needs to be investigated in future studies.

With regard to the second set of research questions (What is the weight of each behavior in terms of its influence on energy performance? Which occupant behaviors are more robust than others?), according to the results of the MC analysis, this study found that the energy performance of a dwelling was most sensitive to the thermostat setting ($r = .34$), followed by the ventilation rate ($r = .20$), presence ($r = -.14$), and the radiator setting ($r = -.11$). (The findings related to presence and the thermostat setting were discussed at the beginning of this section.) The ventilation finding was recorded during the 11:00 pm-6:00 am time period, indicating that ventilating at night and early in the morning has a great influence on the energy performance of a dwelling. The attribute that was least influential to energy performance was the radiator setting, which is an interesting finding that merits further investigation since the inputs of radiator-control behaviors varied broadly. In terms of minimum indoor resultant temperature, sensitivity was most affected by the thermostat setting ($r = .32$), followed by the ventilation rate ($r = -.21$), presence ($r = .17$), and the radiator setting ($r = .15$).

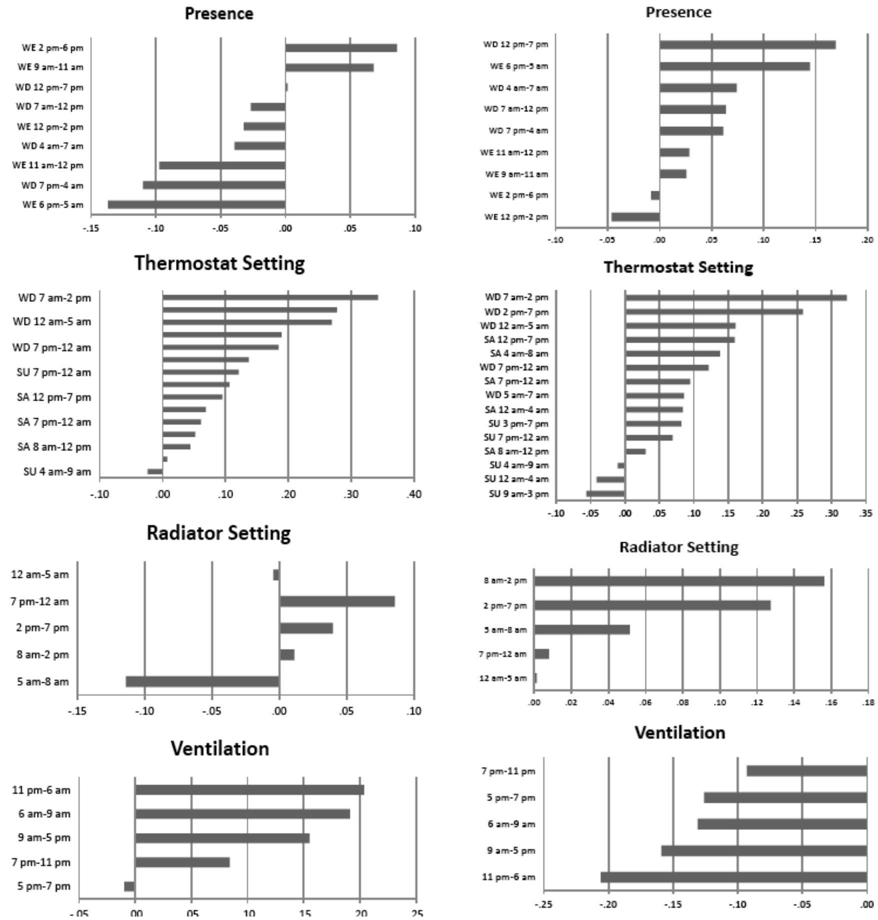

FIGURE 3.9 PCC values for heating energy demand (left) and minimum indoor resultant temperature (right). (WE = weekend, WD = weekday, SA = Saturday, and SU = Sunday). The values for radiator setting and ventilation are an average of both weekend and weekday values. PCC values reveal the correlations between input (presence, thermostat setting, radiator setting, ventilation) and output data (heating energy demand, minimum indoor resultant temperature). The positive values in the chart represent a positive correlation with the output parameter, meaning as the value of the input parameter increase, the output value increase with a factor of the correlation coefficient, while negative values represent an negative correlation with the output parameter, meaning as the value of the input parameter increase

In order to discuss the second part of the hypothesis (i.e., investigating the effect of behaviors by statistically modeling patterns obtained from a dataset) and address the third research question (How do the results of inductive models differ from those of deductive models in terms of calculating the influence of occupant behavior on energy performance?), the authors compared their results with those of a previous deductive analysis conducted on the same sample (Guerra Santín, 2010), as explained in the literature review.

