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Occupant behavior and energy consumption in dwellings

An analysis of behavioral models and actual energy consumption in the dutch housing stock

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Door

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To my parents

Contents

Abbreviations

AC/h	Air change per hour
ADEME	French Environment and Energy Management Agency
B (in regression analysis)	Regression coefficients
BEMS	Building Energy Management System
Beta (in regression analysis)	Standardized coefficients
BMRDA	Bombay Metropolitan Regional Development Authority
BREEAM	Building Research Establishment Environmental Assessment Method
°C	Centigrade degrees
CAS	Central Access Server
CBS	Centraal Bureau voor de Statistiek (Central Office for Statistics)
CIBSE	Chartered Institution of Building Services Engineers
CMHC	Canada Mortgage and Housing Corporation
CO2	Carbon dioxide
dB(A)	A-weighted decibels; relative loudness of sounds in air perceived by the human ear
DBTA	Difference between the theoretical and actual consumption
DG	Distributed generation
DHES	Dwelling, Household, Economic, System
DLMS	Device language message specification
COSEM	Companion specification for energy metering
dm3/s	Decimeter cubes per seconds
dm3/s/m2	Decimeter cubes per seconds per meter squares
EC	European Commission
ECEEE	European Council for an Energy Efficient Economy
ECN	Energy Research Centre/ the Netherlands
EEE	Economic savings, energy, environment
EPC	Energy Performance Coefficient
EPBD	Energy Performance Buildings Directive
ESA	Energy saving appliances
ERC	European Research Council
EU	European Union
°F	Fahrenheit degrees
GJ	Gigajoule
HEMS	Home energy management system

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HQPI	Housing Quality and Process Innovation
HRV	Heat recovery ventilation
HVAC	Heating ventilation air conditioning
ICE	Information, communication, entertainment
ICT	Information, communication, technology
IEA	International Energy Agency
IEA-SHC	International Energy Agency - Solar Heating and Cooling Program
IEH	Industrial excess heat
IVAM	Interfaculty Environmental Science Department of the University of Amsterdam
KMO	Kaiser-Meyer-Olkin
KEMA	Keuring van Elektrotechnische Materialen te Arnhem
kWh	Kilowatt hour
kWh/m2	Kilowatt hour per square meters
kWh/year	Kilowatt hour per year
LBO	Vocational secondary school (junior)
LED	Light-emitting diode
Ls-1	Liters per second (air flow per second)
m	Meter
m/s	Meter per second
MW/h	Megawatt per hour
m2	Meter square
m2K/W	Meter square Kelvin per Watt (measurement of thermal transmittance)
m3	Meter cubes
m3/h	Meter cubes per hour
MJ/m2	Mega joules per square meter
MC	Monte Carlo
NEN	Dutch standard
NMN	National Measurement Network
NO2	Nitrogen dioxide
NSHQ	National Survey on Housing Quality
OTB	Onderzoek voor de Gebouwde Omgeving (Research for the Built Environment)
p (in regression analysis)	Probability value
PCC	Pearson product-moment correlation coefficient
Pj	Peta joule
PV	Photovoltaic
PMV	Predicted mean vote
PROBE	Post Occupancy Review of Buildings and their Engineering

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R2 (in regression analysis)	Coefficient of determination
RFID	Radio Frequency Identification
RVO	Rijksdienst voor Ondernemend Nederland (Government Office for Enterprises Netherlands)
SA	Saturday
SEREC	Socio-technical Factors Influencing Residential Energy Consumption
SBS	Sick Building Syndrome
SA	Sensitivity Analysis
SSL	Solid-state lighting
SD	Standard deviation
Senter Novem	Dutch Organization for Energy and Environment
SU	Sunday
TNO	Netherlands Organization for applied scientific research
TUS	Time-Use Survey
TV	Television
VCR	Video cassette recorder
WE	Weekend
WD	Weekday
U value	Heat transfer / thermal transmittance coefficient
UK	United Kingdom
US	United States of America
USSU	Use of space and the circulation between spaces
WoON	WOONonderzoek Nederland (Database of the Dutch Ministry of Housing)
WV	Wateringse Veld
LR	Leidsche Rijn
WH	West of the Netherlands
ZEBs	Zero-energy buildings
nZEBs	Near-Zero energy buildings

Summary

Much is known about the increasing levels of energy consumption and environmental decay caused by the built environment. Also, more and more attention is shown to the energy consumption of dwellings, from the early design stage until the occupants start living in them. The increasing complexity of building technologies, the occupants' preferences, and their needs and demands make it difficult to achieve the aimed energy consumption levels. The goal of reducing the energy consumption of dwellings and understanding the share of occupant behavior in it form the context of this research.

Several studies have demonstrated the 'energy performance gap' between the calculated and the actual energy consumption levels of buildings, and have explored the reasons for it. The energy performance gap is either caused by calculation drawbacks, uncertainties of modeling weather conditions, construction defects regarding air tightness and insulation levels, or by occupant behavior. This research focuses on the last aspect, i.e. analyzing the relationship between occupant behavior and energy consumption in dwellings, understanding the determinants of energy consumption, and finding occupants' behavioral patterns.

There are several dimensions of occupant behavior and energy consumption of dwellings: dwelling characteristics including the energy and indoor comfort management systems, building envelope, lighting and appliances; occupant characteristics including the social, educational and economical; and actual behavior, including the control of heating, ventilation and lighting of spaces, and appliance use, hot water use, washing, bathing, and cleaning. Attempting to understand this complexity asks for a methodology that covers both quantitative and qualitative methods; and both cross-sectional and longitudinal data collection, working interdisciplinary among the domains of design for sustainability, environmental psychology, and building and design informatics.

The main question that this thesis deals with is: **How much does the occupant behavior influence the energy consumption of dwellings in the Netherlands, and how could we identify the determinants of consumption, as well as the behavioral patterns and profiles?**

In order to research this question, the following questions are formulated:

I What is the sensitivity of a dwelling's heating energy consumption to occupant behavior? (Chapter 3)

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?

II What is the influence of lighting and appliance use on the total electricity consumption in dwellings? (Chapter 4)

1 What are the main direct and indirect determinants of electricity consumption? (Direct determinant: such as number of appliances and duration of appliance use …; Indirect determinant: such as household size, dwelling size, dwelling type …)

2 How much of the variance in electricity consumption in dwellings can be explained by direct and indirect determinants?

III What are the behavioral patterns and profiles of energy consumption?

1 What are the behavioral patterns of thermostat control? How do they relate to the household characteristics, revealing behavioral profiles? (Chapter 5)

2 What are the behavioral patterns of electricity consumption? How do they relate to the household characteristics, revealing behavioral profiles? (Chapter 6)

In this thesis, occupant behavior is modeled in different chapters using sensitivity, correlation, regression, repeated measures, and cluster and factor analyses, based on data on dwelling and household characteristics, actual behavior, and energy use. The structure of the thesis is based on the kind of energy use: heating energy and electricity for appliance and lighting. First, a sensitivity analysis for occupant behavior and heating energy consumption is conducted. Afterwards, determinants of occupant behavior in relation to heating energy consumption is explored through existing research. Determinants of electricity consumption for lighting and appliances are analyzed using correlation and multiple regression methods. In-depth analyses of behavioral patterns regarding heating energy are realized by repeated measures and cluster analyses, and electricity consumption by factor analysis. The research combined deductive and inductive methodologies. In this thesis, the deductive method is defined to operate on the macro level, using cross-sectional data on the dwelling and its systems, and include population data collected with one-time questionnaires and energy consumption characteristics based on yearly bills. The inductive method operates bottom up, applying monitoring and other longitudinal data collection methods and use actual data on thermostat control behavior. Research using inductive and deductive methods display a significant variance in explaining the sensitivity of energy consumption to occupant behavior.

Three datasets were used in this research. The first one is based on data collected in Wateringse Veld in The Hague, and Leidsche Rijn in Utrecht. The data was collected through a questionnaire in the autumn of 2008. The inhabitants were asked to respond to questions regarding the architectural typology, the heating and ventilation systems, the envelope properties of their dwellings, the number and use of lighting and electrical household appliances, and the energy consumption, in addition to the economical, educational and social characteristics of the household and the individual, the presence patterns in the house and in different rooms, the indoor comfort and energy management behavior patterns, habits, hobbies, and health conditions. This dataset consists of 323 dwellings.

The second dataset is comprised of 61 dwellings chosen randomly among the clients of one energy company. The household characteristics are representative for the Dutch average. Data on thermostat control behavior was collected by monitoring during March and April 2011, while a questionnaire was used for an inventory of household characteristics and behavioral attitudes, before the monitoring started.

Lastly, the WoON survey was used as a validation database for the first dataset. The WoON Database of the Dutch Ministry of Housing includes data of 4500 dwellings and is assumed to be representative for the Netherlands. This database includes a household survey, data on occupant behavior, dwelling inspections and reports on energy consumption in 4500 dwellings across the Netherlands.

In relation to the research questions, the main conclusions of this research can be summarized as follows:

Q I: Sensitivity analysis can be used as a method of evaluating the impact of occupant behavior on heating energy consumption. Heating energy consumption of a dwelling is the most sensitive to thermostat control, followed respectively by ventilation control and presence. Both heating energy consumption and the resultant indoor temperature are the most robust to radiator settings, meaning that heating energy consumption and resultant indoor temperature change minimal if the occupants change the radiator control.

Q II: Total appliance use (ownership and duration of use of appliances) is calculated based on the direct detereminants of electricity consumption. DHES (Dwelling, Household, Economic, System) characteristics of dwellings, i.e. household size, dwelling type, the number of showers, use of dryer and washing cycles are the indirect determinants, and the combined model of direct and indirect determinants explains 58% of the variance in electricity consumption.

Q III - 1: Four occupant profiles are identified for heating energy consumption: (1) no pattern, (2) one-off, (3) comforty, (4) controller. The first profile does not have significant common household characteristics, and displays no pattern of thermostat use. This profile requires detailed investigation of the household behaviors. The second profile, 'one-off' households pick a single set point over a period of hours (morning, day time, evening, and night time), and this is repetitive during two months. These households can be characterized with higher educated males and gadget lovers, not necessarily interested in energy saving. The third profile, 'comforty' households have a thermostat control of more than one set point and intervals, with high temperature preferences, in different days of the week, which is identified as a pattern during the two months. This group is composed of homeowners with a high income and larger dwellings, and are not interested in energy saving, also prefer higher temperatures. Lastly, the fourth profile, 'controller' households prefer one or two set point temperatures and intervals, with low temperature preferences, in different days of the week, repetitive for two months. Group four is composed of households with an energy saving agenda, mostly families and sometimes the elderly, where the parents/couples take decisions regarding energy consumption together.

Q III - 2: Behavioral factors of electricity consumption are total appliance use, the use of Information, Communication, Entertainment (ICE) devices, presence, personal hygiene and household cleaning, and energy conservation behavior. Based on these, the behavioral patterns are defined as appliance use, the use of technology / occupant presence, personal hygiene and household cleaning / occupant presence, and energy conservation. The correlations between behavioral factors, and household and dwelling characteristics reveal the behavioral profiles. These are the specific groups of users with corresponding behavioral characteristics: (1) family (couples (sometimes with a kid) with average user behavior), (2) techie (households that possess a lot of ICE devices), (3) comforty (larger households with a higher income that have a high usage of lighting and appliances, as well as heating), (4) conscious (smaller size family, elderly, lower income, higher education households who consume less, as well as owning solar panels, energy saving lamps, etc.). The behavioral patterns and the behavioral

profiles are statistically significantly different from each other in relation to electricity consumption.

In relation to the main question; **"how much does the occupant behavior influence the energy consumption of dwellings in the Netherlands, and how could we identify the determinants of consumption, as well as the behavioral patterns and profiles?"** we could summarize the following:

This thesis has been interested in determining occupant behavior in relation to energy consumption, claiming that the buildings' energy consumption can be validated in total, only during occupancy, when the design is tested on actual use. Referring to the lack of research, this study combined the deductive (cross-sectional, macro data, macro level statistics) and the inductive methods (longitudinal data, detailed high frequency data, performance simulation), by considering both the determinants of behavior and the actual behavior itself. We found that deductive methods are much faster in calculating and dissecting energy consumption into its factors, such as household characteristics, dwelling characteristics, behavioral aspects, etc; and inductive methods model actual behavior from bottom up experimenting and validating energy consumption levels. In addition, this research has found that the heating energy consumption of a dwelling is the most sensitive to thermostat control, followed respectively by ventilation control and presence. Both heating energy consumption and indoor resultant temperature are the most robust to radiator control. Calculating a regression model on the determinants of electricity consumption, this research has found that using the total duration of appliance use and parameters of household size, dwelling type, number of showers, use of dryer and washing cycles, and presence in rooms, 58% of the variance in electricity consumption could be explained. Introducing behavioral profiles and patterns contribute to the modeling of energy consumption and occupant behavior, this research revealed that household composition, age, income, ownership of dwelling, and education are the most important elements of behavioral profiling.

This thesis addresses occupant behavior in dwellings in the field of sustainability and building energy consumption by using interdisciplinary methodologies, i.e. by combining different modeling and data collection methods. It reveals unknown aspects of the relationship between energy consumption and occupant behavior, and reveals occupants' behavioral patterns and profiles of energy consumption.

For the energy and indoor comfort engineering industry, the knowledge gained through this research means support for designing systems that are more effective in reducing energy consumption, in addition to influencing users towards energy efficient behaviors. For policy, building industry, and design informatics (particularly

simulation based energy performance assessment and design tools), this research illustrates the benefit of considering occupant behavior in early phases of design in renovating existing housing stock and for new housing when aiming for sustainability. Furthermore, this thesis could contribute to the better design and implementation of energy control systems and products. Further research could utilize this knowledge to increase the energy efficiency of dwellings.

Samenvatting

Er is veel bekend over het toenemend energieverbruik en de milieuvervuiling die worden veroorzaakt door de gebouwde omgeving. Er wordt steeds meer aandacht besteed aan het energieverbruik van woningen, vanaf de vroege ontwerpstadia tot aan het moment dat bewoners intrekken. De toenemende complexiteit van bouwtechnologieën, de voorkeuren van de bewoners en hun behoeften en eisen maken het moeilijk om de beoogde energieverbruiksniveaus te bereiken. Het doel van het verminderen van het energieverbruik van woningen en het begrijpen van het aandeel van het bewonersgedrag hierin, vormen de context van dit onderzoek.

Verschillende studies hebben een 'energy performance gap' ('energieprestatiekloof') tussen het berekende en het werkelijke energieverbruik van gebouwen aangetoond en de redenen daarvoor onderzocht. De 'energy performance gap' wordt ofwel veroorzaakt door berekeningsproblemen, onzekerheden in het modelleren van weersomstandigheden, bouwfouten met betrekking tot luchtdichtheid en isolatieniveaus, of door bewonersgedrag. Dit onderzoek richt zich op het laatste aspect, dat wil zeggen het analyseren van energieverbruik in woningen in relatie tot bewonersgedrag in woningen, en het begrijpen van determinanten en gedragspatronen.

Bewonersgedrag en de energieverbruik van woningen kennen meerdere dimensies: woningkenmerken, waaronder energie- en klimaatbeheersingssysteem, bouwenvelop, verlichting en huishoudelijke apparaten; gebruikerseigenschappen, waaronder sociale, educatieve en economische aspecten; en feitelijk gedrag, waaronder het verwarmen, ventileren en verlichten van ruimten, het gebruik van huishoudelijke apparaten en heet water, en het was-, bad- en schoonmaakgedrag. Pogen deze complexiteit te begrijpen, vraagt om een methodologie die zowel kwantitatieve als kwalitatieve methoden omvat; zowel transversale als longitudinale dataverzameling, interdisciplinair werkend binnen de domeinen duurzaam ontwerp, omgevingspsychologie en bouw- en ontwerpinformatica.

De hoofdvraag van dit proefschrift is: **In hoeverre beïnvloedt bewonersgedrag het energieverbruik van woningen in Nederland en hoe kunnen we de determinanten en patronen van deze relatie identificeren?**

Om deze vraag te onderzoeken, zijn de volgende deelvragen geformuleerd:

I Wat is de gevoeligheid van het verwarmingsenergieverbruik van een woning voor bewonersgedrag? (Hoofdstuk 3)

1 Wat zijn de bestaande berekeningsmodellen voor energieverbruik en hoe is gebruikersgedrag hierin opgenomen? En hoe zijn de resultaten van deze modellen in termen van het berekenen van de invloed van beroepsgedrag op energieprestaties?

2 Hoe kan gedrag worden gemodelleerd om de robuustheid van de energieverbruik in woningen naar bewonersgedrag te beoordelen?

3 Wat is het gewicht van elk gedragsaspekt in termen van invloed op het energieverbruik?

II Wat is de invloed van verlichting en apparaat op het totale elektriciteitsverbruik in woningen? (Hoofdstuk 4)

1 Wat zijn de belangrijkste directe en indirecte determinanten van het elektriciteitsverbruik? (Directe determinant: zoals aantal apparaten en duur van het gebruik van het apparaat ...; Indirecte determinant: zoeken als huishoudelijke grootte, woninggrootte, woningtype ...)

2 Hoeveel van de variantie in het elektriciteitsverbruik in woningen kan worden verklaard door directe en indirecte determinanten?

III Wat zijn de gedragspatronen en profielen van energieverbruik?

1 Wat zijn de gedragspatronen van thermostaat controle? Hoe hebben ze betrekking op de huishoudelijke eigenschappen, onthullende gedragsprofielen? (Hoofdstuk 5)

2 Wat zijn de gedragspatronen van het elektriciteitsverbruik? Hoe hebben ze betrekking op de huishoudelijke eigenschappen, onthullende gedragsprofielen? (Hoofdstuk 6)

In dit proefschrift wordt bewonersgedrag in verschillende hoofdstukken gemodelleerd op basis van gevoeligheid, correlatie, regressie, herhaalde metingen en cluster- en factoranalyses, gebaseerd op gegevens over woning- en huishoudenskenmerken, daadwerkelijk gedrag en energieverbruik. De structuur van het proefschrift is gebaseerd op het soort energiegebruik: verwarmingsenergie en elektriciteit voor huishoudelijke apparaten en verlichting. Eerst wordt een gevoeligheidsanalyse voor bewonersgedrag en verwarmingsenergieverbruik uitgevoerd. Daarna worden de determinanten van bewonersgedrag in relatie tot verwarmingsenergieverbruik verkend door middel van bestaand onderzoek. Determinanten van elektriciteitsverbruik voor verlichting en huishoudelijke apparaten worden geanalyseerd met behulp van correlatie en meervoudige regressiemethoden. Diepgaande analyses van gedragspatronen met betrekking tot verwarmingsenergie worden gerealiseerd door herhaalde metingen en clusteranalyses; die met betrekking tot elektriciteitsverbruik door factoranalyse. Het onderzoek combineert deductieve met inductieve methodologieën. De deductieve methoden zijn op macroniveau, met behulp van transversale gegevens over de woning en haar systemen, inclusief populatiegegevens verzameld met eenmalige vragenlijsten en energieverbruikskarakteristieken gebaseerd jaarlijkse facturen. De inductieve methoden zijn bottom-up, passen monitoring en andere longitudinale dataverzamelingsmethoden toe en gebruiken actuele gegevens over thermostaatbedieningsgedrag. Inductieve en deductieve onderzoek vertonen een significante variantie in het verklaren van de gevoeligheid van het energieverbruik voor bewonersgedrag.

In dit onderzoek werden drie datasets gebruikt. De eerste is gebaseerd op gegevens verzameld in Wateringse Veld in Den Haag en Leidsche Rijn in Utrecht. De gegevens werden verzameld met behulp van een vragenlijst in 2008. De inwoners werden gevraagd om te reageren op vragen over de architectonische typologie, de verwarmings- en ventilatiesystemen, de eigenschappen van de bouwenvelop van hun woning, de hoeveelheid en het gebruik van verlichting en huishoudelijke apparaten, en het energieverbruik, in aanvulling op de economische, educatieve en sociale kenmerken van het huishouden en het individu, de aanwezigheidspatronen in het huis en in verschillende kamers, het binnencomfort en gedragspatronen van het energiebeheer, gewoontes, hobby's en de gezondheidstoestand. Deze dataset bestaat uit 323 woningen.

De tweede dataset bestaat uit 61 willekeurig gekozen woningen onder de klanten van een energiebedrijf. De huishoudelijke kenmerken zijn representatief voor het Nederlandse gemiddelde. Gegevens over thermostaatbediening werden verzameld door monitoring gedurende maart en april 2011, terwijl een vragenlijst werd gebruikt voor een inventarisatie van huishoudelijke kenmerken en houdingen ten aanzien van gedrag, voordat de monitoring begon.

Ten slotte werd de WoON-enquête gebruikt als validatiedatabase voor de eerste dataset. De WoON-database van het Ministerie van Volkshuisvesting (www.vrom.nl) bevat gegevens van 4500 woningen en wordt verondersteld representatief te zijn voor Nederland.

Met betrekking tot de onderzoeksvragen kunnen de belangrijkste conclusies van dit onderzoek als volgt worden samengevat:

Q I: Gevoeligheidsanalyse is een methode om de impact van beroepsmatig gedrag op het energieverbruik te verhogen. Het verwarmen van energieverbruik van een woning is het meest gevoelig voor thermostaat controle, gevolgd door ventilatie controle en aanwezigheid. Beiden zijn de belangrijkste factoren bij het bepalen van de temperatuur van de radiator.

Q II: Het is mogelijk om een regressiemodel op te stellen over het gedrag van de bewoners en het elektriciteitsverbruik met gebruik van de totale gebruiksduur van het toestel en DHES (Woning, Huishouden, Economisch, Systeem) eigenschappen van woningen, dwz huishoudelijke grootte, woningtype, aantal douches, Gebruik van droger- en wascycli, en dit model legt 58% van de variantie in het elektriciteitsverbruik uit.

Q III - 1: Vier inzittende profielen zijn geïdentificeerd voor het verwarmen van energieverbruik: (1) geen patroon, (2) eenmalige, (3) comfortabele, (4) regelaar. Het eerste profiel heeft geen belangrijke gemeenschappelijke huishoudelijke kenmerken, en geeft geen gebruik van een thermostaatpatroon. Dit profiel vereist gedetailleerd onderzoek naar het huishoudelijke gedrag. Het tweede profiel, 'one-off' huishoudens kiest een enkele set point over een aantal uren (ochtend, dagtijd, avond en nacht) van thermostaatgebruik. Deze groep kan worden gekenmerkt als hoger opgeleide mannen, gadgetliefhebbers, maar niet per se geïnteresseerd in energiebesparing. Het derde profiel, 'comfortabele' huishoudens kiest voor een thermostaat gebruik van meer dan één setpoint en interval met hoge temperatuurvoorkeuren in verschillende dagen van de week. Deze groep bestaat uit huiseigenaren met een hoog inkomen, die grotere woningen hebben, zijn niet geïnteresseerd in energiebesparing en verkiezen hogere temperaturen. Ten slotte verkiezen het vierde profiel 'huishoudelijk' huishoudens een- of dubbele set-temperatuur en intervallen met lage temperatuurvoorkeuren in verschillende dagen van de week, evenals tijdens maart en april. Groep 4 bestaat uit huishoudens met een energiebesparingsagenda, die meestal families en soms ouderen zijn, waarbij de ouders / koppels samen besluiten nemen over het energieverbruik.

Q III - 2: Gedragsfactoren van het elektriciteitsverbruik zijn het totale gebruik van apparaten, het gebruik van informatie, communicatie, entertainment (ICE) apparaten, aanwezigheid, persoonlijke hygiëne en huishoudelijke schoonmaak en energiebesparende gedragingen. Op basis hiervan worden de gedragspatronen gedefinieerd als gebruik van het apparaat, het gebruik van aanwezigheid van techniek / bewoner, persoonlijke hygiëne en de aanwezigheid van huishoudelijke schoonmaak / bewoner, en energiebesparing. De correlaties tussen gedragsfactoren en huishoudelijke en woningkenmerken onthullen de gedragsprofielen. Dit zijn de specifieke groepen gebruikers met overeenkomstige gedragseigenschappen: (1) familie (koppels (soms met een kind) met gemiddeld gebruikersgedrag), (2) techie (huishoudens die veel ICE-apparaten bezitten), (3) comfortabel Grotere huishoudens met een hoger inkomen met een hoog gebruik van verlichting en apparaten, evenals verwarming), (4) bewust (kleinere familie, ouderen, lager inkomen, huishoudens met een hogere opleiding die minder consumeren en zonnepanelen bezitten, Energiebesparende lampen, enz.). De gedragspatronen en de gedragsprofielen zijn statistisch significant verschillend van elkaar in verhouding tot het elektriciteitsverbruik.

Met betrekking tot de hoofdvraag **“Hoeveel kost de bewoner te beïnvloeden het energieverbruik van woningen in Nederland, en hoe kunnen we identificeren van de determinanten van de consumptie, evenals de gedragspatronen en profielen?”** We kunnen het volgende samenvatten:

Dit onderzoek gaat over het bepalen van het gedrag van de gebruiker in relatie tot energieverbruik. Het energieverbruik van een gebouw kan in totaal worden gevalideerd, alleen tijdens de bezetting. Deze studie combineerde de deductieve en de inductieve methoden en gebruikt gegevens over de bepalende factoren van gedrag en het actuele gedrag. We ontdekten dat deductieve methoden veel sneller zijn bij het berekenen van het energieverbruik, en inductieve methoden modelleren het werkelijke gedrag van onderop. Bovendien is uit dit onderzoek gebleken dat het energieverbruik van een woning voor verwarming het meest gevoelig is voor thermostaatregeling, gevolgd door ventilatiecontrole en aanwezigheid. Zowel het energieverbruik van de verwarming als de resulterende binnentemperatuur zijn het meest robuust voor radiatorregeling. Uit dit onderzoek is gebleken dat het gebruik van de totale duur van het gebruik van het apparaat en de parameters van de grootte van het huishouden, het type woning, het aantal douches, het gebruik van de droger en wascycli en de aanwezigheid in de kamers 58% van het verschil in elektriciteitsverbruik kunnen worden verklaard. Het introduceren van gedragsprofielen en -patronen draagt bij aan het modelleren van energieverbruik en het gedrag van inzittenden. Dit onderzoek heeft aangetoond dat samenstelling, leeftijd, inkomen, bezit van het huishouden en onderwijs de belangrijkste elementen van gedragsprofilering zijn.

Dit proefschrift behandelt bewonersgedrag op het gebied van duurzaamheid en energieverbruik van gebouwen met behulp van interdisciplinaire methodologieën en het combineren van verschillende modellerings- en dataverzamelingsmethoden. Het onthult onbekende en foutieve aspecten van de bestaande berekeningsmodellen en stelt nieuwe gebruikersprofielen voor.

Voor de energie- en klimaatbeheersingsindustrie betekent de kennis die door middel van dit onderzoek vergaard is ondersteuning voor het ontwerpen van systemen die effectief zijn in het verminderen van energieverbruik en worden gebruikers bovendien aangezet tot meer energie-efficiënt gedrag. Voor beleid, de bouwindustrie en ontwerpinformatica (met name op simulatie gebaseerde energieprestatiebeoordeling en ontwerpinstrumenten) illustreert dit onderzoek het voordeel van het overwegen van het bewonersgedrag in de eerste fasen van het ontwerp bij het renoveren van de bestaande woningvoorraad en voor nieuwe woningen bij het streven naar duurzaamheid. Bovendien zou dit proefschrift kunnen bijdragen aan beter ontwerp en implementatie van energiecontrolesystemen en -producten. Verder onderzoek zou gebruik kunnen maken van deze kennis om woningen energiezuiniger te maken.

1 Introduction

There is an increasing need for ensuring high energy savings throughout the building lifecycle, from the early design phases until post occupancy. Utility (services) and firmness (robustness) are principles of good design since Vitruvius, but sustainability was added as a new principle after 1980s, for a distinct understanding, evaluation and action development on energy consumption and environmental impact of buildings. Today, we are able to measure the consumption levels and environmental impact of our buildings, manage their indoor comfort, and combine this further with our personal desires.

Sustainability means decreasing waste and pollution, the demand for physical resources (energy, material…) and the impact on climate change, while maintaining the indoor comfort and health conditions in a building. Design decisions for sustainability include that of land use, microclimate management, form, spatial organization, building envelope, and managing water, waste, and energy systems. The essence of sustainability lies in designing all these factors with a holistic approach, while making sure that the building is usable for the occupant. Energy efficient housing requires less energy and uses renewable energy resources in the most efficient way for the energy needed during occupancy. Kim and Rigdon (1998) define the three basic principles of sustainable design as efficient use of resources (reduce, reuse, recycle); assessment of resource consumption during construction and use; and human centered design (the interaction between the human being and the environment). This research addresses the latter, the human aspect.

The buildings' energy consumption estimated by simulation software can be validated in total, only during occupancy, when the design is tested on actual use. For residential buildings, we know that sometimes the actual energy use levels are different than the expected/calculated (Lutzenheiser, 1992; Jeeninga et al., 2001; Guerra Santin, 2010; Majcen, 2013). A couple of reasons to this can be calculation drawbacks, incorrect construction applications and unexpected occupant behavior. Therefore, better understanding of the relationship between occupant behavior and energy consumption can enable more efficient design and operation of (residential) buildings, which are more suitable to the occupants' use considering thermal, acoustical, visual, environmental comfort, health and safety.

Policy on energy efficiency in buildings focuses mostly on building characteristics and mechanical systems like heating and ventilation. Although there is strong evidence for the influence of occupant behavior on energy consumption, the effort made to gain more insight to this relationship stayed behind for a long time. This study addresses the influence of occupant behavior on energy consumption for heating and electricity use for appliances and lighting, in residential buildings.

This research is conducted as a joint effort at Delft University of Technology, Faculty of Architecture, between the chair of Design Informatics; research program Computation and Performance, and the chair of Housing Quality and Process Innovation (HQPI). Chair Design Informatics, research program Computation and Performance aims to improve the performance of buildings by using computational methods for model generation and analysis, decision-making and design communication, in an interdisciplinary context. This research could contribute to the further development of computational model(s) and tools in support of user's decision-making processes. Furthermore, one of the research goals of chair HQIP is to understand the influence of occupant behavior to energy consumption in dwellings. The PhD research of Guerra Santin (2010) and Majcen (2016) of the chair HQIP specifically focus on occupant behavior and energy consumption. This research is built partially on the same datasets as Guerra Santin ('OTB dataset' and 'WoON survey'), with different research questions. Findings of Guerra Santin and Majcen's research are referred to, in the relevant sections of this thesis. Most of the research conducted under the title of this PhD was published between 2009 and 2013.

§ 1.1 Research Motivation

The building sector has a prominent share in energy consumption and environmental impact. Urban sprawl, over-consumption of energy and release of CO2 emissions, use of natural resources, excessive use of fossil fuels, and waste production damage the environment significantly. Residential buildings share 41% of final energy consumption at EU level (ODYSSEE, 2012); the construction and use of buildings account for 50% of natural resources consumption, 40% of energy and 16% of water use (Gauzin-Müller et al., 2002). Besides the impact on the environment, building and resource economy has a major share in the efforts towards sustainability, since energy independency is an advantage for all. Especially for the last 4 decades, improving energy efficiency in all sectors has been a major concern in the European context. Undoubtedly, this dedication requires long term involvement of all stakeholders in developing policy, mechanisms, measures, technology, monitoring, and re-evaluating.

Thanks to the accelerating effort on the energy performance regulations in member states, and on the EU level, and research focusing on passive and low to zero energy housing, residential buildings have incrementally improved in terms of their energy efficiency. However, the visionary goals seem not to be achieved, neither on EU level, nor on residential sector level (EC, 2012). Not achieving the calculated energy performance levels and significant energy consumption differences observed in dwellings even with similar building characteristics (e.g. Lutzenheiser, 1992; Jeeninga et al., 2001; Guerra Santin, 2010) raise curiosity to look into this variance. For instance, Guerra Santin (2010) found that the actual energy consumption for heating is half of the expected use in dwellings with low energy efficiency, and the actual energy use is even higher than the expected in very energy efficient houses. This finding is similar to others such as Tigchelaar et al., 2011 and Cayre et al., 2011. Lutzenheiser's research (1992) proves that actual energy consumption of households with similar characteristics in similar dwellings may differ by 3 times. Jeeninga (2001), who studied the theoretical energy consumption of dwellings with similar households, found a factor of 2. Majcen et al. (2016) found that the occupant behavior is crucial in actual energy consumption, accounting for as much as 50% of the variance in heating consumption. The potential variance of occupant behavior in dwellings with identical building characteristics suggests that its influence on energy consumption should be taken more seriously into consideration during calculations and design.

§ 1.2 Problem Areas

The variance of energy consumption in dwellings is expected to be based on design stage calculation drawbacks and incorrect construction applications in the implementation stage (Guerra Santin, 2010). In addition, ignoring occupant behavior in design processes, low resolution of the behavioral model in design stage, lack of knowledge on the determinants of occupant behavior and the rebound effect are the problems related with occupancy in the dwellings. Rebound effect is defined as occupant behavior reducing the potential energy savings, depending on their increased use of more efficient products, while replacing their inefficient products with more efficient ones (Terpstra, 2008). Today, most of the difference between the calculated/theoretical energy performance and actual energy consumption is defined as the energy performance gap, which is presented more in detail in Chapter 2.

§ 1.2.1 Calculation drawbacks, precision and sensitivity of calculation models

'Building' is a process that involves several professions, and parameters related to the decisions of the professions on design and construction. Collecting all the intense and specialized data, related to the whole process of building from design to post occupancy, is rather difficult, and requires many crosschecks among professions. The resolution and language of the data, including the data on occupant behavior, change significantly according to different fields, which also asks for calibration and optimization on different levels. The lack of comprehensive data of the whole process creates calculation drawbacks.

The ambiguity and several assumptions during conceptual design stage, the level of abstraction in modeling, the resolution of data, and the precision and sensitivity of the statistical model, software's built-in assumptions of energy management systems are the obstacles that might come across in regard to occupant behavior, when calculating energy performance through simulation based modeling (Judkoff et al., 1983). Statistical models (correlation, regression ...) are claimed to be faster and easier tools than simulation models to predict energy consumption in large sample size of dwellings (Schuler et.al. 2000; Pachauri, 2004; Freire et al. 2004). Indeed, the precision and sensitivity level of simulation tools might be too high to model occupant behavior in comparison to statistical models. However, simulation tools can help in modeling detailed aspects of behavior in a way that statistical models cannot, or ignore.

§ 1.2.2 Problems related to building construction and inspection

In addition to calculation drawbacks, the variance in energy consumption is expected to be because of construction defects/mistakes in thermal insulation, detailing, airtightness, and HVAC systems installations. Nieman (2007) showed that in a sample of 154 dwellings in the Netherlands, 25% did not meet the energy performance certificate requirements because of implementation being different than the expected. Gommans' (2007) monitoring in another sample proved that 25% of the heat pumps reached the expected efficiency, 40% of solar boilers functioned poorly. Exploring each of these issues will not only explain this variance in energy consumption but also emphasize the potential new fields of action for further energy efficiency.

§ 1.2.3 Occupant behavior

§ 1.2.3.1 Resolution of data on behavior

As also mentioned before, one of the first problems related with modeling the relationship between occupant behavior and energy performance is that there is not enough detailed data collected on occupant behavior (Mahdavi, 2011). Hence behavior is included in design process based on large assumptions of patterns, which many times do not reflect the real situation (e.g. Haas et al., 1998; Branco et al., 2004; Groot et al, 2006).

§ 1.2.3.2 Rebound effect

More and more our daily routines are equipped with appliances, complex systems and technologies in dwellings. We use smart control devices, real time feedback and smart meters to manage indoor comfort, and energy efficient appliances with the promise of saving energy and/or to manage our life at home easier, quicker and more efficiently. In some cases, it is proven that occupant behavior reduces the potential energy savings, depending on the occupants' increased use of more efficient products, while replacing their inefficient products with more efficient ones. This is called rebound effect. This leads to a reduction of the expected energy savings in dwellings. Berkhout (2000) explains part of the consumption difference between high and low energy efficient dwellings by rebound effect.

§ 1.2.3.3 Including occupant behavior in design / Designing for the user

One of the problems of the current building process is that the occupant is not known during the design phase. However, any system or product should meet users' needs and be usable (ISO, 1999) in order to obtain better performing buildings. This is very much related with the architectural design, as well. These buildings will have a better chance to be more energy efficient, since they will inherently reduce the miss-use related energy loss. As early as 1985, Gould and Lewis explain the elements of such design processes as early focus on occupants and tasks, empirical measurement, and iterative design. Haines (2014) lists those as the occupant behavior and its environment being studied, the occupants' characteristics being researched and designed for, the occupants being included in the design and development of building process. A user-centered design process would help to reduce the variance between the calculated and the actual levels of consumption. Several studies point out to the necessity to take occupant behavior into consideration in the design phase, and later on, for predicting their influence on energy consumption (Soebarto and Williamson, 2001; Dell'isola and Kirk, 2003; Yudelson, 2010; Azar and Menassa, 2012; Peschiera et. al., 2010).

§ 1.2.3.4 Determinants of behavior

In order to bring about a meaningful reduction in the energy consumed in the housing stock, we also need to know more about the underlying determinants of occupant behavior. In addition to occupant's interaction with systems and appliances, and determinants of energy consumption; perception of indoor comfort (thermal, acoustic, indoor/outdoor air quality) might vary considerably according to the characteristics of the dwelling and household (age, occupation, gender, income, etc.), which influences energy consumption, indirectly. How the household characteristics interact with building characteristics create the ground to explore further, for the reduction of energy consumption in dwellings.

§ 1.2.4 Occupant behavior and energy consumption

The advancements in energy performance regulations and various implementations in the field lead the way to reduce the energy consumption and the resulting environmental burden for buildings. However, the energy reductions might fall short of expectations. As mentioned before, occupant behavior, quality of the construction, and calculation drawbacks might be undermining the effect of the regulations. Little is known about how occupants interact with dwellings, what the background to this interaction is, and the resulting influence on energy consumption.

Developing insight into occupant behavior at home would improve the understanding of the effect of building regulations on energy consumption, which could further help to better integrate the calculation of user behavior's impact on energy consumption, in the energy regulations for buildings. This way, instead of assumptions about behavior, we can actually develop more adequate ways to model behavior in energy performance calculations.

The ability to make accurate predictions of the energy use of households is already an important issue for energy companies and will become even more important with the emergence of smart grids. Specifically, for electricity it is possible to make accurate predictions of the total consumption when the duration of use of each electrical appliance is known as well as its required power. Through the installation of smart meters and pattern recognition, the use of appliances and occupant behavior can be analyzed in individual homes. Unfortunately, as such data are difficult to collect by energy companies, especially at macro-level, therefore we need to establish more easily accessible parameters with an explanatory power to determine the level and variance of electricity consumption in households.

Calculating energy performance adopts a variety of tools. For instance, the EPC (Energy performance coefficient) calculation for energy consumption, is based on a standard number of people and behavioral patterns in the Netherlands. This instrument has been in effect since December 1995 in the country, and imposes the norm requirements on the energy performance of new buildings. It is a known fact that different methodologies for new buildings, like EPC, EPBD (Energy performance buildings directive), or other tools/methods calculate different levels of energy performance for the same building and the contribution of the occupant behavior to the energy performance levels. More exploration is necessary on the existing models of occupant behavior and energy performance, and their approaches of data collection, processing data, and so on. This topic is further elaborated in the Methodology sub-section.

Ultimately, it is interesting that the building regulations on energy consumption are formulated based on building and system characteristics and make assumptions of occupant behavior through a more static formula, while in essence, it is the people who dynamically cause energy consumption, not buildings. The growing number of households and size of dwellings, while the household size getting smaller, points to a future where inhabitants will have an even greater contribution to the energy consumption in housing.

The aim of this research is to reveal the relationship between occupant behavior and energy consumption, both in terms of heating energy and electricity used for lighting and appliances. The determinants of occupant behavior, robustness of dwelling energy consumption to user behavior, and defining user patterns/profiles are the main elements of this work. This research will help understanding the occupant related factors of energy consumption in dwellings, which will contribute to the better design of products, systems, dwellings, and achieving more advanced regulations.

§ 1.3 Research Questions

This thesis deals with occupant behavior and actual energy consumption in the Dutch dwelling stock. The overall question of this research is: **How much does the occupant behavior influence the energy consumption of dwellings in the Netherlands, and how could we identify the determinants of consumption, as well as the behavioral patterns and profiles?**

In order to research this question, the sub-questions are formulated as follows:

1 **What is the sensitivity of a dwelling's heating energy consumption to occupant behavior? (Chapter 3)**

Research on energy consumption of dwellings covers thorough investigation of the behavioral performance during the use of the dwellings, as well as the aspects that are involved in the design and building processes. There has been extensive progress on the building physics aspects of energy consumption; 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. Recent research attempts to construct models for the effects of occupancy on building energy performance, and the physical and psychological descriptions of occupancy (Mahdavi, 2011).

The sub-questions are:

a 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?
b How can behavior be modelled in order to assess the robustness of the energy performance in dwellings to occupant behavior?
c What is the weight of each behavioral aspect in terms of its influence on energy consumption?

2 **What is the influence of lighting and appliance use on the total electricity consumption in dwellings? (Chapter 4)**

This question aims to gain insight into the types of occupant behavior that influence electricity consumption. Discerning the determinants of behavior will help with the fields of action, to promote reducing energy consumption among inhabitants.

a What are the main direct and indirect determinants of electricity consumption? (Direct determinant: such as number of appliances and duration of appliance use ...Indirect determinant: such as household size, dwelling size, dwelling type ...)
b How much of the variance in electricity consumption in dwellings can be explained by direct and indirect determinants?

3 **What are the behavioral patterns and profiles of energy consumption? (Chapter 5-6)**

Following finding out the sensitivity of energy performance of dwellings to occupant behavior and its determinants, this question looks into exploring behavioral patterns of energy consumption. This will contribute to addressing occupant behavior in policies towards energy efficiency. Besides, determining how behavioral patterns relate to household characteristics will improve energy calculations and simulation programs for modeling occupant behavior more accurate as well as energy performance levels.

a What are the behavioral patterns of thermostat control? How do they relate to the household characteristics, revealing behavioral profiles? (Chapter 5)
b What are the behavioral patterns of electricity consumption? How do they relate to the household characteristics, revealing behavioral profiles? (Chapter 6)

§ 1.4 Research Approach and Methodology

The methodology for modelling the influence of occupant behavior on the energy performance of buildings follows two main approaches: The deductive and the inductive. This terminology refers to the data processing track and the hierarchy of data used in the analysis. The deductive approach utilizes the data on the characteristics of household and energy consumption and income levels to find statistical correlation between the energy use and occupant behavior, whereas the inductive approach calculates the energy consumption of a building based on actual occupancy and behavior patterns determined by presence, circulation, and operation of lighting, system control devices and appliances.

Inductive behavioral models focus on a single zone model based on one space in the building, or the whole building, or more zones with fewer details on use, and more articulation on movement. This underlines the gap of modelling occupant behavior in residences, in a manner that involves both the use of space and circulation patterns

TOC

in relation to the dwelling energy performance. In terms of the kind of data used, the deductive approach works with household characteristics like age, education, hobbies, habitual use of systems and appliances, income and energy consumption levels based on energy consumption bills; whereas the inductive approach works with the actual behavioral data about presence, circulation and system operation patterns. The time frequency of the collected data may change from a period of 3 months, a year etc. in the deductive, to a period of a minute, an hour, etc. in the inductive approach. A survey (cross-sectional data) is the most common method of collecting data in deductive approach, however in the inductive approach, monitoring and/or observation of behavior (longitudinal data) are preferred. In terms of the analysis of the data, the deductive approach mainly uses statistical methods, and whereas the inductive approach might work with both statistics and simulation. Considering the differentiation of outputs; a big part of the research with deductive approach estimates the influence of behavior on energy use from 1 to 12% (e.g. Andersen, 2009; Vringer, 2005; Tommerup et. al, 2007), whereas the behavior models built up with the inductive approach calculate this impact as 20-50% (e.g. Page et al., 2008; Borgeois, 2005; Gaceo et al., 2009).

This study's methodological approach combines the deductive and the inductive methodologies, by considering both the determinants of behavior and the behavior itself. The details of the datasets, of which this thesis is concerned, are explained further in Section 1.4.1. Dataset 1 is analyzed with the deductive approach. The data collected is cross-sectional: a questionnaire applied at a certain time for once, on certain number of households, asking about the characteristics of the household and their behavior. Statistical methods such as regression and correlation applied. A test on Dataset 1 was made by modeling the sample with a dynamic simulation program, to see the sensitivity of dwelling energy consumption to occupant behavior. This test is a first attempt to bring together the deductive and the inductive methodologies, by using cross-sectional data in a dynamic energy performance simulation program. Dataset 2 is analyzed with inductive approach. Longitudinal data of Dataset 2 about thermostat control behavior of a sample monitored over 2 months is modeled by repeated measures, and cluster analyses.

In this study, behavior is considered as presence patterns in a space, together with the actual heating (thermostat setting and radiator control) and ventilation patterns (operation of windows, grids, and mechanical systems), and the use of lighting and appliances. Occupant behavior is claimed to be determined by household characteristics, lifestyle and cognitive variables such as motivation, values and attitudes. The interaction between the user and the systems, and thermal properties of the building are the other fields of exploration. This research looks at the building and household characteristics that determine occupant behavior, as well as habitual (surveyed) and actual (monitored) occupant behavior.

In addition, in this research 'energy performance' of a building is considered as the amount of energy consumption estimated to meet the different needs associated with a standardized use of the building (EC, 2002) and 'energy consumption' is considered as energy supplied to the final consumer's door for all energy uses (EU, 2016), which is about the actual occupant behavior. Robustness is "the ability of a system to resist change and to perform without failure under a wide range of conditions." (Wieland and Wallenburg, 2012)

PHASE	SENSITIVITY ANALYSIS	DETERMINANTS OF ELECTRICITY USE	BEHAVIORAL PATTERNS OF ELECTRICITY USE	BEHAVIORAL PATTERNS OF GAS USE (HEATING + HOT WATER)
CASE	WV & LR	WV & LR	WV & LR	WH
VALIDATION CASE	WV & LR & WoON	WoON		
METHOD	MONTE CARLO & MARKOV CHAIN	CORRELATION & REGRESSION	CORRELATION, FACTOR ANALYSIS, & ANOVA	CORRELATION & REPEATED MEASURES
	LITERATURE REVIEW			

FIGURE 1.1 Research phases, cases, and methods used that constitute the structure of the thesis (abbreviations: WV: Wateringse Veld; LR: Leidsche Rijn; WH: West Holland)

§ 1.4.1 Datasets

§ 1.4.1.1 Dataset 1: Wateringse Veld and Leidsche Rijn (OTB Dataset)

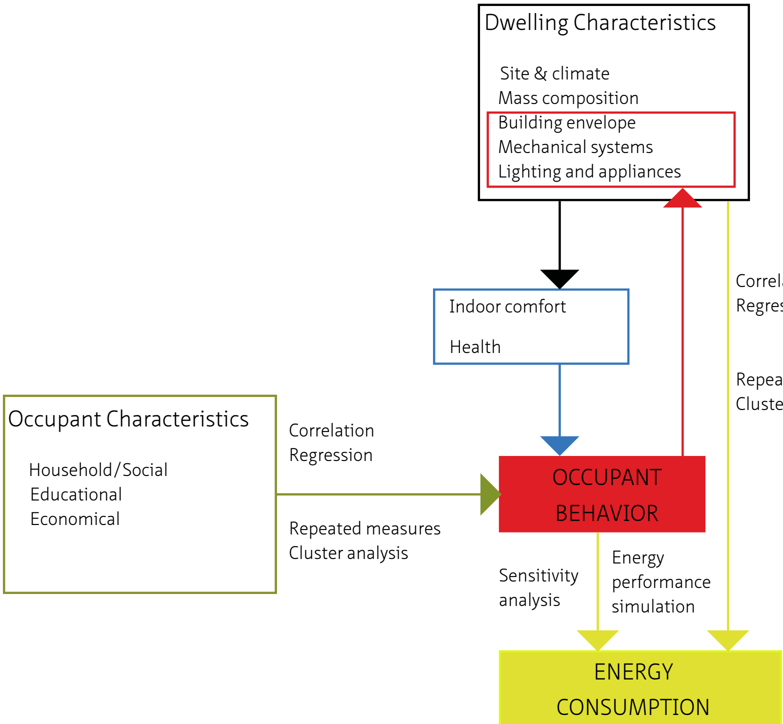

FIGURE 1.2 Explanation of research methods and data used in the research

Wateringse Veld (WV) , in the Hague is a neighborhood that started to be built in 1996. Leidsche Rijn neighborhood in Utrecht started to be constructed almost parallel to WV, in 1997 and is projected to be completed in 2025. Guerra Santin (2010) analyzed occupant behavior and heating energy consumption extensively in her research based on the OTB dataset. 6000 questionnaires were distributed in these two neighborhoods in The Hague and Utrecht. A response rate of 5% was achieved. The low rate can probably be explained by the fact that the inhabitants were uncomfortable with personal questions about their lifestyles and income levels, etc. The households were sent reminders to potentially increase the response rate.

The survey provided information on 323 dwellings that covered a range of topics in the questionnaire with regard to household characteristics, individual's characteristics, economic characteristics, energy consumption, presence, dwelling characteristics, heating behavior, ventilation behavior, appliance use, lighting devices, and others. All the dwellings in Wateringse Veld had individual central heating as opposed to Leidsche Rijn, where all but four had district heating. Dwellings with balanced ventilation was better represented in Wateringse Veld. There were far fewer maisonettes and detached houses in the sample than terraced houses, corner houses and flats. However, terraced and corner houses and flats are more common in the Netherlands. The questionnaire is provided in Appendix I.

<table>
<tr><td colspan="2" rowspan="2">DATA</td><td>CASE 1:
WATERINGSE VELD & LEIDSCHE RIJN</td><td>CASE 3:
WoON</td><td>CASE 2:
WEST HOLLAND</td></tr>
<tr><td>N: 323
2 neighborhoods built after 1995
data collection: in 2008
questionnaire</td><td>N: 4724
entire housing stock
data collection: in 2005
questionnaire</td><td>N: 61
random sampling
data collection: in 2011
questionnaire & monitoring</td></tr>
<tr><td rowspan="7">DWELLING CHARACTERISTICS</td><td rowspan="4">Layout</td><td colspan="2">dwelling size</td><td></td></tr>
<tr><td colspan="3">dwelling type</td></tr>
<tr><td colspan="3">dwelling location</td></tr>
<tr><td colspan="2">number of bedrooms</td><td></td></tr>
<tr><td>Envelope</td><td colspan="3">envelope design</td></tr>
<tr><td rowspan="2">Systems</td><td colspan="2">heating system type</td><td rowspan="2"></td></tr>
<tr><td colspan="2">ventilation system type</td></tr>
<tr><td rowspan="9">HOUSEHOLD CHARACTERISTICS</td><td rowspan="4">Household Characteristics</td><td colspan="3">household type</td></tr>
<tr><td colspan="3">education</td></tr>
<tr><td colspan="2">background</td><td></td></tr>
<tr><td colspan="3">income</td></tr>
<tr><td>Presence</td><td colspan="2">presence at home</td><td></td></tr>
<tr><td rowspan="4">Actual Behavior</td><td colspan="3">heating system use</td></tr>
<tr><td colspan="2">ventilation system use</td><td></td></tr>
<tr><td colspan="3">lighting/appliances use</td></tr>
<tr><td colspan="3">shower/bath frequency</td></tr>
<tr><td>ENERGY USE</td><td>Energy use</td><td colspan="2">energy consumption</td><td></td></tr>
</table>

FIGURE 1.3 Collected data in the three datasets

The actual energy consumption of households was asked to the respondents in the questionnaire, in the form of the energy consumption specified in their last available energy bill. Respondents living in dwellings with individual central heating reported their consumption in m3 of gas, while the ones with district heating in GJs. In the Netherlands, gas consumption in general includes space, water heating and cooking and electricity consumption includes mechanical ventilation, space cooling, lighting and appliances. In dwellings with district heating, heating energy is used for space and water, while electricity is used for cooking, mechanical ventilation, space cooling, lighting and appliances.

Characteristics			Behavior				
Household	Individual	Dwelling	Presence	Heating	Ventilation	Light & App	Consumption
Size	Age	Type	Nu of occupants	Thermostat type	Ventilation type	Nu/duration of domestic appliances use	Actual consumption figures
Composition	Gender	Room function	Duration of occupation at home	T. set point	V.T. previous h.		
Change in composition	Education	Number of rooms		T. set point duration w.day/w.end	Window operation: location/time/duration/angle	Nu of appliances in living room	Nu/power of solar panels
Years of residence	Occupation	Kitchen type	Duration of occupation in each room			Nu/duration of stand by appliances use	Nu/power of PV panels
Awareness of energy use	Hours spent outside house	Thermostat type		Shower &bath use	Grilles operation location/time/duration/angle	Nu of stand by appliances in living room	
Electricity tariff	Background	Ventilation type (V.T.)	Presence w.day/w.end & winter/summer	Comfort	Mechanical ventilation set point w.day/w.end duration	Appliance size & label	
Income	Health	V.T. in previous house				Washing mach. & dishwasher load & temper.	
Ownership	Smoking		Presence of pets		Comfort	Lighting appliances: location/nu/efficiency	

TABLE 1.1 Dataset 1, OTB sample, categories of collected data

§ 1.4.1.2 Dataset 2: The West of Netherlands Sample (WH)

A two months monitoring-pilot on a total of 61 dwellings in the Netherlands was conducted in 2011, by several commercial parties such as Eneco (an energy company in the Netherlands), to assess the effectiveness of a newly developed home energy monitor, and a follow-up study by researchers from Delft University of Technology.

The energy monitor includes a sensor, a sending unit, and a display (Figure 4). The sensor and sending unit are connected to the electricity and gas meters. The sending unit and the display communicates via the radio signal. The display has three settings, the standard one showing the consumption levels in real time (with a delay of up to 10 seconds). The display also indicates the daily consumption (over the past 24 hours), and compares daily consumption with a personal savings target. The daily target was corrected to the individual's fluctuations in consumption throughout the week. The monitor was designed to be simple to use, participation in the dataset-study was on a voluntary basis. The baseline consumption of the sample was 3614 kWh, the same as the Dutch average (which increased at an average rate of 1.1% per year between 1998 and 2008) (EnergieNed, 2009), while the household size of 2.4 was slightly above the Dutch average of 2.3. The large majority involved in the pilot were homeowners.

FIGURE 1.4 Smart thermostat display in Dataset 2

Occupant characteristics			Behavior
Household	**Individual**	**Dwelling**	**Heating**
Size	Age	Type	Thermostat setpoint day/night
Income	Gender	Floor area	
Electricity tariff		Insulation level	Lower temp. at night
Satisfaction with thermostat		Water-saving shower head	Lower temp. when absent
Selection of energy company		Nu of energy saving lamps	current thermostat program
		Double glazing	room temperature

TABLE 1.2 Dataset 2, West Holland dataset, categories of collected data

§ 1.4.1.3 Dataset 3: WoON (WoONonderzoek Nederland) Database

WoON Database of the Dutch Ministry of Housing (www.vrom.nl) includes 4500 cases and is assumed to be representative for the total housing stock of the Netherlands. The latest WoON used for this study was carried out in 2005. The dataset covers a household survey including occupant behavior, dwelling inspections and reports on energy consumption in the 4500 dwellings.

§ 1.4.2 Methods

This study applies a variety of statistical and simulation models, in relation to the deductive and inductive approaches.

Correlation and regression analyses are used on Dataset 1 (OTB Dataset), to model the relationship between occupant behavior and electricity consumption. This also revealed the determinants of electricity consumption. Later on principal component analysis and cluster analysis is applied to Dataset 1 for drawing electricity consumption behavior patterns and relevant user profiles. These cover the deductive methods of the work. Repeated measures analysis is used on Dataset 2 (WH Dataset) to reveal the users' thermostat management patterns over two months. Cluster analysis, afterwards, is used to generate user patterns for thermostat control. Applying building energy performance simulation tools and Monte Carlo analysis on Dataset 1 reveals the sensitivity of energy consumption of a dwelling to occupant behavior.

This thesis does not necessarily esteem the deductive or inductive methodologies; on the contrary, it tries to make us of both. The methods used to answer each research question are explained more in detail in relevant chapters.

§ 1.4.3 Limitations

One possible limitation of the Dataset 1 sample is the low response rate to the questionnaire (5%) and the other is that the survey was conducted in two similar neighborhoods, Leidsche Rijn and Wateringse Veld, from around similar periods of development.

The low response rate may be caused by the number and intricacy of questions. Except for the twelve blank forms, the returned questionnaires were filled in almost completely. The general characteristics of the sample were representative of the Netherlands (in comparison with Dataset 3: The National Survey: WoON Database) with the exception of income and education, which were higher than the national average. The Dataset 1 was representative for dwelling type, but not for HVAC systems used in the Netherlands. Another problem of the OTB dataset was the small number of dwellings with balanced ventilation and solar boilers; and no dwellings with heat pumps. Dataset 3 included dwellings with heat recovery ventilation.

Previous work on occupant behavior and energy consumption in dwellings use similar sample sizes, e.g. Curtin et al., 2000; Jeeninga, 2001; Uitzinger, 2004; Keeter et al., 2006. These studies claim that a low response rate might not influence the accuracy of the results. As far as the vintage of Wateringse Veld and Leidsche Rijn, these were chosen specially to be able to work on new buildings with low EPC values. The deviations from the national averages are caused by focusing on these two recently built neighborhoods.

Another limitation relates to the tracking and recording system for energy consumption in the Netherlands. Energy provider companies ask occupants to send in their meter readings once a year. These companies actively check the meter readings as well, but they have different schedules. If the occupant fails to send in the meter readings, the electricity consumption is calculated on the basis of the previous reading by the provider, which may be up to three years ago (more than 3 years is not allowed under the Dutch regulations). This could create a bias in the accuracy of the energy consumption data.

Dataset 2 has limitations resulting from monitoring. The real time energy consumption figures recorded by the thermostats were not used, because of the inconsistency of the data. The most precise data were collected in March and April 2011, out of 6 moths that the monitoring was conducted. Besides, there is a probability that thermostat behavior has not changed substantially during March and April, because of little outside temperature change.

In Dataset 2, 45 households' monitoring data was used over the sample size of 61. 8 households did not provide reliable data in March and April, and 8 cases for either March or April. Besides, 4 April and 12 April 2011 were the days that monitoring was problematic for all households. Another limitation was that the data was collected from the consumers of one energy company. Being the subscriber of this company might have brought in essential differences between this group and the rest of the households in the country, based on income level, awareness level, availability of infrastructure, and further.

§ 1.5 Relevance of This Research and its Contributions

The scientific contribution of this research is characterized by the combination several domains, i.e. design for sustainability, policy and building regulations for energy efficiency, construction and management of buildings (developers, contractors, housing associations…), management of energy supply (energy companies) and behavioral studies. The contribution of this research is new knowledge on heating energy and electricity consumption of dwellings in Dutch context, in terms of their determinants and patterns, in relation to occupant behavior. The relevance of this research and contributions is discussed more in detail in the Conclusion chapter of this thesis.

For the design and engineering industry, and energy companies, the knowledge gained through this research means support for designing systems that are effective in reducing energy consumption, in addition to influencing users towards energy efficient behaviors. For building industry and design informatics (particularly simulation based energy performance assessment and design tools), this research illustrates the benefit of considering the occupant behavior in early phases of design in renovating existing housing stock and for new housing. For policy, this research could help in improving the models and calculations of occupant behavior in building regulations; hence the theoretical consumption levels could be more realistic.

The knowledge produced with this research is reported for the improvement of energy policy and regulations, as well as advice to housing associations and energy companies. Furthermore, this thesis could contribute to the better design and implementation of management systems and products in new design. Further research could utilize this knowledge to increase the energy efficiency of dwellings.

§ 1.6 Thesis Structure

Chapter 2 provides a literature review of the field of energy consumption from urban to user scale, a review of energy performance modelling methods, a review of energy performance gap, and determinants of heating energy and electricity consumption. This review first helped to set up a reference point for the reasons to actual occupant behavior, how perception, lifestyle, norms, rules lead to various actions at home. Secondly, through the review, a framework for the relationship between occupant behavior and energy consumption is created (Figure 1 and Figure 2), based on the determinants of behavior, i.e. occupant characteristics (education, economy, social), and dwelling characteristics (envelope, systems, lighting and appliances…). This literature review sets the context and also the first steps of this research. The determinants found through this review hold the content and structure for the questions of the survey designed for OTB dataset.

Existing research on understanding the relationship between occupant behavior and energy consumption has utilized a variety of methodologies: Deductive: macro level, using cross-sectional data on dwelling, system, economical, energy consumption characteristics; and Inductive: bottom up, applying monitoring, using actual data on behavior patterns of heating, ventilation, lighting and appliance use. It is well known that inductive and deductive methods display a significant variance in explaining the sensitivity of energy consumption to occupant behavior. Chapter 3 presents a sensitivity analysis of heating energy consumption to occupant behavior, using the OTB dataset.

Despite the efforts to improve the energy efficiency of electrical appliances, the growing population, the increasing number of households and the wider use of electrical appliances could be instrumental factors in the rising levels of electricity consumption. To bring about a meaningful reduction in the electricity consumed by the housing stock, we need to know more about the underlying determinants. Chapter 4 explores determinants of electricity consumption in Dutch dwelling stock.

Chapter 5 scrutinizes thermostat control behavior in Dutch dwellings, looking through data obtained by monitoring 61 dwellings during two months in Spring 2011. It also discusses monitoring as an approach towards understanding occupant behavior and energy consumption relationship. A smart thermostat was designed for dwellings, which will display and record the chosen thermostat settings, energy consumption, weather, and traffic conditions. This chapter reveals how the thermostat use pattern changes from day to day, weekdays to weekend, and between different weeks and months based on monitoring data. Following, households with similar patterns of thermostat use are identified, and these are related to other characteristics of household and/or thermostat use.

Creating user patterns and profiles of appliances and comparing them for electricity consumption is addressed in Chapter 6. This will provide better understanding of the behavioral aspects of electricity consumption. The ability to make accurate predictions of the electricity usage of households is already an important issue for energy companies and will become even more important with the emergence of smart electricity grids. It is possible to make accurate predictions of electricity consumption when the duration of use of each electrical appliance is known as well as its voltage. Unfortunately, as such data are difficult to collect by energy companies, especially at macro-level, therefore we need to establish more easily accessible parameters with an explanatory power to determine the level and variance of electricity consumption in households.

Chapter 7 is dedicated to the conclusions of this thesis.

References

Andersen, R. V. (2009). Occupant behavior with regard to control of the indoor environment. PhD thesis, Department of Civil Engineering, TU Denmark.

Berkhout, P.H.G., Muskens, J.C., Velthuijsen, J. W. (2000). Defining the rebound effect. Energy Policy, 28 (6–7), 425–432.

Bourgeois, D. (2005). Detailed occupancy prediction, occupancy-sensing control and advanced behavioral modeling with-in whole-building energy simulation. PhD Thesis, Universite Laval, Quebec.

Branco, G., Lachal, B., Gallinelli, P., Weber, W. (2004). Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data. Energy and Buildings, 36 (6), 543–555.

Cayre, E., Allibe, B., Laurent, M. H., Osso, D. (2011). There are people in this house! How the results of purely technical analysis of residential energy consumption are misleading for energy policies. Proceedings of the European Council for an Energy Efficient Economy (eceee) Summer School, 6–11.06.2011, Belambra Presqu'ıle de Giens, France.

Curtin, R., Presser, S., Singer. E. (2000). The effects of response rate changes on the index of consumer sentiment. Public Opinion Quarterly, 64 (4), 413-428.

Eames, M., Kershaw, T. & Coley, D. (2011). The appropriate spatial resolution of future weather files for building simulation. Journal of Building Performance Simulation, 5, 1-12.

EC (2002) Directive 2002/91/EC of the European Parliament and of the Council of 16 December 2002 on the energy performance of buildings, 4.1.2003 Official Journal of the European Communities L 1/65 online at: http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:001:0065:0071:EN:PDF (last access: 26.11.2016)

EnergieNed (2009). Energieinformatiebank, Energy Dataset. http://www. energiened.nl/Content/Datasets/EnergieDataset.aspx?MenuItemID=9 (last accessed 20.05.2011).

EU (2016) EU energy in figures, Statistical Pocketbook 2016, Luxembourg: Publications Office of the European Union, 2016, online at: https://ec.europa.eu/energy/sites/ener/files/publication/pocketbook_energy-2016_epub-final_final.pdf (last access: 26.11.2016)

Euractiv, Energy efficiency (2016) The year of delivery? http://www.euractiv.com/section/energy/video/energy-efficiency-2016-the-year-of-delivery/?nl_ref=14169270 (last access: 05.06.2016)

Freire, R. Z., Oliveira, G.H.C., Mendes, N. (2004) Development of regression equation for predicting energy and hydrothermal performance of building. Energy and Buildings, 40, 810-820.

Gaceo, S.C., Vazquez, F.I., Moreno, J.V. (2009). Comparison of standard and case-based user profiles in buildings energy performance simulation, 11th International IBPSA Conference, Glasgow, Scotland (27-30.07.2009) 584-59.

Gauzin-Müller, D., Favet, N., Purver, K. (2002). Sustainable Architture and Urbanism: Concepts, Technologies, Examples. Princeton Architectural Press, USA.

Gommans, L.J. (2007). Energy performances of energy efficient buildings. (in Dutch) TVVL magazine, September 2008, 18-24.

Gould and Lewis (1985). Designing for usability: key principles and what designers think. Communications of the ACM 28, 3, 300-311

Groot-Marcus, J.P., Terpstra, P.M.J., Steenbekkers, L.P.A., Butijn, C.A.A. (2006). Technology and Household Activities. Book chapter in User Behavior and Technology Development: Shaping Sustainable Relations Between Consumers and Technologies. Springer Publications. Dordrecht, the Netherlands.

Guerra Santin, O. (2010). Actual Energy Consumption in Dwellings, the Effect of Energy Performance Regulations and Occupant Behavior. PhD Thesis, OTB Research Institute, Delft University of Technology, the Netherlands.

Haas, R., Auer, H., Biermayr, P. (1998). The impact of consumer behavior on residential energy demand for space heating. Energy and Buildings (27) 195-205.

Haines, V. (2014). The Role of User Centred Design in Domestic Energy Demand Reduction. PhD Thesis, Loughborough University, United Kingdom.

ISO (1999), nr. 13407, Human-centred design processes for interactive systems https://www.iso.org/standard/21197.html (last seen 8 November 2017)

Jeeninga, H., Uyterlinde, M., Uitzinger, J. (2001). Energieverbruik van energiezuinige woningen. ECN rapport: ECN-C-01-072.
Judkoff, R. Wortman, D. Burch, J. (1983) Measured versus predicted performance of the SERI Test House: A validation study. SERI/TP-254-1953, Solar Energy Research Institute.
Keeter, S., Kennedy, C., Dimock, M., Best, J., Craighill, P. (2006). Gauging the impact of growing nonresponse on estimates from a national RDD telephone survey. Public Opinion Quarterly, 70 (5), 759-779.
Kim, J.J. and Rigdon, B. (1998) Education, Sustainable Architecture Module: Introduction to Sustainable Design. Ann Arbor MI: National Pollution Prevention Center for Higher Education, University of Michigan.
Lutzenheiser, L. (1992). A question of control – Alternative patterns of room air conditioner use. Energy and Buildings (18), 193-200.
Mahdavi, A. (2011). The human dimension of building performance simulation. Proceedings of the 12th IBPSA Building Simulation Conference, 14-16.11.2011, Sydney, 16-33.
Majcen, D., Itard, L., Visscher, H. (2013). Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications. Energy Policy (54).
Majcen, D. (2016). Actual Energy Consumption in Dwellings, the Effect of Energy Performance Regulations and Occupant Behavior. PhD Thesis, OTB Research Institute, Delft University of Technology, the Netherlands.
Nieman, P. (2007). Final report housing quality indoor environment in new built dwellings. (in Dutch) report Wu060315aaA4.PK, Vrom inspectie Regio Oost, Arnhem.
ODYSSEE (2012). Energy efficiency trends in buildings in the EU, Lessons from the ODYSSEE MURE project: http://www.odyssee-indicators.org/publications/PDF/Buildings-brochure-2012.pdf
ODYSSEE-MURE (2012). Energy efficiency policies and measures in the Netherlands, Monitoring of EU and national energy efficiency targets:
http://www.odyssee-indicators.org/publications/PDF/netherlands_nr.pdf
Pachauri, S. (2004). An analysis of cross-sectional variations in total household energy requirements in India using micro survey data. Energy Policy, 32(15), 1723-1735.
Page, J., Robinson, D., Morel, N., Scartezzini, J. –L. (2008). A generalized stochastic model for the simulation of occupant presence. Energy and Buildings (40), 83-98.
Schuler, A., Weber, C., Fahl, U., (2000). Energy consumption for space heating of west-German household: Empirical evidence, scenario projections and policy implications. Energy Policy (28), 877-894.
Tigchelaar, C., Daniels, B., Maenkveld, M. (2011). Obligations in the existing housing stock: who pays the bill? Proceedings of the European Council for an Energy Efficient Economy (eceee) Summer School, 6–11.06.2011, Belambra Presqu'ıle de Giens, France.
Tommerup, H., Rose, J., Svendsen, S. (2007). Energy-efficient houses built according to the energy performance requirements introduced in Denmark in 2006. Energy and Buildings 39(10), 1123-1130
Uitzinger J. (2004). Analysis of EPC and energy use in dwellings (in Dutch). IVAM/SenterNovem report.
Vringer, K., Aalbers, T., Blok, K. (2007). Household energy requirement and value patterns. Energy Policy (35), 553–566.
Wang, L., Mathew, P., Pang, X. (2012). Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building. Energy and Buildings (53), 152-158.
Wieland, A., Wallenburg, C.M. (2012). Dealing with supply chain risks: Linking risk management practices and strategies to performance. International Journal of Physical Distribution & Logistics Management 42(10).
De Wilde, P. and Coley, D. (2012). The implications of a changing climate for buildings. Building and Environment (55), 1-7.

2 Existing Knowledge About Occupant Behavior and Energy Consumption

Introductory note

Chapter 2 provides an overview of a literature study of the existing knowledge on energy consumption from the urban to the user scale, energy performance modelling methods, the energy performance gap, and insights to determinants of heating energy and electricity consumption.

This review first helped to set up a reference point for the reasons to actual occupant behavior, how perception, lifestyle, norms, rules lead to various actions at home (Figure 1). Secondly, through this study, a framework for the relationship between occupant behavior and energy consumption was created (Figure 2), based on the determinants of behavior, i.e. occupant characteristics (educational, economic, social), dwelling characteristics (envelope, systems, lighting and appliances...). This literature study set the context and also the first steps of this research. The determinants found through this review (Table 2) gave input to the content and structure of the questions of the survey designed for the OTB dataset.

The paper below was written by Bedir. The co-authors commented on the drafts and gave advise on the structure, and the content of the paper. The co-authors have given their permission to include the paper in the thesis. The review of determinants of energy consumption was first published as:

Bedir, M. Hasselaar, E. Itard, L. (2008) A Review of Energy Performance and Comfort in Dwellings: The Human Factor. Proceedings of the Conference on Sustainable Building SB08 Melbourne, Australia p.3009-3016

§ 2.1 A Review of Research on Energy Efficiency in Buildings

Housing more than half of global population in 2013, cities account for about two-thirds of primary energy demand, and 70% of total energy-related carbon dioxide (CO2) emissions (IEA, 2013). The energy and carbon footprint of cities will increase with urbanization and the growing economic activity of citizens. This puts cities at the heart of the sustainable energy transition. Efforts aimed at fostering sustainable urban energy paths, a vision for meeting demand for end-use energy services in cities while at the same time significantly reducing primary energy use and its environmental impacts, are crucial to meet energy ambitions. Improvement in the rural areas is also important, since buildings in rural areas might have greater potential to be sustainable. However, the current trends of urbanization attract more attention to cities, zero-energy buildings (ZEBs) and near-zero energy buildings (nZEBs) remain as the niche fields of development more for rural areas. The scope of this review is the urban, in relation to the focus of this thesis.

Urban planning and buildings, mobility and transportation, low-carbon/efficient energy supply and smart energy networks are the main fields of research and development. Attention is growing for the concept of 'prosumers' i.e. active citizens taking initiative in issues of energy, environment and sustainability.

§ 2.1.1 Urban planning and buildings

Achieving the goal of limiting global temperature rise to 2 C degrees would require an estimated 77% reduction in total CO2 emissions in the building sector by 2050, compared to today's level. If no action is taken to improve energy efficiency in the buildings sector, the energy demand is expected to rise by 50% by 2050 (EC, 2012). This increase is driven by rapid growth in the number of households, residential and services floor area, higher ownership rates for existing electricity-consuming devices and increasing demand for new products. However, this growth could be limited to just over 10% by implementing several energy efficient installations in dwellings including high-performance windows, optimal levels of insulation, reflective surfaces, sealants, heat pumps, solar thermal heating, co-generation, energy efficient appliances and equipment, efficient cook stoves and solid-state lighting (SSL), among others. Another important first step in improving the energy efficiency of the global building stock is to establish and enforce stringent building codes that include minimum energy performance for new and refurbished buildings.

Though no one-size-fits-all solution exists to ensure energy and environmental sustainability, compact and dense urban development is a structural assumption towards energy use reduction. For instance, compact urban form and density create the premises for reduced demand for mobility and for greater efficiency of energy use in buildings. Urban form that incorporates mixed-use and public-transport oriented developments, as well as size, density, maturity, economy and the local policy-making capacities of urban areas will heavily influence the appropriate choices of policies and technologies for sustainability.

Improved building envelopes in all regions allow for the downsizing of heating and cooling equipment, and for a significant reduction in energy use. Tougher regulations are needed to reduce the electricity demand for lighting, appliances and cooling. Efficient district heating systems benefit from thermal energy storage coupled with waste heat and renewables, offering increased systems efficiency and flexibility. While low or zero energy buildings (nZEB) are well applicable in rural areas; they are still a niche field of implementation in urban areas. High densities, limited on-site renewable potential and cultural heritage conventions are some of the reported reasons that constrain the potential for broader implementation of nZEB's in cities.

Energy renovation of existing buildings is as important as the advanced implementations for new buildings, especially in highly urbanized areas, and where population is not expected to grow more in future. In these contexts, reducing building energy demand through renovation can facilitate electricity export, avoid grid infrastructure investments, unlock biomass to substitute fossil fuels in transport and enable deployment of new technologies such as low temperature district heating and cooling systems. Reduced energy demand also brings together important energy security benefits. Building renovation could be supported by more advanced building technologies and intelligent energy management systems that empower consumers and encourage behavior change.

The speed of urbanization is an opportunity to the transition towards low-carbon/low-energy urban energy systems, new buildings, retrofits of existing buildings and new transport infrastructure to service the growing urban population. The greater density of urban areas leads to infrastructure investments like public transport, cycling, district heating and cooling, and utilization of excess heat. This tempers the additional costs to achieve lower energy consumption levels in urban areas compared with rural areas. Advanced building and laboratory programs striving for zero-energy buildings need to continue.

§ 2.1.2 Energy efficient supply

Renewable energy sources located in urban areas can make an important contribution to meeting the energy needs of cities while at the same time increasing energy resilience and retaining economic value within communities. Among renewable energy sources that can be deployed in urban areas, rooftop solar photovoltaic (PV), solid waste (SW), and sewage and wastewater gas are already cost-effective today and can play a relevant role in covering the electricity, heating and cooling needs of cities. Though the potentials from SW, sewage, and wastewater gas are not large, these energy resources can provide relevant cost savings for waste and water treatment services. Rooftop solar PV can make a significant contribution to meeting electricity demand in cities. The technical potential for rooftop solar PV could provide up to 32% of urban electricity demand and 17% of global total electricity demand by 2050. The solar PV potential is larger in small cities, due to the lower density (ECEEE, 2016).

Currently, space heating and cooling together with water heating are estimated to account for nearly 60% of global energy consumption in buildings (IEA, 2016). They therefore represent the largest opportunity to reduce buildings energy consumption, to improve energy security and reduce CO2 emissions. Meanwhile, cooling demand is growing rapidly in countries with highly carbon-intensive electricity systems. A systems approach, where equipment upgrades are coordinated in particular with improved building envelopes, is crucial to achieving higher energy efficiencies and a low-carbon heating and cooling supply. The use of electric resistance heaters in existing buildings is promoted to be avoided, and eventually be prevented for new installations and equipment replacements. Instead, heat pumps, solar thermal and co-generation for space heating and cooling as well as hot water are prioritized (ECEEE, 2016).

In regions that are highly dependent on traditional biomass, energy use in buildings represents as much as 80% of total final energy use (IEA, 2016). In these regions, a major initiative seems to be needed to promote modern biomass equipment that can reduce air pollution and improve human health, while allowing more of the scarce resource to be used in central systems. The priority for countries with hot climates seems to be highly reflective external surfaces to reduce the need for cooling, and the development and wide adoption of high-performance cost-effective air conditioners. The implementation of minimum efficiency standards helps to improve energy efficiency and control the growth in electricity demand from this end-use. This will be particularly beneficial in reducing peak loads, which often coincide with demand for space cooling.

Cities can decrease the carbon footprint of their thermal demand by reusing excess heat from industrial plants located in the proximity of urban areas. The cost-effectiveness of using industrial excess heat (IEH) in cities depends on local conditions such as the existence of thermal distribution networks and the quality of the heat source among others. Systems integration of distributed energy services in cities can allow accelerated penetration of distributed energy sources and renewable sources, increasing the resilience and security of energy systems. In a global scenario characterized by a high build-up of renewables and distributed generation (DG), smarter urban energy infrastructure is an important prerequisite, providing additional non-climate benefits. The monitoring and control potential from ICT is incorporated into urban grid planning.

Lighting has significant potential for energy efficiency improvements through the application of more efficient technologies, better matching of lighting intensity to need, and continued emphasis on technical and behavioral solutions that turn off or reduce lighting levels when no longer needed. With better use of natural lighting and adoption of highly efficient lamp technologies, buildings energy consumption for lighting is reduced by 40% in 2050 compared to current levels (IEA, 2016). Variable controls and sensors are added to the existing lighting systems via retrofit programs.

In many countries, appliances and other electrical equipment represent the fastest-growing end-use for energy in buildings. Some improvements have been realized, but additional effort is required to address stand-by energy use. Innovative, low-cost sensors and controls for appliances and electronic equipment could reduce peak loads on average by about 15%. Cooking is currently one of the largest end-uses in the residential sub-sector, accounting for nearly one-quarter of global residential energy consumption and about 20% of total buildings energy use (IEA, 2016). Common medium- and long-term targets for implementing building codes and minimum energy performance standards for lighting, appliances, heating and cooling equipment seem to require immediate action.

§ 2.1.3 Smart energy networks

Smart urban energy networks can leverage the combined potential of DG and integrated urban energy grids to provide increased flexibility to the main energy system. Smart, ICT-enabled distributed energy resources (including energy storage) within urban smart energy networks are claimed to provide a range of technical services, allowing grid operators to better plan and operate main power systems and, in turn, increase the hosting capacity for renewable and decentralized energy technologies at lower cost. Integrating power, heat and fuel networks is claimed to increase the utilization of the system, reduce total costs and offer the national electricity system greater flexibility (ECEEE, 2016). For instance, a district heating network can link power and heat production and consumption locally, providing operational flexibility to accommodate periods of excess or scarce variable renewable generation in the national grid. Overall, the greater flexibility provided by such urban power-to-heat systems can not only balance variable renewable generation in the main system but also provide local balancing and other system services to support the integration of distributed energy sources. By enabling a more distributed system where energy is produced and consumed locally, smarter integrated urban energy grids can reduce the need for investments in the main energy infrastructure. More broadly, they can also enhance energy security through greater redundancy and resilience to external shocks.

Innovative management models for effective system integration at the urban level are interesting. New models such as micro-grids or the various existing models that turn consumers into producers and "prosumers", enable a wide range of benefits at the local level, including reduced environmental impact, reduced energy cost for urban communities, increased energy access and greater security of supply.

§ 2.1.4 Energy technology and innovation

Energy technology and innovation is central to meeting climate mitigation goals while also supporting economic and energy security objectives. Continued dependence on fossil fuels and recent trends such as unexpected energy market fluctuations reinforce the role of countries, individually and collectively, to stimulate targeted action to ensure that resources are optimally aligned to accelerate progress.

The buildings sector uses a wide array of technologies including the building envelope and its insulation, space heating and cooling systems, water heating, lighting, appliances and consumer products, and business equipment. Broader deployment of district heating, heat pumps and solar heating helps to transition the energy supply away from fossil fuels and direct electric heating. In cities with district heating, it seems it may be more cost effective to pursue only moderate building energy efficiency improvements together with investments in low-carbon district heat supply with lower temperatures and peak demand.

Primary strategies and technologies needed for efficient building include high-performance envelopes optimized to harvest passive solar energy and daylight, combined with advanced windows, optimal insulation and proper sealing, along with reflective surfaces in hot climates. With buildings in some countries lasting well over 100 years and expensive to retrofit, urgent action is needed to ensure that high-performance building envelopes rapidly gain market share and quickly become the standard for all new construction globally. More than 40% of the savings expected in heating and cooling energy demand under a low-carbon scenario can be directly attributable to improvements in the building envelope (ECEEE, 2016). Lower heating and cooling requirements will also allow downsizing of the equipment needed to reach a desired indoor temperature.

Among energy end uses, heating and cooling systems offer substantial potential for energy efficiency. The energy sector accounted for around two-thirds of global CO2 emissions in 2012, highlighting the benefits of clean energy technologies that are essential for de-carbonization. Wind and PV power have the potential to provide 22% of reduction in annual electricity sector emissions in 2050; to fully exploit the performance improvements achieved through technology (ECEEE, 2015).

In 2015, clean energy technologies continued their advancement as mainstream energy solutions in 2015. The threshold of one million electric cars was crossed in 2015, with an overall annual sales growth rate of 70%. Renewable power generation grew by an estimated 5% in 2015 and now accounts for around 23% of total electricity generation globally. Energy efficiency improvements continued at a steady pace, with buildings and appliances improving at a faster rate than other end uses. Despite a notable scale-up of production capacity over 2014-2015; advanced biofuels are not on track to meet 2DS targets. Global solar heat deployment has slowed in recent years due to challenging economics, insufficient support and non-economic barriers. Broader integration of sustainable energy into policy and market frameworks is needed, as well as strategic planning in all energy end-use sectors. In the transport sector, improved land-use, infrastructure and integrated territorial planning are important for curtailing energy demand. Necessary further effort is emphasized for technological advancements in district energy, car technology, and lighting (IEA, 2016).

§ 2.1.5 Prosumers

The European Commission recognizes the importance of putting citizens at the core of the energy transformation, but citizens still do not have their rights set up on the EU level. In order for the EU Energy Union to work, individuals and communities should no longer be treated only as passive consumers of established energy companies, but also as potential energy producers, or 'prosumers', particularly through self-generation of renewable energy, storage, and energy conservation, and participation in demand response (Clientearth, Greenpeace, 2016).

However, prosumers now currently face a number of obstacles due to the lack of a dedicated legal framework in the EU, and their situation varies from state to state. Not only do prosumers contribute to the energy transition, they themselves benefit from reduced energy bills as well.

§ 2.2 Determinants of Energy Consumption and Occupant Behavior

The human being shapes the physical environment around itself and in response; the physical environment that he deformed begins to change it. Currently, this mutual interaction has been leading to environmental depletion and energy resource decay in broad terms. On the other hand, the measures proposed for reducing energy consumption have to meet the demands for the optimum livable environment for the inhabitant. Nevertheless, in most cases, these two goals cannot be achieved at the same time, either because of the design of building systems and components, or resulting from the behavior of the occupant. The aim of this section is to develop an understanding of the relation between occupant behavior, indoor comfort and energy consumption in dwellings, based on previous research. Literature on the subject matter is analyzed in order to derive out the following: what the actual behavior of an occupant is, how it occurs, and what they mean in terms of comfort, health and energy consumption; as well as to produce a framework for evaluating the relationship.

Considered literature focuses on the relationship between occupant behavior and energy performance/consumption or occupant behavior and comfort/health. Few studies make assessments of actual occupant behavior from both energy consumption and comfort/ health respects. This kind of research is mainly within the context of a specific dwelling type (single family dwellings-multifamily dwellings/apartments), condition of the dwelling (renovation/new built or old/new), the energy conservation approach ('energy efficient'/conventional), or from a project framework. Besides, when the occupant behavior is considered, it is either a typical activity domain (heating, cooling, ventilation...) or an activity scenario (studying, eating, cooking....).

Reviewed literature is classified according to the parameters related to the occupant behavior (Figure 1). In the literature reviewed, the common method used is post occupancy evaluation. Data about actual behavior of occupants are collected mainly through interviews, questionnaires and diaries; and in some of the cases through measurements like photography, micro switches and observation. Data about indoor air quality, thermal comfort and energy performance is collected also through field measurements and evaluated with simulation and/or statistical analysis.

§ 2.2.1 Actual behavior of the occupant

Planned behavior is a consequence of behavioral intentions. These intentions result from attitudes, norms, and perception. Underneath behavior lie beliefs of behavior, norms and control. In Giddens's structuration theory, the analysis of environmental behavior focuses principally on the behavioral or social practices in which human agents participate. Discursive and practical consciousness affects behavior through lifestyle; rules and resources affect behavior through provision systems (in Spaargaren et al. 2000).

As actual behavior influences indoor air quality and energy consumption in dwellings, existing or resulting indoor air quality influence behavior through perception (Figure 2). For example, ventilation behavior (Engvall et al. 2004) is strongly correlated with indoor air quality through perception. The occupant (re)acts depending on how he perceives fresh/ stuffy air, dry/humid air, cooking odors and other strong odors. At this point it should be emphasized that adaptation is also involved in perception. Occupants adapt to the changing indoor air quality levels in every 15 minutes. Besides, adaptation raises the acceptability to indoor pollutants when the pollutant source is human behavior (like smoking), whereas building originated pollutants are less acceptable. Also, cross adaptation is observed when among many sources of pollution; acceptability changes according to the change of concentration of the main pollutant that the occupant is exposed to (Gunnarsen et al. 1992).

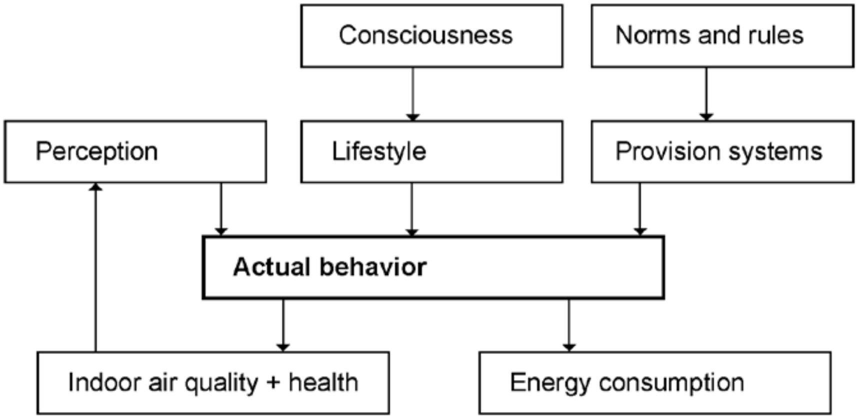

FIGURE 2.1 Framework of causes and impact of actual occupant behavior and energy consumption (interpreted from literature review)

§ 2.2.2 Relation between occupant behavior – energy consumption and Health

Analyzing energy consumption of a dwelling has building related and occupant behavior related aspects. The occupant influences energy performance through its daily activities like studying, watching TV, washing up etc.; through internal heat gain generated from metabolic rate; and through reactions to the changes in the indoor environment (Tanimoto et al. 2008). Since indoor air quality and indoor comfort level have health consequences, health could also be an indicator to evaluate indoor air quality and energy consumption. It is important to build and sustain low energy buildings that are also healthy. In some cases, energy efficient measures and interventions modestly improve some aspects of physical health of occupants in dwellings (Fisk, 2000; Wilson et. al., 2014; Willand et. al., 2015), while in many cases, this cannot be managed (Roulet et.al., 2006).

Energy technologies and occupant behavior have been treated separately in the domains of indoor environment, energy engineering, and social fields (Moezzi and Lutzenhiser, 2010). In literature, occupant behavior in dwellings is analyzed by specific daily activities, most of which are, in fact, interrelated in terms of the output patterns such as heating and electricity use, cooling and ventilation etc. Relation between occupant behavior, energy consumption and health is bilateral: Either the occupant behavior affects them and/or they affect occupant behavior.

§ 2.2.2.1 Occupant characteristics

A Household characteristics (Social)

Size and composition of a household has an influence on occupant behavior (Fleury et al. 2001; Liddament, 2001; Ndiaye and Gabriel, 2010; Yohannis et al., 2008; Genjo et al., 2005; Bartiaux and Gram-Hanssen, 2005; Rooijers et al., 2003; ECN, 2009), and especially in terms of electricity consumption by the use household appliances and lighting (Papakostas et al. 1997; Al-Mumin et al. 2003; Tyler et al. 1990). Household size (Vringer, 2005; Biesiot & Noorman, 1999) together with poor ventilation, volume of the house and heating system has a significant impact on NO2 concentration, as well as energy consumption. Increase in NO2 concentration may lead to health problems like asthma and allergen illnesses (Zota et al. 2005).

Some studies claim that occupant's lifestyle has strong effects in energy consumption and should be changed through education for energy conservation (Groot-Marcus et al. 2006), whereas some others show that differences in lifestyle do not have much effect on space heating energy behavior (such as Emery et al. 2006). Occupant's age is an important predictor of both heating energy and electricity consumption at home (Brasche et al. 2005; Liao & Chang, 2002; Linden et al., 2006; Yohannis et al., 2008; O'Doherty et al., 2008; Baker and Rylatt, 2008).

Habits are also major elements of behavior; the motivation to achieve a goal within a context and with cues create habits. Repeating the habit strengthens it, and then, even when the original motivation is not there, habits will still be triggered by the contextual cues. Most of everyday behaviors are claimed to be led by habits, especially using technologically advanced devices and systems. At home, research shows higher probability that occupants will act upon habits; because at home behavior with cues do not require cognitive effort (Maréchal, 2010; Pierce, et. al., 2010; Martinez, 2011; Ortiz, et. al., 2017). Habits allow the individual to achieve goals in a quick and effective way that requires minimal thought (Maréchal, 2009). In other words, the stronger the habits are the weaker the influence of knowledge and attitude on behavior (Verplanken et al. 1994). For example, clothing habit is a means for the occupants of the dwelling to maintain their own energy balance with indoor climatic conditions, and the extent to which they rely on physiologic responses to maintain that energy balance determines the magnitude of their thermal discomfort and attendant dissatisfaction. Indoor thermal conditions influence body heat balance which leads to thermal discomfort feeling through physiological strain and this process results in behavioral thermoregulation (clothing) (Morgan et al. 2003; Baker and Rylatt, 2008; ODYSSEE, 2008). In naturally ventilated buildings, clothing behavior of the occupants is more

TOC

related with outdoor temperature than mechanically ventilated buildings (De Carli et al. 2007).

A Educational characteristics

The increase in education level of the occupant (Mansouri et al., 1996) may result in awareness about energy consumption and environment, hence reducing energy consumption. Motivation is another important determinant of electricity consumption (Vringer & Blok, 2007; Linden et al., 2006), and could be created through educational and economic measures. In a study in Finland, economic reasons provided the motivation for households to save energy: the occupants were eager to save energy by changing their lighting appliances, sealing windows, lowering room temperature and reducing hot water consumption. Further, households wished to get advice on use of electricity, space heating, ventilation and use of water. Half of the users began to turn down lights in the rooms not occupied, 29% reduced water use, 27% change clothing habits (Haakana et al. 1997).

In Denmark, eco accounts were used to provide information (Jensen, 2003) for tenants; after one year, heating energy consumption was reduced by 9% and electricity consumption by 22%. Product information about energy conservation also affects behavior but relies on the actual willingness of the user to initiate or change specific behavior patterns (Wiese et al. 2004). Provided feedback and general information about energy consumption to the occupants have strong influence on occupant behavior. For example, in many cases occupants do not know that ventilation demands are only met at the highest speed level of the exhaust fan, and they do not operate it correctly. This results in poor indoor air quality (Ginkel et al. 2003, Liddament, 2001). Feedback should not be handled alone; factors such as the conditions of housing, personal contact with a trustworthy advisor when needed, and support from utilities and government which can provide the technical, training and social infrastructure are important to make learning and change possible (Darby, 2000). Satisfaction of the occupant and education about using the energy efficient features, good performance of a passive house, and about cleaning and maintenance requirements are important behavioral aspects. Lastly, occupant involvement in design stage is crucial for achieving intended energy performance levels (Blum et al. 1989).