Guerra Santín's (2010) analysis of the relationship between occupant behavior and energy consumption in dwellings revealed that the most important factor in energy use was the number of hours that the thermostat was at the highest chosen setting. She also found correlations with the number of hours the radiators were turned on, the number of bedrooms that were used as living areas, and the presence of a programmable thermostat (which was associated with more hours with the radiator on). Guerra Santín found that (1) there were statistically significant differences in energy consumption depending on whether the windows in the living room were sometimes open or always closed; (2) the effect of open grilles on energy consumption was independent of the effect of open windows, though both played an important role in energy consumption; and (3) households tended to use natural ventilation (windows and grilles) more than mechanical ventilation.

While this paper did not look specifically at the number of hours the thermostat was at a specific temperature setting, it did find that the thermostat setting between 7:00 am and 2:00 pm was the most significant parameter for energy performance in dwellings, and this finding incorporates the number of hours at a particular thermostat setting.

In terms of ventilation, it was not possible to investigate the sensitivity of a dwelling's energy performance to occupants' behaviors regarding natural versus mechanical ventilation due to limitations in the simulation software. However, this study did find that the ventilation rate had the second greatest influence on energy performance. The highest ventilation rates occurred in the afternoon, but they were most influential on energy performance in the evening and early morning.

Comparing our results with those of Guerra Santín (2010), it appears that our method may be used to generate homogenous sample characteristics by statistically remodeling the actual dataset, but further research using real-time measurements should be carried out for validation.

§ 3.7 Conclusion

This paper has focused on exploring the sensitivity of a dwelling's energy performance to different occupant behavior patterns, investigating presence, heating control (thermostat and radiator), and ventilation control (natural and mechanical) patterns in the winter for both weekdays and the weekend for a sample of Dutch residents. Occupant behavior served as the input, while the outputs were heating energy demand and its triggered factor, minimum indoor resultant temperature. The sample dwelling was a typical Dutch row house.

In this sample, more people spent more time at home on the weekends, when the maximum thermostat setting was 1°C higher than during the week. Radiators were mostly used at the maximum setting during the evening (7:00 pm-11:00 pm), both during the week and on the weekend. Ventilation was used most in the morning and during the day (6am-3pm). The minimum indoor resultant temperature was 7°C, and the resulting heating energy demand was 347.18 kWh.

Heating energy demand and minimum indoor resultant temperature were most sensitive to the thermostat setting (r = .34 and .32 respectively) and most robust in relation to the radiator setting (r = -.11 and .15 respectively). A comparison of the heating energy demand and minimum indoor resultant temperature sensitivities reveals that both outputs were most sensitive to ventilation and thermostat settings at roughly the same times of day (evening and morning/midday respectively). However, heating energy demand was most sensitive to the radiator setting in the early morning hours, while minimum indoor resultant temperature was most sensitive to the radiator setting later in the morning and early afternoon.

The results of the PCC analysis revealed a direct, positive relationship between presence and minimum indoor resultant temperature. In contrast, ventilation had the most negative relationship with minimum indoor resultant temperature. As a triggering factor of heating energy demand, the minimum indoor resultant temperature was most sensitive at night, when presence (and therefore the internal heat gain caused by the presence of occupants) was at its highest. Heating energy demand is closely related to system operation, hence the thermostat setting would appear to be the most sensitive parameter in this regard. Interestingly, the high negative PCC values show an indirect relation, as when presence was high (like at night and on weekends), heating energy demand actually decreased.

In conducting this research, it became apparent that creating a model of a dataset of occupant behavior using our approach would make it possible to work on the data in a more general way, without necessarily relating our results specifically to the original sample.

One of the most important next steps for further research is to collect more real-time data in order to validate the proposed model. Second, modeling thermal comfort and indoor air quality could lead to results that would further explain the sensitivity of certain factors. Future studies to model other dwelling, household, and system types would also be helpful.

Notes

The envelope characteristics and energy use for the reference houses were updated in 2006, 2013, and 2015. This research used the 2006 version and was completed before the 2013 and 2015 versions were published. Following a government restructuring, SenterNovem merged with other agencies and was incorporated into the Rijksdienst voor Ondernemend Nederland (RVO.nl) in 2014. Data for the current versions of the reference houses can be found on the RVO.nl website (RVO.nl, 2015).

The data in this paper are based on the 2010 version of NEN 5128; the standard was updated in 2013 and again in 2015. Likewise, this paper uses the 2006 version of NEN 5129; the standard was updated in 2011. NEN 1087 has not been updated since it was published in 2001. The current Dutch standards can be found on the NEN website (https://www.nen.nl)

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