B Economical characteristics

Economics treat attitudes, beliefs, values and the like as mere preferences, and tastes are exogenous to economic models. Economic psychology provides psychological and financial influence in combined and contrasting means (Brandon et al. 1999). Psychological influence could be observed in owner occupied houses where energy consumption level is less compared to the similar conventional (Schneiders et al., 2006). Financial influence could be used by supplying energy consumption feedback to users (Haakana et al. 1997). Design Context Booklet, the report of Task VIII conducted in IEA-SHC program, states the economical determinants of user behavior as ownership (as well as O'Doherty et al. 2008 and Leth-Petersen and Togeby, 2001), income level (as well as in Vringer, 2005; Biesiot and Norman, 1999), savings, employment situation or general; subsidy and advancement, tax reduction, energy (as well as Linden et al. 2006), building and appliances costs (as well as Lohnert et al., 1989).

§ 2.2.2.2 Building characteristics

In this study, the components of a dwelling that have impact on occupant behavior directly or indirectly are categorized as site & climate, building envelope, mass composition, mechanical system and lighting and appliances.

A Site and climate

Outdoor air temperature, horizontal global irradiance, wind velocity and wind direction have an impact on user behavior in terms window opening (Erhorn, 1988; Feustel et al. 1985). Users tend to open windows less depending at night and temperature below 12 C degrees and when the wind velocity is greater than 3 m/s whereas horizontal global irradiance has a minor impact on user behavior in correlation with outdoor temperature. The use of windows is linearly correlated with the outside temperature for temperatures between -10 C degrees and 25 C degrees and inversed correlated with wind velocities. When it is raining or snowing, windows are less often used (Hainard et al. 1986). In mild climates, residents' behavior during the summer season and whether the residents opened windows/doors or operated air conditioners is very different (Iwashita et al. 1997). Next to the weather characteristics, the quality of the outdoor environment; air pollution (odour) and noise (Van Dongen et al. 1990) are important factors. People shut the windows when the outside noise level is between 60 and 65 dB(A) and take more serious precautions like sound insulation, changing spatial organization, when it is noisier than 65 dB(A) (Lambert et al. 1984). On the corridor side of the apartments the windows or vent-lights were opened maximum half an hour on average and on the balcony side maximum 1.4 hour when nobody was at home.

Fear for burglary plays a role here, but also fear for escaping of pets (Van Dongen, 1990).

B Building envelope

Basic natural ventilation is through the cracks in building envelope (Van Dongen, 1990). Air tightness of the wall and material choice for infill, insulation and cladding are also influencing. Thus, construction quality and maintenance are crucial. Reducing the air tightness of the envelope may cause an impaired air quality perception and may lead to health-related consequences (Stymne et al. 1994; Singh, 1996; Engvall et al. 2005). This is a proof of the necessity for further studies to figure out occupant reaction to the change in indoor air quality conditions. However, a profound review about airborne particles in the indoor environment reveals that existing scientific evidence does not necessarily prove that indoor air quality has direct health consequences (Schneiders et al. 2003).

C Mass composition

Occupants use natural ventilation less when volumes of rooms are smaller; windows are less oriented to sun and more oriented to the prevailing wind direction (Van Dongen, 1990). Windows that are fixed on the bottom of the frame and that open inwards are more often open than other types of windows (Wouters et al. 1986). Upper wings of windows are open twice more often than the lower ones that are opening outwards. If the window in open stand cannot be fixed at several positions through a grip, it is possible that the window will never be used (Van Dongen, 2004).

Type of dwelling and floor area are important determinants of occupants' energy consuming behavior at home (Linden et al, 2006; Yohannis et al., 2008; O'Doherty et al., 2008; Bartiaux and Gram-Hanssen, 2003; Vringer et al., 2007; Baker and Rylatt, 2008; ODYSSEE, 2008; Fuks and Salazar, 2008; Rooijers et al., 2003; ECN, 2009)

The location of the dwelling (Yohannis et al., 2008; O'Doherty et al., 2008) is another important parameter and the age of the dwelling (O'Doherty et al., 2008; Vringer et al., 2007) also appears to have a significant impact on electricity consumption. Lastly, the number of rooms (Baker and Rylatt, 2008; ECN, 2009) and bedrooms (Baker and Rylatt, 2008) also emerge as significant predictors of electricity consumption.

D Mechanical systems

The type of heating system plays a role. In dwellings with central heating windows are less often open than in other dwellings (Wouters et al. 1986). In addition, several studies focus on the effect of the type of thermostat control on energy use. Households with programmable thermostats are claimed to set the thermostat temperature at a lower level when nobody is at home or during night time. Nevius and Pigg (2000) found that presence of thermostat has a minimal effect on energy use, and temperature settings do not significantly differ between dwellings with programmable and manual thermostats. Shipworth et al. (2010) research showed that households with thermostats set the mean temperature slightly lower than those without thermostat. Lutzenhiser (1992) proved that households with manual thermostats consume less energy in comparison to households with programmable thermostats. The other parameters are heating system type and appliances (Haas et al., 1998; Leth-Petersen and Togeby, 2001; Papakostas and Sotiropoulos, 1997).

Closely related with heating system, ventilation system is important both in terms of occupant use and indoor air quality effects (Liddament and Orme, 1998; Iwashita and Akasaka, 1997; Erhorn, 1988). Ventilation rate should be as low as possible for energy conservation. On the other hand, to sustain indoor air quality it should be at a certain level which may conflict with energy conservation target. This relation is open to the impact of occupant behavior (Dubrul, 1988; Soldaat et al., 2007). Behavior is related with ventilation system type: Natural and/or mechanical ventilation use differ depending on household size, dwelling age, single/multifamily (Stymne et al. 1994). When a household includes elderly and children, mechanical ventilation is less used. Grills are preferred more than windows for natural ventilation (Van Dongen, 1990). However, air temperature fluctuations may cause feeling of draught in rooms, largest temperature fluctuations appear in mechanical exhaust ventilation system, and the minor changes are measured with balanced ventilation systems (Melikov et al., 1997).

Besides thermal comfort, health aspects are means for ventilation behavior: Higher ventilation reduces the prevalence of air borne infectious diseases. Ventilation rates below 10 Ls-1 per person are associated with a significantly higher prevalence of one or more health or perceived air quality outcomes. Increases in ventilation rates above 10 Ls-1 per person, up to approximately 20 Ls-1 per person, are associated with a significant decrease in the prevalence of Sick Building Syndrome (SBS) symptoms or with improvements in perceived air quality (Wouters et al. 1986). Poor ventilation in longer periods would lead to fungi growth in bathrooms, but there is no clear relationship stated between ventilation and dust mite allergies (Ginkel et al. 2003). Ginkel et al. further state that number showers, together with age of the ventilation system has a direct relationship with the mold growth in bathrooms (Ginkel et al.

2005). However, Seppanen (2001) puts forward respiratory allergies and asthma as health consequences of poor ventilation system use. On average, the prevalence of SBS symptoms is higher in mechanically ventilated buildings than in naturally ventilated buildings. Better hygiene, building commissioning, operation and maintenance of air handling systems may be particularly important for reducing the negative effects of HVAC systems.

Römer indicates that together with the introduction of balanced ventilation to houses, as energy consumption decreased around 15-20%, health risk is elevated mainly due to the change in tap water temperature, relative humidity, dust and air exchange rate (Römer, 2001). Lembrechts et al. (1996) point out that seldom use of the mechanical ventilation system in full capacity result in radon increase in Dutch dwellings, in addition to the decrease in air tightness levels and building material use change. Dirty filters/heat recovery cores/HRV (Heat Recovery Ventilation) cabinets, substandard ventilation and unbalanced supply and exhaust air flows create health problems in dwellings (CMHC, 1999).

Satisfaction and comfort level with respect to heating and ventilation system performance is another important factor in ventilation and indoor air quality. If the air inlets do not fit with the aesthetical preferences of the occupants, they may remove them. Noise from ventilation system also plays a main role (Van Dongen, 2004). In a field study about HRV use, it is found out that; cooking, noise from outside, smoking, shower and cooling are the mentioned behaviors not to use HRV, so additional exhaust ventilation is required. Occupants have complaints about perceived air quality and dust around filters, nevertheless feel control over the HRV system and satisfied (Macintosh et al. 2005). Most failures leading to discomfort and dissatisfaction are observed owing to bad manufacturing of components, improper selection and installations of components, bad system flow balancing, and inadequate commissioning, too high sound emission at supply and extract terminals and sound transmission, excessive window airing by occupants and general poor acceptability (Dorer et al. 1998).

E Lighting and appliances

Lighting behavior in a dwelling depends on the type and characteristics of the dwelling, the type and duration of activities performed there, and the lighting habits of the members. Variations and behavioral factors about lighting and appliances among households can also be explained, in part, by the demographic composition of an area or country and its institutional setting (Bartlett, 1993). Several studies are conducted to measure how different household appliances are used (Papakostas et al. 1997; Al-Mumin et al. 2003; Tyler et al. 1990) and it could be stated that use of household

TOC

appliances is also directly and mostly related with culture and habits. Appliance control behavior is clearly different according to occupant characteristics and thermal comfort level (Vine et al. 1989).

Appliance ownership and size are proved to be significant predictors of electricity consumption. The appliance index of Cramer et al. (1985) included number, frequency of use, location in dwelling, published efficiency, and estimated seasonality factor. Appliance index combined with the air conditioning index explained the variance in electricity consumption by 51%. Cramer's research further included electricity price, income, education, ethnic background, occupation, age, thermal comfort, conservation, environmentalism, and energy knowledge scales were able to explain 34%, and the combined model of appliance, air conditioning indexes and household characteristics was able to explain 58% of the variance in summer electricity consumption. The appliance index of Tiwari (2000), on the other hand, was based on ownership of appliances and their power data. Tiwari's work also included household and dwelling characteristics, i.e. dwelling age, type, and location, number of rooms, household size and age, income and electricity tariff.

In addition, number of household appliances (Yohannis et al., 2008; O'Doherty et al., 2008; Genjo et al., 2005; Mansouri et al., 1996; Bartiaux and Gram-Hanssen, 2003; Vringer et al., 2007; Saidur, 2007; Baker and Rylatt, 2008; ODYSSEE, 2008; Parti and Parti, 1980; Fuks and Salazar, 2008), number and type of lighting appliances (Vringer et al. 2007), labels of appliances (Mansouri et al., 1996) were found as crucial factors of electrical energy consumption in dwellings.

§ 2.2.2.3 Determinants of behavior and energy consumption: A framework

Occupant behavior is influenced by (1) occupant's educational and economical background and household characteristics, (2) dwelling's outdoor environment and climate characteristics, envelope and mass composition, mechanical systems installed, and lighting and appliances used in the house. Behavior is either a reflection of the occupant's inherited and developed personal characteristics or a reaction to the perception of the indoor comfort conditions created. Dwelling's architectural characteristics, service systems and outdoor environment affect occupant behavior in terms of their contribution to the indoor comfort conditions. Therefore, in order to understand the occupant behavior with respect to indoor comfort and energy performance of the house, these relations must be analyzed in correlation (Figure 1). However, in the literature revised, there is little research that covers these aspects in correlation but rather, approaching from one aspect.

Guerra Santin et al. conducted research on the occupant behavior and heating energy consumption using OTB dataset (2010), and revealed that the determinants of heating energy consumption are household size, age of the respondent, ownership of the house and income, the number of heated bedrooms and thermostat settings.

Perception of comfort is an important part of occupant behavior and adaptation to indoor comfort might have a considerable impact on energy consumption. Ioannour and Itard (2015) explain the three forms of adaptation: psychological adaptation, i.e. a person's thermal expectations based on his past experiences and habits (Humphreys and Hancock, 2007; Shove, 2004; Holmes and Hacker, 2007) physiological adaptation to a thermal environment over a period of time; and behavioral adaptation, i.e. modifications or actions of an individual that changes in the heat and mass fluxes governing the body's thermal balance (Brager and de Dear, 1998). Adaptations are interrelated and affect one another, besides modifications are grouped as personal (Holmes and Hacker, 2007; Fiala and Lomas, 2001; Baker and Standeven, 1996), technological or environmental adjustments (ASHRAE, 2004).

In literature, systematic studies are missing covering both occupant and dwelling related aspects; research generally focuses on energy consumption or indoor comfort/ health. It should be emphasized that long term measurement covering both winter and summer behavior in relation to energy performance and comfort, and validation is needed. Occupant and building characteristics that are covered in literature are categorized in Table 1 and Figure 2.

Moreover, it is important to realize if behavior should be modified or the technology should be adapted to achieve reduced energy consumption levels and how. Practical information is necessary for the actors in building process about the design of systems and equipment to better adapt the systems to user behavior. In addition, more information for legislation especially about air tightness and ventilation rate standards is needed. In some studies, the abovementioned characteristics were able to explain as much as 75% of the variance in electricity consumption. More research on the voltage of appliances, the use of battery charged appliances and stand-by/on-off function use seems lacking in existing body of literature.

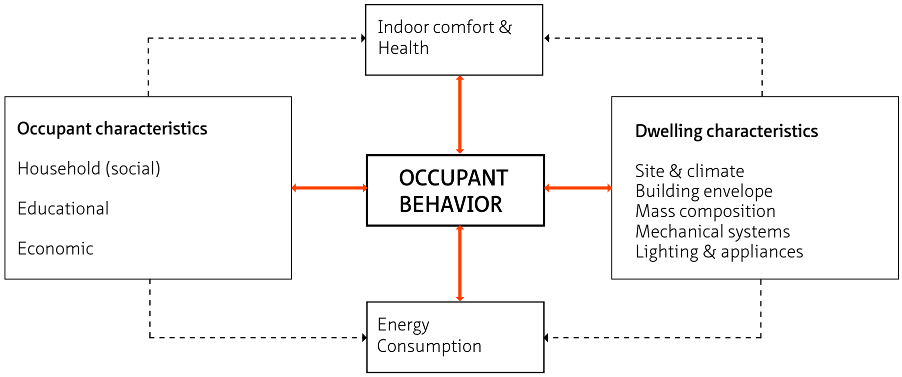

FIGURE 2.2 Framework for evaluation of occupant behavior in relation to indoor comfort and health, and energy consumption (interpreted from literature review)

Occupant characteristics			Building Characteristics				
Household	**Educational**	**Economic**	**Site & Climate**	**Building envelope**	**Mass composition**	**Mechanical systems**	**Lighting & appliances**
Age	Awareness	Ownership	Irradiance	Air tightness	Floor height	Heating	Lighting
Occupation	Knowledge	Energy use	Wind	Material use	Window design	Ventilation	Appliances
Culture	Realization	Income level	Noise	Insulation	Design elements	Hot water	
Lifestyle	Attitude		Odor				
Hobbies	Motivation						
Habits	Sensitivity						
Health							

TABLE 2.1 Characteristics affecting occupant behavior (interpreted from literature review)

§ 2.3 Energy Performance Gap

There is significant evidence to suggest that buildings do not perform as expected when they are completed as was expected when they were being designed (such as Bordass et. al., 2001; Bordass, 2004; Demanuele, et. al., 2010). The difference between expected and actual performance is known as the energy performance gap (Menezes et al. 2012). Energy performance gap means that products and systems developed for energy efficiency do not meet expected levels. In addition, differences in occupant behavior is responsible for part of energy performance gap. This is a serious threat for negotiating energy conservation with policymakers, with sectoral actors, consumers/users, … Furthermore, in terms of the developing technologies and experiments, if this gap exists to such an extend today, it might be too difficult to catch up with later on, reducing the possibilities of implementing new technologies in future in more radical occupancy and user patterns, and climate conditions. Therefore, it's important to identify the source(s) of energy performance gap and bridge them.

Findings from studies such as PROBE (Post Occupancy Review of Buildings and their Engineering) which assessed 23 'exemplar designs' in the Building Services Journal between 1995 and 2002, revealed that actual energy consumption in buildings is often twice as much as predicted (Designing Buildings (last view: 2017)). More recent studies (Zero Carbon Hub; Carbon Trust (last view 2016); Carbon Buzz, 2011; Turner and Frankel, 2008; Menezes et al. 2012) have suggested that in-use energy consumption can 2 to 10 times higher than compliance calculations carried out during the design stage. Leeds Metropolitan's monitoring research on 700 dwellings show a significant gap between the energy use expected before construction and the actual, once the house is occupied. Thermal bridges on the building envelope, but also between adjacent dwellings have the largest share in this discrepancy (Wingfield et al., 2011).

§ 2.3.1 Uncertainties

The energy performance gap is mainly due to uncertainties (Ramallo-González, 2013). As early as 1978, Gero and Dudnik presented a methodology to solve the problem of designing subsystems (HVAC) subjected to uncertain demands. After that, several studies looked into the uncertainties that are present in building design, including measurement errors, lack of information, and a poor or only partial understanding of the driving forces and mechanisms (Lomas and Eppel, 1992; Hopfe, 2009, and Rabl and Rialhe, 1992; Turner and Frankel, 2008; Wang et. al., 2011; Lee and Chen, 2008; Saporito et. al., 2001 found in Ioannou and Itard, 2015). Uncertainties a limit on the reliability of the output of the model (Hamby et al., 1994; Helton et al., 2006; Saltelli et al., 2000). The uncertainties in building design/construction are categorized in three different groups: environmental, workmanship, and occupant behavior.

Uncertainties on climate data concern the consideration of climate change in weather data and the use of synthetic weather data files. Regarding the former, long life span of buildings makes them likely to operate with climates that might change due to global warming. De Wilde and Coley (2012) proved the importance of designing buildings that are resilient to extreme weather conditions. Regarding the latter, the uncertainties in weather data may cause great variations (0.5% - 57%) in energy demand calculations (Wang et al., 2012; Eames et al., 2011; Soebarto and Williamson, 2001; Dell'isola and Kirk, 2003).

As early as 1994, Pettersen researched the uncertainties regarding workmanship and occupant behavior in energy performance calculations. He showed that the total energy use follows a normal distribution with a standard deviation of around 7.6% considering the uncertainties due to occupant behavior, and of around 4.0% considering those by building characteristics. Following research showed that lack of information on the building's envelope and installations might have a share in the discrepancies between theoretical and actual energy use, as low as 30% and as high as 100% in some cases (Soebarto and Williamson, 2001; Dell'isola and Kirk, 2003; Majcen et. al., 2013; Majcen et. al., 2013; Guerra Santin and Itard, 2012; Yudelson, 2010).

Hopfe and Hensen (2011) proved that the uncertainty in the value used for infiltration is the factor that is likely to have the largest influence on cooling and heating demands. Another study performed by de Wilde and Wei Tian (2009), compared the impact of most of the uncertainties affecting building energy calculations taking into account climate change. In addition to infiltration value, they introduced factors including uncertainties in weather, U-Value of windows, and other variables related with occupants' behavior (equipment and lighting). Uncertainties could be due to the underestimation of the role of, and the variance in occupant behavior, also proving that occupants have a substantial influence on energy use (Blight and Coley, 2012; Richardson et. al., 2008; Soebarto and Williamson, 2001; Yudelson, 2010; Clevenger and Haymaker, 2006).

§ 2.3.2 Sources of energy performance gap

De Wilde and Jones (2014) make a summary of the sources of energy performance gap under five titles during four phases of building: actual occupant behavior; weather conditions; workmanship/installation errors; systems' control settings and modelling issues:

1 In design stage, issues of communication among the different actors within the team can be a root cause for the later performance gap issues (Newsham, et al. 2009), where the design itself might constitute an initial issue, incorporating inefficient systems, missing construction details, or lack simplicity and buildability. At this stage, it is hard to predict the future occupancy and user patterns. Energy saving technologies

planned in the design stage might not meet the manufacturer's energy performance specifications and are subject to degradation over time, which lead to a performance gap once the building is operational (Newsham et al. 2012). Predictions made on energy performance might not account for all energy uses in buildings, unregulated sources of energy consumption such as small power loads, server rooms, external lighting, and so on. Appropriate tools and models, or adequate training of the analyst might be lacking in calculating the building energy performance. Any calculation at this stage includes a degree of uncertainty. Building energy performance modelling and uncertainty analysis are fields that still need further development (Reddy and Panjaporn, 2007; Ryan and Sanquist, 2012).

2. During a building's construction process, other factors might also contribute to the energy performance gap (Bell et al. 2010). Implementing the defined insulation and airtightness levels are challenging, construction defects might be hidden from view inspection, thermal bridges might occur.
3. Building commissioning is a difficult process, when a full performance testing might not be possible due to budget and time constraints (Bunn and Way, 2010).
4. During post occupancy phase, one issue is that actual building use and real weather conditions might not match the assumptions made during the design process. Thermostat control and the Building Energy Management System (BEMS) might not fit the design intentions, might be used quite differently by occupants. Furthermore, metering itself might come with uncertainties (NMN, 2012) especially capturing contextual factors such as weather data and occupant behavior. Measurement/monitoring can often have issues of calibration, accuracy, missing data, which causes an energy performance as well.

§ 2.3.3 Energy Performance Gap in Dwellings

Majcen et al.'s (2013) article about understanding the reasons to the discrepancies between theoretical and actual gas consumption is based on a regression analysis on the Energy Label and CBS (Central Office for Statistics), coupled by housing register (WoONruimtereregister), municipal records (Gemeentelijke Basisadministratie), employment dataset (Social Statistisch Bestand Banen), and the WoON survey. The analysis revealed that variables such as floor area, ownership type, salary and the value of the house, which predicted a high degree of change in actual gas consumption, were not significant (ownership, salary, value) or had a minor impact on theoretical consumption (floor area). Besides, the installation system predictors showed that there was more overestimation in less energy-efficient systems. These are most likely a consequence of occupant behavior influencing actual energy use. In her sensitivity analysis, average indoor temperature was found to have a large influence on the theoretical gas consumption together with the ventilation rate. The number of occupants together with internal heat load have a more limited impact on theoretical gas consumption.

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).

Majcen et al.'s (2015) second (more in-depth) study on theoretical and actual heating energy consumption focused on a survey conducted in a subset of Amsterdam dwellings that had an official energy label, which provided a deeper understanding of the performance gap. Upon evaluating descriptive results of several statistical tests, several regression analyses were performed on different subsamples. They proved once more that occupant behavior has a large effect on heating consumption, in particular where it accounts for almost half of the variance. Also in theoretical consumption and in the difference between the theoretical and actual consumption (DBTA) occupant behavior accounted for over 7.5 and 9.1% of variance, which is still remarkable. The research found significant differences in the separate analysis of under and over predictions of heating energy consumption. Water saving shower head and programmable thermostat are the two factors that seem to effect DBTA in under-predictions but these two were not significant with regard to theoretical gas use. Some presence variables (morning and midday) were significant predictors, but were also difficult to interpret, since the results were conflicting (positive predictive power for morning and negative for midday presence).

Majcen et al. (2015) found that occupant behavior explained the most variance in actual gas use, and comfort relevant for only the DBTA. They proved that actual gas use could be predicted with a higher correlation of household and behavioral variables with, which was detected in household composition, the ability to pay energy bills, presence at home, set point temperature and efficiency of behavior. Presence and indoor temperature were found to be two very important parameters in determining real gas use of a dwelling. Midday presence related to a decreased DBTA, which could mean that households who spend more time at home somehow matched conditions assumed by the theoretical calculations better. On the other hand, occupants who spent more time at home during the night tended to have an increased DBTA. It also seemed that people who were not often sleeping elsewhere tended to have a larger DBTA. Conversely, the ones that often slept elsewhere had a smaller DBTA.

Current concerns and future work regarding energy performance gap

Most work on the performance gap is based on deterministic predictions and measurements. Work at Plymouth University has piloted a probabilistic approach, contrary to several other works which follow more deterministic methods (Field, 2005;

de Wilde, et al. 2013). De Wilde makes a summary of the current concerns and future work regarding energy performance gap, as follows:

1. There are different types of energy performance gap that vary over time and with context. The models used for energy performance simulation of buildings are sensitive to input parameters. The accurate representation of the building in these models depend on the correct modelling of the sensitive parameters (Lam et. al., 2008; Lam and Hui, 1996; Rabl and Rialhe, 1992, Ioannou and Itard, 2015).
2. Need for further monitoring: In spite of the advancement in measurements and monitoring in building energy consumption field, the resolution of data necessary to clearly understand the main causes of energy performance gap is still rather low.
3. Actors and responsibilities of a building's energy performance: The responsibility for the energy performance gap has not been shared by different actors in the design, construction and post occupancy stages of building, hence the actors and their responsibilities are unclear to bridge the performance gap.
4. Most research into the energy performance gap focusses on non-domestic buildings; hence the uncertainties for dwelling sector remain unclear. Determining the exact U-values of walls is very important. Considering that dwellings' vintage might influence the amount of information that can be gathered on building characteristics, a faster and more reliable method is needed for the determination of the U-values of the building envelope (Ioannou and Itard, 2015; Majcen et. al., 2013).

§ 2.4 Modelling User Behavior: A Review of Methodologies

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 3) (for further reading, see Bedir, et al., 2011).

Chapter 3 of this thesis 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.

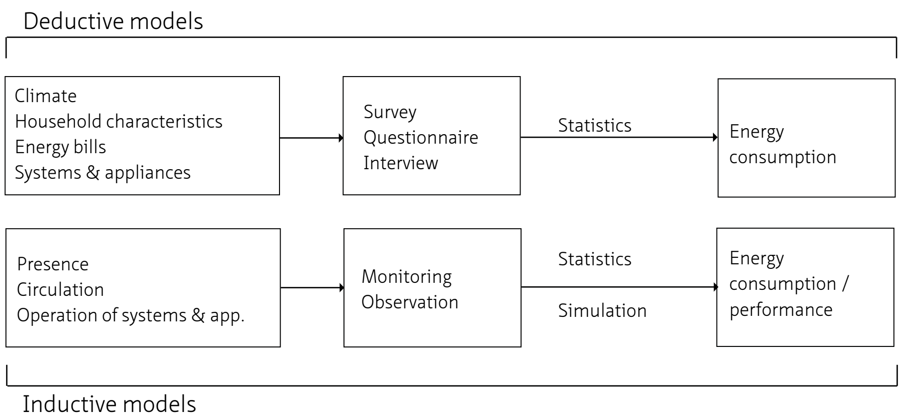

FIGURE 2.3 The inductive and deductive models of occupant behavior-energy consumption relationship

Chapter 3 presents a Sensitivity Analysis (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.

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 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. 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. Chapter 3 of this thesis 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. Chapter 3 of this thesis uses a global SA.

§ 2.5 A Review of Behavioral Patterns

Lutzenhiser (1993), in his cultural model, proposes to look at household types for studying energy consumption. Raaij and Verhallen (1983) and Tyler and Schipper (1990) investigate energy consumption from a lifestyle point of view, and consider lifestyle as patterns of activities. Groot et al. (2008) and Paauw et al. (2009) combine this consideration with household characteristics. Another common approach to lifestyle is about values, motivations, needs and attitudes (Gladhart, 1986; Ajzen, 1991; Assael et al., 1995; Poortinga et al., 2005; Vringer and Blok, 2007). A series of energy studies adopt Bourdieu's concept of lifestyle on energy consumption (found in Holm Pedersen et al, 1997; Kuehn et al, 1998), and therefore focus on social classes. Lastly, Gram-Hanssen's (2004; 2010) and Shove's (2003) works imply that lifestyle could be used only partially to understand routines and to explain energy consumption. They propose to look at routines and habits, as well as household and building characteristics.

Routines and habits may oppose the cognitive and financial drive and dominate other rational alternatives (Heijs et al, 2006); therefore, they could indeed become alternative predictors of electricity consumption (van Raaij and Verhallen, 1983). In addition, because electricity consumption seems to depend far less on the physical characteristics of a house, than space and water heating (Wright, 2008), routines of electrical appliance use might provide us with more articulated insight into household and user behavior. This could be important for research and policies which focus on influencing individuals and households to consume less energy.

§ 2.5.1 Heating behavioral patterns

According to an empirical study by ECN and IVAM (2001), an energy intensive lifestyle in an energy efficient dwelling can lead to higher energy consumption than an energy extensive lifestyle in a less energy efficient dwelling. If we are able to understand determinants and behavioral patterns related to energy consumption clearer, we might be able to develop advise for energy consumption to be further reduced. The goal would be to ascertain how occupant behavior interacts with the influence of building regulations on energy consumption of dwellings.

Energy use for space heating depends on the heat gains and losses of a dwelling, which are determined by its technical and architectural characteristics on the one hand and by the behavior of the residents on the other (Papakostas & Sotiropoulos, 1997). Guerra Santin (2009) proved that 42% of the variation in the energy consumed in the Dutch dwellings for heating space and water could be explained by type of dwelling, type of HVAC system, and insulation level. An additional 4.2% could be explained by household characteristics and occupant behavior.

User profiles and their behavioral patterns related to energy consumption for space heating have been defined with household characteristics such as household composition, income, age, education, and household size (Groot et al., 2008; Paauw et al., 2009; Assimakopoulos, 1992; Vringer, 2007); lifestyle (Raaij & Verhallen., 1983a; Groot et al., 2008; Paauw et al., 2009; Assimakopoulos, 1992); and cognitive variables such as values, motivations, needs, and attitudes (Assael, 1995; Ajzen, 1991; Vringer, 2007; Poortinga et al, 2005). In addition, Hens discusses habitual behavior and rebound effect in relation to energy consumption, extensively (Hens, 2010). As early as 1983, Raaij and Verhallen found that 5% of the variation in energy consumption could be explained by energy-related attitudes that could be categorized under price, environment, energy concern, health concern, and personal comfort.

In a study by TNO-ECN (2006) five groups of households were studied on the basis of consumption: Single inhabitant, couple, single-parent, family, and seniors. Four profiles were built: convenience/ease (comfort is of priority, saving money, energy or the environment is not a consideration), conscious (comfort is of priority, while environment and cost consideration appears), cost (awareness of energy costs, and saving money), climate/environment (concern for the environment).

Poortinga et al. (2005) found that seniors, singles and low-income households were less willing to apply energy-saving measures at home. Vringer (2007) researched the influence of values, motivation and perception of climate change on the energy consumption of Dutch households. He grouped the households according to household size, age, income, and education. He didn't find any significant differences in the energy consumption of groups of households with different values and motivations.

Groot et al. (2008) and Paauw et al. (2009) worked with five groups of households in the Netherlands, which were studied on the basis of household composition: singles, couples, single-parents, families and seniors (>60). Four profiles were built according to the responses to questions about potential reasons to energy consumption in relation to income, environmental concern and personal comfort: 'convenience/ ease' (comfort/ important, no interest/ saving energy, money or the environment), 'conscious' (comfort/ important, some environmental and cost awareness), 'costs' (energy costs and saving money/ important) and 'climate/environment' (environment/important).

Raaij & Verhallen (1983) defined five patterns of energy behavior in relation to heating and ventilation habits: conservers, spenders, cool, warm, and average. They found significant differences according to the age and educational level, while ascertaining no differences for income and employment. Another output was that the inhabitants' lifestyle(s) influences energy-related attitudes and behavior. Family size and composition, besides presence at home, had a direct effect on behavior and energy consumption.

Guerra Santin's (2010) work takes account only of behavior defined as the use of heating and ventilation systems and other home amenities. Previous studies have already revealed a relationship between energy consumption and occupant behavior (Branco et al., 2004; Linden et al., 2006; Haas et al., 1998, Groot et al., 2008; Leth Petersen & Togeby, 2001; Andersen et al., 2009; Papakostas and Satiropoulos, 2007).

Relationships between energy consumption and household (Andersen et al., 2009; Sardianou, 2008; Schweiker and Shukuya, 2009; Lenzen et al., 2006; Liao and Chang, 2002; Biesiot and Noorman, 1999) and building characteristics (Andersen et al., 2009; Sardianou, 2008; Hirst & Goeltz, 1985; Caldera et al., 2008; Tiberiu et al., 2008; Olofsson et al., 2009; Sonderegger, 1977-78) have also been found in other research.

§ 2.5.2 Electrical appliance use patterns

Energy savings in households can be achieved by changing residents' behavior and/ or attitudes. Behavioral changes are planned to be achieved through campaigns, awareness, and information (Verbeek and Slob, 2006; Wilhite, 2008; Dahlbom, 2009; Barbu et. al., 2013). Ouyang and Hokao (2009) showed that an average of 14% energy savings could be achieved by merely improving occupants' behavior. Wood and Newborough (2003) reported energy savings of more than 10% (20% in some of the groups) in households included in their study. Similarly, Darby (2014) reported reduced consumption by up to 20% in cases where improved feedback was used. More research on user patterns and profiles at home could help a great deal, to prove both the assumed behavior change and guide to improve the information feedback strategies.

Abreu et al. (2012) adopted a pattern recognition method to identify user profiles of electricity consumption. The study explained that approximately 80% of household electricity use results from the persistent daily routines and patterns of consumption or baselines, typical of specific weather and daily conditions. The applicable "profiles" for this population were unoccupied baseline, hot working days, temperate working days, cold working days, and cold weekend days. Widen et al. (2009) produced load profiles over 5 existing time use data sets, collected in Sweden in 1996, 2006 and 2007. The results showed that household behavior patterns regarding cooking, washing, lighting, TV, PC and audio use were able to be modeled using time use data of electricity consumption. Electricity consumption was closely related to occupancy, and grouping of appliances according to specific activities could be a good way to cluster/model consumption.

Coleman et al. (2012) monitored 14 households in the UK and included between March 2008 and August 2009. They found that usage patterns varied widely between households, in both size and make-up, the average (mean) household electricity consumption from ICE (information, communication and entertainment) appliances equated to around 23% of average whole house electricity consumption (median 18%). Of this, standby power modes accounted for 11.5 kWh, which was around 30% of ICE appliances consumption and around 7% of average whole house electricity consumption. O'Doherty et al. (2008) analyzed the determinants of domestic electrical appliance ownership in the Irish housing stock. Their survey conducted in 2001 and 2002 on 40 000 houses revealed that newer and more expensive houses had more appliances, but also more energy saving appliances (ESA). Lutzenheiser's theoretical study (1993) proposed a new cultural model, which built itself on "recognizable lifestyles or cultural forms". For instance, in the US, these were classified under typology such as: retired working class couples, middle aged couples, low income rural families, suburban executive families, and young urban families.

§ 2.6 Conclusion

Aspects of urban sprawl, over-consumption of energy and release of CO_2 emissions, use of natural resources, excessive use of fossil fuels, and waste production make evident the growing share of the building sector in energy consumption and environmental depletion. Especially for the last 4 decades, improving energy efficiency in all sectors has been a major concern in the European context.

Improving energy efficiency of buildings requires a holistic approach, the close collaboration of several professions, and the consideration of the occupancy period. What we know for sure is that there are large variances between the calculated energy performance and the actual energy consumption of dwellings in energy efficient housing. This energy performance gap could be caused by several reasons, such as unexpected occupant behavior, lack of comprehensive data of the whole building process, calculation drawbacks, the construction defects/mistakes in building construction.

This research is focused on the relationship between occupant behavior and energy consumption in dwellings. It is interested in contributing to the problem areas regarding occupant behavior, which are about (1) collecting more detailed data on the determinants and actual occupant behavior, (2) bringing together cross-sectional and longitudinal methods of analyzing occupant behavior, (3) identifying the determinants, patterns, and profiles of behavior, so that occupant behavior could be represented more articulately in the building design, energy performance simulation, sensivity analysis, and energy consumption calculation processes. This way energy efficiency calculations, and policies, consequently the energy efficiency of dwellings could be improved.

This research contributes to literature in the following areas: (1) applying sensitivity analysis in a large sample size of households/dwellings, (2) combining inductive and deductive methodologies, where cross-sectional data on the determinants and the actual behavior, as well as energy consumption figures in larger household/dwelling samples is brought together with longitudinal data on occupant behavior, (3) revealing behavioral patterns and profiles of electricity consumption, (4) revealing behavioral patterns and profiles of heating energy consumption. This research will help to understand the occupant related factors of energy consumption in dwellings, which will contribute to the better design of products, systems, dwellings, and achieving more advanced regulations.

References

Abreu, J. M., Pereira, F. C., Ferrão, P. (2012). Using pattern recognition to identify habitual behavior in residential electricity consumption. Energy and Buildings (49), 479–487.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes (50), 179-211.

Al-Mumin, A., Khattab, O., Sridhar, G. (2003). Occupant's behavior and activity patterns influencing the energy consumption in the Kuwaiti residences. Energy and Buildings (35), 549-559.

Andersen, R. V. (2009). Occupant Behavior with Regard to Control of the Indoor Environment. PhD thesis, Department of Civil Engineering, Technical University of Denmark.

Assael, H. (1995). Consumer Behavior and Marketing Action. South Western College Publishing, Cincinnati, USA.

Armitage, C., Christian, J. (2003). From attitudes to behavior: Basic and applied research on the theory of planned behavior. Current Psychology, 22(3), 187-195.

Assimakopoulos, V. (1992). Residential energy demand modelling in developing regions. Use of multivariate statistical techniques. Energy Economics 14(1), 57-63.

ASHRAE A. (2004) Standard 55-2004, Thermal environmental conditions for human occupancy, Atlanta, American Society of Heating Refrigerating, and Air-conditioning Engineers, Inc., USA

Azar, E., Menassa, C.C. (2012). Agent-based modeling of occupants and their impact on energy use in commercial buildings. Journal of Computation and Civil Engineering 26 (4) 506-518

Barbu, A.D. Griffiths, N. Morton, G. (2013). Achieving Energy Efficiency Through Behavior Change: What Does It Take? Publications Office.

Bartlett, S. (1993). Shedding light on residential consumers. Energy, 18(2), 171-183.

Baker, N., Standeven, M. (1996). Thermal comfort for free-running buildings, Energy and Buildings 23 (3) 175-182

Baker, K., Rylatt, M.R. (2008). Improving the prediction of UK domestic energy demand using annual consumption data. Applied Energy (85), 475–482.

Bartiaux, F., Gram-Hanssen, K. (2005). What works and who delivers. ECEEE 2005 Summer Study, 1313–1325.

Brager, G.S. de Dear, R.J. (1998). Thermal adaptation in the built environment: a literature review. Energy and Buildings 27 (1) 83-96

Bedir, M., Hasselaar, E., Itard, L. (2011). Occupant behavior and energy performance in dwellings: A case study in the Netherlands. Proceedings of PLEA 2011: Architecture and sustainable development, Vol. 1. Louvain-la-Neuve, Belgium: Presses Universitaires de Louvain, 469-474.

Bell, M., Wingfield, J., Miles-Shenton, D., Seavers, J. (2010). Low Carbon Housing: Lessons from Elm Tree Mews, Joseph Rowntree Foundation Publications: USA.

Biesiot, W., Noorman, K.J. (1999). Energy requirements of household consumption: a case study of NL. Ecological Economics (28), 367-383.

Blight, T.S., Coley D. A. (2012). The impact of occupant behavior on the energy consumption of low-energy dwellings. 2nd Conference on Building Energy and Environment. Boulder, USA.

Blum, S., Holtz, M.J., Tavino, R.R. (1989). Post construction activities. IEA- Solar Heating and Cooling Program-Task VIII Report. US GPO Publish, USA.

Bordass, B. Cohen, R. Standeven, M. Leaman, A. (2001). Assessing building performance in use 3: energy performance of the Probe buildings. Building Research and Information 29 (2) 114–128

Bordass, B. (2004). Energy performance of non-domestic buildings: closing the credibility gap, in: Proceedings of the 2004 Improving Energy Efficiency of Commercial Buildings Conference, Citeseer

Branco, G., Lachal, B., Gallinelli, P., Weber, W. (2004). Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data. Energy and Buildings 36 (6), 543–555.

Brandon, G., Lewis, A. (1999). Reducing household energy consumption: a qualitative and quantitative field survey. Journal of Environmental Psychology (19), 75-85.

Brasche, S., Bischof, W. (2005). Daily time spent indoors in German homes – baseline data for the assessment of indoor exposure of German occupants. International Journal of Hygiene and Environmental Health (208), 247-253.

BSRIA (website): https://www.bsria.co.uk/

Bunn, R., Way, M. (2010). Soft Landings. Building Services Research and Information Association and Usable Building Trust Publication: USA.
Caldera, M. Corgnati, S.P. Filippi, M. (2008). Energy demand for space heating through a statistical approach; application to residential buildings. Energy Build (40), 1972-1983
Canada Mortgage and Housing Corporation (1999). Field survey of heat recovery ventilation systems. Research Report, http://www.cmhc-schl.gc.ca/publications/en/rh-pr/tech/96215.htm (last viewed: 19.03.2008)
RIBA CIBSE platform (website) Carbon Buzz, Performance gap, Benchmarking data. (last viewed: 26.08.2016)
http://www.carbonbuzz.org/index.jsp#performancegap
Carbon Trust (website) https://www.carbontrust.com/media/81361/ctg047-closing-the-gap-low-carbon-building-design.pdf (last viewed: 26.08.2016)
Client earth, Greenpeace (2016). Prosumer Rights: Options for an EU legal framework post-2020. Client earth, Brussels http://www.documents.clientearth.org/library/download-info/prosumer-rights-options-for-an-eu-legal-framework-post-2020/
Carbon Buzz (2011). Closing the Gap: Lessons learned on realizing the potential of low carbon building design.
Carbon Trust (2014). Closing the gap between design and as-built performance. Evidence review report.
Coleman, M., Brown, N., Wright, A. S., Firth, K. (2012). Information, communication and entertainment appliance use—Insights from a UK household study. Energy and Buildings (54), 61–72.
Corson, G.C. (1992). Input-output sensitivity of building energy simulations. ASHRAE Transactions (98), Part I, 618-626.
Cramer, J.C., Miller, N., Craig, P., Hackett, B.M. (1985). Social and engineering determinants and their equity implications in residential electricity use. Energy (10) 12, 1283–1291.
Clevenger, C.M., Haymaker, J. (2006). The impact of the building occupant on energy modeling simulations, In: Joint International Conference on Computing and Decision Making in Civil and Building Engineering, Montreal, Canada, Citeseer. 1-10
Darby, S. (2000). Making it obvious: Designing feedback into energy consumption. Proceedings of the 2nd International Conference on Energy Efficiency in Household Appliances and Lighting. Italian Association of Energy Economists/ EC-SAVE program.
Darby S. (2014). The effectiveness of feedback on energy consumption. Oxford, United Kingdom. www.eci.ox.ac.uk/research/energy/downloads/smart-meteringreport.pdf (30.06.2014).
De Carli, M., Olesen, B.W., Zarrela, A., Zecchin, R. (2007). People's clothing behavior according to external weather and indoor environment. Building and Environment (42), 3965-3973.
Dell'Isola, A.J., Kirk, S.J. (2003). Life cycle costing for facilities: economic analysis for owners and professionals in planning, programming, and real estate development: designing, specifying, and construction, maintenance, operations, and procurement, Robert s Means Co., Kingston, MA
Demanuele, C. Tweddell, T. Davies, M. (2010). Bridging the Gap Between Predicted and Actual Energy Performance in Schools, World Renewable Energy Congress XI, UAE Abu Dhabi, 25–30
Designing Buildings: http://www.designingbuildings.co.uk/wiki/Building_services
van Dongen, J.E.F., Phaff, J.C. (1990). Ventilation behavior in Dutch apartment dwellings during summer. Proceedings of Indoor Air Quality and Ventilation in Warm Climates Conference, Portugal, 105-116.
Van Dongen, J.E.F. (1990). The influence of different ventilation devices on the occupants behavior in the dwelling. Proceedings 11th AIVC Conference, Italy.
Van Dongen, J.E.F. (2004). Occupant behavior and attitudes with respect to ventilation of dwellings. RESHY-VENT Report, Brussels.
Dorer, V., Breer, D. (1998). Residential mechanical ventilation systems: Performance criteria and evaluations. Energy and Buildings (27), 247-255.
Dubrul, C. (1988). Inhabitant behavior with respect to ventilation- A summary report of IEA annex VIII. IEA Annex VIII, UK.
Eames, M., Kershaw, T. & Coley, D. (2011). The appropriate spatial resolution of future weather files for building simulation. Journal of Building Performance Simulation (5), 1-12.
EC (2012). Energy roadmap 2050. Brussels, Belgium.
https://ec.europa.eu/energy/sites/ener/files/documents/2012_energy_roadmap_2050_en_0.pdf
ECEEE (2015). Excellent ratings and high participation
https://www.eceee.org/summerstudy/about/evaluations/ (last viewed: 07 November 2017)
ECEEE (2016). Industrial efficiency
https://www.eceee.org/summerstudy/about/evaluations/ (last viewed: 07 November 2017)

Energy Research Center (2009). MONITWeb. http://www.energie.nl/index2. html?stat/index.html (last accessed 20.05.2011).
Emery, A.F., Kippenhan, C.J. (2006). A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific northwest constructed according to improved thermal standards. Energy (31). 677-693.
Engvall, K., Norrby, C., Sandstedt, E. (2004). The Stockholm indoor environment questionnaire: A sociological approach to validate a questionnaire for the assessment of symptoms and perception of indoor environment in dwellings. Indoor Air (14), 24-33.
Engvall, K., Wickman, P., Norback, D. (2005). Sick building syndrome and perceived indoor environment in relation to energy saving by reduced ventilation flow during heating season: A 1-year study in dwellings. Indoor Air (15), 120-126.
Ehrhardt-Martinez, K. (2011). Changing habits, lifestyles and choices: the behaviors that drive feedback-induced energy savings, in: Proceedings of the 2011 ECEEE Summer Study on Energy Efficiency in Buildings, Toulon, France, 6–11
Erhorn, H. (1988). Influence of meteorological conditions on inhabitants' behavior in dwellings with mechanical ventilation. Energy and Buildings (11), 267-275.
Feustel, H.E., Lenz, T.P. (1985). Patterns of infiltration in multifamily buildings. Building and Environment 20(1), 7-13.
Field, A., (2005). Discovering statistics using SPSS (2nd ed.) Sage Publications Ltd., London, UK.
Fiala, D., Lomas, K. (2001). The dynamic effect of adaptive human responses in the sensation of thermal comfort, Proceedings of Windsor Conference, 147–157
Fisk, W.J. (2000). Health and productivity gains from better indoor environments and their relationship with building energy efficiency, Annual Review Energy Environment 25 (1) 537-566.
Fleury, B., Nicolas, C. (1992). Occupant's behavior with respect to window opening: A technical and sociological study. Proceedings of the 13th AIVC Conference, Nice, France, 197-206.
Fuks, M., Salazar, E. (2008). Applying models for ordinal logistic regression to the analysis of household electricity consumption classes in Rio De Janeiro, Brazil, Energy Economics (30), 1672–1692.
Fürbringer, J.M., Roulet, C.A. (1999). Confidence of simulation results: Put a sensitivity analysis module in your MODEL: The IEA-ECBCS Annex 23 experience of model evaluation. Energy and Buildings 30(1), 61-71.
Van Ginkel, J., Hasseelaar, E. (2003). Impact of resident behavior versus ventilation system design in indoor air quality and human health. Proceedings of the 4th International Conference on Cold Climate HVAC, Norway, 1-9.
Van Ginkel, J., Hasselaar, E. (2005). Housing characteristics predicting mold growth in bathrooms. Proceedings of Indoor Air Conference, 2425-2429.
Gladhart, P., Morrison, B., Zuiches, J. (1986). Energy and Families. Michigan State University Press, USA.
Genjo, K., Tanabe, S., Matsumoto, S., Hesegawa, K., Yoshino, H. (2005). Relationship between possession of electric appliances and electricity for lighting and others in Japanese households. Energy and Buildings (37), 259–272.
Gero, J. S., Dudnik, E. E. (1978). Uncertainty and the Design of Building Subsystems - a Dynamic Programming Approach. Building and Environment 13 (3), 147-152.
Gram-Hanssen, K., Kofod, C., Nærvig Petersen, K. (2004). Different everyday lives. Different patterns of electricity use. ACEEE Summer Study on Energy Efficiency in Buildings: Breaking Out of the Box.
Gram-Hanssen, K. (2002). Technology and culture as explanations for variations in energy consumption. Proceedings of the American Council for an Energy Efficient Economy Summer Study in Buildings.
Groot-Marcus, J.P., Terpstra, P.M.J., Steenbekkers, L.P.A., Butijn, C.A.A. (2006). Technology and household activities. User Behavior and Technology Development: Shaping Sustainable Relations between Consumers and Technologies, Eco-Efficiency in Industry and Science Series (20) Springer, Dordrecht.
Dahlbom, B. (2009). Changing Energy Behavior: Guidelines for Behavioral Change Programs, IDAE, 2009
De Groot, E., Spiekman, M., Opstelten, I. (2008). Dutch research into user behavior in relation to energy consumption of residence. Proceedings PLEA conference
Guerra-Santin, O., Itard L., Visscher, H. (2009). The effect of occu- pancy and building characteristics on energy use for space and water heating in Dutch residential stock. Energy and Buildings (41), 1223-1232.
Guerra Santin, O. (2010). Actual Energy Consumption in Dwellings: The Effect of Energy Performance Regulations and Occupant Behavior, PhD thesis, TUDelft.

Guerra-Santin, O., Itard, L.C.M. (2012). The effect of energy performance regulations on energy consumption, Energy and Buildings 5 (3) 269-282
Gunnarsen, L., Ole Fanger, P. (1992). Adaptation to indoor air pollution. Environment International (18), 43-54.
Haakana, M., Sillanpaa, L., Talsi, M. (1997). The effect of feedback and focused advice on household energy consumption. Proceedings of ECEEE 1997 Summer Study, Panel 4: Human Dimensions of Energy Use and Efficiency, ID 38, 1-11.
Haas, R., Auer, H., Biermayr, P. (1998). The Impact of Consumer Behavior on Residential Energy Demand for Space Heating. Energy and Buildings (27), 195-205.
Heijs, W. (2006). Household energy consumption. Habitual Behavior and Technology, Springer.
Hainard, F., Rossel, P., Trachsel, C. (1986). A sociological perspective on tenant behavior with regard to domestic ventilation- an example at Lausanne, Switzerland. Proceedings of 7th AIC Conference, Stratford- up-on-Avon, pp. 12-20.
Hamby, D. M. (1994). A review of techniques for parameter sensitivity analysis of environmental models. Environmental Monitoring and Assessment 32(2), 135-154.
Hansen, H.T.R. (2007). Sensitivity analysis as a methodical approach to the development of design strategies for environmentally sustainable buildings. Unpublished PhD thesis, Aalborg University, Denmark.
Harputlugil, G.U., Hensen. J., Çelebi, G. (2011). A prospect to develop a thermally robust outline design and to explore its applicability to the different climate necessities of Turkey. International Journal of Low-Carbon Technologies 6(1), 76-85.
Helton, J.C., Johnson, J.D., Sallaberry, C.J., Storlie, C.B. (2006). Survey of sampling-based methods for uncertainty and sensitivity analysis. Reliability Engineering and System Safety 91 (10-11), 1175-1209.
Hens, H., Parijs, W. Deurinck, M. (2010). Energy Consumption for heating and rebound effects, Energy and Buildings, 42, 105-110.
Hirst, E., Goeltz, R. (1985). Comparison of actual energy savings with audit predictions for homes in the north central region of the US. Building and Environment 20(1), 1-6.
Holm Pedersen, L., Broegaard, E. (1997). Household Electricity Consumption: An Analysis of Attitudes and Behavior on Energy and The Environment. Copenhagen: Transaction Books.
Holmes, M.J., Hacker, J.N. (2007). Climate change, thermal comfort and energy: Meeting the design challenges of the 21st century. Energy and Buildings. 39 (7) 802-814
Hopfe, C.J. and Hensen, J.L.M. (2011). Uncertainty analysis in building performance simulation for design support. Energy and Buildings (43), 2798-2805.
Hopfe, C.J. (2009). Uncertainty and Sensitivity Analysis in Building Performance Simulation for Decision Support and Design Optimization (PhD dissertation), Eindhoven University, Eindhoven.
Humphreys, M.A., Hancock, M. (2007). Do people like to feel ‘neutral’? Exploring the variation of the desired thermal sensation on the ASHRAE scale, Energy and Buildings 39 (7) 867-874
IEA (213). World Energy Outlook 2013 - International Energy Agency
https://www.iea.org/publications/freepublications/publication/WEO2013.pdf (last access: 07 November 2017)
IEA (2016). World Energy Outlook 2016 - International Energy Agency
https://www.iea.org/newsroom/news/2016/november/world-energy-outlook-2016.html
Iwashita, G., Akasaka, H. (1997). The effects of human behavior on natural ventilation rate and indoor air environment in summer- a field study in southern Japan. Energy and Buildings (25), 195-205.
Jensen, O.M. (2003). Visualisation turns down energy demand. Proceedings of ECEEE 2003 Summer Study: Time to Turn Down Energy Demand, 451-454.
Jokl, M., Kabele, K. (2007). The Substitution of Comfort PMV Values by a New Experimental Operative Temperature, Czech Technical University, Clima Well Being Indoors
Kuehn, S. (1998). Of lifestyle on energy consumption. Sociology Institute. Copenhagen.
Lam, J.C., Hui, S.C.M. (1996). Sensitivity analysis of energy performance of office buildings. Building and Environment 31(1), 27-39.
Lam, J.C. Wan, K.K., Yang, L. (2008). Sensitivity analysis and energy conservation measures implications. Energy Conservation Management 49 (11) 3170-3177
Lambert, J., Simonnet, F., Vallet, M. (1984). Patterns of behavior in dwellings exposed to road traffic noise. Journal of Sound and Vibration 92(2), 159-172.
Lee, W., Chen, H. (2008). Benchmarking Hong Kong and China energy codes for residential buildings. Energy and Buildings 40 (9) 1628-1636

Lembrechts, J., Jannsen, M., Stoop, P. (2001). Ventilation and radon transport in Dutch dwellings: Computer modelling and field measurements. The Science of the Total Environment (272), 73-78.
Lenzen, W., Cohen, H., Pachauri, S. (2006), A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan, Energy 31, 181-207.
Leth-Petersen, S., Togeby, S. M. (2001). Demand for space heating in apartment blocks: measuring effect of policy measures aiming at reducing energy consumption. Energy Economics (23), 387-403.
Liao, H.C., Chang, T.F. (2002). Space-heating and water-heating energy demands of the aged in the U.S. Energy Economics (24), 267-284.
Liddament, M.W., Orme, M. (1998). Energy and ventilation. Applied Thermal Engineering (18), 1101-1109.
Liddament, M.W. (2001). Occupant impact on ventilation. Technical note: 53, AIVC, Brussels.
Linden, A.L., Carlsson-Kanyama, A., Eriksson, B. (2006). Efficient and ineffi- cient aspects of residential energy behavior: what are the policy instruments for change? Energy Policy (34), 1918-1927.
Lohnert, G., Schmid, H-M. (1989). Design context. Design Information Booklet Number 2, IEA-SHC Program Task VIII, Germany, 120-121.
Lomas, K.J. Eppel, H. (1992). Sensitivity analysis techniques for building thermal simulation programs, Energy and Buildings 19 (1) 21-44
Lutzenhiser, L. (1992). A Question Of Control – Alternative Patterns Of Room Air- Conditioner Use, Energy and Buildings, 18, 193-200.
Lutzenheiser, L. (1993). Social and behavioral aspects of energy use. Annual Review of Energy and the Environment (18), 247-289.
Macdonald, I.A. (2004). Assessing the significance of design changes when simulating building performance including the effects of uncertain input data. ESim 04 Conference. Vancouver, Canada (9-11 June).
Macintosh, A., Steemers, K. (2005). Ventilation strategies for urban housing: Lessons from a PoE case study. Building Research and Information 33(1), 17-31.
Mahdavi, A. (2011). The human dimension of building performance simulation. 12th International IBPSA Conference: Building Simulation 2011. Sydney (14-16.11.2011).
Majcen, D., Itard, L., Visscher, H. (2013). Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications. Energy Policy (54) 125-136.
Majcen, D., Itard, L.C.M., Visscher, H. (2013). Actual and theoretical gas consumption in Dutch dwellings: What causes the differences? Energy Policy (61) 460-471
Majcen, D., Itard, L., Visscher, H. (2015). Statistical model of the heating prediction gap in Dutch dwellings: Relative importance of building, household and behavioral characteristics. Energy and Buildings (105).
Mansouri, I., Newborough, M., Probert, D. (1996). Energy consumption in UK households: impact of domestic electrical appliances. Applied Energy (54), 211-285.
Maréchal, K. (2009). An evolutionary perspective on the economics of energy consumption: the crucial role of habits. Journal of Economic Issues 43 (1) 69–88.
Maréchal, K. (2010). Not irrational but habitual: the importance of behavioral lock-in in energy consumption. Ecological Economy, 69 (5) 1104–1114
Menezes, C., Cripps, A., Bouchlaghem, D., Buswell, R. (2012). Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. Applied Energy (97), 355-364.
Melikov A.K., Kruger, U., Zhou, G., Madsen, T.L., Landkilde G. (1997). Air temperature fluctuations in rooms. Building and Environment 32(2), 101-114.
Moezzi, M. Lutzenhiser, L. (2010). What's Missing in Theories of the Residential Energy User, ACEEE Summer Study on Energy Efficiency in Buildings, American Council for an Energy Efficient Economy, Washington, DC.
Morgan, C., de Dear, R. (2003). Weather, clothing and thermal adaptation to indoor climate climate research. Clim Res (24), 267-284.
National Measurement Network (2012). The Building Performance Gap - Closing it through Better Measurement. National Physical Laboratory, USA.
Nevius, M.J., Pigg, S. (2000). Programmable thermostats that go berserk? Taking a social perspective on space heating in Wisconsin, ACEEE Summer Study in Energy Efficiency in Buildings.
Ndiaye, D., Gabriel, K. (2010). Principal component analysis of the electricity consumption in residential dwellings. Energy and Buildings 1–8, http://dx.doi.org/10.1016/j.enbuild.2010.10.008
Newsham, G., Mancini, S., Birt, B. (2009). Do LEED-certified buildings save energy? Yes, but... Energy and Buildings (41), 897–905.

Newsham, G., Birt, B., Arsenault, C., Thompson, L., Veitch, J., Mancini, S., Galasiu, A., Macdonald, I., Burns, G. (2012). Do green buildings outperform conventional buildings? Indoor Environment and energy performance in North American offices. Report RR- 329, Natural Research Council Canada.

O'Doherty, J., Lyons, S., Tol, R. (2008). Energy-using appliances and energy-saving features: determinants of ownership in Ireland. Applied Energy (85), 650–662.

ODYSSEE, Energy Efficiency Profile: Energy Netherlands (2008). www.odyssee-indicators.org/publications/PDF/netherlands nr.pdf (last accessed 20.05.11).

OECD/IEA, 2013. Transition to Sustainable Buildings Strategies and Opportunities to 2050. IEA, Paris, 2013

http://www.iea.org/publications/freepublications/publication/Building2013_free.pdf

OECD/IEA, 2016. Energy Technology Perspectives 2016. IEA, 2016

http://www.iea.org/publications/freepublications/publication/EnergyTechnologyPerspectives2016_ExecutiveSummary_EnglishVersion.pdf

Olofsson, T., Andersson, S., Sjogren, J.U. (2009). Building energy parameter investigations based on Multivariate Analysis, Energy and Buildings, 41, 71-80.

Ortiz, M. Kurvers, S. Bluyssen, P. (2017). A review of comfort, health, and energy use: Understanding daily energy use and wellbeing for the development of a new approach to study comfort. Energy and Buildings 152, 323–335

Ouyang, J., Hokao, K. (2009). Energy-saving potential by improving occupants- behavior in urban residential sector in Hangzhou City, China. Energy and Buildings 41(7), 711-720.

Paauw, J., Roossien, B., Aries, M.B.C., Guerra Santin, O. (2009). Energy pattern generator – understanding the effect of user behavior on energy systems, Proceedings 1st European Conference on Energy Efficiency and Behavior.

Papakostas, K.T., , B.A. (1997). Occupational and Energy Behavior Patterns in Greek Residences. Energy and Buildings (26), 207-213.

Parti, M., Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. The Bell Journal of Economics 11 (1), 309–321.

Pettersen, T.D. (1994). Variation of energy consumption in dwellings due to climate, building and inhabitants. Energy and Buildings (21), 209-218.

Peschiera, G., Taylor, J.E., Siegel, J.A. (2010). Response–relapse patterns of building occupant electricity consumption following exposure to personal, contextualized and occupant peer network utilization data, Energy and Buildings 42 (8) 1329-1336

Pierce, J. Schiano, D.J. Paulos, E. (2010). Home, habits, and energy examining domestic interactions and energy consumption, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, ACM, 1985–1994

Poortinga, W., Steg, L., Vlek, C., Wiersma, G. (2005). Household preferences for energy-saving measures: A conjoint analysis. Journal of Economic Psychology (29), 49-64.

Rabl, A., Rialhe, A. (1992). Energy signature models for commercial buildings: test with measured data and interpretation, Energy and Buildings 19 (2) 143-154

Ramallo-González, A.P. (2013). Modelling Simulation and Optimization of Low-energy Buildings. PhD Thesis. University of Exeter.

Ramallo-González, A. P., Blight, T., Coley, D. A. (2015). New optimization methodology to uncover robust low energy designs that accounts for occupant behavior or other unknowns. Journal of Building Engineering (2), 59-68. doi:10.1016/j.jobe.2015.05.001

Reddy, T., Maor, I., Panjapornporn, C. (2007). Calibrating detailed building energy simulation programs with measured data - Part I: general methodology. HVAC&R Research 13(2), 221-241.

Richardson, I., Thomson, M., Infield, D. (2008). A high-resolution domestic building occupancy model for energy demand simulations. Energy and Buildings (40), 1560-1566.

Rooijers, F., Sevenster, M., van Loo, L., Slingerland, S. (2003). Energie en gedrag in de woning. VROM, DG, Wonen CE rapport, Delft.

Römer, J.C. (2001). Simulation of demand controlled ventilation in a low-energy house. Proceedings of 7th International IBPSA Conference, Brazil.

Roulet, C.A. Flourentzou, F. Foradini, F. Bluyssen, P. Cox, C. Aizlewood, C. (2006). Multicriteria analysis of health, comfort and energy efficiency in buildings. Building Research Information, 34 (5)

Ryan, E., Sanquist, T. (2012). Validation of building energy modelling tools under idealized and realistic conditions. Energy and Buildings (42), 375-382.

Saporito, A., Day, A., Karayiannis, T., Parand, F. (2001). Multi-parameter building thermal analysis using the lattice method for global optimization, Energy and Buildings 33 (3) 267-274

Sardianou, E. (2008). Estimating space heating determinants: an analysis of Greek households. Energy and Buildings, 40 (6), 1084–1093

Saidur, R., Masjuki, H., Jamaluddin, H., Ahmed, S.M.Y. (2007). Energy and associated greenhouse gas emissions from household appliances in Malaysia. Energy Policy (35), 1648–1657.

Saltelli, A. (2000). What is sensitivity analysis? In A Saltelli, K Chan, and EM Scott (Eds.), Sensitivity analysis. New York: John Wiley & Sons, 3-14.

Schneider, J., Hermelink, A. (2006). Cepheus results: Measurements and occupant's satisfaction provide evidence for passive houses being an option for sustainable building. Energy Policy (34), 151-171.

Schneiders, T., Sundell, J., Bischof, W., Bohgard, M., Cherrie, J.W., Clausen, P.A., Dreborg, S., Kildeso, J., Kjaergaard, S.K., Lovik, M., Pasanen, P., Skyberg, K. (2003). EUROPART: Airborne Particles in The Indoor Environment. An interdisciplinary review of scientific evidence on associations between exposure to particles in buildings and health effects. Indoor Air (13), 38-48.

Schweiker, M., Shukuya, M. (..). Comparison of Theoretical and Statistical Models of Air-Conditioning-Unit Usage Behaviour in a Residential Setting under Japanese Climatic Conditions, Building and Environment, 44, 2137-2149.

Seppanen, O.A., Fisk, W.J. (2001). Summary of human responses to ventilation. Indoor Air (14). 102-118.

Shipworth, M., Firth, S.K., Gentry, M.I., Wright, A.J., Shipworth, D.T., Lomas, K.J. (2010). Central heating thermostat settings and timing: building demographics. Building Research and Information (38), 50-69.

Shove, E. (2003). Converging conventions of comfort, cleanliness and convenience. Journal of Consumer Policy (26), 395–418.

Shove, E. (2004). Social, architectural and environmental convergence, Environmental Diversity in Architecture,19–30

Singh, J. (1996). Impact of indoor air pollution on health, comfort and productivity of the occupants. Aerobiologia (12), 121-127.

Soebarto, V.I., Williamson, T.J. (2001). Multi-criteria assessment of building performance: theory and implementation, Building and Environment 36 (6) 681-690

Soldaat K., Itard L., (2007). Influence of occupants on the energy use of balanced ventilation. Proceedings of CLIMA 2007 - Wellbeing Indoors, Finland, 8-16.

Sonderegger, R.C. (1977-78). Movers and Stayers: the resident's contribution to variation across houses in energy consumption for space heating. Energy and Buildings, 1, 313-324.

Spaarrgaren, G., Van Vliet, B. (2000). Lifestyles, consumption and the environment: The ecological modernisation of domestic consumption. Environmental Politics 9(1), 50 - 77.

Spitler, J.D., Fisher, D.E., Zietlow, D.C. (1989). A primer on the use of influence coefficients in building simulation. Proceedings of Building Simulation '89. Vancouver: IBPSA, 299-304.

Stymne, H., Boman, C.A., Kronvall, J. (1994). Measuring ventilation rates in the Swedish housing stock. Building and Environment 29(3), 373-379.

Tanimoto, J., Hagishima, A., Sagara, H. (2008). A methodology for peak energy requirement considering actual variation of occupants' behavior schedules. Building and Environment (43), 610-619.

Tiberiu, C., Virgone, J., Blanco E. (2008). Development and Validation of Regression Models to Predict Monthly Heating Demand for Residential Buildings, Energy and Buildings, 40,1825-1832.

Tiwari, P. (2000). Architectural, demographic, and economic causes of electricity consumption in Bombay. Journal of Policy Modelling 22 (1), 81–98.

Turner, C., Frankel, M. (2008). Energy performance of LEED for new construction buildings (Final Report), New Buildings Institute.

Tyler, S., Schipper, L. (1990). The dynamics of electricity use in Scandinavian households. Energy 15(10), 841-863.

Verbeek, P. Slob, A. (2006). User Behavior and Technology Development, Springer

Verplanken, B., Aarts, H., van Knippenberg, A., van Knippenberg, C. (1994). Attitude versus general habit: Antecedents of travel mode choice. Journal of Applied Social Psychology 24(4), 285-300.

Vine, E., Barnes, B.K. (1989). Monitored indoor temperatures and reported thermostat settings: How different are they? Energy 14(5), 299-308.

Vringer, K., Blok T.A.K. (2007). Household energy requirement and value patterns, Energy Policy (35), 553-566.

Wang, J., Zhai, Z.J., Jing, Y., Zhang, X., Zhang, C. (2011). Sensitivity analysis of optimal model on building cooling heating and power system. Applied Energy 88 (12) 5143-5152

Wang, L., Mathew, P., Pang, X. (2012). Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building. Energy and Buildings (53), 152-158.

Westphal, F.S., Lamberts, R. (2005). Building simulation calibration using sensitivity analysis. Proceedings of Building Simulation '05. Montreal: IBPSA, 1331-1338.

Widen, J., Lundh, M., Vassileva, I., Dahlquist, E., Ellegard, K., Wackelgard, E. (2009). Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation. Energy and Buildings (41), 753–768.

Wiese, B.S., Sauer, J., Ruttinger, B. (2004). Consumer use of product information. Ergonomics 47(11), 1180-1194.

de Wilde, P., Tian, W. (2009). Identification of key factors for uncertainty in the prediction of the thermal performance of an office building under climate change.

Building Simulation (2), 157-174.

de Wilde, P., Coley, D. (2012). The implications of a changing climate for buildings. Building and Environment (55), 1-7.

de Wilde, P., Sun, Y., Augenbroe, G. (2013). Quantifying the performance gap – a probabilistic attempt, EG-ICE 2013: Conference on Intelligent Computing in Engineering, Vienna, Austria.

de Wilde, P., Jones, R. (2014). The building energy performance gap: up close and personal (last accessed 29.08.2016) https://pearl.plymouth.ac.uk/

Wilhite, H. (2008). New thinking on the agentive relationship between end-use technologies and energy-using practices, Energy Efficiency, 1 (2) 121–130

Willand, W. Ridley, I. Maller, C. (2015). Towards explaining the health impacts of residential energy efficiency interventions—a realist review. Part 1: pathways, Social Science Medicine 133, 191–201

Wilson, J. Dixon, S.L. Jacobs, D.J. Breysse, J. Akoto, J. Tohn, E. Isaacson, M. Evens, A. Hernandez, Y. (2014). Watts-to-wellbeing: does residential energy conservation improve health? Energy Efficiency 7 (1) 151–160van Raaij, F., Verhallen, T. (1983). A behavioral model of residential energy use. Journal of Economic Psychology (3), 39–63.

Wingfield, J., Bell, M., Miles-Shenton, D., South, T., Lowe, B. (2011). Evaluating the impact of an enhanced energy performance standard on load-bearing masonry domestic construction. Understanding the gap between designed and real performance: Lessons from Stamford Brook. London: Department for Communities and Local Government

Wood, G., Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: environment, behavior and design. Energy and Buildings (35), 821–841.

Wouters, P., De Baets, D. (1986). A detailed statistical analysis of window use and its effect on the ventilation rate in 2400 Belgian houses. Proceedings of 7th AIC Conference, Stratford-upon-Avon, 33-53.

Wright, A. (2008). What is the relationship between built form and energy use in dwellings. Energy Policy (36), 4544–4547.

Yohannis, Y., Jayanta, G., Mondol, D., Wright, A., Norton, B. (2008). Real-life energy use in the UK: how occupancy and dwelling characteristics affect domestic electricity use. Energy and Buildings (40), 1053–1059.

Yudelson, J. (2010). Greening Existing Buildings, McGraw-Hill, New York

Zota, A., Adamkiewicz, G., Levy, J.I., Spengler, J.D. (2005). Ventilation in public housing: implications for indoor NO2 concentrations. Indoor Air (15), 393-401.

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).

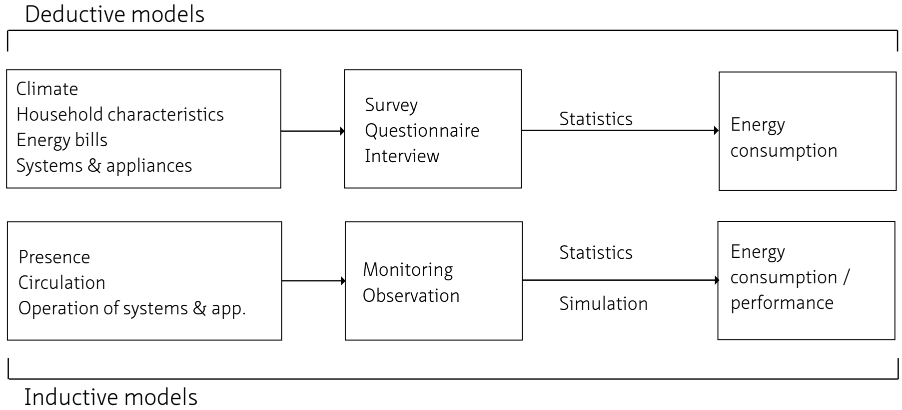


FIGURE 3.1 The inductive and deductive models of occupant behavior-energy performance relationship

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

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.

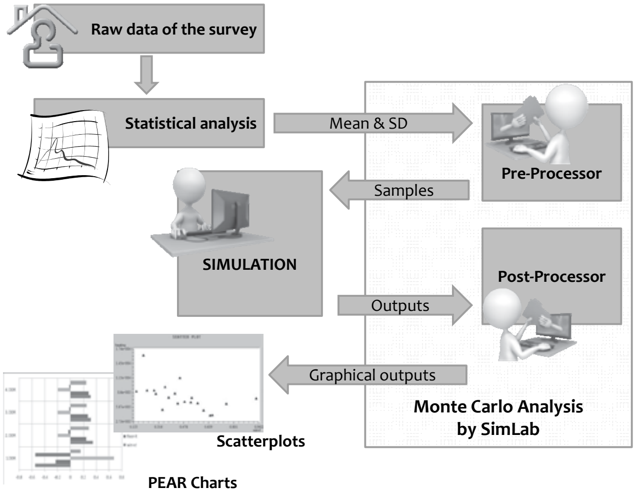


FIGURE 3.2 Flow chart of the study methodology

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 ventilation 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 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).

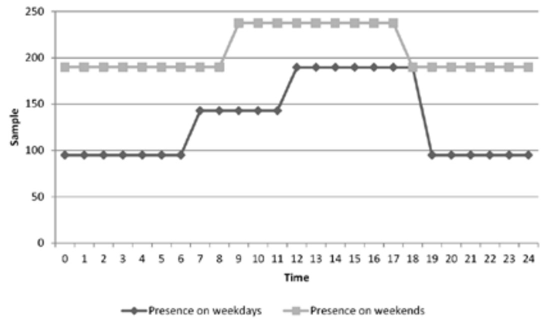


FIGURE 3.4 Average hourly presence at home pattern

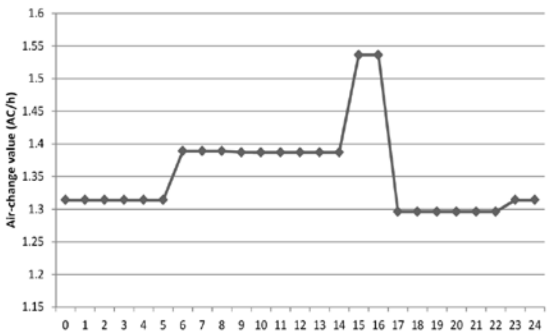


FIGURE 3.5 Average air change rate (per hour) during the day

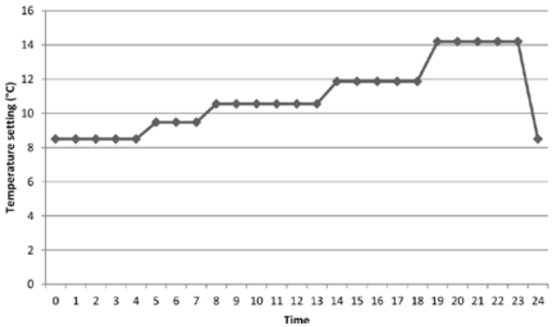


FIGURE 3.6 Average hourly radiator-thermostat setpoint preference during the day

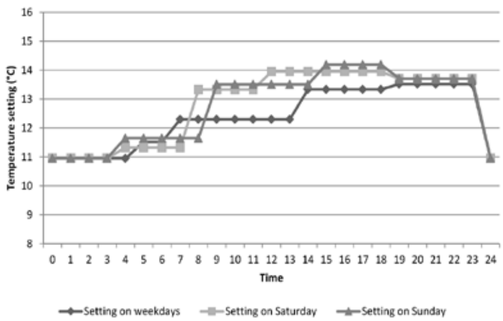


FIGURE 3.7 Average hourly thermostat-set point preference during the day

§ 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.

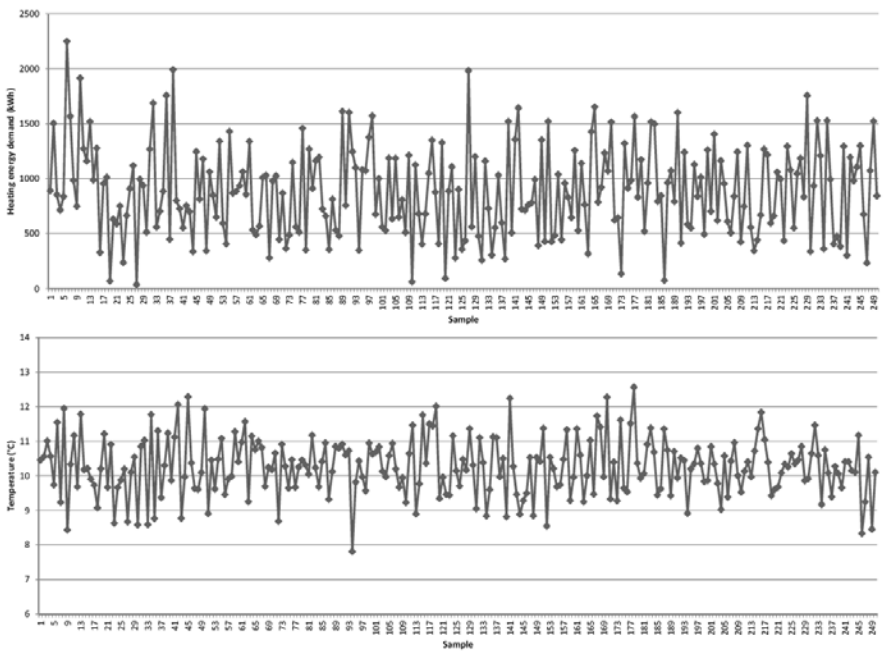


FIGURE 3.8 (Top) Heating energy demand and (bottom) minimum indoor resultant temperature values for the entire dataset

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.

TOC

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).

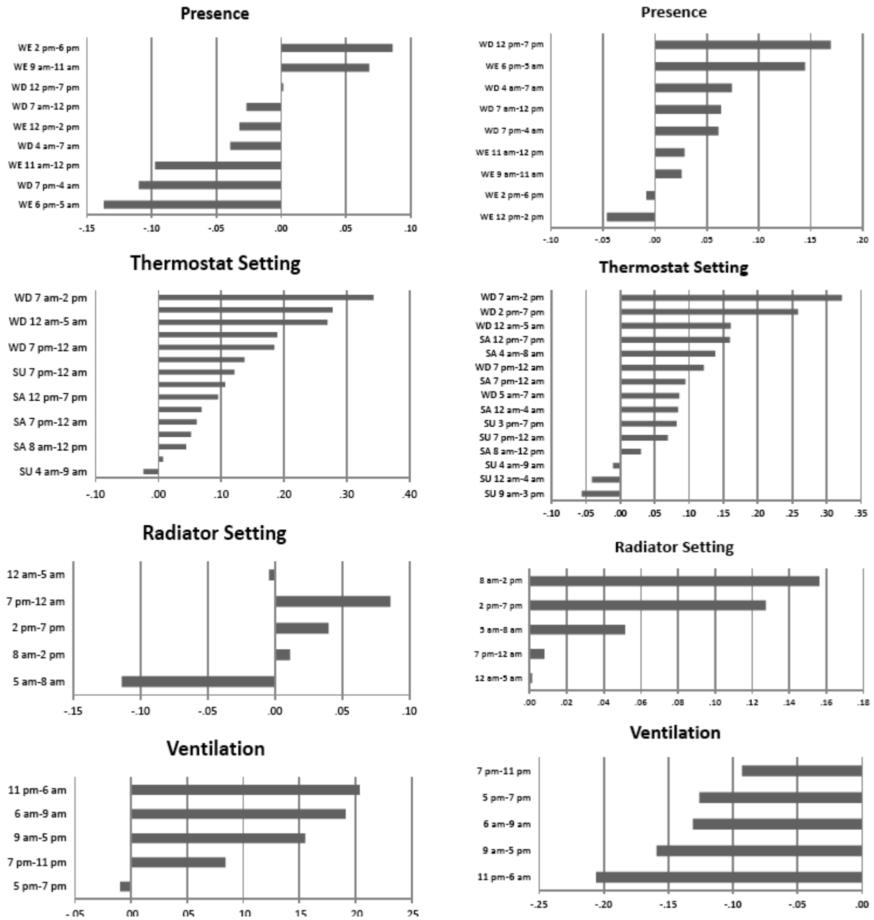


FIGURE 3.9 PCC values for heating energy demand (left) and minimum indoor resultant temperature (right). (WE = weekend, WD = weekday, SA = Saturday, and SU = Sunday). The values for radiator setting and ventilation are an average of both weekend and weekday values. PCC values reveal the correlations 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)

References

Andersen, R. V. (2009). Occupant Behavior with Regard to Control of the Indoor Environment. PhD thesis, Department of Civil Engineering, Technical University of Denmark.

Baetens, R., Saelens, D. (2011). Integrating occupant behavior in the simulation of coupled electric and thermal systems in buildings. Proceedings of the 8th International Modelica Conference. Sweden: Linköping University, 847-855.

Bedir, M., Hasselaar, E., Itard, L. (2011). Occupant behavior and energy performance in dwellings: A case study in the Netherlands. Proceedings of PLEA 2011: Architecture and sustainable development, Louvain-la-Neuve, Belgium: Presses Universitaires de Louvain, 469-474.

Bourgeois, D., Reinhart, C., Macdonald, I. (2006). Adding advanced behavioral models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control. Energy and Buildings 38(7), 814-823.

CIBSE (2006). CIBSE guide A: Environmental design. London: CIBSE.

Corson, G.C. (1992). Input-output sensitivity of building energy simulations. ASHRAE Transactions 98(Part I), 618-626.

Fritsch, R., Kohler, A., Nygard-Ferguson, M., Scartezzini, J.L. (1990). A stochastic model of user behavior regarding ventilation. Building and Environment 25(2), 173-181.

Fürbringer, J.M., Roulet, C.A. (1999). Confidence of simulation results: Put a sensitivity analysis module in your MODEL: The IEA-ECBCS Annex 23 experience of model evaluation. Energy and Buildings 30(1), 61-71.

Guerra Santín, O. (2010). Actual Energy Consumption in Dwellings: The Effect of Energy Performance Regulations and Occupant Behavior (Sustainable urban areas series 33). Amsterdam: Delft University Press.

Haas, R., Auer, H., Biermayr, P. (1998). The impact of consumer behavior on residential energy demand for space heating. Energy and Buildings 27(2), 195-205.

Hamby, D.M. (1994). A review of techniques for parameter sensitivity analysis of environmental models. Environmental Monitoring and Assessment 32(2), 135-154.

Hansen, H.T.R. (2007). Sensitivity Analysis as A Methodical Approach to the Development of Design Strategies for Environmentally Sustainable Buildings. Unpublished PhD thesis, Aalborg University, Denmark.

Harputlugil, G.U., Hensen, J., Çelebi, G. (2011). A prospect to develop a thermally robust outline design and to explore its applicability to the different climate necessities of Turkey. International Journal of Low-Carbon Technologies 6(1), 76-85.

Helton, J.C., Johnson, J.D., Sallaberry, C.J., Storlie, C.B. (2006). Survey of sampling-based methods for uncertainty and sensitivity analysis. Reliability Engineering & System Safety 91(10-11), 1175-1209.
Hirst, E., Goeltz, R. (1985). Comparison of actual energy savings with audit predictions for homes in the north central region of the US. Building and Environment 20(1), 1-6.
Hoes, P., Hensen, J.L.M., Loomans, M.G.L.C., de Vries, B., Bourgeois, D. (2008). User behavior in whole building simulation. Energy and Buildings 41(3), 295-302.
Hopfe, C., Hensen, J., Plokker, W. (2007). Uncertainty and sensitivity analysis for detailed design support. Proceedings of the 10th IBPSA building simulation conference, September 2007. Beijing: Tsinghua University, 1799-1804.

Ioannou, A., Itard, L.C.M. (2015). Energy performance and comfort in residential buildings: Sensitivity for building parameters and occupancy. Energy and Buildings (92) 216-233
Jeeninga, H., Uyterlinde, M.A., Uitzinger, J., (2001). Energieverbruik van Energiezuinige Woningen: Effecten van Gedrag En Besparingsmaatregelen op De Spreiding in en De Hoogte van Het Reële Energieverbruik (Report ECN-C-01-072) (Dutch). Petten: Energy Research Centre of the Netherlands.
Lam, J.C., Hui, S.C.M., (1996). Sensitivity analysis of energy performance of office buildings. Building and Environment 31(1), 27-39.
Linden, A.L., Carlsson-Kanyam, A., Eriksson, B. (2006). Efficient and inefficient aspects of residential energy behavior: What are the policy instruments for change? Energy Policy 34(14), 1918-1927.
Lomas, K.J., Eppel, H. (1992). Sensitivity analysis techniques for building thermal simulation programs. Energy and Buildings 19(1), 21-44.
Macdonald, I.A. (2004). Assessing the significance of design changes when simulating building performance including the effects of uncertain input data. Proceedings of ESim 04 Conference. Vancouver, Canada.
Mahdavi, A., Pröglhöf C. (2009). User behavior and energy performance in buildings' Internationalen Energiewirthschaftstagung an der TUWien, Vienna, 1-13.
Mahdavi, A. (2011). The human dimension of building performance simulation. 12th International IBPSA Conference: Building Simulation 2011. Sydney.
NEN (2001) NEN 1087: Ventilatie van gebouwen – bepalingsmethoden voor nieuwbouw (Dutch). Delft, The Netherlands: NEN.
NEN (2006) NEN 5129: Energieprestatie van WOONfuncties en WOONgebouwen – rekenprogramma (EPW) (Dutch). Delft, The Netherlands: NEN.
NEN (2010) NEN 5128: Energieprestatie van WOONfuncties en WOONgebouwen – bepalingsmethode (Dutch). Delft, The Netherlands: NEN.
Page, J., Robinson, D., Morel, N., Scartezzini, J.L. (2008). A generalised stochastic model for the simulation of occupant presence. Energy and Buildings 40(2), 83-98.
Reinhart, C.F. (2004). Lightswitch-2002: A model for manual and automated control of electric lighting and blinds. Solar Energy 77(1), 15-28.
Richardson, I., Thomson, M., Infield, D. (2008). A high-resolution domestic building occupancy model for energy demand simulations. Energy and Buildings 40(8), 1560-1566.
Rijal, H.B., Tuohy, P., Humpreys, M.A., Nicol, J.F., Samuel, A., Clarke, J. (2007). Using results from field surveys to predict the effect of open windows and thermal comfort on energy use in buildings. Energy and Buildings 39(7), 823-836.
RVO.nl (2015) Referentiewoningen nieuwbouw (Dutch). www.rvo.nl/onderwerpen/duurzaamondernemen/gebouwen/wetten-en-regels-gebouwen/energieprestatie-epc/referentiewoningen. (last viewed: 17 May 2016).
Saelens, D., Parys, W., Baetens, R. (2011). Energy and comfort performance of thermally activated building systems including occupant behavior. Building and Environment 46(4), 835-848.
Saltelli, A. (2000). What is sensitivity analysis? Sensitivity Analysis. New York: John Wiley & Sons. 3-14.
SenterNovem (2006). Referentiewoningen nieuwbouw (Publication no. 2KPWB0620) (Dutch). Retrieved from www.senternovem.nl, December 2006.
Spitler, J.D., Fisher, D.E., Zietlow, D.C. (1989). A primer on the use of influence coefficients in building simulation. Proceedings of Building Simulation '89. Vancouver: IBPSA, 299-304.
Tabak, V., de Vries, B., Dijkstra, J., Jessurun, J. (2006). Interaction in activity location scheduling. Proceedings of the 11th International Conference on Travel Behavior Research, Kyoto, Japan.

Tabak, V., de Vries, B., Dijkstra, J. (2008). Validating an office simulation model using RFID technology. Proceedings of the 9th International Conference on Design & Decision Support Systems in Architecture and Urban Planning. Eindhoven: Eindhoven University of Technology.

Tanimoto, J., Hagishima, A., Sagara, H. (2008). A methodology for peak energy requirement considering actual variation of occupant's behavior schedules. Building and Environment (43), 610-619.

Uitzinger, J. (2004). Analyse EPC en energieverbruik bij woningen (Dutch). Amsterdam: IVAM.

Westphal, F.S., Lamberts, R. (2005). Building simulation calibration using sensitivity analysis. Proceedings of Building Simulation '05. Montreal: IBPSA, 1331-1338.

4 Behavioral determinants of electricity consumption in dutch dwellings

Introductory note

Following the sensitivity analysis on heating energy consumption in Chapter 3, Chapter 4 is an analysis on the determinants of electricity consumptions in Dutch dwellings. The OTB sample was used for analysis, and it was validated with analysis of the WoON sample. The work was published as:

This Chapter deals with the Research Question II of this thesis:
(Chapter 1, Section 3, pg. 16-17)
"II. What is the influence of lighting and appliance use on the total electricity consumption in dwellings?"

The sub-questions are:

1. *What are the main direct and indirect determinants of electricity consumption? (Direct determinant: such as number of appliances and duration of appliance use … Indirect determinant: such as household size, dwelling size, dwelling type …)*
2. *How much of the variance in electricity consumption in dwellings can be explained by direct and indirect determinants?"*
   The research reported in this Chapter was conducted by Bedir. The data was collected by a questionnaire prepared by Guerra Santin and Bedir, using OTB's means of data collection. The analysis was done, and the paper was written by Bedir. The co-authors commented on the drafts and gave advise on the structure, and the content of the paper. The co-authors have given their permission to include the paper in the thesis.

This Chapter was published as:
Bedir, M. Hasselaar, E. Itard, L. (2013) Determinants of electricity consumption in Dutch dwellings. Energy and Buildings, 58. p. 194-207

§ 4.1 Introduction

Operation of heating, ventilation and air-conditioning systems, lighting, and domestic appliances account for the electricity consumption in dwellings. This paper explores the contribution the use of lighting and domestic appliances to electricity consumption and how it is determined. Households consume electricity via domestic appliances that serve different functions such as cooking and cleaning. The type and number of appliances and the duration of use vary across households and through time, depending on the energy needs of the households and the accessibility and affordability of the appliances. Biesiot and Noorman (1999) split the electricity consumption patterns for the Netherlands into three main periods since World War II (Fig. 1). During the first period, the post- war reconstruction (1950–1965), the emphasis was on rebuilding society. During the second, the welfare state (1965–1980), households had easier access to resources and appliances and electricity consumption was 5–6 times higher than in the first period. The third period (1980–1999) started after the oil crisis, when environmental concerns increased in general, but so did dependence on electrical appliances. Indeed, the consumption of electricity in the third period was as high as in the second.

Biesiot predicted that electricity consumption would rise if people increased their use of electrical appliances. His predictions have been borne out by the results of recent research (Jeeninga et al., 2001; IEA, 2009; EnergieNed, 2009; ERC, 2008; ERC, 2009; ODYSSEE, 2008). In the 27 EU-member states, electricity efficiency has improved by almost 1.5% a year since 1990 (ODYSSEE, 2008). However, in 15 EU countries, larger homes and an increasing number of appliances are pushing up the consumption per household by about 0.4% a year (ADEME, 2007). These two factors almost completely offset the progress of the past two decades (Figure 2).

§ 4.1.1 Electrical domestic appliances

Households account for 23% of the total electricity consumption in the Netherlands (IEA, 2008). At European level, white goods and lighting are responsible for 40% of the electricity consumed by households and brown goods for 60% (13). Electronics capabilities led to the emergence of a distinction between “white goods” (the typically enameled kitchen appliances such as fridges and cookers) and “brown goods” (such as wood- or bakelite-cased record players, radios, and TVs) (Miles, 1999). Since 1996, the energy efficiency of electrical domestic appliances has been a major concern for policy, research and the market. Today, almost all such appliances consume less electricity than in 1990 (ODYSSEE, 2007).

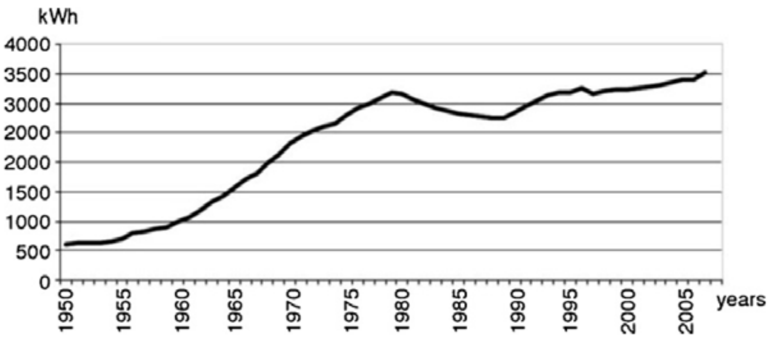


FIGURE 4.1 Average electricity consumption per household in the Netherlands (EnergieNed, 2009)

The average consumption of a washing machine has decreased by 28% since The average consumption of a washing machine has decreased by 28% since 1995, but the use of washing machines has increased by 32% (Itard et al., 2009). Dryers show less improvement in energy efficiency (12% decrease in electricity consumption between 1990 and 2007), but the use of dryers has increased considerably (38%). The same trend can be observed for dishwashers (25% decrease in specific electricity consumption between 1990 and 2007, 150% increase in use). The only appliance that has consistently been consuming more energy since 1990 is the TV – 2.5 times higher in 2007 than in 1990. This increase reflects the growing popularity of larger TVs and flat screens. Of course, when it comes to the total energy consumption per dwelling, it is not only the energy consumed by specific appliances that is important, but also the percentage of households with one or more of these appliances (ERC, 2009) (Fig. 3).

Despite the efforts to improve the energy efficiency of electrical appliances, the growing population, the increasing number of households and the wider use of electrical appliances could be instrumental factors in the rising levels of electricity consumption. To bring about a meaningful reduction in the electricity consumed by the housing stock, we need to know more about the underlying determinants. The ability to make accurate predictions of the electricity usage of households is already an important issue for energy companies and will become even more important with the emergence of smart electricity grids. It is possible to make accurate predictions of electricity consumption when the duration of use of each electrical appliance is known as well as its voltage. Unfortunately, as such data are difficult to collect by energy companies, especially at macro-level, we need to establish more easily accessible parameters with an explanatory power to determine the level and variance of electricity consumption in households. Variables of presence, household and dwelling characteristics, and technical system characteristics should be investigated. This paper reports electricity consumption of dwellings can be explained by the use of lighting and electrical appliances and to identify the underlying determinants of use.

This paper begins with a review of previous research on electricity consumption in dwellings. This review formed the basis for the hypotheses and the research questions. Section 3 describes the methodology and the data used in the study. Variables from the literature were grouped and tested in our sample. The data were collected via a questionnaire filled in by the occupants of 323 dwellings in two neighbourhoods in the Netherlands in the autumn of 2008. Three regression models were built for the direct and the indirect determinants (see Section 3): the first was based on the total duration of use of the appliances (direct) and presence in the dwelling and in rooms (indirect); the second was based on the number of lighting and household appliances (direct) and the characteristics of the dwelling (indirect) (economics, heating and ventilation systems and household – henceforth referred to as DHES characteristics) and the third was based on the total duration of use of the appliances (direct) and DHES characteristics (indirect). The results are presented in Section 4 and the discussion in Section 5. Finally, the conclusions are presented in Section 6.

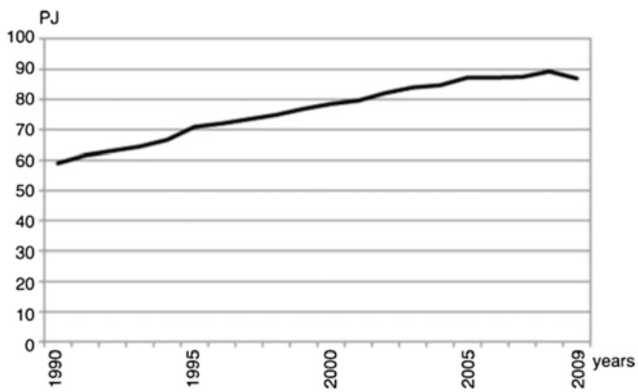


FIGURE 4.2 Total electricity consumption of households in the Netherlands (CBS, 2004; 2009; 2010)

§ 4.2 Literature, Hypotheses and Research Questions

The results of existing research on electricity consumption in dwellings vary according to the type of fuel that is used to heat space and water and the presence or absence of air conditioning (in relation to electricity consumption in summer). Only two dwellings in our sample had air conditioning (cooling). Electric radiators are not used for space heating in the Netherlands, and there was no heating by electric pumps in our sample.

Cramer et al. (1985) conducted a study on 192 dwellings in Lodi, California in 1981 with the aim of combining the engineering and social determinants of electricity consumption. The analyzed data was the summer consumption data, so air conditioning was an important determinant together with the appliance index. The appliance index included ownership, frequency of use, location in the dwelling, published average efficiencies, and estimated seasonality factors. Results of the linear regression analysis for engineering determinants, namely, the appliance index and the air conditioning index, were able to explain 51% of the variance in summer electricity consumption; the social determinants of expected electricity price, income, education, membership of a minority group, employment of spouses, if respondent is under 35, the presence of an infant (under 3), the presence of an elderly resident (over 65), number of people aged 3–18, number of people over the age of 18, thermal comfort scale (Likert-type items were used for the thermal comfort scale, conservation scale included 4, and environmentalism scale included 5 items. Energy knowledge scale was created on the basis of the level of the participant's knowledge of energy consumption. For further reading, the reader is referred to the document, itself), conservation scale, environmentalism scale, and energy knowledge scale were able to explain 34% and the combined model of engineering and social determinants was able to explain 58% of the variance in summer electricity consumption.

Appliance index and air conditioning index contributed significantly to the model in both the engineering and the combined model. In the social determinants model, income (increasing electricity usage), membership of a minority group (decreasing electricity usage), number of people aged 3–18 (increasing electricity usage), number of people of over the age of 18 (increasing influence), thermal comfort scale (increasing electricity usage), and energy knowledge scale (increasing electricity usage) were significant. In the combined model, income (increasing electricity usage), respondent age (decreasing electricity usage) and thermal comfort scale (increasing electricity usage) were significant.

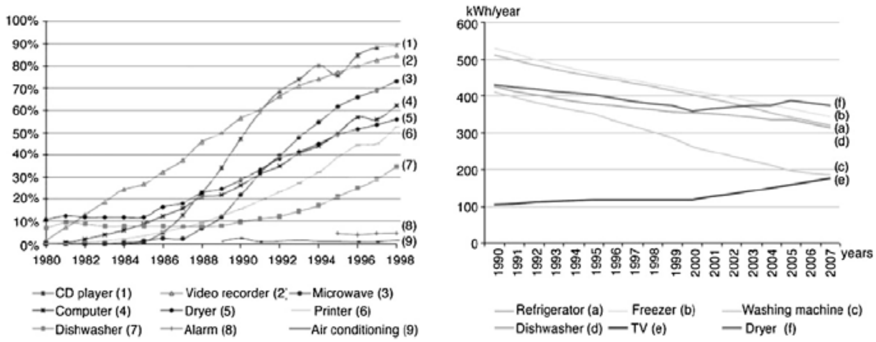


FIGURE 4.3 Ownership of appliances (left) (Jeeninga et. al., 2011); Energy consumption of specific appliances (right) (ECN, 2009) in the Netherlands.)

Ndiaye and Gabriel (2010) made an analysis of 62 cases in Oshawa, Canada, with 59 predictors. The 59 predictors were reduced to nine with the latent root regression method of Hawkins. This model could predict 75% of electricity consumption; the predictors were number of occupants in the house (increasing influence), dwelling ownership status (owner-occupied dwellings consumed more), number of weeks per year on vacation (decreasing influence), type of fuel for the pool (increasing influence from 'not applicable' to 'solar energy' and 'natural gas'), type of fuel for the space heating system (increasing influence from 'natural gas' to 'oil' and 'electricity') and the domestic hot water (increasing influence from 'natural gas' to 'electricity'), presence of air-conditioning system (increasing influence), type of air-conditioning system (decreasing influence from 'not applicable' to 'heat pump', and to 'central system'), each value under 50 Pa (increasing influence from '1.5' to '13.3').

Yohannis et al. (2008) monitored 27 dwellings in detail in Northern Ireland for a year. Type of dwelling, location, ownership and size, household appliances, number of occupants, income, age, and occupancy patterns seemed to have a significant influence on electricity consumption. They found a clear correlation between electricity consumption and floor area and that electricity consumption per person decreased as the household size increased. The electricity consumption for homes that were occupied during the day by unemployed or retired people was generally lower. In homes with no daytime occupants, electricity consumption was 2.5 times higher than the average in total, and 1.5 times higher during the day than those occupied during the day. They had peak consumptions in the morning (prior to working hours) and in the evening. Houses with no presence during the day had a bigger floor area than the others and were occupied by higher income families, which could explain the higher average electricity consumption.

O'Doherty et al. (2008) carried out a survey on dwelling characteristics and problems and household members in 40 000 households in Ireland (National Survey on Housing Quality – NSHQ). The survey included data on the main electricity-consuming appliances (order in the number of dwellings that possess these appliances: refrigerator, telephone, TV, VCR, microwave oven, washing machine, freezer, dryer, electric shower, personal computer, dishwasher). The other variables were years of residence in the dwelling, dwelling value, location of the dwelling, ownership of dwelling, dwelling type, dwelling age, weekly income, electricity tariff, occupant age, occupation, and household composition. All variables were found to be significant. The regression analysis showed that the factors that increase electricity consumption were electricity tariff (low tariff households consumed more – household is on low tariff for off-peak mains electricity; this is normally used by households with electric central heating), house value (high-value dwellings consumed more), income (high-income households consumed more), dwelling age (more recent dwellings consumed more) and household type (consumption was higher in households with elderly people or children). The factors that have a negative influence on electricity consumption are years of residence in dwelling (shorter occupation in the dwelling = lower consumption), ownership of dwelling (tenants used less), occupation (groups that were present less often used less), dwelling type (apartments, semi-detached, terraced houses used less than detached houses), location (non- urban dwellings used more), age (people over 64 used less than the people below 40, and people below 40 used less than people between 40 and 64).

Genjo et al. (2005) conducted a survey on the possession of appliances in 505 Japanese households. They found that lighting and appliances account for 3 MW/h and 60% of the variance in annual electricity consumption in dwellings. They also found that owner- ship of appliances reflected the lifestyle of the residents. Income (Beta = 35, $p < 0.05$), household size (Beta = 0.23, $p < 0.05$), and number of appliances (Beta = 0.062, $p < 0.05$) were the factors behind electricity consumption.

Mansouri et al. (1996) conducted a survey among 1000 people in the South-East of England in 1994. The survey was about attitudes and beliefs, ownership of appliances, usage patterns of appliances, purchasing, and labelling schemes. They found that ownership of the dwelling had an increasing influence on electricity consumption and that people who expected an increase in electricity prices consumed less.

Bartiaux and Gram-Hanssen's (2005) paper, based on SEREC, and ODYSSEE project datasets compared electricity consumption between Danish and Belgian households. Dwelling type, floor area, and household size proved significant in both countries and explained 30–40% of the variance in electricity consumption in Denmark and 10–30% in Belgium. Growing size of dwellings, growing ownership of appliances, and the number of single-person households emerged as key factors in electricity consumption and therefore in the energy efficiency policies.

Vringer et al. (2007) researched household energy requirements (heating energy demand and electricity demand) and value pat- terns on the basis of a survey in the Netherlands with a respondent size of 1272. They defined eight social categories (caring faithful, conservatives, hedonists, balanced, materialists, professionals, broad-minded, socially-minded) and 4 consumption categories (low income-low energy, low income-high energy, high income-low energy, and high income-high energy). They found that high-energy households require between 10% (high income) and households are more likely to own a relatively older, semi-detached and 10–15% larger dwelling. Interestingly, the electricity requirement was not too different in the four energy categories, only in low energy-low income group was it fairly low. High-energy house- holds own 10% more electrical appliances; however, no differences were found between the low and high-energy households for the possession of energy-saving light bulbs and food preparation appliances.

Saidur's (2007) analysis of electricity consumption from the use of appliances in Malaysia revealed that the refrigerator/freezer is the main energy-consuming appliance, followed by the air conditioner, washing machine, fan, rice cooker and iron. Baker and Rylatt (2008) conducted a questionnaire in 190 dwellings in Leicester and Sheffield in the UK in 2005. The predictors were floor area, occupancy, age, number of rooms, number of bedrooms, home working, main heating, number of TVs, digiboxes, PCs, portable electric heaters in use, and showers per week. The regression analysis showed that all the variables had a significant influence on increasing the electricity consumption in dwellings. Number of bedrooms and home working were the most important parameters for electricity consumption.

Tiwari's (2000) regression model on the 1987–1988 household survey of the Bombay Metropolitan Regional Development Authority (BMRDA), which included a total of 6358 dwellings, analyzed the impact of the structure of the dwelling, age of the dwelling, location of the dwelling, number of rooms, household size, age of respondent, appliance index (ownership of an appliance and the voltage), income and electricity tariff on electricity consumption. The electricity consumption increased with the income of the family, household size, age of the dwelling, number of rooms, age of respondent, and appliance index and decreased as the electricity tariff increased. Chawl, flat, and bungalow dwellings consumed more electricity than huts.

ODYSSEE research (2008) measured the impact of lifestyle factors on the average electricity consumption per dwelling. Three main influences were found in this research: increase in the average size of dwelling, the diffusion of electrical appliances and central heating, i.e. the influence of increased appliance ownership and the comfort-related behavior (mainly increasing use of hot water). Parti and Parti (1980) created an economic model with data on 5286 dwellings in San Diego County in 1975. The dataset included data on demographics, appliance ownership, electricity consumption, electricity price and weather characteristics. The regression model with air conditioning and space heating, water heating and appliances explained around 60% of the electricity consumption.

A similar economic model by Fuks and Salazar (2008) introduced a bottom-up approach to electricity consumption modelling by using the proportional odds, partial proportional odds methods, and the generalized ordered logit. The data were collected from dwellings in Rio de Janeiro, in 2004. Income, appliance index, floor area of the house, and if the household is new in the dwelling (more than one year, less than one year) were used to set up both models. The proportional odds model was able to estimate the consumption correctly in 53% of the cases, the partial proportional odds model in 55%.

Rooijers et al.'s (2003) research about energy consumption and behavior at home in Dutch context, revealed that household size and floor area are the crucial determinants and household income is equally significant. Similarly, ERC (2009) conducted a research named MONITWeb in Dutch dwellings, where they applied linear regression analysis and found that the household size, and the floor area of the dwelling are the important factors of electricity an analysis on a sample of more than 300,000 Dutch homes and their occupants (Central Office for Statistics, Netherlands dataset). The results indicated that residential electricity consumption varied directly with household composition, in particular income and family composition. Dwelling size is strongly related to total energy consumption; electricity consumption is substantially larger in detached and semi-detached houses than in row houses or apartments. Besides, an additional room decreases electricity consumption by 0.5 percent. Age is not monotonically related to electricity consumption. Households with children – particularly teenagers – consume much more electricity than other household units. They found that a one-percent increase in disposable income is associated with an eleven percent increase in household electricity usage.

On the basis of the literature review, the determinants of electricity consumption in dwellings were classified under appliance ownership and use, dwelling characteristics, household characteristics, economic characteristics, and heating, ventilation and air-conditioning (HVAC) system characteristics.

Appliance ownership and size are proved to be significant predictors of electricity consumption. The appliance index of Cramer et al. (1985), included number, frequency of use, location in dwelling, published efficiency, and estimated seasonality factor. The appliance index of Tiwari (2000), on the other hand, was based on ownership of an appliance and the power data. Dwelling type and floor area were identified as significant predictors of electricity consumption in much of the previous research. The location of the dwelling is another important parameter and the age of the dwelling also appears to have a significant impact on electricity consumption. Lastly, the number of rooms and bedrooms also emerged as significant predictors of electricity consumption.

Household size is the main and most common predictor of electricity consumption, common to all existing research. Age, thermal comfort, employment/working at home and occupancy patterns are also important. People who expect electricity prices to rise were shown to consume less electricity. Households with several weeks' holiday in a year and households that are new to the dwelling consume more electricity. Lastly, education, and belonging to a minority group have also proven important factors in electricity consumption.

Income was identified as a significant predictor of electricity consumption as well as home ownership, the electricity tariff and the value of the house. An air-conditioning index, space and the type of water heating system, the type of fuel for heating the pool water and the domestic hot water were confirmed as important factors.

Electricity consumption in dwellings can be explained by direct and indirect determinants. The direct determinants are the number, the voltage, and the total duration of use of lamps and domestic appliances. In this research, we did not use any data on the voltage and the total duration of use of the lamps and the voltage of appliances, as these are generally impossible to collect without inspecting the dwelling. Also, most occupants skip the questions on the voltage of appliances in a survey, probably because they do not know this information by heart (in our survey, the questions on label and size of appliances were left empty). Accordingly, we used only the number of lamps and appliances and the total duration of use of appliances. In addition, we related the use of appliances to the indirect determinants of presence in the dwelling and rooms and to the DHES characteristics.

The determinants of electricity consumption mentioned in the literature were tested in our survey dataset. Section 3 contains a detailed description of the survey data, as used in the regression analysis. Having reviewed the literature, the main research questions addressed in this paper are:

- How much of the variance in electricity consumption in dwellings can be explained by direct and indirect determinants?

- What are the main direct and indirect determinants of electricity consumption?
- Do our results correspond with the results obtained in the Netherlands by Biesiot and Noorman (1999), Rooijer et al. (2003), Vringer et al. (2007), ODYSSEE (2008), and Brounen et al. (2011)?

§ 4.3 Methodology

The study data were collected via a survey in two districts (Wateringse Veld and Leidsche Rijn) in the Netherlands in the autumn of 2008. The dataset of 323 cases covered a range of topics in the questionnaire with regard to household characteristics (size, composition, years of residence in the dwelling, change in household composition in the previous year), individual characteristics (age, education, occupation, hours spent outside home), economic characteristics (income, ownership, electricity tariff), presence (number of people and duration of occupation in each room), dwelling characteristics (type, number of rooms, function of rooms), appliance use (number of domestic appliances, number of appliances in the living room, standby appliances, chargers, duration of use, appliance labels, sizes), and lighting devices (number, type).

Correlation and multiple regression were used to set up a model to explain electricity consumption via (1) direct use: lighting and appliances, and (2) indirect use: factors that influence the use of lighting and appliances. First, by correlation analysis, the variables in each category in Table 1 were investigated to find if and how strong a correlation occurred with electricity consumption. Afterwards, using a stepwise (backward) technique, the variables that were found to be correlated were placed in the regression analysis. The variables that emerged as significant were then combined in the final regression models. Three regression models were constructed for the use of appliances and electricity consumption (Table 1 and Figure 4). Model I (technical/engineering approach) uses the duration of use of each appliance (direct use) and hours of presence in dwellings and in rooms (indirect use). Model II (social approach) uses the number of lamps and appliances (direct use) and the DHES characteristics (indirect use). Model III (combining engineering and social) uses the total duration of use of each appliance and DHES characteristics.

As we explained in Section 1, it is possible to make accurate predictions of electricity consumption when we know the duration of use, and voltage of each electrical appliance. However, this data is difficult to gather by energy companies, so we are looking for more 'easy to gather determinants' with good explanatory power.

The reasons for building three separate models were: (1) to evaluate and compare the social and the engineering approaches, many examples of which are mentioned in the literature review, and combine them to see if it is possible to achieve a stronger and more explanatory model, (2) to determine how much of the variance could be explained with the number and duration of use of the appliances separately, and in combination, and (3) the indirect use variable of presence created collinearity with the indirect use variables of DHES characteristics.

§ 4.3.1 Description of the Data

The survey data were examined with a view to the multiple regression analysis. Outliers were analyzed, variable frequencies were checked to see how many of the variables could be used for statistical analysis and the categorical variables were transformed into dummy variables.

§ 4.3.1.1 Outliers

Out of the 323 cases in the dataset, the electricity consumption data for seven were exceptionally high, probably because the occupants did not actually record the electricity consumption in the past year, but took the meter reading. Twelve questionnaires were returned blank. These 19 cases were therefore excluded from the dataset, leaving a final sample size of 304.

§ 4.3.1.2 Missing data

Some of the data in the dataset were insufficient to be included in the statistical analysis, namely:

- The number of weeks when nobody is at home;
- The volume and label data for the appliances (fridge, freezer, washing machine, dishwasher, dryer);
- Whether the electricity and gas meters were checked regularly;
- Whether there was a PV/solar collector in the dwelling.

§ 4.3.1.3 Variables

Transformed variables:

'Electricity tariff' can take two values in the Netherlands: (1) single tariff consumption – one daytime and evening rate on weekdays and weekends, (2) double tariff consumption – two different rates, one for during the day and another for evenings, nights and weekends. The electricity consumption data obtained from the survey were based on kWh values. Some cases had single tariff consumption records (9%), and some had double records (91%). In order to obtain a final variable for electricity consumption, a check was performed to determine whether a single or double electricity tariff made a difference. No significant correlation was found, so the single and the double tariff recordings were computed to one electricity consumption category.

Variables for 'Use of appliance' were computed into different continuous variables according to the number and function of the appliances (see Table 1):

- General appliances: according to their frequencies, the appliances that were found in most of the dwellings: TV, computer (desk- top, laptop), stereo, wireless telephone, dishwasher, and fridge. Since a fridge and washing machine were present in most of the dwellings, they were categorized as general appliances, and not as food preparation or cleaning appliances.
- Food preparation appliances: coffee machine, electric kettle, electric grill, microwave oven, toaster, induction cooker, electric hot plate, freezer;
- Cleaning appliances: dryer, dishwasher, iron, vacuum cleaner;
- Hobby appliances: video games console, home cinema system, hard disc recorder, video camera, video recorder, wireless inter- net, solarium, jacuzzi, sauna, waterbed, aquarium, terrarium;
- Extra ventilation appliances: air conditioner, fan.

Variables for 'Presence in dwelling' and 'Presence in rooms' that were originally obtained on an hourly basis were computed into different continuous variables according to times of the day, week- day/weekend. Our point in investigating the parameter 'presence' in detail is that 'presence in a room' could give more information than 'presence in dwelling' because activities that lead to electricity consumption may be related to the rooms with certain functions. Presence in room 1, 2, or 3 represents presence in rooms with a function other than living room. These rooms have a function of bedroom, study, hobby, etc. (see Table 1).

- Total hours of presence in living room and in other rooms;
- Weekdays and weekend patterns of presence; presence patterns in certain parts of the day: morning (05.00–08.00), day (08.00–17.00), evening (17.00–23.00), night (23.00–05.00).

Dummy variable for 'Dwelling type': flats and maisonettes on top floors, flats and maisonettes on ground floors, corner, semi- detached and detached dwellings and terraced houses. Terraced houses were taken as the reference case, so they do not appear in the final model.

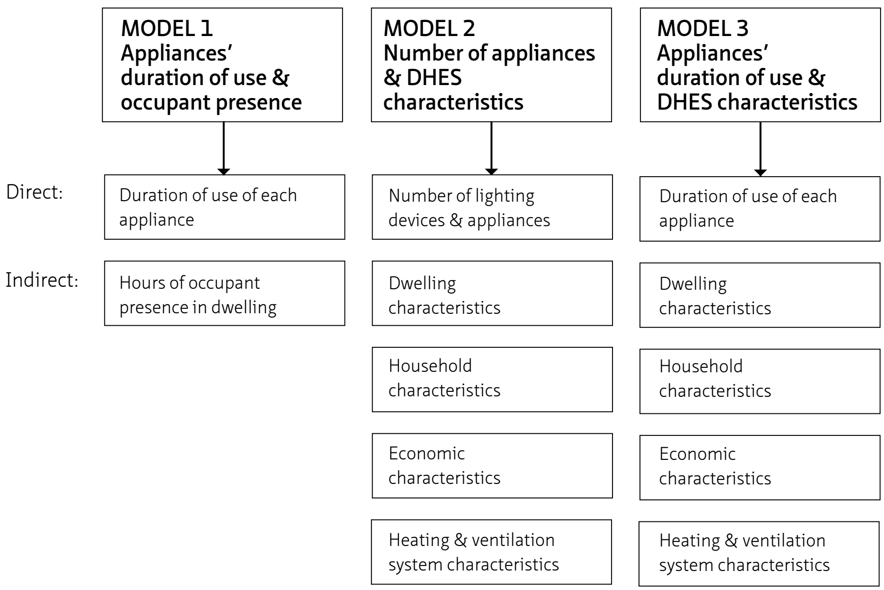


FIGURE 4.4 Model I (duration of appliance use and hours of presence in the dwelling), Model II (number of lamps and appliances and DHES characteristics), and Model III (duration of appliance use and DHES characteristics).

§ 4.4 Results

This section explains the correlations and the three regression models. In all the models the influence of 'direct use' variables on the electricity consumption is explained first, followed by the 'indirect use' variables and finally the combination of direct and indirect use variables.

§ 4.4.1 Correlations

First step was to find the correlations between the variables listed in Table 1 and electricity consumption. In Annex 1.1, a correlation table for all the p and r values of all the variables are displayed. Later, the correlated variables are used to set up the regression models.

The duration of use of general appliances ($r = 0.47$, $p < 0.00$), cleaning appliances ($r = 0.33$, $p = 0.00$), food preparation appliances ($r = 0.20$, $p < 0.01$), and hobby appliances ($r = 0.33$, $p < 0.00$; and the number of general appliances ($r = 0.41$, $p < 0.00$), cleaning appliances ($r = 0.25$, $p < 0.00$), food preparation appliances ($r = 0.23$, $p < 0.00$), hobby appliances ($r = 0.35$, $p < 0.00$), standby appliances ($r = 0.14$, $p < 0.04$), battery chargers ($r = 0.16$, $p < 0.03$), light bulbs ($r = 0.20$, $p < 0.04$), energy-saving light bulbs ($r = -0.18$, $p < 0.05$) are found to be significantly correlated to electricity consumption.

List of variables used			
Group	Variable	Variable type	Unit
Appliances	Duration of use, general appliances	Continuous	Minutes a day
	Duration of use, cleaning appliances		
	Duration of use, food preparation appliances		
	Duration of use, hobby appliances		
	Number of general appliances/ number of general appliances in living room		
	Number of cleaning appliances/ number of cleaning appliances in living room		
	Number of food preparation appliances/ number of food preparation appliances in living room		
	Number of hobby appliances/ number of hobby appliances in living room		
	Number of extra ventilation appliances/ number of extra ventilation appliances in living room		
	Number of standby appliances/ number of standby appliances in living room		
	Number of battery chargers/ number of battery chargers in living room		
	Number of light bulbs/number of light bulbs in living room		
	Number of energy-saving lights/ number of energy-saving lights in living room		
Presence in dwelling	Presence in living room and kitchen	Ordinal	Hours: all day/morning/day/evening/night in w.days & w.ends
	Presence in room 1		
	Presence in room 2		
	Presence in room 3		
	Presence in bathroom		
	Presence in attic		
Dwelling characteristics	Dwelling type (1) Terraced, (2) top floor apartment/ maisonette, (3) ground floor apartment/maisonette, (4) semi detached/corner/detached	Categorical	
	Number of rooms	Continuous	
	Number of bedrooms		
	Number of study/hobby rooms		
	Floor area of the house		m2
	Rented/owner occupied	Dichotomous	

TABLE 4.1 Variables tested with regression analysis

List of variables used			
Group	**Variable**	**Variable type**	**Unit**
Economic characteristics	Rent/mortgage	Continuous	Euros
	Electricity included in rent	Dichotomous	
	Electricity tariff		
	Income	Continuous	Euros
	Gas consumption, yearly		kWh
Household characteristics	Household size	Continuous	
	Years of residence in the same house		Years
	If the household composition has changed in recent years	Dichotomous	
	Occupation (1) At home, (2) work outside, (3) work at home, (4) other	Categorical	
	Working outside hours	Continuous	h/week
	Education	Ordinal	
	If there are elderly people in the household	Dichotomous	
	If there are infants in the household		
	Age groups (1) 0–6 years, (2) 6–18 years, (3) 18–65 years, (4) over 65	Categorical	
	Any hobby including use of electricity	Dichotomous	
	Dishwasher use	Continuous	Cycles a week
	Washing machine use		
	Number of hot washes (90 oC)		
	Number of cold washes (30 oC)		
	Dryer use		
	Number of baths	Continuous	Times a week
	Number of showers		
	Duration of shower		Min.s per shower
Heating & ventilation system characteristics	Mechanical ventilation set point adjustment for flow rate (hour/day during w.day/w.end & winter/summer)	Ordinal	
	Ventilation system off	Continuous	Weeks/ year
	Heating system type (District heating or individual boiler)	Dichotomous	

TABLE 4.1 Variables tested with regression analysis

Presence in room 1 (week – all day) ($r = 0.20$, $p < 0.00$), room 2 (week – all day) ($r = 0.23$, $p < 0.00$), bathroom (week – morning) ($r = 0.23$, $p < 0.00$), room 3 (week – during day) ($r = 0.01$, $p < 0.04$) are significantly correlated to electricity consumption.

In terms of household and dwelling characteristics, dwelling type ($r = 0.14$, $p < 0.03$), number of study/hobby rooms ($r = 0.00$, $p < 0.01$), income of the household ($r = 0.17$, $p < 0.01$), yearly gas consumption ($r = 0.12$, $p < 0.03$), household size ($r = 0.38$, $p < 0.00$), years of residence in the current house ($r = 0.11$, $p < 0.04$), hours of working outside ($r = 0.16$, $p < 0.01$), age groups ($r = 0.14$, $p < 0.04$), dishwasher use ($r = 0.31$, $p < 0.00$), washing machine use ($r = 0.37$, $p < 0.00$), number of hot (90 C degrees) ($r = 0.18$, $p < 0.01$) and cold washes (30 C degrees) ($r = 0.33$, $p < 0.00$), dryer use ($r = 0.39$, $p < 0.00$), number of baths ($r = 0.16$, $p < 0.01$) and showers ($r = 0.30$, $p < 0.00$), duration of shower ($r = 0.23$, $p < 0.00$); and lastly the heating system type ($r = -0.15$, $p < 0.02$) appeared to be significantly correlated to the electricity consumption.

We found no correlation between the location of appliances, the existence and duration of use of mechanical ventilation, the duration of use of ventilation appliances, the number of energy- saving light bulbs in the living room, or in the rest of the house and electricity consumption. In addition, home ownership and electricity-inclusive rent did not emerge as significant predictors of electricity consumption. Gender, education, existence of elderly people and infants in the household, change in household composition in the previous year did not appear to influence electricity consumption either.

§ 4.4.2 Regression Model I: duration of appliance use and presence

The model for the use of the appliance and presence was constructed from the duration of use (minutes/day) of the appliances in the five groups (general, food preparation, cleaning, hobbies, and extra ventilation) and presence at home and in rooms (hours per day).

The descriptive statistical analysis on the significant variables is shown in Table 2, and Table 3 displays the regression model set up with the same variables. Although cleaning appliances are used for only a short time every day, they exert the greatest influence on the variance in electricity consumption (mean = 107.37, $B = 4.24$, $Beta = 0.30$, $p < 0.001$) together with hobby appliances ($B = 0.39$, $Beta = 0.31$, $p < 0.001$). The use of general appliances has an important impact on the model ($p < 0.01$), but the influence on electricity consumption is not as high as the use of cleaning appliances

(B = 0.43). The last group is the duration of the use of food preparation appliances, which makes no significant contribution to the model (Beta = 0.01). Duration of appliance use explains 37% of the variance in electricity consumption

Predictor	Mean	SD
Total electricity consumption	3058.57	1585.26
Daily use/general appliances (min)	3272.28	1279.81
Daily use/cleaning appliances (min)	107.37	105.52
Daily use/food preparation appliances (min)	1270.58	690.26
Daily use/hobby appliances (min)	1440.21	847.59
Presence in room 1 all day (h)	13.60	5.34
Presence in room 2 all day (h)	5.18	6.08
Presence in bathroom in the morning (h)	1.18	1.17
Presence in room 3 during the day (h)	0.15	1.02

TABLE 4.2 Mean and standard deviations of predictors in the regression model for the duration of appliance use and presence (Model I)

Model	B	Std. error	Beta
(Constant)	587.59	368.88	
Daily use/cleaning appliances (min)	4.24	1.02	0.30***
Daily use/hobby appliances (min)	0.39	0.10	0.31***
Daily use/general appliances (min)	0.43	0.14	0.23**
Daily use/food preparation appliances (min)	0.02	0.11	0.01

Note: R2 = 0.370.
** $p < 0.01$.
*** $p < 0.001$.

TABLE 4.3 B, standard error of B, and beta values of predictors in the regression model for the duration of appliance use

If variable 'presence' is considered, presence in rooms 1–3 and bathroom appears to be significant. (Note that room 1 is the first room after the living room in the dwelling.) Presence in the living room and kitchen does not appear to explain any variance in electricity consumption. Presence in room 3 during the day and in the bathroom in the morning have the greatest influence on electricity consumption, followed by room 1 and room 2 all day long. This model explains 14% of the variance in electricity consumption (Table 4).

When the predictors of duration of appliance use and presence are combined (see Table 5), the model still explains 37% of the variance in electricity consumption. The significance of the use of general appliances increases in this model and the significance of the use of hobby appliances and presence at home and in rooms decreases. Therefore, presence data does not add valuable information to the model in terms of the duration of appliance use (hobby, cleaning and general). This is probably because the duration of appliance use (a) does not relate to presence at home or in rooms for a number of appliances (e.g. fridge) or (b) it already includes presence at home.

Model	B	Std. error	Beta
(Constant)	1996.61	305.29	
Presence in room 1 all day (h)	52.95	20.53	0.17**
Presence in room 2 all day (h)	29.66	18.12	0.11**
Presence in bathroom in the morning (h)	234.72	94.98	0.17**
Presence in room 3 during the day (h)	401.68	127.55	0.20**
Note: R2 = 0.141. ** p < 0.01.			

TABLE 4.4 B, standard error of B, and beta values of predictors in the regression model for presence.

Model	B	Std. error	Beta
(Constant)	569.51	409.74	
Daily use/general appliances (min)	0.37	0.10	0.30***
Daily use/cleaning appliances (min)	3.97	1.10	0.29***
Daily use/food preparation appliances (min)	0.01	0.12	0.01
Daily use/hobby appliances (min)	0.41	0.14	0.22**
Presence in room 1 all day	34.65	23.26	0.11*
Presence in room 2 all day	15.00	20.20	0.06*
Presence in bathroom in the morning	11.33	101.05	0.01*
Presence in room 3 during the day	73.54	131.02	0.04*
Note: R2 = 0.370. * p < 0.05. ** p < 0.01. *** p < 0.001.			

TABLE 4.5 B, standard error of B, and beta values of predictors in the combined regression model for duration of appliance use and presence (Model I)

§ 4.4.3 Regression Model II: number of lighting devices and appliances and DHES characteristics

Regression Model II was set up with the number of lamps and appliances in the dwellings and the DHES characteristics. This model explains 52% of the variance in electricity consumption.

Although significantly correlated with the electricity consumption, the number of halogen and energy saving light bulbs did not appear in the regression model. Similarly, income, hours that the inhabitants work outside the house, age groups, dishwasher use, cold and hot washing machine load number, and the number of baths taken per week and its duration did not appear in the regression model, either (Table 6).

In the first step the number of general appliances explains the largest part of the electricity consumption ($B = 149.07$, $p < 0.001$). Hobby appliances come next ($B = 139.75$, $p < 0.01$). In this model the number of food preparation and cleaning appliances do not appear to be significant. The number of appliances explains 21% of variance in electricity consumption (Table 7).

Predictor	Mean	SD
Number of general appliances	8.66	2.84
Number of food preparation appliances	5.56	1.59
Number of cleaning appliances	3.56	0.91
Number of hobby appliances	3.10	2.10
Household size	2.56	1.20
Years of residence in current house	5.49	3.03
Number of washing machine loads per week	4.62	2.95
Number of dryer loads per week	1.96	2.42
Number of study/hobby rooms	0.67	0.81
Outside working hours / weekly (household)	24.63	13.30

TABLE 4.6 Mean and standard deviations of predictors in the regression model for number of appliances and DHES characteristics (Model I).

Model	B	Std. error	Beta
(Constant)	630.11	499.65	
Number of general appliances	149.07	38.20	0.26***
Number of hobby appliances	139.75	51.67	0.18**
Number of food preparation appliances	90.16	64.71	0.10
Number of cleaning appliances	107.24	109.69	0.07

Note: R2 = 0.206.
** p < 0.01.
*** p < 0.001.

TABLE 4.7 B, standard error of B, and beta values of predictors in the regression model for number of appliances used

Model	B	Std. error	Beta
(Constant)	948.14	511.70	
Household size	589.46	165.20	0.47***
Gas consumption	0.74	0.15	0.31***
Number of bedrooms	-526.07	198.65	-0.33**
Number of dryer loads per week	127.74	41.38	0.21**
Dummy (house type: flat & maisonettes on ground floor)	719.24	336.02	0.15*
Dummy (house type: corner & semi-detached)	193.59	220.90	0.06*
Dummy (house type: flats & maisonettes on top floor)	83.07	306.74	0.02
Number of study/hobby rooms	90.43	126.72	0.04*
Heating system type (individual/district)	-178.85	194.97	-0.06*
Number of washing machine loads per week	69.43	43.49	0.13*
Number of showers taken per week	28.48	16.40	0.14*
Years of residence in current house	11.38	32.87	0.02
Outside working hours/weekly (household)	-0.03	6.99	0.01

Note: R2 = 0.421.
* p < 0.05.
** p < 0.01.
*** p < 0.001.

TABLE 4.8 B, standard error of B, and beta values of predictors in the model for DHES characteristics.

Model	B	Std. error	Beta
(Constant)	791.24	658.54	
Number of appliances (general appliances)	115.99	35.09	0.21**
Number of appliances (food preparation appliances)	101.78	56.21	0.12*
Number of appliances (cleaning appliances)	14.40	105.11	0.01
Number of appliances (hobby appliances)	59.54	46.60	0.08
Gas consumption	0.68	0.15	0.28***
Household size	447.124	156.38	0.36**
Number of dryer loads per week	109.12	40.28	0.17**
Years of residence in current house	31.10	30.85	0.06*
Number of bedrooms	-404.54	187.23	-0.26*
Number of study/hobby rooms	102.29	118.57	0.05*
Number of washing machine loads per week	87.30	40.86	0.16*
Number of showers per week	15.51	15.50	0.07*
Dummy (house type: flat & maisonettes on ground floor)	712.19	314.26	0.15*
Dummy (house type: corner and semi-detached)	235.70	206.66	0.07*
Dummy (house type: flats and maisonettes on top floor)	297.37	288.65	0.07
Heating system type (unit/district)	-59.28	193.39	-0.02
Outside working hours/weekly (household)	1.78	6.55	0.02

Note: R2 = 0.517.
* p < 0.05.
** p < 0.01.
*** p < 0.001.

TABLE 4.9 B, standard error of B, and beta values of predictors in the combined regression model for number of appliances and DHES characteristics (Model II)

Household size and gas consumption appear to be the most important predictors of electricity consumption in household and dwelling characteristics ($p < 0.001$), followed by number of bedrooms and number of dryer loads per week. The third group with $p < 0.05$ consists of flats and maisonettes on the ground floor and semi-detached/corner/detached dwellings, number of hobby rooms, heating system type, number of washing machine loads and number of showers per week. Flats and maisonettes on the top floor, years of residence in current house and outside working hours do not appear to be significant in this model. This model can explain 42% of the variance in electricity consumption (Table 8).

When the number of appliances and the household and dwelling characteristics are combined, general appliances, gas consumption, household size and number of dryer loads per week emerge as the most important predictors. Food preparation appliances, years of residence in current house, flats on ground floor, semi-detached/corner/detached dwellings, number of bedrooms, number of study/hobby rooms, number of washing machine loads and number of showers per week are secondarily significant. In this combined model cleaning and hobby appliances, outside working hours, flats and maisonettes on top floors, and heating system type do not appear significant. This model explains 52% of the variance in electricity consumption (Table 9).

§ 4.4.4 Regression Model III: duration of appliance use and DHES characteristics

Lastly, we combined the total duration of appliance use and DHES characteristics of the dwellings in the dataset to set up a final model for electricity consumption. This model explains 58% of the variance in electricity consumption (Table 10). According to this model, general appliances and household size are the most significant determinants of electricity consumption. These are followed by hobby appliances, years of residence in current house, number of bedrooms, number of study/hobby rooms, dwelling type (flats/maisonettes on ground floor and corner and semi-detached), number of showers per week and number of dryer loads per week.

We did not find any significant influence for food preparation appliances and duration of use of cleaning appliances, number of washing machine loads, dwelling type (flats/maisonettes on top floor) and outside working hours.

For all three models, there is no multicollinearity among variables. Durbin–Watson test for Model I appears as 1.96, for Model II as 2.05, and for Model III as 2.01. We ran analyses of residual statistics for all three models, where we saw almost always the same 9 cases were outside the ±2 standard residual. When we compare this number to our sample size 9/304, '2% of cases lie outside standard residual limits' puts us on the safe side (the statistically allowed threshold is 5%). Cook's distances for any of these 9 cases are above 1; in addition, the centered levarage values, and the Mahalanobis distance values are well around limits. Normality/homocedasticity of residuals: We took graphs of ZRESID and ZPRED, where the values look like a 'random array of dots with no curving, and evenly dispersed around zero'. Considering the collinearity statistics, all the VIF values are very close to 1, and there is no tolerance value below 0.2.

Model	B	Std. error	Beta
(Constant)	394.56	633.74	
Daily use/general appliances (min)	0.51	0.17	0.37**
Daily use/hobby appliances (min)	0.75	0.31	0.20*
Daily use/food preparation appliances (min)	0.08	0.21	0.05
Daily use/cleaning appliances (min)	1.25	0.79	0.14
Household size	335.77	166.24	0.33**
Gas consumption	0.04	0.07	0.05*
Years of residence in current house	23.55	1 34.36	0.06*
Number of bedrooms	-198.88	204.84	-0.15*
Number of study/hobby rooms	136.97	129.66	0.09*
Dummy (house type: flats and maisonettes on ground floor)	888.58	392.83	0.22*
Dummy (house type: corner and semi-detached)	540.91	240.48	0.21*
Dummy (house type: flats and maisonettes on top floor)	49.61	342.98	0.01
Number of showers taken per week	36.78	16.76	0.24*
Number of dryer loads per week	0.04	0.10	0.03*
Number of washing machine loads per week	0.46	0.87	0.05
Outside working hours/weekly (household)	-6.36	8.63	-0.07

R2 = 0.576.
* p < 0.05.
** p < 0.01, ***p < 0.001.

TABLE 4.10 B, standard error of B, and beta values of predictors in the combined regression model for duration of appliance use and DHES characteristics (Model III).

§ 4.5 Discussion

In this section, we will first discuss the results of the correlation and then the regression models. Considering the duration of use and the number of appliances; general appliances and hobby appliances are the most significantly correlated to electricity consumption ($p < 0.00$), followed by food preparation and cleaning. This shows a direction for designers, engineers, policy makers, and energy companies, about which appliances to focus on, for energy conservation. Considering presence, the hours of presence all day during the weekdays in room 1 and room 2, and in the mornings during the weekdays in bathroom, are the most significant rooms to study the variance in electricity consumption. Although number of standby appliances, battery chargers, halogen light bulbs, energy-saving light bulbs are found to be significantly correlated with electricity consumption, they do not appear in any of the regression models.

In terms of household and dwelling characteristics, household size, dishwasher, washing machine, and dryer use, number of baths, showers, and the duration of shower appear to be the most significantly correlated parameters ($p < 0.00$), number of study/hobby rooms, income of the household, hours of working outside, and the number of hot washes (90 C degrees) are also found to be correlated parameters with electricity consumption, but with less significance ($p < 0.01$). The last group consists of dwelling type, yearly gas consumption, heating system type, years of residence in the current house, and age groups of the household composition ($p < 0.05$). This result points out that household size and the patterns of use of water in dwellings could give important clues about electricity consumption in dwellings. This topic is articulated further below. Income and number of hot washes, and age groups of household composition are found to be correlated to electricity consumption; however, these parameters did not appear in regression models, either.

No correlation was found between electricity consumption and mechanical ventilation systems, probably because these systems were seldom used in our sample (people disabled them or hardly used them at all) (Guerra Santin, 2010). Similarly, there was no correlation between the use of extra ventilation appliances and electricity consumption, because usage was too low (14% of the respondents said they had a fan). Lastly, we could not check the impact of renewable energy because of the insufficient response to the question (10%) in the survey.

The first regression model, with duration of appliance use and presence patterns, explains 37% of the variance in electricity consumption; the second, with number of lamps and appliances and DHES characteristics, explains 52%, and the third and last model, with duration of appliance use and DHES characteristics, explains 58%. In the first regression model, the most important groups of appliances are the general, cleaning, and hobby appliances. In the second, these are general and hobby appliances. This difference may be due to the fact that although every household possesses approximately the same number of cleaning appliances, the duration of use may vary strongly depending on lifestyle preferences and values. Food preparation appliances do not contribute to the electricity consumption in either model, probably because they are owned by all households and they are used for only short periods. In the third model, general and hobby appliances again appear to be the most significant predictors (in terms of appliances). The importance of general appliances may be attributable to the very different duration of use and the specific energy consumption levels of TVs. In cleaning appliances, the dryer makes the biggest difference. There is a straightforward explanation for the significant share of hobby appliances in the variance in electricity consumption: it differs widely per household and may consume large amounts of energy. Our results show a similarity with the model of Ndiaye et al., which explains 75% of the variance in electricity consumption. It should be noted, however, that the sample size of Ndiaye et al. was relatively smaller (62 dwellings) and included additional predictors such as the use of renewable energy systems, air conditioning, and vacation weeks in a year. Another study with similar results, Bartiaux and Gram-Hanssen's regression model, was able to explain 30–40% of the variance in electricity consumption in Denmark and 10–30% in Belgium. Our model provided a better explanation. Fuks and Salazar's bottom-up model predicted 53% of electricity consumption, but their research was methodologically different from ours. Genjo's regression model on Japanese households explains 60% of electricity consumption with lighting and appliances. The methodological approach closest to our own was applied by Cramer et al. whose model explained 51% of electricity consumption with number of appliances, 34% with the indirect determinants and 58% in total. It should be mentioned that their indirect determinants model included social aspects that we did not take into account, such as knowledge, educational level, etc.

Having briefly explained the capacity of our model and com- pared it with existing models, we shall now discuss the predictors that we found. In Model I, presence in rooms 1 and 2 all day, bathroom in the morning, and room 3 during the day explain 14% of the variance in electricity consumption and appear to be the most important indirect predictors. This result runs parallel with the decreasing influence of number of bedrooms and the increasing influence of number of study/hobby rooms on electricity consumption in Models II and III. According to Model I, electricity consumption rises only if rooms 1 and room 2 are occupied for more hours all day and if room 3 is occupied for more hours during the day (rooms 1 and 2 are used mostly as bedrooms, and room 3 as a study/hobby room). However, in contrast with the direct predictor 'Duration of Appliance Use', 'presence at home or in the rooms' does not contribute to the combined model (explained 37% of the variance). These results show that hourly data on presence at home or in rooms do not help to explain electricity consumption with regression analysis. It could therefore be argued that hourly data on presence is not necessarily valuable for further research on electricity consumption, when the total duration of use of each appliance is known.

On the other hand, the only research in the literature that takes account of presence is a study by Baker and Rylatt which states that presence in the dwelling has an increasing influence on electricity consumption. They only considered weekly hours of presence at home, however, our point in investigating the parameter 'presence' in dwelling/room detail was that 'presence in a room' could give more information than 'presence in dwelling' because activities that lead to electricity consumption could be related to the rooms with certain functions. In the second regression model the most important indirect predictors are household size, gas consumption, number of dryer loads per week, dwelling type (ground floor flats, and corner/semi-detached houses), number of study/hobby rooms, number of bedrooms, years of residence in the dwelling, number of washing machine loads per week, and number of showers per week. Dwellings on the ground floor appeared to have a significant influence on the variance in electricity use, possibly because more artificial lighting was needed to compensate for the loss of natural light, and the corner/semi- detached/detached houses, because of the household and dwelling size. Bartiaux and Gram-Hanssen, Yohannis, Fuks and Salazar, and O'Doherty emphasize the significant influence of dwelling type on electricity consumption, but they do not consider the variable 'dwelling type' as we did in our research. We did not test the variables of dwelling age and dwelling location because all the dwellings in our sample were in the same neighborhoods and built around the same time. We found no correlation between floor area and electricity consumption, probably because the floor area was similar for all the dwellings in the sample. Baker and Rylatt also pointed out that number of rooms and number of bedrooms have an incremental impact on electricity consumption. Contrary to their results, we could say that the number of bedrooms has a decreasing impact and the number of study/hobby rooms an increasing impact on electricity consumption. This finding may be attributable to the fact that a bedroom is normally used only in the evening-at night and early in the morning for a short while, whereas a study or hobby room is used more often and contains more electrical appliances.

Electricity consumption increases with household size. These results correspond with those of Nnidaye, Bartiaux and Gram- Hanssen, Yohannis, and Genjo, who claimed that household size is an important predictor of electricity consumption in dwellings. The households that consume more gas also seem to consume more electricity. A variable that has proven significant in other research but not in ours is 'age'. Although we tested this variable in various forms (elderly people, infants in the household, the respondent's age, and age groups) we found no correlation. This could be a reflection of similarities in appliance use among the different age groups in our sample.

Another variable that was found in the literature to have a decreasing impact on electricity consumption (see Ndiaye et al.) is the 'number of vacation days'. The responses to our question about weeks in the year when nobody is at home were not enough for analysis, however. Our questionnaire did not ask respondents about their expectations of rising electricity rates, but it did check whether electricity tariff influences electricity consumption and found no correlation. The number of showers per week has an increasing influence on electricity consumption, thus suggesting a comfort-related dimension. Both Baker and Rylatt and the ODYSSEE reports mention that increasing comfort-related preferences (showers per week, greater use of hot water) result in higher levels of electricity consumption. Our sample displays an average self-cleaning habit of taking a shower 2 times a day per person that lasts 20 min in total, but less than once a week bathing. Although we found a strong relationship between number of showers taken per week and electricity consumption, the duration of shower did not appear significant. Bathing times a week, and duration did not appear significant either.

‘Showers taken per week’ gives the clue of a comfort related aspect of electricity consumption, considering the evolution of personal cleaning habits from bathing to showering in the last century. It seems like changes in lifestyle preferences might have an increasing influence on consumption patterns. Supporting these findings, Shove describes the contemporary enthusiasm for regular power showering as “an emphasis on image and appearance, on the curative and therapeutic properties of invigoration, and on a distinctive blending of pleasure and duty.” (Shove, 2003). Here we should add that, the 8/40 h working day/week also might be influencing the preferences for showering. This topic also requires further investigation.

Fuks and Salazar found that new residents in dwellings consume more electricity, which is contrary to our result that households that have resided in dwellings for longer periods consume more electricity. This may be because the longer people stay in the same house, the older and less energy-efficient the appliances become. Lastly, we did not find any correlation between education, background of the occupant and electricity consumption, probably because the respondents had similar educational levels and the majority were Dutch (86%). Similarly, household incomes in the sample were within the same range and most of the homes were owner-occupied (79%). Electricity was included in the rent in only one dwelling. This might explain why we did not find household income as a significant determinant of electricity consumption.

The number of dryer and washing machine loads in Model I and the number of dryer loads in Model III appear to be significant. The influence of number of dryer loads per week on electricity consumption corresponds with the first model, where the duration of use of cleaning appliances appeared important. In addition, after the TV, the dryer is potentially the most energy-consuming appliance in the market.

The variables for electricity consumption in the Dutch research literature are household size, household composition, dwelling size (type of dwelling and number of rooms), floor area, and income. We found household size, appliance ownership, and increased comfort preferences as important parameters for electricity consumption, but no significance for floor area, income, and education (see the potential reasons stated previously in this section). Age groups in household are found to be correlated to electricity consumption, but it did not appear in the regression models. In our research we found a difference between bedrooms and study/hobby rooms, former having a decreasing, latter having an increasing influence on electricity consumption. In addition, we also found dwelling type is significantly related to electricity consumption.

One possible limitation in this research is the low response rate to the questionnaire (5%). This may be connected with the number and intricacy of questions. Except for the twelve blank forms, the returned questionnaires were filled in almost completely.

The general characteristics of the sample were representative of the Netherlands (The National Survey: WOON Database (2009)) with the exception of income and education, which were higher than the national average. On the other hand, the fact that 'income' and 'education' were not found significant in our study may be due to the absence of variation in the levels in our sample. The same could apply to 'floor area': the survey was conducted in two neighborhoods with similar architectural characteristics, so there was very little variation in the floor areas of the dwellings.

Another limitation relates to the tracking and recording system for electricity consumption in the Netherlands. Electricity providers ask occupants to send in their meter readings once a year. These providers actively check the meter readings as well, but they have different schedules. If the occupant fails to send in the meter readings, the electricity consumption is calculated on the basis of the previous reading by the provider, which may be up to three years ago (more than 3 years is not allowed under the Dutch regulations). This could create a bias in the accuracy of the electricity consumption data.

Lastly, the use of appliances such as the TV, washing machine and dryer, the energy labels of appliances, and the influence of lifestyle on the electricity consumption in dwellings require further investigation. In this research we could only take account of the number of light bulbs in the living room and in the rest of the house. Further research is needed on the duration of use of lighting devices.

§ 4.6 Conclusion

This research aimed to ascertain how far the use of lighting and electrical appliances are responsible for electricity consumption and to identify the determinants of use. The data used in the survey were collected via questionnaires completed by 323 dwellings in two neighborhoods in the Netherlands. Three regression models were built for the direct and indirect determinants, one based on the duration of appliance use (direct) and presence (indirect), one on the number of appliances (direct) and DHES characteristics (indirect), and one on the total duration of appliance use and DHES characteristics.

We found that, in the first model, total duration of appliance use alone explained 37% of the variance in electricity consumption. Presence in rooms explained 14% alone and 37% in the combined model. This means that hourly data on presence did not con- tribute to modelling electricity consumption in dwellings, when it was considered together with the total duration of appliance use. Study/hobby rooms emerged as important factors in the relationship between presence and electricity consumption, whereas living room and kitchen did not.

In the second model the number of appliances explained 21% of the variance in electricity consumption alone and 42% when combined with DHES characteristics. Household size, dwelling type, the number of showers, use of dryer and washing cycles appeared significant. The significant connection that was identified between electricity consumption and ground-floor dwellings points to the need for a detailed study on lighting. The number of showers is an interesting output, pointing to a possible relationship between the occupants' perception of comfort and electricity consumption. Use of the washing machine and dryer suggest a need for a study on the cleaning patterns of users, including the washing and drying durations, temperatures, cycles and loads as well as the appliance labels.

The final (third) model, with the total duration of appliance use and DHES characteristics, was quite close to the second in terms of the DHES characteristics that were found to be significant. The main difference was that gas consumption and the number of washing machine loads were not found to be significant in the third model. As this model explained 58% of the variance in electricity consumption, it may be possible to set up a model on occupant behavior and electricity consumption with duration of appliance use and DHES characteristics. The specific consumption of appliances and the duration of use of lighting devices would enhance this model.

Comparing all three models, this research showed that duration of appliance use and dwelling and household characteristics are important predictors in models of electricity consumption. Further research on the functions of appliances (cleaning, food preparation, hobby, etc.) and the activity patterns of occupants would provide deeper insight into electricity consumption in housing. A follow- up study could be based on a detailed analysis of the relationship between gas and electricity consumption and the lifestyles and comfort preferences of occupants.

References

ADEME (2007). Evaluation and Monitoring of Energy Efficiency in the New EU Member Countries and the EU-25, Intelligent Energy Europe. http://www2.ademe.fr/servlet/getDoc?sort=-1&cid=96&m=3&id=51262 &ref=
17618&nocache=yes&p1=111 (last accessed 20.05.2011).

Baker, K., Rylatt, M.R. (2008). Improving the prediction of UK domestic energy demand using annual consumption data. Applied Energy (85), 475–482.

Bartiaux, F., Gram-Hanssen, K. (2005). What works and who delivers, ECEEE 2005 Summer Study, 1313–1325.

Biesiot, W., Noorman, K.J. (1999). Energy requirements of household consump- tion: a case study of the Netherlands. Ecological Economics (28), 367–383.

Brounen, D., Kok, N., Quigley, J.M. (2011). Residential energy use and conservation: Economics and demographics. European Economic Review (last accessed 20.05.11) http://www.nilskok.com/2011/01/residential-energy-use- and-conservation-economics-demographics-and-standards.html

CBS (2004). Statistical Yearbook 2004, Voorburg, 2004. www.cbs.nl
(last accessed 20.05.2011).

CBS (2009). Energieverbruik Door Huishoudens, 1990–2009. http://www.compendiumvoordeleefomgeving.nl/ indicatoren/nl0035-Energieverbruik-door-huishoudens.html?i=6-40 (last accessed 20.05.2011).

CBS (2010). Statistical Yearbook 2010, The Hague, 2010. www.cbs.nl
(last accessed 20.05.2011).

Cramer, J.C., Miller, N., Craig, P., Hackett, B.M. (1985). Social and engineering determinants and their equity implications in residential electricity use. Energy 10 (12), 1283–1291.

EnergieNed (2009). Energieinformatiebank, Energy Dataset. http://www. energiened.nl/Content/Datasets/EnergieDataset.aspx?MenuItemID=9 (last accessed 20.05.2011).

ERC (2008). Energieverslag Nederland. www.energie.nl (last accessed 20.05.2011).

ERC (2009). MONITWeb. http://www.energie.nl/index2. html?stat/index.html (last accessed 20.05.11).

Fuks, M., Salazar, E. (2008). Applying models for ordinal logistic regression to the analysis of household electricity consumption classes in Rio De Janeiro, Brazil. Energy Economics (30), 1672–1692.

Genjo, K., Tanabe, S., Matsumoto, S., Hesegawa, K., Yoshino, H. (2005). Relationship between possession of electric appliances and electricity for lighting and others in Japanese households. Energy and Buildings (37), 259–272.

Guerra Santin, O. (2010). Actual energy consumption in dwellings, the effect of energy performance regulations and occupant behavior. Ph.D. Thesis, OTB Research Institute, TUDelft.

IEA (2008). Statistics for 2008 / Energy balances for 2008. www.iea.org (last accessed 20.05.2011).

IEA (2009). Gadgets and Gigawatts. www.iea.org (last accessed 20.05.2011).

Itard, L., Meijer, F. (2008). Towards a Sustainable Northern European Housing Stock: Figures, Facts and Future, TUDelft, the Netherlands.

Itard, L., Meijer, A., Guerra Santin, O. (2009). Consumentenonderzoek Lenteakkoord, OTB Research Institute, TUDelft.

Mansouri, I., Newborough, M., Probert, D. (1996). Energy consumption in UK house- holds: impact of domestic electrical appliances. Applied Energy 54 (3), 211–285.

Miles, I. (1999). Home informatics: New Consumer Technologies. Society on the Line: Information Politics in the Digital Age, MIT Press, Cambridge.

Ndiaye, D., Gabriel, K. (2010). Principal component analysis of the electricity consumption in residential dwellings. Energy and Buildings, 1–8, http://dx.doi.org/10.1016/j.enbuild.2010.10.008

O'Doherty, J., Lyons, S., Tol, R. (2008). Energy-using appliances and energy-saving features: determinants of ownership in Ireland. Applied Energy (85), 650–662.

ODYSSEE (2008). Energy Efficiency Profile: Energy Netherlands. www.odyssee-indicators.org/publications/PDF/netherlands nr.pdf (last accessed 20.05.2011).

Parti, M., Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. The Bell Journal of Economics 11 (1), 309–321.

Rooijers, F., Sevenster, M., van Loo, L., Slingerland, S. (2003). Energie en gedrag in de woning, VROM, DG, Wonen, CE, rapport, Delft.

Saidur, R., Masjuki, H., Jamaluddin, H., Ahmed, S.M.Y. (2007). Energy and associated greenhouse gas emissions from household appliances in Malaysia. Energy Policy (35), 1648–1657.

Shove, E. (2003). Converging conventions of comfort, cleanliness and convenience. Journal of Consumer Policy (26), 395–418.

Tiwari, P. (2000). Architectural, demographic, and economic causes of electricity consumption in Bombay. Journal of Policy Modelling 22 (1), 81–98.

Uyterlinde, M., Uitzinger, J. (2001). Energieverbruik van energiezuinige woningen, ECN rapport: ECN-C-01-072.

Vringer, K., Aalbers, T., Blok, K. (2007). Household energy requirement and value patterns. Energy Policy (35), 553–566.

WOON Energie (2009). WOON Onderzoek Nederland, module Energie, VROM

Yohannis, Y., Jayanta, G., Mondol, D., Wright, A., Norton, B. (2008). Real-life energy use in the UK: how occupancy and dwelling characteristics affect domestic electricity use. Energy and Buildings (40), 1053–1059

5 Analysis of thermostat control in dutch dwellings: occupants' behavioral profiles

Introductory note

In the previous Chapter we made a sensitivity analysis based on actual energy consumption and heating behavior, on the whole OTB sample using methods like Markov chain and Monte Carlo analysis. In this Chapter (Chapter 5) a deeper analysis of heating behavioral patterns is reported. The study included 61 houses randomly chosen from the Netherlands, monitored for 2 months during March and April 2011. The thermostat use patterns of households were studied as well as chosen maximum and minimum set points each day for the whole sample. Then these patterns were correlated with the household and dwelling characteristics of the sample. Unfortunately, the collected energy consumption data for this sample was not reliable to be included in the analysis.

This Chapter deals with the Research Question III-1 of this thesis:
(Chapter 1, Section 3, pg. 16-17)
" III. What are the behavioral patterns and profiles of energy consumption?

The sub-question is:
What are the behavioral patterns of thermostat control? How do they relate to the household characteristics, revealing behavioral profiles?"

The research reported in this Chapter was conducted by Bedir, borrowing the dataset of Sonja van Dam. The data was collected through monitoring, by and for Sonja van Dam for her PhD research, using ENECO's means of data collection. The analysis in this Chapter was done, and the paper was written by Bedir. The co-author has given permission to include this research in this thesis.

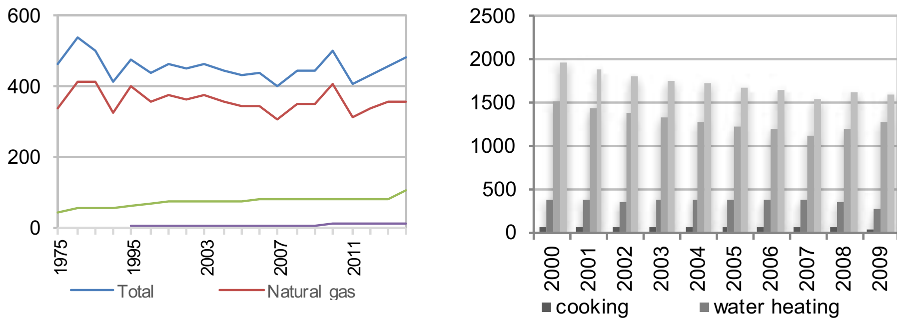
This chapter is being prepared to be published as a scientific journal article. It was formerly published as a conference paper:
Bedir, M. Van Dam, S. (2013) Analysis of Thermostat Control Behavior in Dwellings: Evidence from monitoring in the Netherlands. Plea 2013, Proceedings of 29th Conference of Sustainable Architecture for a Renewable Future, Germany (CD)

§ 5.1 Introduction

Heating energy consumption has the largest share in energy consumption of dwellings in the Netherlands. As the total yearly electricity consumption of Dutch dwellings slowly, but steadily increases between 1975 and 2014, the yearly natural gas consumption fluctuates, with an overall tendency of increase since 2007 (Figure 1-left (CBS, 2016)). Space heating, which is a function of thermostat control behavior, has by far the largest share (76%) of heating energy consumption in dwellings (Figure 1-right (SenterNovem, 2013)). Efforts in reducing the heating energy consumption have focused on improving thermal characteristics of the dwelling envelope, as well as the efficiency of systems and products. However, expected energy performance levels are not achieved, and significant energy consumption differences are observed in similar buildings. Occupant behavior is claimed to be one of the reasons for this variation (Jeeninga et al., 2001; Branco et al., 2004; Linden et al., 2006; Haas et al, 1998).

National programs on stimulating occupant behavior towards less use of heating energy have been put into effect, in addition to the several bottom up public and private initiatives (Jeeninga et al., 2001, and Guerra Santin et al., 2010). In addition, several studies have claimed that households can achieve more energy savings by changing occupant behavior (Papachristos, 2015; Ouyang et al., 2009; Wood et al., 2003; Darby, 2014; Røpke, 2012). Therefore, it is important to analyze the share of occupant behavior in energy consumption in detail.

Guerra Santin's study (2010) on the relationship between occupant behavior and heating energy consumption in dwellings reveals that the most important factor in energy use is the hours that the thermostat is at the highest chosen setting of the day. Following is the number of hours that radiators are turned on, and the number of bedrooms used as living area. These results go in-line with the findings of Jeeninga et al., 2001; Haas et al., 1998; Linden et al., 2006; Hirst et al., 1985; Harputlugil and Bedir, 2016. In existing research, factors related to energy conservation in dwellings have been identified, as well as the occupant characteristics that are related to higher levels of energy consumption. These studies point to the potential of energy consumption reduction, if energy efficiency policies are articulated according to different behavioral profiles (van Raaij et al., 1983; Poortinga et al., 2005; Guerra Santin, 2010; van Dam, 2013). More research on occupant behavior would help in analyzing and predicting behavioral patterns and profiles, and their relationship to heating energy consumption.



1 Total energy consumption (Pj/years)

2 Gas use in Dutch dwellings (m3/years)

FIGURE 5.1 Dutch averages for energy consumption and gas use

Existing research uses methodologies based on reported and/or monitored behavior data (Bedir et al., 2011; Vine et al., 1989), where the former has limitations on data being cross-sectional (collected once, at a certain time) and based on memory, and the latter has limitations on data collection being costly, time-inefficient, and requiring technological improvement. The other challenges of research on occupant behavior are further explained as the retrospective methods of data collection by the energy companies, the assumed usage patterns of systems and appliances in most calculation tools, the uncertainties in collecting and analyzing data, and the issues of energy performance gap (Guerra Santin, 2010; Dasa Majcen, 2016). More detailed investigation of thermostat control behavior is needed, in terms of the chosen temperature setting, the duration of the chosen temperature setting, but also how these preferences change over time and how they relate to household and dwelling characteristics, and behavioral attitudes. This means that a combination of different methods, collecting data via questionnaire, interview, and monitoring would be the most insightful when working on occupant behavior. However, the amount of this kind of research is small, and the resolution of data on occupant behavior is still rather low.

Our research investigates thermostat control behavior in 61 Dutch dwellings in detail, using an applied questionnaire on household and dwelling characteristics, and behavioral attitudes, as well as monitoring data on chosen thermostat settings collected by a home energy management system (HEMS) for two months in Spring 2011. The aim of our research is to (1) determine the behavioral patterns related to energy consumption for space heating, based on monitored thermostat control behavior, (2) find the household and dwelling characteristics and behavioral attitudes that are related with the behavioral patterns, based on data collected with questionnaire. This leads to determining the behavioral profiles. The paper also evaluates monitoring as a methodology for understanding the relationship between occupant behavior and energy consumption. The research covers data from 61 dwellings monitored for 2 months, hence our results would not be representative of the whole population. To deal with this limitation, we compare our findings with former research. In addition, comparisons with Van Dam's work (2013) are made, who researched the same sample using a questionnaire, interviews and focus group discussions.

The methodology of this research includes a descriptive analysis of thermostat control, followed by a repeated measures analysis to reveal how the thermostat control behavior have changed from day to day, weekdays to weekend, and between different weeks and months. Hierarchical cluster analysis is used to determine behavioral patterns of thermostat use. Patterns also refer to reliable acts, tendencies or other characteristics of a person or group. Based on this, the patterns that emerge in thermostat control need to be considered together with the characteristics of the occupant (Van Dam, 2013). Thus, behavioral profiles are determined based on the occupants' patterns of thermostat use; and the household characteristics, dwelling characteristics, and behavioral attitudes.

Our work contributes to the literature by: (1) combining different methods that brings together continuous data on actual behavior, and cross-sectional data like household and dwelling characteristics, and (2) deriving behavioral patterns and profiles and linking them to each other. Determining behavioral profiles using continuous actual behavior data could lead to more accurate prediction of energy consumption in dwellings, as well as planning the targeted energy saving measures, and helping energy companies for better calculations. In addition, this research could provide more detailed and articulated input to further research and policy, which focus on motivating/encouraging individuals and households towards more energy efficient behavior. Defining behavioral patterns and profiles could provide significant input to product/systems design and architecture.

Section 2 provides the literature related to the topic; Section 3 presents the research framework, methodology, and data; and Section 4 the results of the analyses. Section 5 and 6 are dedicated to the discussion and conclusions of this work.

§ 5.2 Literature Review

In this section, we present the studies that have focused particularly on occupants' heating behavioral patterns and profiles, in relation to household characteristics (Lutzenheiser, 1993; de Groot et al., 2008; Paauw et al., 2009), lifestyle (Poortinga et al., 2005; de Groot et al., 2008; Paauw et al., 2009; Assimakopoulos, et al., 1992; Tyler et al., 1990) cognitive variables such as values, motivations, attitudes (Poortinga, 2005; Vringer, 2007), and routines and habits (Gram-Hanssen et al., 2004; Gram-Hanssen, 2002; Shove, 2003). Lutzenheiser's (1993) theoretical evaluation based on a literature review on modeling household energy consumption analyzed the engineering, economical, psychological, sociological and anthropological models of energy consumption in US. He proposed a new cultural model, which is built on "recognizable lifestyles or cultural forms". In his work, these were classified under typologies such as retired working class couples, middle aged couples, low income rural families, suburban executive families, and young urban families.

In the Netherlands, van Raaij and Verhallen were the pioneers of energy profiling (1983). They identified 5 profiles (single inhabitant, couple, single-parent, family, and seniors) of energy behavior based on education, household size, and energy consumption among 145 households in the Netherlands and 5 patterns: Conservers (higher education, smaller household size), spenders, cool, warm (oldest group) and average. They found no differences regarding income and employment parameters. The research of Groot et al. (2008) and Paauw et al. (2009) developed 4 profiles of energy consumption: convenience/ease (comfort important, no interest in economic savings, energy, or the environment (EEE)); conscious (comfort important, interest in savings for EEE), cost (awareness of economy and hence energy and the environment); and climate/environment (concern for EEE). Raaij, Groot and Paauw's work found statistically significant differences in energy consumption among their groups.

Poortinga et al.'s survey (Poortinga et al., 2005) of 455 households in Dutch dwellings showed that seniors, single residents and low-income households were less willing to apply energy saving measures at home, and the acceptability of these measures varied among different socio-demographic groups. Vringer's work (2007) grouped households in the Netherlands according to income, age, education and household size. He found no significant differences in the energy consumption of groups of households with different value patterns, though he did establish that families that were least motivated to save energy used 4% more energy.

Guerra Santin's research (2010) on 319 dwellings about profiling household heating energy consumption revealed 5 groups according to the use of appliances, and heating and ventilation systems: (1) Spenders: use of more space, more use of electronics, more hours of heating, more hours of ventilation, no energy-saving concerns; (2) Affluent-cool: use of more space, more hours of ventilation; (3) Conscious-warm: use of more space, more use of electronics, more hours of heating, fewer hours of ventilation, energy-saving concerns; (4) Comfort: more use of electronics, more hours of heating, more hours of ventilation; (5) Convenience-cool: more use of electronics, more hours of ventilation.

In relation to the behavioral patterns of use of HEMS, literature reveals that there are big differences among households in the use of HEMS (Ueno et al., 2006). Van Dam et al. (2013) claimed that households who save energy, use the control systems more. Liikkanen (2009) identified three profiles of occupant behavior: the wisdom seekers, the detectives, and the judges, based on the consumption figures of an energy meter for individual devices that occupants used for one week. Van Dam's research (2013) focused on qualitative methods like interviews and focus group discussions over 50 households, and it categorized 5 groups of occupant patterns of HEMS: (1) Techies, who love gadgets and feel at home with products that look technical, who keep track of their energy consumption and see it as a hobby, are less motivated to save energy. (2) One-off occupants, who, like techies, are technically inclined and love gadgets, are interested in the consumption of individual appliances. (3) Managers, who do not necessarily have any affinity with technical things but like to keep a watchful eye out, may or may not go for energy saving consequently. (4) Thrifty spenders, who are like managers, but are motivated by money rather than altruism, have learned about thriftiness and energy saving ingrained in their behavior. (5) Joie de vivres, who enjoy living to the full, are not overly interested in energy or keeping track of their meter readings.

Research about occupants' behavioral patterns of thermostat control focus on behavioral characteristics of household size, composition, age, income, education, urban/rural background; and considerations of comfort, cost, energy, environment for behavioral patterns. In our work, we used these parameters in the analysis of behavioral patterns and profiles. Existing research uses two different methodologies that are based on cross-sectional vs longitudinal data collection, and very few have combined the two. Our work contributes to the literature by combining the two, and deriving behavioral patterns and profiles, and linking them to each other. This might provide deeper insight into reasons and motivations of behavior, in addition to the possibility of understanding long term behavioral changes. Determining behavioral profiles using continuous actual data on behavior could lead to more accurate prediction of energy consumption in dwellings, as well as planning the targeted energy saving measures. In addition, this research could provide more detailed and articulated input about occupant behavior in product and systems design, and architecture.

§ 5.3 Methodology

§ 5.3.1 Research Framework and Methods

In this paper, occupant behavior is considered as the actual behavioral patterns of thermostat control of the occupants. Patterns refer to a reliable sample of traits, acts, tendencies or other observable characteristics of a person, group or institution. This suggests that the patterns that emerge in thermostat control need to be considered together with the characteristics of the occupant (Van Dam, 2013). For a coherent description of the occupants' thermostat control behavior and the significant differences among them, the results of our analyses are clustered according to the types of behavior and types of occupants. Types of behavior are named as behavioral patterns; types of occupants are named as behavioral profiles. This paper also presents an evaluation of monitoring as a method for understanding the relationship between occupant behavior and energy consumption.

In order to determine the thermostat control patterns, we analyzed the quantitative data collected for 2 months in Spring 2011, from 61 dwellings by monitoring their use of home energy management systems, as well as the questionnaires filled in by households. Afterwards we compared our results with existing research, especially with Van Dam's work (2013) on the same sample, which had used the qualitative data collected with interviews and focus group discussions. Data collection and quality of data is further explained in Sub-section 3.2.

The maximum and the minimum thermostat settings were analyzed for the whole sample during the months of March and April 2011. The main chosen thermostat set points, and the durations of these set points were clarified during the morning (06.00-12.00), day (12.00-17.00), evening (20.00-22.00), and night (22.00-06:00) of everyday. Repeated measures analysis was conducted to reveal if and how the thermostat set points change in different cases from day to day, during two months. As a second step, (agglomerative) hierarchical cluster analysis was applied on the sample to see how the cases group in terms of their thermostat control behavior. This means that, the clusters were set up first based on the change of thermostat set point during the two months, and secondly based on selected thermostat set point temperature and duration. Correlation analysis was used to relate the thermostat control patterns to household, dwelling characteristics, and behavioral attitudes, which provided us with behavioral profiles (Figure 2 and 3). Lastly, the thermostat control patterns and profiles we found were compared former research.

The main questions of this research are:

- What are the thermostat control patterns derived by observing the long-term use of home energy management systems?
- How do the maximum and minimum chosen thermostat settings change, in terms of the temperature, the time of the day, and the duration of the chosen setting?
- Are there common temperature preferences for certain parts of the day?
- How do these relate to the household, dwelling characteristics, and behavioral attitudes? and which behavioral profiles are revealed?

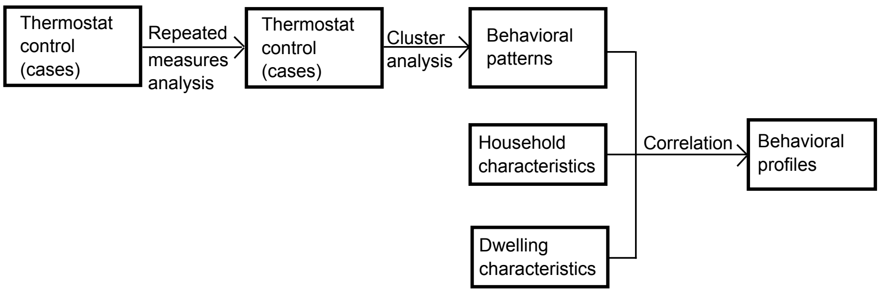


FIGURE 5.2 Research methodology

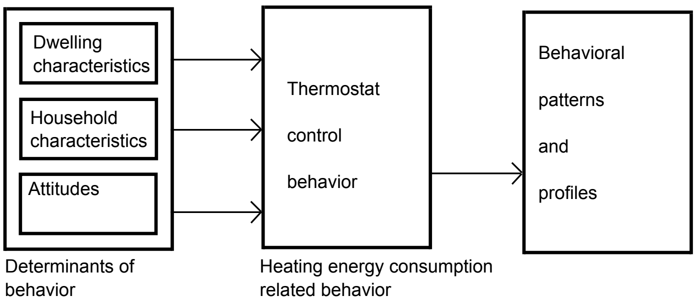


FIGURE 5.3 Research methodology: Research framework

§ 5.3.2 Data Collection

Data was collected from 61 dwellings in the Netherlands, during March and April 2011. The details of monitoring and questionnaire is explained in Table 1 and Figure 4. For selection of the households involved in the study, the client database of an energy company was used. A questionnaire was sent out to the households in the database with questions on the household's technical installations, demographics and environmental concerns, and participants were asked if they would accept to be part of a monitoring study. 61 households were included in the monitoring. Participants for monitoring were selected under the condition of forming a distributed mix of the Dutch population in terms of age, gender and education. Additionally, they did not have specific affinity with energy consumption through their work.

§ 5.3.2.1 Monitoring

The multifunctional HEMS consisted of an 8" touchscreen, 0–2 sensors for the gas and electricity meter, 1–2 transmitting units for the meters, an adapter and depending on the house 0–3 repeaters (to increase the signal strength of the wireless communication between transmitting unit(s) and the display). Communication between the parts happened by means of z-wave, but a wireless router was also installed for communications with the energy provider and the manufacturer. All households were to receive the same hardware, although there were variations in the peripheral devices to fit the different types of meters installed. A visualization of the HEMS can be found in Figure 4. The multifunctional HEMS was installed at the same location as the home's previous thermostat (because of the existing wiring infrastructure). This location was almost always the living/dining room and often near the entrance from the hallway, although the HEMS was occasionally installed in the hallway (Van Dam, 2013).

Monitored data was recorded with half a minute intervals. This data included thermostat set point temperatures, the time that thermostat set point was changed, the number of times that the thermostat screen was touched. Real time data on energy consumption was proved to be not reliable, therefore it was excluded from the analysis.

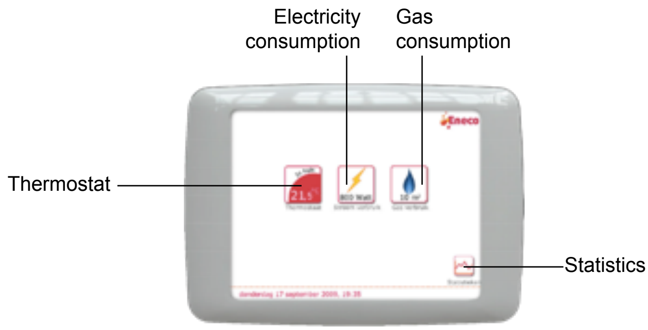


FIGURE 5.4 Multifunctional HEMS used to collect dataset 2

§ 5.3.2.2 Questionnaire

In addition to the monitored data, a questionnaire was applied over the whole sample, where respondents were asked about the dwelling type and size, energy tariff, household size, gender, year of birth, education and income level, day time and night time temperature preferences (based on how much they remember), who made energy related decisions in the household, energy saving measures, which time of the day/ daily activity thermostat control was related to, if the household had an understanding/awareness of their consumption, how much they followed their consumption from the previous and the current year, if they used a programmed thermostat setting, if they used, or got used to using some functions like continuous, free day, not at home, etc. (Table 1). The questionnaire was applied before the monitoring.

§ 5.3.3 Limitations

45 households' monitoring data was used over the sample size of 61. 8 households did not provide reliable data in March and April, and 8 cases for either March or April. Besides, 4 April and 12 April 2011 were the days that monitoring was problematic for all households. For minimum set point temperature, monitoring data of 19 and 21

April included outlier data. The measured energy consumption data by the HEMS was not reliable, therefore this study only explored thermostat control behavioral patterns, but could not research their relationship to energy consumption. Another limitation was that the data was collected from the consumers of one energy company. Being the subscriber of this company might mean essential differences between this group and the rest of the households in the country, in terms of values, attitudes, etc. Lastly, the Hawthorne effect (McCarney et al., 2007) must be mentioned, i.e. the participants of monitoring were aware that their heating thermostat control behavior and energy consumption was being observed and recorded.

Group	Parameter	N	Mean	SD
Thermostat use	Number of set temperature change times	45	3.89	1.03
	Number of thermostat control touch times	45	8.71	5.60
	Monitored temperature day time (C degrees)	45	18.8	1.70
	Monitored temperature night time (C degrees)	45	14.48	2.19
	Reported temperature day time (C degrees)	45	19.94	0.96
	Reported temperature night time (C degrees)	45	15.55	1.61
Household characteristics	Household size	45	5.25	1.25
	Person decides on energy control in the house	45	3*	0.83
	Gender	45	1*	0.42
	Birth year	45	1973	9.95
	Education	45	5*	2.24
	Total income (Euros)	45	4*	1.05
	Day/night energy tariff	45	1**	0.46
Dwelling characteristics	Dwelling size (m2)	45	110	38.2
	Owned/rented house	45	1***	0.35
	Type of house	45	3**	1.25

TABLE 5.1 Descriptive statistics of parameters about thermostat use, household and dwelling characteristics, reported attitude and behavior, during the two months monitoring continued.

Group	Parameter	N	Mean	SD
Reported behavior (or attitude)	I change the thermostat when I get up	45	1a	0.75
	I change the thermostat before I leave the house	45	2b	1.37
	I change the thermostat when I get home	45	1a	0.31
	I change the thermostat before I go to sleep	45	1a	0.96
	I check current temperature and time	45	Y: 40	N: 5
	I adjust the temperature manually	45	Y: 34	N: 11
	I set up a thermostat program	45	Y: 32	N: 23
	I check electricity consumption	45	Y: 28	N: 27
	I check gas consumption	45	Y: 28	N: 27
	I set a saving target button	45	Y: 8	N: 37
	The number of energy saving measures I take	45	53	1.33
	I use 'continuous' button	45	2c	.73
	I use 'not at home' button	45	2c	.83
	I use 'free day' button	45	2c	.69
	I use 'holiday' button	45	2c	.41

Notes:
3*: couples take energy-relevant decisions together
1*: male
5*: LBO
4*: 34.000-56.000 euros
1**: Day/night energy tariff
1***: owned house
3**: corner house
1a: everyday
2b: once a week
2c: sometimes

TABLE 5.1 Descriptive statistics of parameters about thermostat use, household and dwelling characteristics, reported attitude and behavior, during the two months monitoring continued.

§ 5.4 Results

Considering the whole sample over 2 months, the distribution of (1) chosen thermostat settings and (2) time of the day that those thermostat settings were chosen, seemed quite consistent (Figure 5); however, the duration that the chosen thermostat setting stayed active varied (Figure 6). In this section, first, the results of total monitoring data analysis on 45 households is presented, i.e. times of thermostat change vs screen touch; mean morning, day, evening, and night minimum and maximum thermostat setting preferences of the whole sample, and durations of chosen thermostat settings, per day. Secondly, the behavioral patterns that were found with hierarchical cluster analysis are explained. Lastly, the behavioral profiles created by relating the patterns (clusters) to household and dwelling characteristics, and behavioral attitudes are reported.

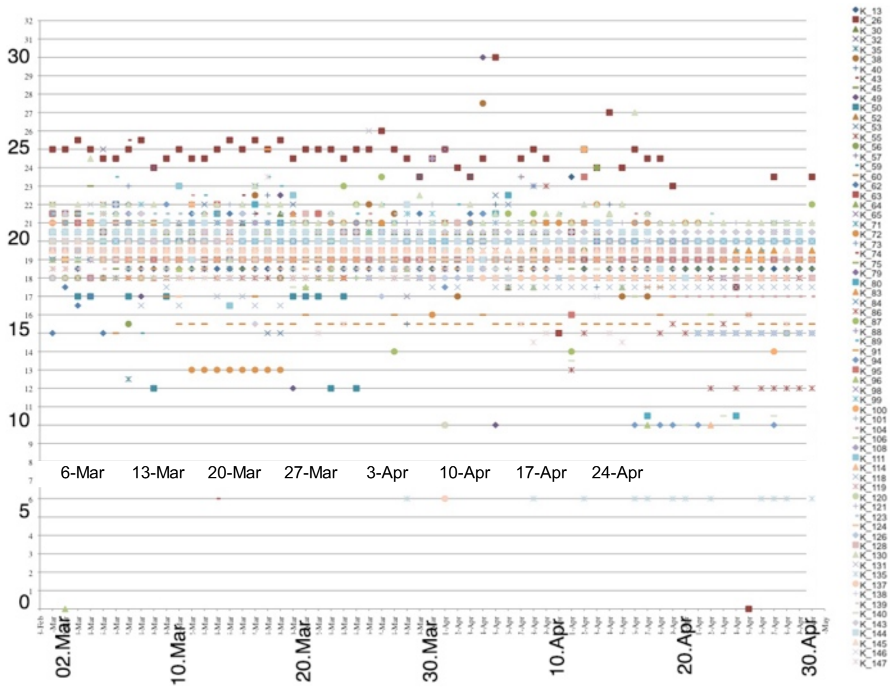


FIGURE 5.5 The distribution of maximum and minimum thermostat settings over two months (C degrees (vertical axis) /days (horizontal axis))

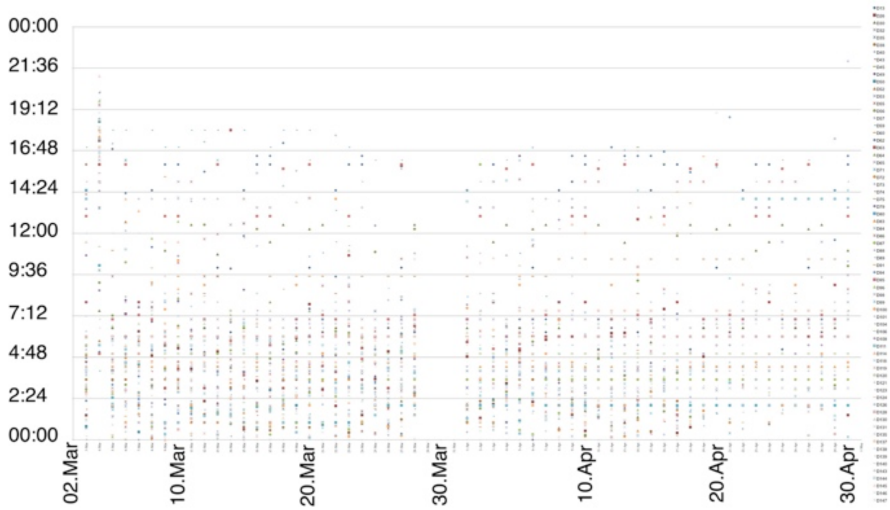


FIGURE 5.6 The distribution of duration of maximum and minimum thermostat settings (hours/days)

§ 5.4.1 Monitoring outputs of thermostat control, for the whole sample

While the touch screen of the HEMS was used between 4 times and 11 times per day, the times of actual thermostat setting change was between 2 times and 5 times on average. The difference could be because the other functions of the home energy management system were used as many times as the thermostat setting function (Figure 7).

For the entire sample, the average thermostat settings in the morning, during the day, in the evening, and at night were 17 C, 18.5 C, 17 C, and 15 C degrees, respectively. The duration of the chosen setting was on average 2 hours in the morning, 3:30 hours during the day, 4 hours in the evening, and 8 hours at night (Figure 8).

For the whole sample, the mean-maximum chosen thermostat set point was 21 C degrees, and was set between 14:30 and 19:00. The mean-minimum thermostat setting remained at 13 C degrees, during the night between 23:00 - 06:00 (Figure 9).

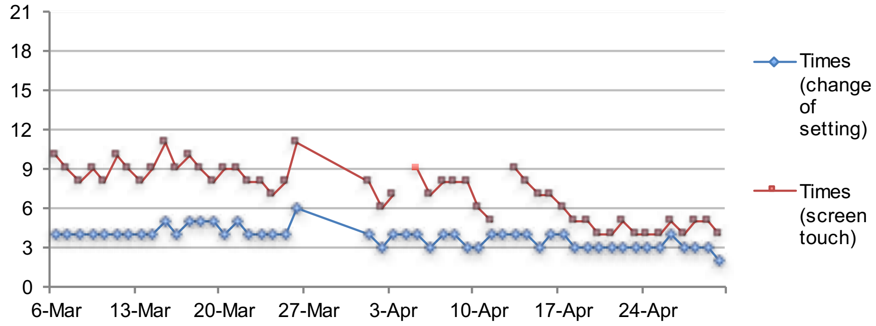


FIGURE 5.7 Times of thermostat setting change and screen touch for the whole dataset (number (vertical) / days (horizontal))

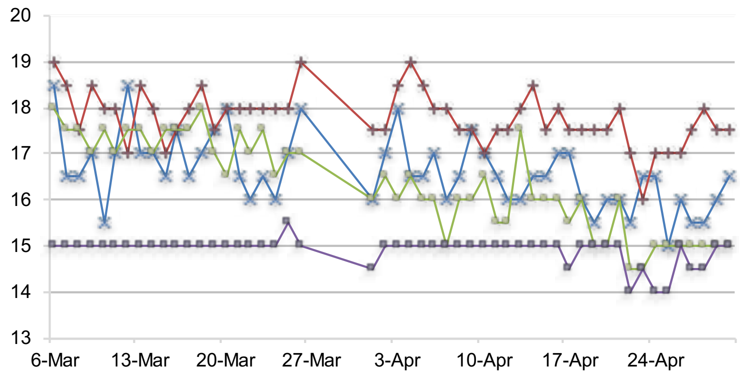


FIGURE 5.8 Average set temperature change during two months over the whole sample (C degrees (vertical) / days (horizontal))

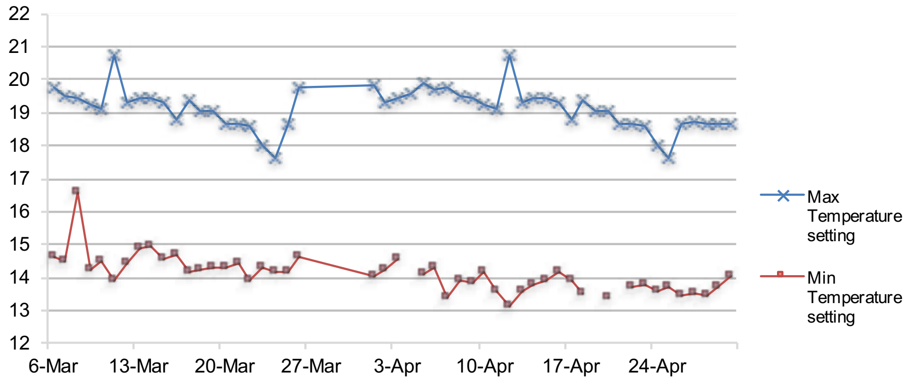


FIGURE 5.9 Maximum and minimum temperature setting change during two months over the whole dataset (C degrees (vertical) / days (horizontal))

§ 5.4.2 Thermostat control patterns

In this section, analysis results of the actual thermostat control behavior both from the questionnaire and from monitoring are presented. Thermostat screen touch times was found to be correlated with the temperature changing times (r=.48, p=<.01), and the number of households that changed the thermostat setting immediately when they arrived home (r=.67, p=<.01). This means that the HEMS was used for thermostat control as a major function, and occupants might be changing thermostat setting prior to major shift of behavior in daily life, and occupancy of the house.

Monitored night time temperature setting was correlated with that of the reported (r=.55, p=<.01), however, there was no correlation between the reported and monitored day time temperature (Figure 10). Reported night time temperature setting was correlated with the use of 'continuous' setting (r=-.52, p=<.05). These together might mean that most of the time questionnaires report the behavior that the occupant remembers, and not the actual one. It is easier to remember the night time thermostat setting because it's a single, continuous period of the day and not interrupted with activities, the same cannot be claimed for the day.

Reported night time temperature setting was correlated with specific thermostat use pattern (r=.42, p=<.05), and with the number of households that changed their thermostat setting when the occupant arrives at home (r=-.52, p=<.05). In addition, the use of 'not at home' setting was found to be correlated with the use of 'free day' setting (r=.61, p=<.01). These meant that the set programs, free day/continuous/not at home settings were usually activated when there would be an undivided activity at home, i.e. sleeping (night time), or when the occupants knew that the house would be unoccupied for a period. In addition, the function settings of 'free day' 'not at home' 'continuous' were possibly used interchangeably.

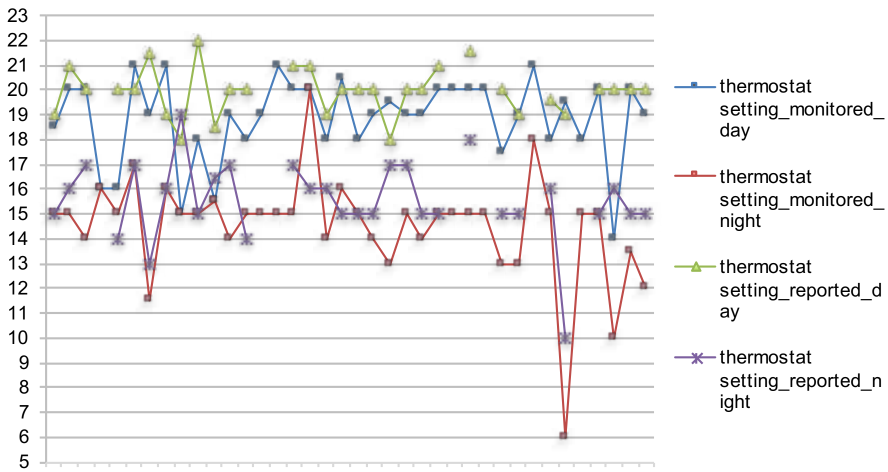


FIGURE 5.10 Monitored vs Reported day and night time thermostat settings (C degrees (vertical) / days (horizontal))

A Repeated measures analysis

We applied repeated measures analysis for every household in the sample, for the chosen morning, day, evening, and night time settings and durations.

For 7 households, Mauchly's test indicated that the assumption of sphericity was violated (X2(5)= 10.23, p=0.45). We did not make a correction for the degrees of freedom in the repeated measures analysis, because our aim was to only explore the significant change in thermostat set point temperature and duration. We interpreted this as the thermostat set point temperature and its duration being different for 7 households, for morning, day time, evening, and night, in the consequent days of March and April 2011.

This left us with a group of 38 households. For the morning thermostat set point and duration (for 26 households), sphericity was not violated, as displayed in the Mauchly's test ($F=1.79$ $p=0.65$, and $F=2.54$ $p=0.55$, respectively). For a group of 12, sphericity was violated in the repeated measures test for the morning and evening set point durations ($X2(4)= 9.12$, $p=0.049$ and $X2(5)= 8.47$, $p=0.044$). This meant that this part of the group had no duration pattern for the morning and evening periods. For the chosen day, evening, and night thermostat settings, the assumption of sphericity was not violated in any tests ($F=1.55$ $p=0.065$; $F=1.62$ $p=0.056$; $F=1.45$ $p=0.059$, respectively). For the chosen day, evening (for 26 households), and night set point durations, sphericity was not violated in any tests ($F=2.42$ $p=0.062$; $F=2.39$ $p=0.071$; $F=1.29$ $p=0.062$, respectively). This meant that each case had a pattern of thermostat control behavior for 2 months, coherent with itself for the mentioned periods.

Afterwards, we started reading the data in detail, the preferred thermostat settings and the durations, for each household, every day. The common patterns that were immediately visible were that some households preferred a single thermostat setting and duration per part of the day, every day; while others had different choices for different days of the week continuous in March and April. We continued to analyze the sample of 38 houses based on the morning/day/evening/night set points and durations, and we used cluster analysis for this.

B Hierarchical cluster analysis

We sought to build a hierarchy of clusters from the cases in the sample. We used agglomerative strategy, i.e. each observation started in its own cluster, and pairs of clusters were merged as one moved up the hierarchy, with a "bottom up" approach. We used Ward's method, aiming to join cases into clusters such that the variance within a cluster is minimized (Field, 2000). The clusters were set up first based on the long-term thermostat control change. Afterwards, within each cluster, the thermostat set point temperature preference and the duration were considered. Behavioral patterns observed on the 38 households based on cluster analysis were: (1) 11 cases/ single thermostat setting throughout two months and one duration for each part of the day (one-off), (2) 12 cases/ different thermostat setting and duration patterns for different days of the week (comforty), (3) 15 cases/ different patterns between the days of the week and during March and April (controller).

§ 5.4.2.1 Single thermostat setting and duration: One-Off

One-off's were households that chose one set point temperature and one duration for the chosen thermostat setting, for each part of the day, during the entire data collection period. 11 cases picked a single set point temperature with a certain interval. In this group, the most chosen thermostat setting was 18 C degrees in the morning, 20 during the day, 19 in the evening and 15 at night (Figure 11). The highest and lowest chosen thermostat settings were 20 C/ 16 C degrees in the morning, 21 C/ 15 C during the day, 21 C/ 15 C in the evening, and 18 C/ 10 C at night. The maximum and minimum durations for the chosen thermostat settings were between 3 and 5 hours in the morning, between 1 and 5 hours during the day, between 1 and 5.30 hours in the evening, and 8 hours at night. This group's selected thermostat temperatures were more constant in the morning and at night, and more diverse during the day and evening. It was also possible to observe a 'One-off-warm' group (set points above 17 C degrees), and 'One-off-cool' group (below 17 C degrees).

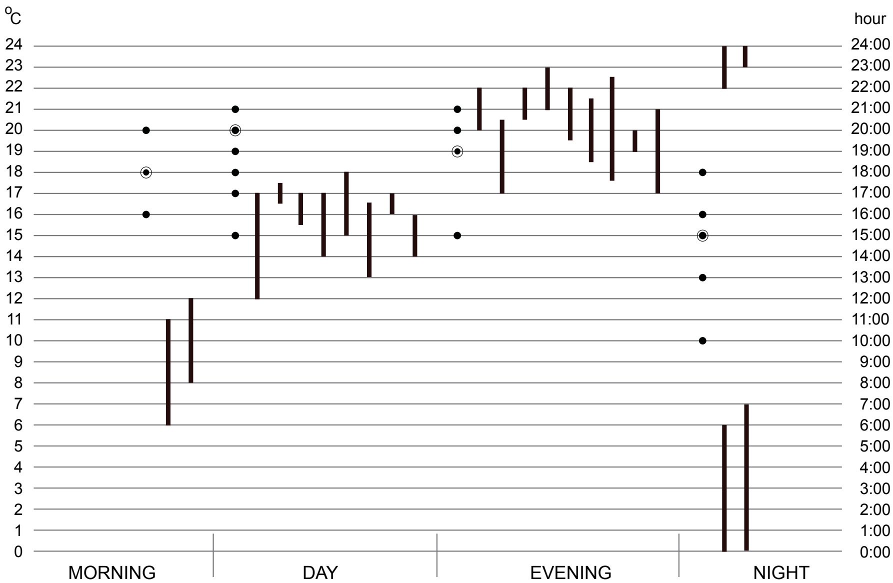


FIGURE 5.11 Clustering of households that chose one set point temperature and one duration for the chosen thermostat setting in March and April. The dots represent the chosen thermostat set point temperatures, and the stripes represent the duration of chosen thermostat settings in morning, day, evening and night. The circled dots mark the most chosen thermostat set points in the sample, for each part of the day.

§ 5.4.2.2 Different thermostat settings for different days of the week: Comforty

12 cases displayed different thermostat set temperatures or periods during the week for each part of the day, but with a certain pattern that repeated weekly, during March and April (Figure 12). This group had no duration pattern for the morning and evenings, and they preferred higher temperatures compared to the other two groups. We could follow a pattern for the morning, day, evening, and night thermostat settings, and a pattern of duration of chosen thermostat setting for the day and night time in this second group. The temperature preferences were between 16 and 21 C degrees in the mornings; between 16 and 20 C degrees during the day; between 16 and 19 C degrees in the evening, and at night, for different days. In terms of the hours of chosen thermostat setting, the maximum and minimum duration of chosen settings were between 2.30 and 5 hours during the day; and between 6.30 and 10 hours at night.

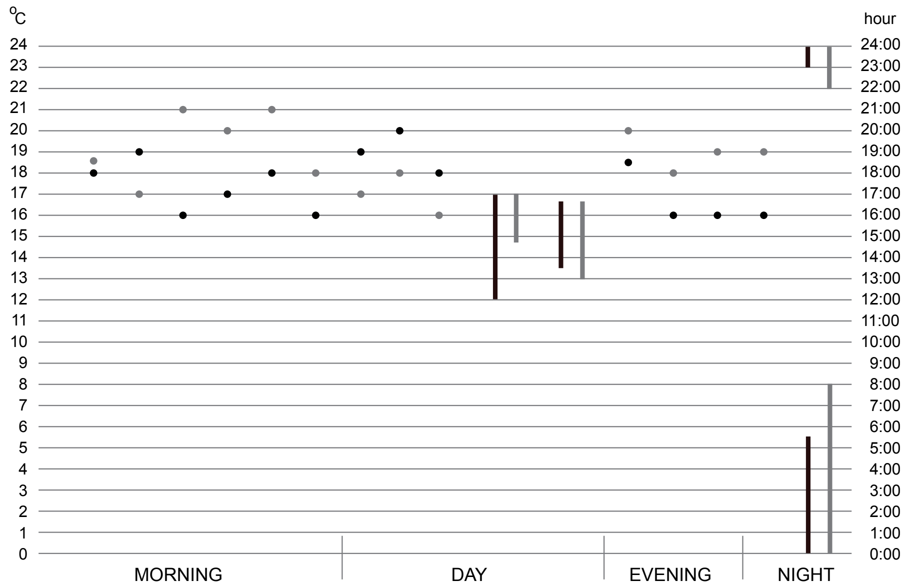


FIGURE 5.12 Clustering of households that use one or more thermostat settings and durations (with a pattern) in different days of March and April. The dots represent the chosen thermostat set point temperatures, the stripes are the intervals of set points chosen in morning, day, evening and night.

§ 5.4.2.3 Different settings for different parts of the week and different months: Controller

15 cases displayed different thermostat set temperature and periods during different parts of the day, between weekdays and weekends, and March and April (Figure 13 and 14). In this group, the morning time thermostat set points changed between 12 and 19, day time set points between 12 and 20, evening time set points between 12 and 19.5, and night time set points between 10 and 15 C degrees. Duration for the morning set point was between 1 hour and 6 hours, day set point was between 1 hour and 5.30 hours, evening set point was between 1 hour and 3.30 hours, and night set point was 4 and 7 hours. Participants of this group preferred lower thermostat set points. The duration of chosen thermostat setting varied a lot within the group, but there was a readable pattern.

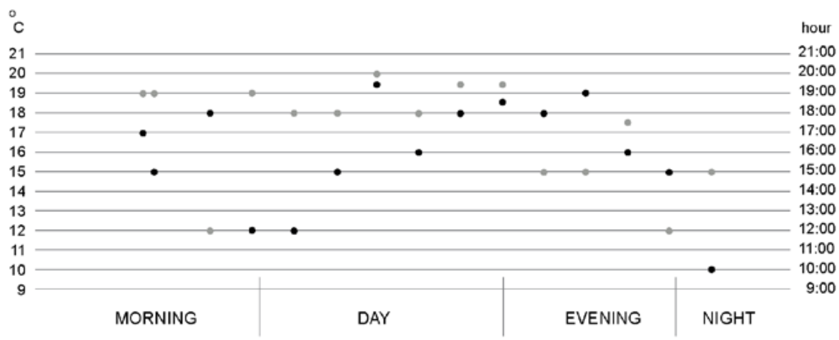


FIGURE 5.13 Clustering of households that use different thermostat setting (with a pattern) for weekdays and weekends, through both March and April. The dots represent the chosen thermostat set point temperatures in the morning, day, evening and night.

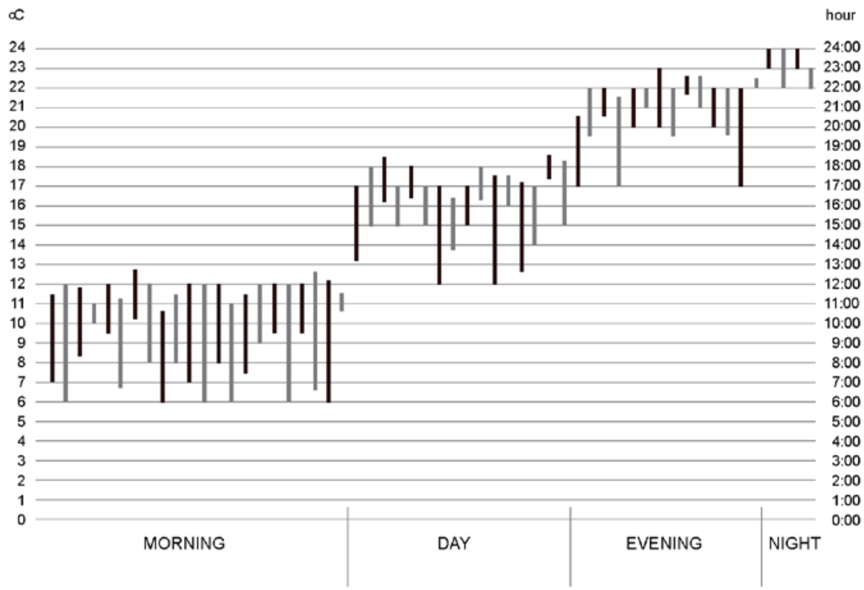


FIGURE 5.14 Clustering of households that use different intervals (with a pattern) for weekdays and weekends, through March and April. The stripes represent the intervals of set points chosen in the morning, day, evening and night..

§ 5.4.3 Thermostat patterns in relation to household and dwelling characteristics, behavioral attitudes

In this section, thermostat control patterns are analyzed in relation to their determinants of behavior (with cross-sectional data from the questionnaire), such as dwelling and household characteristics, and behavioral attitudes (see Table 1). Using the day-night tariff was found to be correlated with household size ($r=-.48$, $p=<.01$), and having a specific thermostat pattern ($r=.45$, $p=<.01$). The use of continuous thermostat setting function was correlated with the number of energy saving measures ($r=.60$, $p=<.05$), and the education level of the household ($r=.54$, $p=<.05$). Setting a thermostat program was correlated with the dwelling size ($r=-.56$, $p=<.05$), the income level of the household ($r=.63$, $p=<.01$) and if the dwelling was owned or rented ($r=.59$, $p=<.01$).

Monitored day ($r=.62$, $p=<.01$) and night time ($r=.55$, $p=<.01$) thermostat set point temperatures were correlated with the household having an energy saving target. Having an energy saving target was correlated with the household size ($r=.59$, $p=<.05$), with checking the current ($r=.62$, $p=<.01$) and past ($r=.59$, $p=<.01$) energy consumption levels of gas and electricity. The number of energy saving measures was correlated with who made the decision of thermostat control in the household (r=.40, p=<.05). These correlations, as well as the behavioral patterns were used to set up the behavior profiles (Table 2).

Name	Behavioral pattern	Behavioral profile
One-off	- single temperature and duration per period during 2 months - 'one-off-cool' and 'one-off-warm' groups based on temperature preference	- gadget lover - thermostat controlled by higher educated males - high frequency of HEMS touch screen use (for part of the group lower frequency). - no interest in energy saving
Comforty	- varied temperature and duration for different days - no morning and evening duration pattern - warmer temperature preference	- comfort lover - owners - bigger size dwellings - higher income - no interest in energy saving
Controller	- varied temperature and duration for different days with a pattern - cooler temperature preference	- keeps control of the thermostat set point and duration - has an energy saving agenda - families where the parents/couples take energy related decisions together - part of the group includes the elderly

TABLE 5.2 Behavioral patterns and profiles of thermostat use explained

§ 5.4.3.1 Behavior profile: 'One-Off'

This group was dominated by higher educated males, who made the decisions of thermostat control in the house. The group also had a high frequency touch screen use of the home energy management system, even if the behavioral pattern was single temperature/period every day. The monitored night time thermostat setting was found to be correlated with the use of 'free day' setting and with the use of 'continuous' setting, which might mean that the chosen night time setting was used when the household was not at home or when the household did not want to make a new adjustment in the temperature.

In this group, the use of continuous thermostat setting was negatively correlated with the number of energy saving measures. This might mean that this group's occupants mostly enjoyed following the temperature and the other features of the home energy management system as a gadget, but they were not necessarily interested in energy saving.

Part of the group had a high frequency of touch screen use of the home energy management system throughout the two months, while the frequency of use for part of the group reduced towards April. This might also be a sign that the group was not actually interested controlling their thermostat setting temperature and or their energy consumption, so as they started to get used to the device, they stopped using it.

Van Dam (2013) explained two patterns that seem to explain further about this group: (1) Techies and (2) One-off's. "Techies like products that look technical and checking their energy consumption is a hobby. They are data analysists, less motivated to save energy, often male and sole occupants of home energy management systems and their feedback. One-off occupants have many similarities with techies regarding their background, interests and use of energy. However, keeping track is not a goal, they are more interested in the consumption of individual appliances. They utilize the HEMS as a very informative but short-term tool to discover where they can save energy and to be able to implement technical solutions or adapt their behavior based on that."

§ 5.4.3.2 Behavior profile: 'Comforty'

This group were mostly owners, had bigger size dwellings, and higher income. Their 'not at home' setting was the same as 'free day,' in contrast to the former group, who used the 'continuous' set point. This group used higher thermostat set point temperatures, compared to the other two groups.

Van Dam (2013) explained this group as 'Joie de vivre,' who enjoyed living to the full and are not overly interested in energy or keeping track of their meter readings. "A desired application of a control system, for this group would be as 'suspicion checker', for being able to discover what the cause of their energy consumption was."

§ 5.4.3.3 Behavior profile 'Controller'

This group was not found to be gadget-lovers, as in One-Off group, i.e. playing with a gadget for learning and interest in technology, but it was obsessed with keeping control of the thermostat set point and duration. In this group, the monitored day and night time thermostat settings were significantly correlated with the household having an energy saving target. Also, the households in this group set the thermostat when they arrived and left home. They also used the day/night tariff of the energy company. It seemed energy saving was seriously in the agenda of this group.

Part of the group was comprised of families, where the parents took energy related decisions together. Also, they checked the current and past energy consumption levels of gas and electricity. The families reported not only the use of day-night tariff, but also the use of a specific thermostat program. The other part of the group included the elderly, where the couples took energy related decisions together. This group used the night thermostat for continuous setting, and checked their energy consumption levels regularly.

Monitored day ($r=.62$, $p=<.01$) and night time ($r=.55$, $p=<.01$) thermostat set point temperatures were correlated with the household having an energy saving target. This meant that households that have an energy saving target are careful with their thermostat control behavior. Having an energy saving target was correlated with the household size ($r=.59$, $p=<.05$), with checking the current ($r=.62$, $p=<.01$) and past ($r=.59$, $p=<.01$) energy consumption levels of gas and electricity. The number of energy saving measures was correlated with who made the decision of thermostat control in the household ($r=.40$, $p=<.05$).

What we defined as 'controller,' based on the monitored thermostat control behavior, was defined in two groups by Van Dam (2013) as 'managers' and 'thrifty spenders.': "Managers are often parents with school-age children, who do not necessarily have any affinity with technical things but take a more behavioristic approach instead. Their goal is to regularly keep a watchful eye out for appliances that are left on unnecessarily. 'Thrifty spenders' have some characteristics similar to those of managers, but they are motivated by money rather altruism. Thrifty spenders are often middle-aged or older. Old lessons learned about thriftiness and turning lights and appliances off are now ingrained in their behavior."

§ 5.5 Discussion

§ 5.5.1 Thermostat control patterns and profiles

Among 61 households, this research has identified 4 groups of occupants, 7 households with no pattern, and 38 households with pattern: one-off (11 households), comforty (12 households), and controller (15 households). The last 3 were explored more in detail in this paper. The research brought together the household and dwelling characteristics, behavioral attitudes, and actual thermostat control behavior to set up these groups. Thermostat set point temperature, the duration of chosen setting, household size and composition, education, age, income, dwelling size, frequency of use of the thermostat were the parameters that were used to define the groups. This identification is valuable because it provides a representation for this group of occupants and suggests directions on the more energy efficient use of thermostat control systems. However, this research does not have a high capacity of representation, since the sample size is rather small.

7 households with no pattern of thermostat control should be studied much more in detail to understand the particularities of their behavior and characteristics. In these houses, we found evidence that the thermostat might not have been controlled by just one person, which meant that there were more occupant characteristics that were not identified within the current method of data collection/analysis. The other possibility is that there might have been technical issues in monitoring, with calibration or recording the data.

The no-correlation between reported and monitored day time temperature might mean that people have reported the temperature as they remembered or felt at the time of the questionnaire, however the actual thermostat setting was a different one. This shows the importance of monitoring, i.e. longitudinal data collection in behavioral studies. The same argument could be asserted based on the frequency of touch-screen use, being much more intensive in March and less in April, a fact that was visible with monitoring, but wasn't reported in the questionnaire.

Occupants might have used 'continuous' 'free day' 'not-at-home' buttons interchangeably for the thermostat control. The correlation between monitored night time temperature setting and 'free day' or 'continuous' setting was probably because people picked a certain setting for the lowest occupancy condition and left it at that chosen setting for a long time. This result might be telling about the occupant's preference to manage the thermostat based on work day/non-work day, or if the households is staying at home longer at the weekend. These results go in line with Van Dam's research (2013) on the same sample based on interviews and focus group discussions.

When partners manage heating together, they actually take more decisions towards energy conservation. Dwellings that are bigger in size, higher in income level of the households, and owner occupied demonstrate a more diverse and comfort oriented decisions of thermostat control behavior, which might be because of the households' less interest in energy saving.

In this research, we were not able to use the monitored energy consumption data, because it was not reliable. More measurements and analysis including energy consumption would provide better insights into the behavioral profiles and their relation to energy consumption.

§ 5.5.2 Comparison with literature

Besides Van Dam's research (2013), which was used for one-to-one comparison, our findings mostly comply with literature in terms of household characteristics, in which age (Raaij et. al., 1983a; Poortinga et. al., 2005; Tyler et. al., 1990; Vringer et. al., 2007), household size (Raaij et. al., 1983a; Guerra Santin, 2010; Raaij et. al., 1983b; Vringer et. al., 2007), household composition (Raaij et. al., 1983a; Poortinga et. al., 2005; Guerra Santin, 2010), income (Poortinga et. al., 2005; Lutzenheiser, 1993; Vringer et. al., 2007), education (Raaij et. al., 1983a; Vringer, 2007), occupation (Lutzenhiser, 1993), use of appliances (Guerra Santin, 2010; Van Dam, 2013) come forward as significant characteristics that determine the behavioral profiles of heating energy consumption. In our research, even if the household characteristics were used to define different profiles, they didn't appear as the only major elements that determine the variance among groups. For example, 'one-off's were composed of higher educated respondents, but this did not mean that there was no representation of high education in the profile 'controller'; but it meant that education was a defining characteristic for 'one-off's, but not for group 'controller.' Similarly, we saw that 'comforty' group cared more about thermal comfort (as in Raaij et. al., 1983a), however, this behavioral attitude was in fact not only in 'comforty.' In this study, behavioral profiles were determined more heterogeneously. Our research is close in attitude to the work of Raaij and Verhallen (Raaij et. al., 1983a).

In addition, unlike Raaij and Verhallen (Raaij et. al., 1983a), Poortinga et al. (2005), and Vringer and Blok (2007), we found that households with higher education were not necessarily often interested in energy saving, and that the elderly did not necessarily always prefer warmer temperatures.

We used Van Dam's analysis (2013) for one to one comparison, since she worked with interviews and focus group discussions with the same group. She categorized 5 groups of occupant patterns of energy management systems: (1) Techies, who love gadgets, but less motivated to save energy; (2) One-off occupants, who love gadgets, and are interested in the consumption of appliances; (3) Managers, who like to keep a watchful eye out, may or may not go for energy saving; (4) Thrifty spenders, who are like managers, but motivated by money; and have learned about thriftiness and energy saving ingrained in their behavior; (5) Joie de vivres, who enjoy living to the full, are not overly interested in energy or keeping track of their meter readings. The profiles we found were complementary to Van Dam's groups, where our first group (One-off's) covered techies and one offs, our second group (Comforty) complemented with joie de vivres, and our third group (Controller) covered managers and thrifty spenders. Our research could complement that of Van Dam's, since we provided the preferred thermostat set temperatures and durations for the profiles. For instance, 'comforty' was the most comfort-preferring group compared to the other two, and chose the highest temperatures. Also, 'one-off's included two groups within, 'warm' and 'cool' group, based on the temperature preferences. This might also explain the behavioral pattern variation between one-off's and techies in Van Dam's grouping. The 'controller' group was the one that used the thermostat control the most, which complies with Van Dam's findings of managers and thrifty spenders.

§ 5.5.3 Methods and limitations

In the literature section, we quoted two methodologies on occupant behavior and energy consumption research (Bedir et. al., 2011; Vine et. al., 1989), where longitudinal and cross-sectional data collection and related methods for analyses were applied on smaller samples, or large populations. In this research, we tried to combine the two methodologies, analyzing continuous data (collected by monitoring) on actual behavior, and cross-sectional data (collected by questionnaire) like household and dwelling characteristics. By doing these, we derived behavioral patterns and profiles, and linked them to each other.

Major issues to deal within the former methodology are on data collection and working with big data; for instance, calibration of the data collected with monitoring, checking the reliability of the data collected (in our case, crucial data on energy consumption was not usable). In addition, existing research using this methodology, including ours, does not have a representation capacity on the whole population, because of their small sample size. However, they provide deeper insight into behavior, and they create the possibility to validate/compare the results of other research.

We used 45 households' monitoring data over the sample size of 61. 8 households did not provide reliable data in March and April, and 8 cases for either March or April. Besides, 4 April and 12 April 2011 were the days that monitoring was problematic for all households. Another limitation was that the data was collected from the clients of one energy company. Being the subscriber of this company might have brought in essential differences between this monitoring group and the rest of the households in the country, based on cognitive variables like attitudes, values, etc. In order to overcome the limitation of representation this might have created, participants for monitoring were selected under the condition of forming a distributed mix of the Dutch population in terms of age, gender and education. Additionally, they did not have specific affinity with energy consumption through their work. In addition, to decrease the impact of the limitations of the research on the quality of the outputs, other published research was consulted to compare and validate the results.

Even if the data obtained during 2 months revealed about behavioral patterns more precisely, it is still time-bound, which means there is a big possibility that different patterns will be observed in a year, two years, and longer on the sample, depending on the changes in lifestyle, household composition, etc. of the households.

Van Dam (2013) discussed the problems of conducting research in collaboration with the industry, stating that the interests of the industry might differ from those of the scientific researchers, and that researchers should be careful about it since the tendency for such collaborations is on the increase: "The difference of interests might result in different priorities for parties, and the merits of scientific research can be assessed differently. Privacy and sharing of data may be interpreted in articulated viewpoints, which might have negative influence on the monitoring process and available data for scientific research." She also reported that finding participants for monitoring might take more effort than expected. Similar challenges were reported in former research, for instance with technical barriers (Nye et. al., 2010) and participants (Hutton et. al., 1986). This shows that preparing good research protocols, especially defining the procedures of sharing and assuring privacy, the involvement of households for monitoring, and the use of data are crucially important.

§ 5.6 Conclusion

This paper investigated thermostat control behavior in 61 Dutch dwellings in detail, using an applied questionnaire on household and dwelling characteristics, and behavioral attitudes, as well as the HEMS recording data on chosen thermostat settings in March and April 2011. The paper analyzed the thermostat control patterns and profiles of the households, and evaluated monitoring as a method for understanding the relationship between occupant behavior and energy consumption.

We found that most households used HEMS mainly to control their thermostat settings. Also, most occupants changed their thermostat setting as part of their main daily activities, when they came home, when they got up in the morning, before going to bed, when they left home, etc. It is also worthy to note that we identified the patterns and profiles of behavior, but this did not mean that these were perfectly homogenous. There were always cross-overs between groups. Gadget obsession, care for comfort, and care for control were the main visible characteristics of the three different profiles.

4 occupant groups were identified, where the group of 'no pattern' required detailed investigation of the behaviors, household and dwelling characteristics to understand the context to the behavior. The other three were (1) 'one-off' households with a single set point per time of the day and interval of thermostat use, composed of higher educated males, gadget lovers, and not necessarily interested in energy saving; (2) 'comforty' households with thermostat use of more than one set point and interval with high temperature preferences in different days of the week, composed of home owners with high income, who had bigger size dwellings, not interested in energy saving and preferred higher temperatures; and (3) 'controller' households with single or double set point temperatures and intervals with low temperature preferences in different days of the week, as well as during March and April, composed of households with energy saving in agenda, who are mostly families, and sometimes the elderly, where the parents/couples took energy related decisions together.

In this study, we covered 2 months of data collection on thermostat use, however the period of data collection were March and April, where the weather conditions were not extreme in terms of temperature. It would be important to repeat/continue monitoring the same sample during Summer and/or Winter. In addition, any research on occupant behavior is inevitably time-bound. Hence, it would be interesting to re-visit the households to see the change in behaviors in the long run. Behavioral patterns regarding thermostat control and energy use could change in the long run. Lastly, this research does not have a representation capacity on its own, because of its small sample size. However, it provides deeper insight into behavior, and creates possibilities for validating its results from other literature.

This research has provided a better understanding of thermostat control and regarding behavioral patterns. By considering these insights, energy performance regulations could be articulated, better design of thermostat control devices could be achieved, more efficient infrastructural implementations could be developed by energy companies, the targeted energy saving measures could be better planned. Using the behavioral patterns, designers could facilitate processes for embedding HEMS in daily life. Energy management systems could be integrated more with thermostat control; this kind of combination might provide more efficient use.

Considering the heterogeneity of the behavioral patterns and profiles, and the possibility that more than one person might be managing thermostat, HEMS could be designed flexible enough to suit various possible activities/conditions at home. In this respect, this research could be furthered in a way that the field work includes all individuals that possibly use the HEMS. The technical issues in measuring and monitoring, as well as calibrating data remain as obstacles to deal with. It is important to emphasize that more consideration should be given to occupant behavior, for a more efficient user–machine interaction, and energy preservation.

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References

Assimakopoulos, V. (1992). Residential energy demand modelling in developing regions. Use of multivariate statistical techniques. Energy Economics 14(1), 57-63.
Bedir, M., Hasselaar, E., Itard, L. (2011). Occupant behavior and energy performance in dwellings: A case study in the Netherlands. PLEA 2011, Architecture and Sustainable Development Conference. Louvain-la-Neuve, Belgium.
Branco, G., Lachal, B., Gallinelli, P., Weber, W. (2004). Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data. Energy and Buildings 36 (6), 543–555.
CBS, Statistics Netherlands, www.cbs.nl (8 November 2016)
http://statline.cbs.nl/Statweb/publication/?DM=SLEN&PA=82375eng&D1=0&D2=a&D3=0,5,10,15,20,25-39&LA=EN&HDR=T,G1&STB=G2&VW=T (8 November 2016)
Darby, S. (2014). The effectiveness of feedback on energy consumption. Oxford, United Kingdom. www.eci.ox.ac.uk/research/energy/downloads/smart-meteringreport.pdf (last accessed: 30.06.2014).
van Dam, S. (2013). Smart Energy Management of Households. PhD Thesis. Delft University of Technology.
Field, A. (2000) Cluster Analysis. www.discoveringstatistics.com/docs/cluster.pdf
Gram-Hanssen, K. (2002). Technology and culture as explanations for variations in energy consumption. Proceedings of the American Council for an Energy Efficient Economy Summer Study in Buildings.
Gram-Hanssen, K., Kofod, C., Nærvig Petersen, K. (2004). Different everyday lives. Different profiles of electricity use, ACEEE Summer Study on Energy Efficiency in Buildings: Breaking Out of the Box.
de Groot, E., Spiekman, M., Opstelten, I. (2008). Dutch research into occupant behavior in relation to energy consumption of residence. Proceedings PLEA conference.
Guerra Santin, O. (2010). Actual energy consumption in dwellings: The effect of energy performance regulations and occupant behavior. PhD thesis, TUDelft.
Guerra Santin, O., Itard, L. (2010). Occupants' behavior. Determinants and effects on residential heating consumption. Building Research and Information 38(3), 318-338.
Haas, R., Auer, H., Biermayr, P. (1998). The impact of consumer behavior on residential energy demand for space heating. Energy and Buildings (27), 195-205.
Harputlugil, G., Bedir, M. (2016). Effects of occupant behavior on energy performance of dwellings: A sensitivity analysis. Intelligent Buildings International, special issue.
Hirst, E., Goeltz, R. (1985). Comparison of actual energy saving with audit predictions from homes in the north central region of the USA. Building and Environment (20), 1-6.

Hutton, R. B., Mauser, G. A., Filiatrault, P., Ahtola, O. T. (1986). Effects of cost-related feedback on consumer knowledge and consumption behavior: a field experimental approach. Journal of Consumer Research 13(3), 327-336.

Jeeninga, H., Uyterlinde, M., Uitzinger, J. (2001). Energieverbruik van Energiezuinige Woningen. Report ECN and IVAM.

KEMA Consulting. (2008). Smart Meter Requirements - Dutch Smart Meter specification and tender dossier. v2.1 final Main. KEMA Consulting. By order of EnergieNed. Retrieved: http://www.netbeheernederland.nl/DecosDocument/Download/?fileName=ME9LdQVsZjHwTjd0nEEAZrYPlkwxcT7vuIfV0_y_Df-8HZQIRp4H7sKD7gXLBnDn9&name=DSMR2.2-Main-Document

Liikkanen, L. A. (2009). Extreme-occupant approach and the design of energy feedback systems. International Conference on Energy Efficiency in Domestic Appliances and Lighting, Berlin, Germany.

Linden, A.L., Carlsson-Kanyam, A., Eriksson, B. (2006). Efficient and inefficient aspects of residential energy behavior: What are the policy instruments for change? Energy Policy (34), 1918-1927.

Lutzenheiser, L. (1993). Social and behavioral aspects of energy use. Annual Review of Energy and the Environment (18), 247-289.

McCarney, R., Warner, J., Iliffe, S., van Haselen, R., Griffin, M., Fisher, P. (2007). The Hawthorne Effect: a randomized, controlled trial. BMC Medical Research Methodology 7(30), DOI: 10.1186/1471-2288-7-30

Nye, M., Smith, G. D., Hargreaves, T., Burgess, J. (2010). The Visible Energy Trial: Report to OFGEM. Norwich: School of Environmental Sciences, University of East Anglia.

Ouyang, J., Hokao, K. (2009). Energy-saving potential by improving occupants- behavior in urban residential sector in Hangzhou. Energy and Buildings 41(7), 711-720.

Paauw, J., Roossien, B., Aries, M.B.C., Guerra Santin, O. (2009). Energy profile generator – understanding the effect of occupant behavior on energy systems, 1st European Conference on Energy Efficiency and Behavior http://www.eceee.org/conference_proceedings/eceee/2009 (last accessed: 08 May 2013).

Papachristos, G. (2015). Household electricity consumption and CO2 emissions in the Netherlands: A model-based analysis. Energy and Buildings (86), 403–414.

Poortinga, W., Steeg, L., Vlek, C., Wiersma, G. (2005). Household preferences for energy saving measures: A conjoint analysis. Journal of Economic Psychology (29), 49-64.

van Raaij, W.F., Verhallen, T.M.M. (1983). Patterns of residential heating behavior. Journal of Economic Psychology (4), 85-106.

van Raaij, F., Verhallen, T. (1983). A behavioral model of residential energy use, Journal of Economic Psychology (3), 39–63.

Røpke, I. (2012). The unsustainable directionality of innovation—the example of broadband transition. Research Policy (41), 1631–1642.

SenterNovem, Energiedata, senternovem.databank.nl (08 May 2013).

Shove, E. (2003). Converging conventions of comfort, cleanliness and convenience. Journal of Consumer Policy (26), 395–418.

Tyler, S., Schipper, L. (1990). The dynamics of electricity use in Scandinavian households. Energy 15(10), 841-863.

Ueno, T., Inada, R., Saeki, O., Tsuji, K. (2006). Effectiveness of an energy-consumption information system for residential buildings. Applied Energy 83(8), 868-883.

Vine, E., Barnes, B.K. (1989). Monitored indoor temperatures and reported thermostat settings: How different are they? Energy 14(5), 299-308.

Vringer, K., Blok, K. (2007). Household energy requirement and value patterns. Energy Policy (35), 553-566.

Wood, G., Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: environment, behavior, design. Energy and Buildings (35), 821-841.

6 Behavioral patterns and profiles of electricity consumption in dutch dwellings

Introductory note

Having investigated the determinants of electricity consumption in relation to household and dwelling characteristics, Chapter 6 provides a closer look at the behavioral patterns of household appliance use and electricity consumption. The OTB sample was used to conduct correlation and factor analysis.

This Chapter deals with the Research Question III-2 of this thesis:
(Chapter 1, Section 3, pg. 16-17)
" III. What are the behavioral patterns and profiles of energy consumption?

The sub-question is:
What are the behavioral patterns of electricity consumption? How do they relate to the household characteristics, revealing behavioral profiles? "

The research reported in this Chapter was conducted by Bedir. The data was collected by a questionnaire prepared by Guerra Santin and Bedir, using OTB's means of data collection. The analysis was done, and the paper was written by Bedir. The co-author (E.C. Kara) commented on methodology of the research. The co-author has given his permission to include the paper in the thesis.

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§ 6.1 Introduction

Residential buildings consume 23% of the electricity in the Netherlands (IEA, 2008). ODYSSEE-MURE project reports that, in European Union (EU) countries, although the consumption of large appliances has decreased considerably between 2000-2012 (Figure 1 (left)), increasing ownership and use of appliances and larger homes push the electricity consumption up by about 0.4% per year, per household (ADEME, 2007). Household electricity consumption in the Netherlands has followed a similar pattern to the one of EU (Figure 1 (center) and (right)). While the efficiencies of washing machine, dryer, dish washer, refrigerator, and freezer have immensely improved and their use remained similar, thus reducing their overall electricity consumption; the ownership, usage time and power of computer, printer, TV, DVD, and other personal electronic devices, electric oven, microwave oven, kettle, and similar have gone up, thus increasing their overall electricity consumption (ECN, 2012).

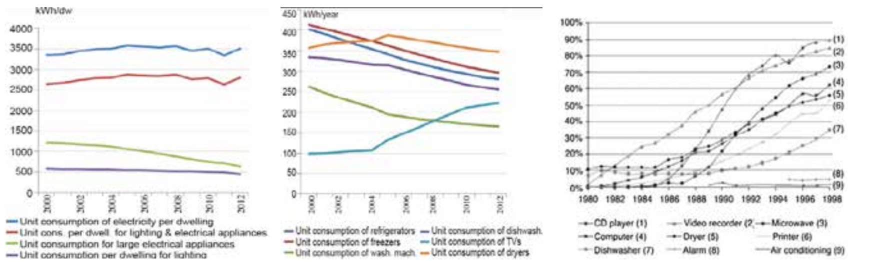


FIGURE 6.1 Average electricity consumption per dwelling in EU (left), Electricity consumption of large electric appliances and TV (middle), Ownership of appliances in the Netherlands (right)

These statistics point to the importance of the influence of occupants' ownership and use of lighting and appliances, and systems on the electricity consumption in dwellings. Several studies have claimed that households can achieve more energy savings by changing occupant behavior (Papachristos, 2015; Ouyang et al., 2009; Wood et al., 2003; Darby, 2006). Therefore, it is important to analyze the share of occupant behavior in energy consumption in detail. More research on the issue is needed; however, there are several reasons to why this is difficult, some of which are the retrospective methods of data collection by the energy companies, the assumed usage patterns of systems and appliances in most calculation tools, the uncertainties in collecting and analyzing data, the issues of energy performance gap (Ropke, 2012).

In existing research, behavioral factors related to heating energy consumption have been identified, as well as the household and dwelling characteristics that are related to these behavioral factors (van Raaij et al., 1983a; Poortinga et al., 2005; Guerra Santin, 2010). The studies point to the potential of energy consumption reduction, if energy efficiency policies are articulated according to different household profiles (van Raaij et al., 1983a; 1983b). The ability to make accurate predictions of the electricity usage of households is an important issue not only for policy but also for energy companies, and will become even more important with the emergence of smart electricity grids (Bedir et al., 2013).

In the Netherlands, various studies have been conducted with the aim of identifying behavioral patterns related to higher levels of heating energy consumption and/or to energy-saving attitudes, however there is no such study for electricity consumption behavior. Our work contributes to the literature by providing detailed information about electricity consumption behavior, and by determining the patterns and profiles of users. Existing research suggests that occupant behavior is more visible in newer than in older dwellings (Guerra Santin, 2010). Accordingly, our sample might be appropriate to study energy consumption behavior, because our data is collected on dwellings built after 1995. In addition, it seems that electricity consumption behavior relates far less to the physical characteristics of a house compared to that of heating energy consumption, therefore routines of electrical appliance use might provide us with more articulated insights into occupant behavior. This research could contribute to the efforts, such as Wright's (Wright, 2008), that focus on encouraging individuals and households towards more energy efficient behavior.

In our previous paper (Bedir et al., 2013), we reported on the variance in the total electricity consumption and researched the determinants of it in dwellings in the Netherlands. We found that using the parameters of duration of use of general, hobby, food, and cleaning appliances, household size, gas consumption, years of residence, number of bedrooms, dwelling type, number of showers, dryers, washing machine loads, and outside working hours, we could explain 58% of the variance in electricity consumption. In this paper, we use the same sample and data we used in our former work. Our first aim is to further analyze the behavioral aspects of household electricity consumption in the Netherlands. For this, we statistically define behavioral patterns and profiles of lighting and electrical appliance usage in relation to electricity consumption. Further, we identify the household and building characteristics, along with clues about lifestyles and attitudes, which provide the evidence to build behavioral profiles.

Our data is collected by a survey from 323 dwellings in the Netherlands on (1) appliance ownership, (2) presence in rooms, (3) activities of cooking, shower and bath, cleaning, (4) household composition and dwelling characteristics. Existing research focuses either on behavioral patterns using the first three groups of data, or on behavioral profiles using the last group of data. Our second aim is to link the patterns and profiles using the behavioral factors as a common denominator, found by factor analysis, which could help to better define occupant behavior in calculations and/or simulation programs.

§ 6.2 Literature and Research Questions

Behavioral patterns and profiles have been defined with household characteristics (Lutzenheiser, 1993; de Groot et al., 2008; Paauw et al., 2009), variables related to lifestyle (van Raaij et al., 1983a; de Groot et al., 2008; Paauw et al., 2009; Assimakopoulos, 1992; Tyler et al., 1990), variables related to values, motivations, attitudes (Poortinga et al., 2005; Gladhart et al., 1986; Ajzen, 1991; Assael, 1995; Vringer et al., 2007), and variables related mainly to routines and habits (Gram-Hanssen et al., 2004; Gram-Hanssen, 2002; Shove, 2003). Abreu et al. (2012) adopted a profile recognition method to identify user profiles of electricity consumption. The electricity consumption data was collected with 15 minute intervals from 15 houses over a period ranging from 3 months to 1 year. Clusters were then created using profile recognition over this quantitative data. Households completed questionnaires to self-report their daily routines, and the usage profiles that were obtained with this 'qualitative' data were compared with the 'quantitative' clusters for validation. The study showed that approximately 80% of household electricity use can be explained through repeated daily routines.

Widen et al. (2009) produced load profiles over 5 existing time-use data sets collected in Sweden in 1996, 2006, and 2007. The number of people included in the surveys varied from 13 to 431 in 5 to 139 households. The activities of people were reported next to measurements of electricity and hot water consumption. The data resolution varied from 5 minutes to 60 minutes. The activity profiles created with reported data were compared to the ones with measured data. The results showed that household behavior profiles regarding cooking, washing, lighting, TV, PC and audio use could be modeled using time-use data of electricity consumption. However, hot water consumption was not successfully modeled. It was clear that electricity consumption was closely related to occupancy and the grouping of appliances according to specific activities, and this could be a good way to modelling electricity consumption.

Coleman et al. (2012) monitored 14 households in the UK between March 2008 and August 2009. The dwellings were selected by snowball sampling, and they had over 220 individual appliances. This research found that usage profiles varied widely between households in both size and make-up, and the average (mean) household electricity consumption from ICE (information, communication and entertainment) appliances equated to around 23% of average whole house electricity consumption (median 18%). Of this, standby power modes accounted for 11.5 kWh, which was around 30% of ICE appliance consumption and around 7% of average whole house electricity consumption. Coleman et al. found that desktop computers and televisions were the appliances that consumed the most electricity, with most of their consumption occurring during the active power mode. Audio appliances, printers, and other play and record equipment were significant end-uses, largely due to standby consumption. In one of the households, computers that were continuously active and connected to the internet were also found to be responsible for a large portion of the sample's electricity consumption.

O'Doherty et al. (2008) analyzed the determinants of domestic electrical appliance ownership in the Irish housing stock. A survey conducted in 2001 and 2002 on 40,000 houses revealed that newer and more expensive houses had more appliances, but also more Energy Saving Appliances (ESA). Years spent at the same address decreased the ownership of ESA. Likewise, householders under the age of 40 had the most appliances but also the most ESA. Dwellings located in dense urban areas had more ESA. Lastly, more suburban, terraced houses had the least ESA. O'Doherty et al.'s (2008) groups were determined based on household and dwelling characteristics together, however no relationship was researched between these groups and electricity use.

Genjo et al. (2005) used cluster analysis to group 505 Japanese households. This research did not necessarily try to identify the specific characteristics of the groups according to their electricity consumption, but some distinct findings of their research were that the possession of electrical appliances was a reflection of residents' lifestyle, larger and multi-function appliances were popular among Japanese households, and economic affluence had a strong influence in grouping the households according to appliance use and electricity consumption.

In the Netherlands, research on behavioral profiles regarding energy consumption focus on heating energy. Even if this research is only on electricity consumption, it is insightful to see and compare ours' to the studies that analyzed heating energy consumption in terms of the household characteristics, behavioral factors, patterns and profiles. van Raaij and Verhallen (1983a) identified 5 profiles of energy behavior among 145 households in the Netherlands: Conservers (higher education, smaller household size), Spenders, Cool, Warm (oldest group) and Average. They found no differences regarding income and employment parameters. The research of Groot et al. (2008) and Paauw et al. (2009) developed 4 profiles of energy consumption: convenience/ease (comfort important, no interest in economic savings, energy, or the environment (EEE)); conscious (comfort important, interest in savings for EEE), cost (awareness of economy and hence energy and the environment); and climate/environment (concern for EEE). van Raaij (1983b), de Groot (2008) and Paauw's (2009) work found statistically significant differences in energy consumption among their groups. Vringer et al.'s work (2007) grouped households in the Netherlands according to income, age, education and household size. Guerra Santin's research (2010) revealed 5 groups (spenders, comfort, affluent-cold, conscious-warm, conscious-cold) according to the use of heating and ventilation systems, household appliances, household and dwelling characteristics. She did not find statistically significant differences between the behavioral profiles and patterns in terms of energy consumption.

Existing research on behavioral patterns of electricity consumption focus on parameters related to 'attitude,' 'motivation,' 'lifestyle,' 'household composition,' 'appliance possession,' 'household and building characteristics.' Methodologically, behavioral patterns and profiles are produced either using continuous data on actual behavior (for example Bagge, 2007; de Almeida et al., 2011; Zimmerman, 2009) or by clustering behavioral profiles based on cross-sectional data about household characteristics (for example Guerra Santin, 2012), and some by combining both (for example Abreu et al., 2012; Widen et al., 2009; Coleman et al., 2012). In existing research, relationships between behavioral patterns, and household and building characteristics have rarely been investigated. Our work contributes to the literature by (1) using (partially) continuous data on actual behavior as well as household and dwelling characteristics, (2) driving behavioral factors, patterns, and profiles, and linking them to each other as well as looking for their relationship with electricity consumption.

There are several studies that focus on identifying the behavioral patterns and profiles for heating energy consumption, but none on electricity consumption behavior in Dutch housing stock. Determining behavioral profiles could lead to more accurate prediction of electricity consumption in dwellings, better planning for the targeted energy saving measures, and helping energy companies for more precise calculations.

§ 6.3 Methodology

§ 6.3.1 Research framework and methods

In this paper, we defined occupant behavior as the presence in a space, the use of lighting and appliances, and the activities at home that directly cause electricity consumption. Figure 2 and 3 display the research framework and methodology. We started with an analysis of the appliance use in the database. Through a descriptive analysis, we reported the maximum, minimum and mean levels of ownership and use of appliances in the database (Section 4.1, Table 1). Secondly, we researched the effect of occupant behavior on electricity consumption in the database, through correlation analysis between the behavioral, household and dwelling characteristics, occupant presence, electricity consumption (Section 4.2, Table 3).

In step three, we conducted exploratory factor analysis to determine the factors underlying behavior of electricity consumption (Section 4.3, Table 4, Figure 4). Behavioral factors are clusters of variables that constitute the drivers of behavior. Following the factor analysis, the household variables were dichotomized according to their scores for each behavioral factor (below the mean = 0, above the mean = 1), which meant that each household had a '0' or '1' score for each factor, and each household had a string composed of '0's or '1's. Categorizing the households according to the common strings, the behavioral patterns were defined (Section 4.3, Table 5, Figure 5).

In step four, the behavioral factors were used in correlation analysis, in order to find out the relationship between behavioral factors and household and dwelling characteristics. The households were distributed into groups based on the correlation outputs, these groups were the user profiles (Section 4.4, Table 6 and 7, Figure 6). Lastly, we looked for the relationship between the behavioral factors, patterns and the behavioral profiles (Section 4.5, Figure 7). Following, the relationship between behavioral patterns, profiles and energy consumption was determined (Section 4.6, Figure 8).

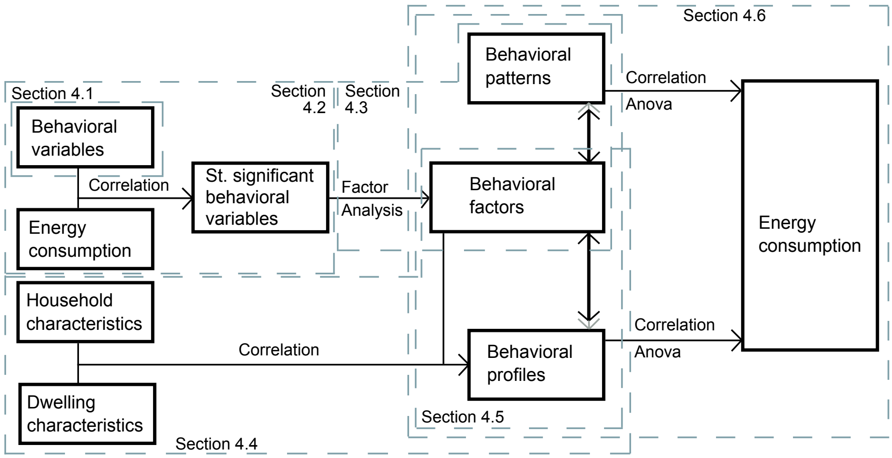


FIGURE 6.2 Research methodology

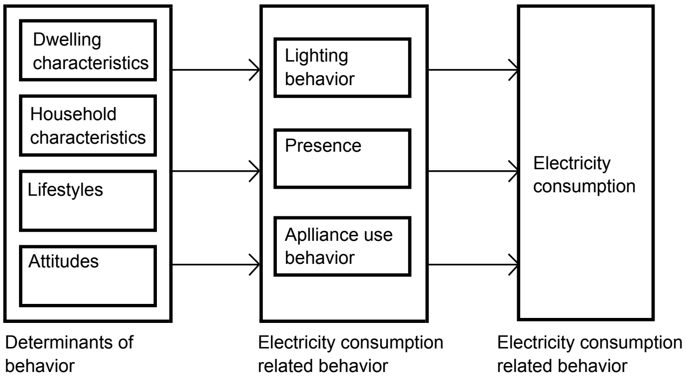


FIGURE 6.3 Research methodology-2: Research framework

§ 6.3.2 Data: Explanation of data, outliers, transformed variables

The study data was collected via a survey in two districts (Wateringse Veld and Leidsche Rijn) in the Netherlands only in the winter of 2008. The database of 323 cases covered a range of topics in the form of a questionnaire, with regard to household characteristics (size, composition, years of residence in the dwelling, changes in household composition in the previous year), individual characteristics (age, education, occupation, hours spent outside the home), economic characteristics (income, ownership, electricity tariff), presence (number of people and duration of occupation in each room), dwelling characteristics (type, number of rooms, function of rooms), appliance use (number of domestic appliances, number of appliances in the living room, standby appliances, chargers, duration of use, appliance labels, sizes), and lighting devices (number, type).

§ 6.3.2.1 Outliers

Outliers were analyzed and variable frequencies were checked to see how many of the variables could be used for statistical analysis. Out of the 323 cases in the database, the electricity consumption data for seven were exceptionally high, probably because the occupants did not actually record the electricity consumption in the past year but took the meter reading. Twelve questionnaires were returned blank. These 19 cases were therefore excluded from the database, leaving a final sample size of 304.

§ 6.3.2.2 Missing data

Some of the data in the database were insufficient to be included in the statistical analysis, hence were not included, namely:

- The number of weeks when nobody is at home;
- Whether the electricity and gas meters were checked regularly
- Appliance labels

§ 6.3.2.3 Transformed variables

The 'electricity tariff' can take two values in the Netherlands: (1) single tariff consumption – one daytime and evening rate on weekdays and weekends, (2) double tariff consumption – two different rates, one for during the day and another for evenings, nights and weekends. The electricity consumption data obtained from the survey were based on kWh values. Some cases had single tariff consumption records (9%), and some had double records (91%). To obtain a final variable for electricity consumption, a check was performed to determine whether a single or double electricity tariff made a difference. No significant correlation was found, so the single and the double tariff recordings were computed to one electricity consumption category.

The respondents retrospectively reported their hourly presence at home and in different rooms, during the week. This data was transformed into total hourly presence in rooms during the morning, the day, the evening, the night and all day.

In terms of the number of appliances owned, and the duration of use of the appliances, we conducted two transformations. First, in order to obtain a total figure of duration of use, we multiplied the number of appliances in the house with the duration of use of each. Secondly, we added up the total duration of use of appliances per function of group. We created 4 groups with functions of 'Information Communication Entertainment (ICE)', 'Cleaning', 'Food preparation' and 'Continuously used' appliances (Table 1).

Following, the results of the study are reported in 4 sections: 1. Descriptive analysis on appliance ownership and use; (2) the impact of occupant behavior on electricity consumption; (3) behavioral factors, patterns, and profiles of electricity consumption; as well as (4) the relationship among them.

§ 6.4 Results

§ 6.4.1 Appliance use behavior

The mean, maximum and minimum number of each appliance in the sample, and their duration of use (minutes per day) were reported and categorized in 4 groups, i.e. 'Information Communication Entertainment (ICE)', 'Cleaning', 'Food preparation' and 'Continuously used' appliances (Table 1). On average, there were 21 appliances in a house and 5 of these appliances were in the living room. The average electricity consumption in our sample was 3058.57 kWh/year.

On average, there was a fridge, a freezer, a wireless internet router, and a telephone that worked continuously in each house. As for cleaning appliances, a dishwasher and a dryer, a vacuum cleaner and an iron were used in each house in the sample. ICE appliances were 2 TVs, a PC, a laptop, a DVD player, and a music player. Lastly, a dishwasher, a microwave oven, a toaster, a grill, a water heater, a coffee maker, and an exhaust hood created the set of food preparation appliances present in each house on average, in our sample. Except for continuously used, all the appliance groups we set up refer to a specific function/activity in the house. Besides, only 'food preparation' appliances is a category that relate to a specific room (kitchen) in the house.

Continuously used appliances						Cleaning appliances				
Appliance	M	Max	Min	SD		M	Max	Min	SD	Appliance
Wireless router	1	3	0	0.56	N	1	1	0	0.47	Dryer
					D	19	130	0	28.18	
Telephone	1	8	0	1.13	N	1	3	0	0.27	Iron
					D	17	150	0	23.78	
Fridge	1	2	0	0.35	N	1	3	0	0.39	Vacuum
					D	16	90	0	23.85	cleaner
Freezer	1	2	0	0.56	N	1	1	0	0.18	Washing
					D	50	90	0	D	Machine
Food preparation appliances						ICE appliances				
Appliance	M	Max	Min	SD		M	Max	Min	SD	Appliance
Coffee machine	1	3	0	0.47	N	2	6	0	0.89	TV
	32	840	0	76.10	D	238	900	0	61.87	
Toaster	1	2	0	0.53	N	1	5	0	0.82	PC
	3	85	0	7.11	D	153	2880	0	09.12	
Electric grill	1	2	0	0.46	N	1	6	0	1.08	Laptop
	14	255	0	23.77	D	190	3060	0	69.92	
Microwave oven	1	2	0	0.36	N	1	4	0	1.07	Stereo
	10	85	0	13.51	D	104	720	0	147.9	
Water heater	1	2	0	0.35	N	1	3	0	0.68	DVD player
	13	85	0	14.54	D	21	360	0	40.92	
Cooker hood	1	2	0	0.42	N					
	30	180	0	32.84	D					
Dishwasher	1	2	0	0.43	N					
	42	240	0	45.33	D					

TABLE 6.1 Appliance use: Ownership and duration (minutes per day) (N: number of appliance; D: duration of use; M: mean; SD: Standard Deviation)

Some of the houses also owned specific appliances. The ownership and/or the use of these appliances were not high enough, so we did not include them in the factor analysis. The number of appliances they possessed were reported in Table 2.

Appliance name	Number of households	Percentage of households in the sample
Electrical cooker	107 houses	36%
Gas furnace	92 houses	31%
Induction cooker	87 houses	30%
Solarium	24 houses	8%
Jacuzzi	8 houses	3%
Sauna	5 houses	2%
Waterbed	13 houses	4%
Aquarium	10 houses	3%
Terrarium	13 houses	4%
Close-in-Boiler	28 houses	9%
Extra heating	14 houses	5%
Ventilator	45 houses	15%
Air Conditioning	13 houses	4%
Video camera	64 houses	21%
Video games	60 houses	21%
Home cinema	80 houses	27%
Hard disc recorder	69 houses	23%
Video recorder	98 houses	33%
Other appliances	33 houses	20%

TABLE 6.2 Specific appliances owned by a percentage of households

§ 6.4.2 Effects of occupant behavior, household and building characteristics on electricity consumption

Correlation analyses were carried out to determine the relationship between occupant behavior and electricity consumption (Table 3). The first set of variables considered were the use of household appliances. ICE (Information-Communication-Entertainment) appliances appeared to have the most significant influence on electricity consumption (r= 0.98***), which was followed by the total duration of use of household cleaning (r= 0.13**), food preparation (r= 0.09*) and continuously used (r= 0.02*) appliances. In the survey, respondents were also asked to report their behavior on the weekly use of appliances, and the total use particularly in the living room, however these variables did not seem to be correlated to electricity consumption, hence they were omitted from the analysis.

Secondly, the influence of the use of stand-by and battery charged appliances, and the ownership of energy saving, non-energy saving lamps, and PV/solar panels were analyzed. The most significant impact on electricity consumption was by halogen lamps (r= 0.17**). The use of battery charged (r= 0.22*), and stand-by (r= 0.15*) appliances had a positive influence on electricity consumption, while energy saving lamps (r= -0.04*), and PV/solar panels had a negative one. The ownership of PV/solar panels did not, in fact, significantly correlate with electricity consumption, however this parameter was included in the factor analysis, to set up behavioral patterns and profiles.

The use of mechanical ventilation was not found to be correlated with electricity consumption, but the use of shower (r= 0.23**), bath (r= 0.14*) and the number of hot laundry cycles (r= 0.19**) were. Showers were calculated in terms of the total duration of showers per week in the household, and bath in terms of total number of them per week in the household.

Presence in rooms (other than the living room) were positively correlated with electricity consumption. The correlation analysis showed that the presence in room 1 (r= 0.22*) and room 2 (r= 0.31*) all day, room 3 (r= 0.12*) during the day, and living room/kitchen (r= 0.21**) and bathroom (r= 0.18**) in the morning were positively and significantly correlated with electricity consumption.

Group	Variable	Definition	Nu of cases	M & SD	Correlation with electricity use
Household appliances	Continuously used	Total daily duration of use of continuously used appliances	H: 118	M: 4895.58	0.02*
			L: 164	SD: 2414.45	N: 282
	Food preparation	Total daily duration of use of food preparation appliances	H: 107	M: 238.77	0.09*
			L: 175	SD: 176.26	N: 282
	Household cleaning	Total daily duration of use of household cleaning appliances	H: 99	M: 116.98	0.13**
			L:183	SD: 105.88	N: 282
	ICE	Total daily duration of use of ICE appliances	H: 89	M: 1457.92	0.98***
			L: 193	SD: 1376.59	N: 282
	Stand-by	Total number of stand-by mode of appliances	H: 120	M: 2.75	0.15*
			L: 174	SD: 3.06	N: 294
	Battery charged	Total duration of battery charged appliances	H: 65	M: 67.5	0.22*
			L: 239	SD: 140.11	N: 304
	Energy saving lamps	Number of energy saving lamps	H: 104	M: 5.89	-0.04*
			L: 190	SD: 6.05	N: 294
	Halogen lamps	Number of halogen lamps	H: 117	M: 14.52	0.17**
			L: 177	SD: 10.07	N: 294
	PV/Solar panel	Presence of PV or solar panels	Y: 46	M: 0.15	-0.79 (r:0.23)
			N: 248	SD: 0.36	N: 294
	Hot wash cycles	Total weekly number hot laundry cycles	H: 62	M: 0.94	0.19**
			L: 230	SD: 1.50	N: 292
	Showers	Total weekly duration of showers in the household	H: 122	M: 139.21	0.23**
			L: 182	SD: 135.28	N: 304
	Bath	Total weekly number of baths in the household	H: 90	M: 1.33	0.14*
			L: 214	SD: 2.59	N: 304
Presence	Room 1	Total hours of presence in room 1 (weekdays/ all day)	H: 167	M: 13.61	0.22*
			L: 109	SD: 5.35	N: 294
	Room 2	Total hours of presence in room 2 (weekdays/ all day)	H: 111	M: 5.18	0.31*
			L: 165	SD: 4.08	N: 294
	Room 3	Total hours of presence in room 3 (weekdays/ during the day)	H: 20	M: 0.97	0.12*
			L: 259	SD: 0.20	N: 294
	Living room-Kitchen	Total hours of presence in living room-kitchen (weekdays/morning)	H: 85	M: 2.52	0.21**
			L: 188	SD: 2.11	N: 294
	Bathroom	Total hours of presence in bathroom (weekdays/ morning)	H: 91	M: 1.28	0.18**
			L: 182	SD: 1.17	N: 294

TABLE 6.3 Descriptive and correlation analysis of household and dwelling characteristics, occupant behavior and electricity consumption

Group	Variable	Definition	Nu of cases	M & SD	Correlation with electricity use
Household characteristics	Household size	Household size	H: 115	M: 2.53	0.38**
			L: 183	SD: 1.17	N: 301
	Years of residence	Years of residence in the same house	H: 151	M: 5.38	-0.16*
			L: 136	SD: 3.13	N: 287
	Age	Presence of age group 6-65 in the household	Y: 214	M: 3.00	-0.72*
			N: 84	SD: 0.75	N: 298
	Income	Monthly household income	H: 171	M: 3.99	0.13*
			L: 113	SD: 1.04	N: 284
	Education	A member of the household has university or higher education	Y: 32	M: 5.46	-0.03 (r:0.22)
			N: 270	SD: 2.03	N: 302
	Working outside	Hours spent outside the house	H: 178	M: 23.60	0.97 (r:0.13)
			L: 124	SD: 14.03	N: 302
Dwelling characteristics	Dwelling type	Type of dwelling (corner/self-standing house, top floor apartm.)	Y: 46	M: 2.95	-0.23*
			N: 255	SD: 1.05	N: 301
	Bedrooms	Number of bedrooms	H: 85	M: 1.84	0.26**
			L: 218	SD: 0.97	N: 303

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes on cases and abbreviations:
H: Number of cases that have higher value than the mean value
L: Number of cases that have lower value than the mean value
Y: Number of cases that have positive response to the question
N: Number of cases that have negative response to the question
Household income: H means higher (L for Lower) than 56 000 Euros
Age: Mean value of age groups in the sample is '16-65 years old.' However, for categorizing households in terms of electricity consumption, we expanded the group to (1) '6-65 years old;' and (2) 'children and elderly.'
Dwelling type: The mean value of 2.95 means row house is the common typology. For categorizing households in terms of electricity consumption in our analysis, we re-categorized this variable according to how much the dwelling might be receiving day light. Thus, we created two groups (1) corner, or self-standing houses, or top floor flats; and (2) row house, or ground or middle level houses.

TABLE 6.3 Descriptive and correlation analysis of household and dwelling characteristics, occupant behavior and electricity consumption

§ 6.4.3 Behavioral factors and patterns

A factor can be described with its measured variables and their relative importance to that factor (Field, 2009). The relationship among different variables in a database can be described using factor analysis, by exploring the factors that help to identify the related behaviors. We used exploratory factor analysis to identify behavioral factors underlying electricity consumption. We used the variables that were significantly correlated to electricity consumption (Table 3). However, some of the variables that were not significantly correlated to electricity consumption were still included in the analysis, considering that they might reveal further about the behavioral patterns.

Accordingly, 19 variables were used for the factor analysis. To start with, we checked if the factor analysis was suitable for our sample: The correlation significance and the coefficient values were checked between the different variables. Majority of the significance values were smaller than 0.05 and coefficient values were lower than 0.9, which meant that there was reasonable factorability, hence none of the variables were eliminated from the analysis. The determinant value was 0.00239, which was greater than 0.00001, therefore multicollinearity was not a problem for the data. Next, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, and Bartlett's test of sphericity were controlled. The KMO value was 0.73, and Bartlett's test was highly significant ($p< 0.000$) showing that factor analysis was appropriate to analyze our sample. Our sample size was greater than 250, we had less than 30 variables, and most of their communalities after extraction were around 0.7, as well as their average communality was 0.67 (which was greater than 0.6), therefore we retained all factors that have Eigen values above 1 (See 35 for a definition, and more explanation on KMO measure, Bartlett's test of sphericity, and Eigen value in factor analysis).

Based on each variable's primary score on each factor, the factor scores were created for the factors. Table 4 displayed the analysis results in terms of the variables defining each of the five factors, as well as the factor loading matrix and their communalities. The initial Eigen values, i.e. degree of variation in the total sample created by each factor, displayed that the first factor explained 16.29 % of the variance in electricity consumption, the second 15.23 %, the third 13.79 %, the fourth 9.00 %, and the fifth 7.84 %, creating a cumulative of 62.15%. Factors 6-19 were able to explain around 3-4% of the variance each. Accordingly, the first 5 factors were chosen to use further in the study. These factors were named as: 'total appliance use,' 'articulation of technology,' 'spatial presence,' '(personal) cleaning behavior' and 'energy conservation' (Figure 4).

Accordingly, Factor 1 was merely about the total duration of appliance use in the dwelling and comprised of the continuously used, food preparation, and cleaning appliances. Factor 2 was about the use of Information, Communication and Entertainment (ICE) appliances, and the use of stand by and battery charged appliances. This factor implied a more technology and device oriented lifestyle, as well as home-office working preferences. Factor 3 related to the presence of the occupants in the rooms, in the kitchen/living room and the bathroom, and the intensive use of halogen lamps. Factor 3 pointed to the relationship between spatial use at home and electricity consumption. Halogen lamps emphasized the less energy conscious attitude against everyday life. Factor 4 related to the intensive laundry and personal cleaning habits. The number of hot washes, the use of dryer and dishwasher, as well as the duration of showers, and the number of baths point to the significance of the influence of cleaning habits on electricity consumption. Factor 3 and 4 also hinted at the relationship between occupant comfort and electricity consumption. Factor 5 related to less use of electricity. The variables that defined this factor were the ownership of PV/solar panels, energy saving lamps, and the laundry habits, where the ownership of PV/solar panels, energy saving lamps, as well as the decreasing number of dryer and hot washing cycles had a negative influence on electricity consumption.

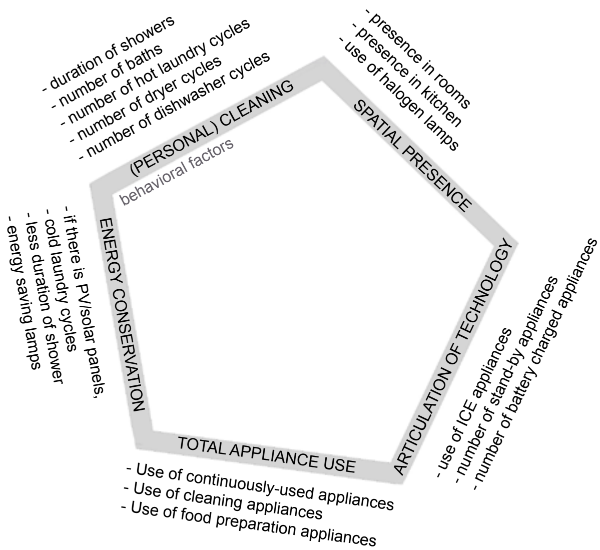


FIGURE 6.4 Behavioral factors and the variables that determine these factors

Variables	Components' factor scores					Communalities
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
Continuously used	0.588					0.677
Food preparation	0.509					0.527
Cleaning	0.468					0.645
ICE		0.721				0.631
Stand-by		0.493				0.525
Battery chargers		0.624				0.676
Energy saving lamps					0.429	0.704
Halogen lamps			0.530			0.754
PV/Solar panel					0.515	0.552
Hot wash cycles				0.448		0.755
Dryer				0.522		0.742
Dishwasher				0.562		0.677
Showers				0.577	0.325	0.695
Bath				0.432		0.589
Room 1			0.487			0.491
Room 2			0.660			0.573
Room 3			0.406			0.602
Living room-Kitchen			0.617			0.605
Bathroom			0.657			0.617

Rotation method: Varimax with Kaiser Normalization (for more explanation on the rotation method, see reference Field, 2005)
Factor scores <0.4 are suppressed.

TABLE 6.4 Factor scores and communalities (principle components analysis)

To determine the behavioral patterns, first we dichotomized the factor scores of the cases in our sample. We did this by comparing each case's factor score to the sample's mean factor score obtained from the factor analysis (if above= 1, if below= 0). Then we repeated it for the five factors. Through this, the five dichotomous scores for each case in the sample, i.e. each household, created a string. The clustering of all strings revealed thirteen categories (Table 5).

Afterwards, these categories were clustered once more, according to the correlation between the behavioral variables that compose the factors and electricity consumption (see Table 3 for the correlation analysis). Eventually, thirteen strings were organized into 4 patterns (Figure 5): Pattern 1: (Appliance use), Pattern 2: (Presence/Technology oriented), Pattern 3: (Presence/Comfort oriented), Pattern 4: (Energy conservation). Table 5 showed the behavioral patterns, the factors, and the distributions of the strings for each behavioral pattern and factor.

Name of pattern	Factor 1: Total appliance use	Factor 2: Articu-lation of technology	Factor 3: Spatial Presence	Factor 4: (Personal) Cleaning	Factor 5: Energy conserva-tion	Number of cases that constitute a string
1. Appliance use	1	1	0	1	1	21
	1	0	1	0	0	24
	1	1	0	1	0	23
2. Presence/ Technology	1	1	1	1	0	25
	1	1	1	0	1	22
	1	1	0	1	0	26
	1	1	0	0	0	21
3. Presence/ (Personal) Cleaning	1	1	1	1	0	19
	1	0	1	1	1	23
	1	1	1	1	0	18
	1	0	1	1	0	22
4. Energy conservation	1	0	0	0	1	18
	1	1	1	0	1	20

TABLE 6.5 Distributions of cases (N) and strings according to factors, and Derivation of behavioral patterns

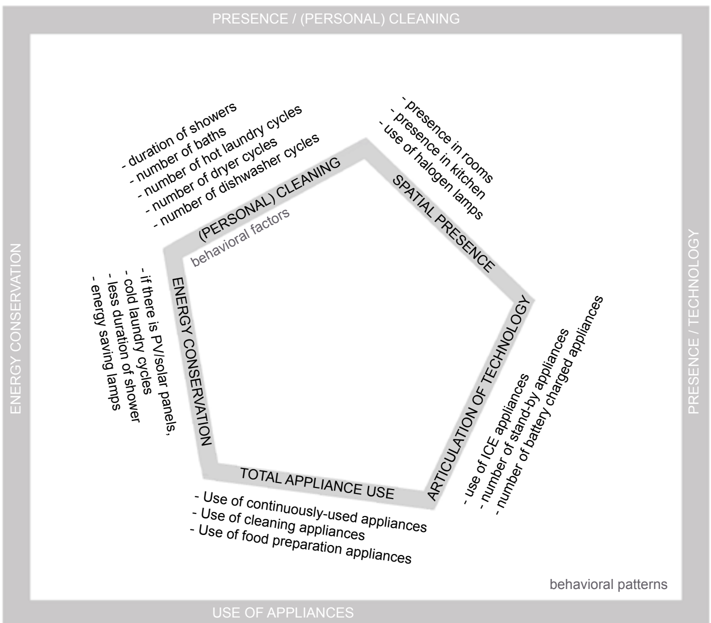


FIGURE 6.5 Behavioral factors and behavioral patterns

§ 6.4.4 Behavioral factors and profiles: Household and building characteristics related to behavioral factors

In order to determine the behavioral profiles in the sample, we analyzed the behavioral factors in terms of their correlation to the household and building characteristics. (Table 6). We saw that spatial presence was not attached to a certain household and/or dwelling characteristic, however it complemented profile 2 and 3.

Analyzing Table 6, we found the household profiles of 'family,' 'techie,' 'comforty,' and 'conscious,' which were explained further within the descriptions of the profiles in the next paragraphs, and in Table 7, Figure 6.

Household and dwelling characteristics		Factor 1: Total appliance use	Factor 2: Articulation of techno-logy	Factor 3: Spatial Presence	Factor 4: (Personal) Cleaning	Factor 5: Energy conserva-tion
Dwelling type (corner/free-st./top fl.)	Pearson Correlation	-0.18	-0.07	-	-0.03	-0.04
	Significance (2-tailed)	0.03	0.38	-	0.05	0.05
Nr. of b.rooms (other than living room)	Pearson Correlation	-0.17	0.31	-	0.08	0.10
	Significance (2-tailed)	0.06	0.00	-	0.03	0.24
Years of resi-dence in the same house	Pearson Correlation	0.01	-0.03	-	0.00	0.03
	Significance (2-tailed)	0.93	0.68	-	0.92	0.70
Household size	Pearson Correlation	-0.16	0.36	-	0.17	-0.11
	Significance (2-tailed)	0.05	0.06	-	0.02	0.02
Presence of children or elderly	Pearson Correlation	0.13	-0.19	-	0.14	0.04
	Significance (2-tailed)	0.15	0.09	-	0.01	0.60
Education level (highest in household)	Pearson Correlation	-0.01	0.01	-	-0.10	-0.03
	Significance (2-tailed)	0.89	0.05	-	0.26	0.04
Hours spent outside the house for work	Pearson Correlation	0.09	0.10	-	0.08	-0.05
	Significance (2-tailed)	0.31	0.03	-	0.02	0.05
Income level	Pearson Correlation	-0.50	0.11	-	0.09	-0.01
	Significance (2-tailed)	0.05	0.02	-	0.04	0.90

TABLE 6.6 Correlations between household and dwelling characteristics and behavioral factors

Factor	Name of Factor	Correlated Household/Dwelling variable
Factor 1	Total appliance use	- (Older couple) - Middle-ground floor dwelling - Lower income - More work outside - Household size (<2)
Factor 2	Articulation of technology	- Number of bedrooms - Work at home - Higher income - Household size (=>2)
Factor 3	Spatial presence	-
Factor 4	(Personal) Cleaning	- Number of bedrooms - Work at home - Higher income - Household size (=>2)
Factor 5	Energy conservation	- University education - Household size (<2) - Work outside - Corner/top floor house

TABLE 6.7 Behavioral factors and behavioral profilesv of heating energy consumption

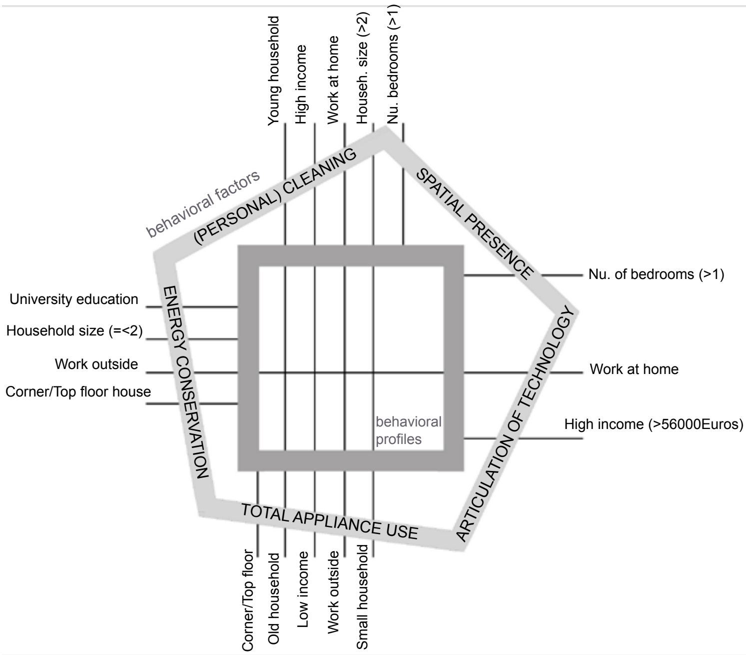


FIGURE 6.6 Household/dwelling characteristics, behavioral factors, and profiles

The results showed that the households that had high correlation values for factor 1: 'appliance use' were mostly young couples, except the few cases of the elderly. These households had the average behavior, both in terms of ownership and usage of continuously used, food preparation and cleaning appliances. They lived on ground or middle floor apartment or row house, which influence the natural light level in the house (hence the electricity consumption). The households had slightly lower income in some cases, compared to the other profiles. We called this profile as 'family.'

The household variables that related to factor 2: 'articulation of technology' had higher education level, higher income level, and in some cases, lower hours of working outside. Variables related to household composition did not appear correlated with this factor, but this profile had young single or couple household. One or both members of the household probably had a flexible working schedule, and possibly freelancing and/or working at home. The higher education and less hours of working outside was potentially related to the higher use of ICE appliances, stand-by and battery charged appliances. This household type was also related to factor 3 'spatial presence,' i.e. bedroom 3 (label 3 refers to the extra bedroom, or extra function of the bedroom other than sleeping) and bathroom. The use of bedroom 3 during the day confirmed working at home or home-office configuration. The use of bathroom in the morning might be related to shower and other personal cleaning behavior, however the factor of 'personal cleaning' was not found correlated with this profile. We named this profile as 'techie.' This group also had the largest number of hard disc recorders, video cameras and video recorders, which were not included in the analysis because of their small amount in the sample.

The variables which were related to Factor 4 ((personal) cleaning behavior), were dwelling typology (corner or freestanding), number of bedrooms, and a household profile of higher income level, bigger household size, and less hours of working outside. This group lived in larger houses with more than one bedroom, one or more children, and possibly one of the parents or both parents-part time stayed at home. This group came forward with its intensive use of appliances that related to dwelling and/or household cleaning, i.e. duration of showers, number of baths, dishwasher use, number of hot laundry cycles and dryer loads. In addition to Factor 4, this group was also related to Factor 3, presence in bedroom 1 and 2, which complemented the correlation with the variables of the number of bedrooms and working less hours outside, and presence in living room and kitchen. This group also used more halogen lamps, which points to less interest in energy saving. We named this group 'comforty.' This group had the largest ownership of induction and electricity cooker, waterbed and air conditioning, video games and home cinema, which were not normally included in the analysis because of their relatively small number in the entire sample.

This household profile related to Factor 5 'energy conservers,' which meant more use of energy saving lamps, and ownership of PV and/or solar panels, however these parameters did not appear significantly correlated with the factor. The household profile had less use of shower compared to other profiles, and it used less of dryer and hot laundry cycles, which related to Factor 4 '(personal) cleaning behavior.' This household profile had higher education level, worked more hours outside the house, had smaller household size, and lived in top floor apartment or corner house in some cases. The profile did not include a significantly correlated income parameter, but it had more income than profile 'family,' and less income than profile 'techie' and 'comforty.' We called this group as 'conscious.''

§ 6.4.5 Relationships between behavioral patterns, profiles, and factors

Figure 7 showed how the behavioral factors, patterns, profiles, and characteristics were related to each other. The behavioral patterns formed the outer layer, the behavioral factors formed the middle pentagon, and the behavioral profiles the inner square. The outer square represented the behavioral patterns. As top and right meant more use of electricity, the left and bottom meant less use of electricity. The middle pentagon showed the behavioral factors, i.e. total appliance use, articulation of technology, (personal) cleaning, and energy conservation. The behavioral patterns and factors seemed to be consistent, except for the factor 'presence,' which appeared both within (personal) cleaning and technology patterns. When electricity consumption and underlying behavioral factors are considered, the patterns of 'presence/technology' and 'energy conservation' seemed to oppose, as well as '(personal) cleaning' and 'use of appliances.'

Household profiles of 'conscious' and 'techie' seemed to oppose, when the household and dwelling characteristics related to the behavioral factors were taken into account. For instance, conservers worked more hours outside compared to techies, and seemed to live in dwellings that get more day light. Techies had more household income. Both groups had high education, although only for conservers this variable was significantly correlated with the behavioral factors. Similarly, 'comforty' and 'family' opposed with each other. 'Comforty' was of younger households, who had higher income and higher number of children, spent more time at home and had bigger houses. 'Family' was older, smaller in household size and income, and spent less hours at home in general.

§ 6.4.6 Relationships between behavioral patterns, behavioral profiles and electricity Use

The correlation analysis between behavioral factors and electricity consumption revealed that factor 1 (appliance use) was correlated with electricity consumption $r = 0.11$, $p<0.05$; factor 2 (articulation of technology) by $r=0.35$, $p<0.00$; factor 3 (presence) was not significantly correlated with electricity consumption ($r=0.14$, $p<0.15$); factor 4 ((personal) cleaning by $r = 0.37$, $p<0.00$; and factor 5 (energy conservation) was significantly correlated with electricity consumption ($r = 0.13$, $p<0.05$). These factors were used to define behavioral patterns.

For determining the differences in electricity consumption for each behavioral pattern, we conducted a one-way Anova test, where we found statistically significant differences ($r=0.17$, $p=0.02$). Both the statistically significant differences among behavioral patterns, and the similarities between our results with those of the literature showed that our research might be used further for research on electricity consumption and occupant behavior. Figure 8 showed the energy consumption for each behavioral pattern (Figure 7).

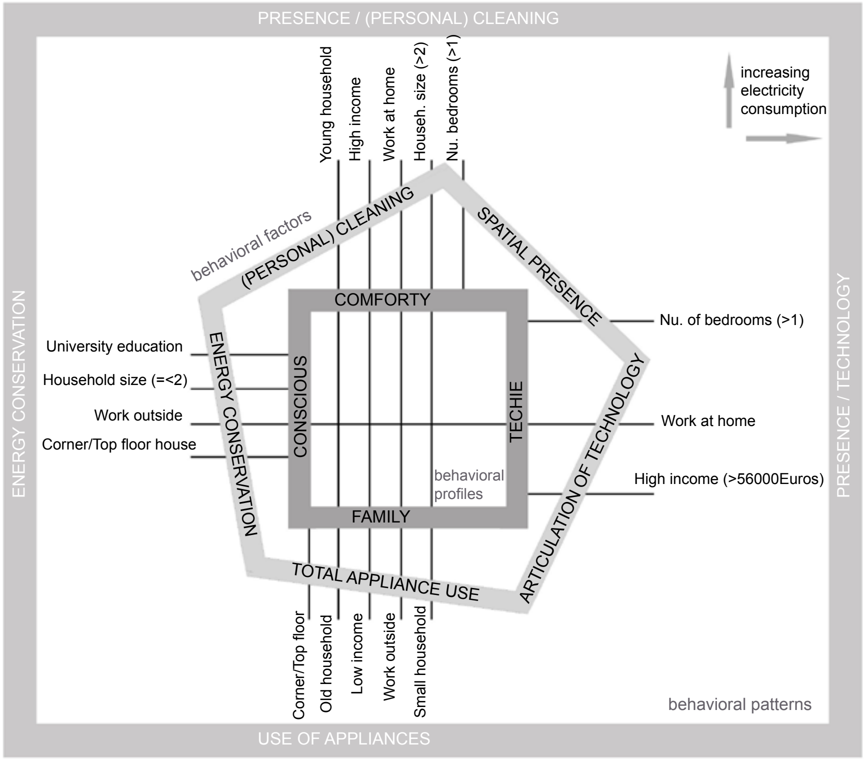


FIGURE 6.7 Relationships found between behavioral factors and household characteristics
Outer square/ Edges= behavioral patterns
Center pentagon/ Edges= behavioral factors
Inner square/ Edges= behavioral profiles
Lines= household characteristics (to the bottom and left characteristics that are related with less electricity consumption; to the top and right characteristics that are related with more electricity consumption are distributed.)

Following, we looked at the behavioral profiles in relation to electricity consumption (Figure 8). 'Family' had a high score for appliance use, 'techie' (technology oriented singles/couples who also worked at home) had a high score for articulation of technology and presence, 'comforty' (large families with high preference for comfort, showers, baths, dryer, etc.) had a high score for presence and (personal) cleaning, and 'conscious' (singles or couples with high education and working outside) for energy conservation (PVs, energy saving lamps, etc.). We found statistically significant differences among the four profiles in terms of electricity consumption (r=0.19, p=0.02).

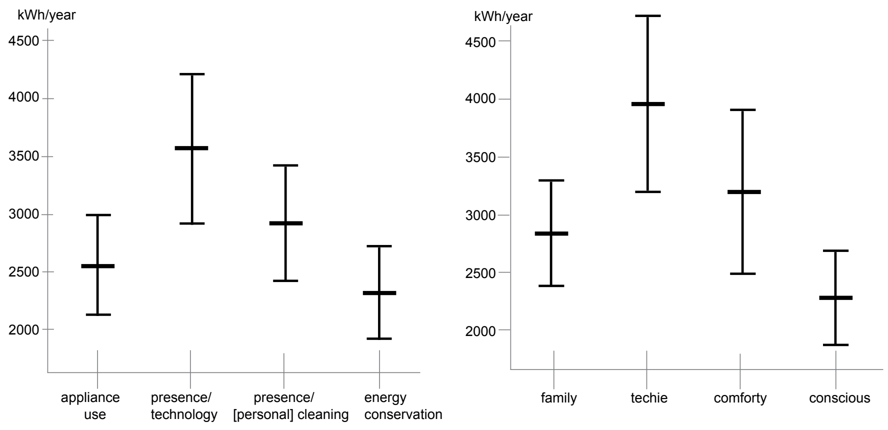


FIGURE 6.8 Mean and 95% Confidence Interval (CI) for electricity consumption in kWh/year for each behavioral pattern (left) and for each behavioral profile (right)

§ 6.5 Discussion

In this paper, we aimed to analyze in detail the behavioral aspects of household electricity consumption in the Netherlands. In this section, we present a discussion (1) on the appliance ownership, use and daily life; (2) on the results of factor analysis, i.e. the behavioral factors, patterns and profiles, and their relationship with electricity consumption; (3) on the comparison of our results with the existing research; and (4) on methodology.

§ 6.5.1 Appliance ownership, use and daily life

In terms of ownership of appliances, every household owning a dryer, a separate freezer, and 6 battery charged appliances is a remarkable result. Presence in rooms/ at home tells us about the times of the day that the appliances are used. In general, it could be said that most appliances, except for ICE are used in the morning (07:00-09:00), and the evening (18:00-20:00).

TOC

In our sample, every household has on average 2 TVs, 1 desktop computer, 1 laptop, 1 stereo system and 1 DVD player. Some households have 1 TV and 1 laptop per person. The total daily hours spent watching TV is 4 hours on average, PC use per day is approximately 2 and a half hours, and laptop use 3 hours. This suggests how central TVs and computers are to our lives. TVs are the most important electricity consumers at home, the energy efficiency of which haven't been improved as well as the other appliances. When we think of this together with the number of battery charged appliances, we could say the possession and use of ICE appliances will be very important for policy efforts in reducing electricity consumption in future.

As for cleaning appliances, a dryer is used 2 times per week and a washing machine 5 times. These numbers show that almost every item of clothing is worn only once before it is washed. When this is considered together with the 17 minutes use of the iron per day and the once or twice showers per person per day, it tells us about the occupations and/or the intense cleaning and comfort preferences of the households.

In terms of food preparation appliances per household (on average), the fact that there is a freezer in continuous use tells us about food storing/eating habits. Perhaps less fresh food is being consumed and/or households might always be preserving food for winter/summer. The grill and microwave oven being used 24 minutes in total per day suggests that the main meals consist of easy-to-prepare food. Lastly, a dishwasher is used 42 minutes per day on average, which means that either the dishwasher is used on the quick cycle every day, or the long cycle nearly 4 times a week.

§ 6.5.2 Behavioral factors/ patterns/ profiles

Using exploratory factor analysis, we found the behavioral factors as total appliance use, articulation of technology, spatial presence, (personal) cleaning behavior, and energy conservation. In consistence with the behavioral factors we found the 4 behavioral patterns as the use of appliances, presence/ (personal cleaning), presence/ technology, energy conservation. Following, the household and dwelling characteristics were included in the analysis, and the behavioral profiles were revealed as 'family', 'techie', 'comforty', and 'consciouss'.

Here we saw that the behavioral factor of spatial presence appeared in two behavioral patterns, i.e. cleaning and technology. While the use of ICE appliances created enough factor score to relate to a separate behavioral factor and pattern, the behavioral factor of presence appeared in two different behavioral patterns ((personal) cleaning and technology). The positive or negative behaviors of (personal) cleaning and use of halogen or energy saving lights also lead to two different patterns ((personal) cleaning and energy conservation).

By defining household characteristics in relation to behavioral factors, and the relationship between behavioral factors and patterns, one could determine the associated behavioral factors and behavioral patterns of a household. For instance, if a household is part of the 'techie' profile, we could expect a high score for 'articulation of technology' and 'presence at home,' which means working/being present high hours in the rooms, and using a lot of technological devices, including ICE appliances, stand-by, and battery charged appliances.

The higher or lower values of household size, income, education, working outside, number of bedrooms, and dwelling type were found to be related to different behavioral factors. For instance, the 'comforty' profile had bigger household size, higher income and number of bedrooms compared to 'family,' while it had lower working outside hours. The 'conscious' profile was found to have more hours of working outside, smaller household size, and higher education, compared to 'techie,' and was found to live in a house that gets more day light. The profile 'conscious' didn't necessarily correlate to income, but it had more income than profile 'family,' less income than 'comforty.' In our sample, considering the electricity consumption, the behavioral profiles did not relate to particular household stereotypes such as single, couple, elderly, etc., but to variables such as working hours, household size, education, and income.

§ 6.5.3 Comparison with literature

Our results were similar to those of Widen et al. (2009): Electricity consumption is closely related to occupants' presence. Besides, appliance use based on specific activities like cooking, washing, lighting, TV and PC use could be a good way to model occupant behavior and electricity consumption, and the related profiles. In our research, we found that the use of ICE appliances (articulation of technology) determined a behavioral pattern on its own. Coleman et al.'s research (2012) also pointed to the significance of ICE appliances: "computers and TVs during the active power mode, and audio appliances, printers, and other play and record equipment during standby consumption are significant end-users (23% of electricity consumption)." According to O'Doherty et al. (2008) householders under the age of 40 had the most appliances but also the most energy saving appliances (ESA). In our sample, the two groups had the most number of appliances were young singles, couples or families, which complied with the results of O'Doherty et al. Lastly, Genjo et al.'s (2005) analysis found that economic affluence had a strong influence in grouping the households according to electricity consumption. Income was one of the household characteristics that we used to determine the behavioral profiles, as well.

In the Netherlands, the research on behavioral profiles regarding energy consumption focus on heating energy, but still they are insightful to compare to our work in terms of their findings. van Raaij and Verhallen (1983a) identified 5 profiles of energy behavior as conservers, spenders, cool, warm and average, and the related household characteristics as household size, education, and age. Groot et al. and Paauw et al. (2008; 2009) developed 4 behavioral profiles based on comfort, interest in energy savings, and awareness of economy. Vringer (2007) grouped households in the Netherlands according to income, age, education and household size. Lastly, Guerra Santin's research (2010) revealed 5 groups according to the use of heating and ventilation systems, household appliances, household and dwelling characteristics. The variables of household size, education, age, comfort, and income were also those that we used in setting up the behavioral profiles in our sample. We didn't look into behavioral attitudes like interest in energy saving or awareness of economy. In terms of the profiles defined, 'conservers,' 'family,' and 'comforty' are the behavioral profiles found in literature, and visible in our results, as well. It might be interesting to look deeper into these profiles, since they might reveal more about the common underlying aspects of behavior that relate to similar electricity and heating energy consumption behaviors.

§ 6.5.4 Methodology

Technological advances and decreasing hardware prices enable new research to utilize smart meters and other continuous data collection methods (for instance Bagge, 2007; de Almeida et al., 2011). Research that works with this kind of data uses analysis tools like profile recognition (for instance Abreu et al, 2007), time use analysis and load modeling (Widen wt al, 2009; Paatero et al., 2006), eigen decomposition (for instance Calabrese et al., 2010) and Markov chains (for instance Bourgeois, 2005). Our research employed data collected by a questionnaire, therefore most of the data is cross-sectional, except for the behavioral data (presence, use of appliances and systems) that was collected based on a weekly calendar. In this kind of methodology, collected cross-sectional data on behavior is modelled by tools like cluster (based on cases) and factor analysis (based on variables). In this research, we worked with factor analysis. Further research could combine these two methodologies, confirming each other's results, as well as providing more insight into occupant behavior and electricity consumption relationship.

In terms of the limitations of this research, because our data is collected with a questionnaire, even if the questions on presence and behavior are detailed on a weekly basis, respondents might have filled in the information based on remembering their habits, but not actual behavior. This could be discussed as a limitation on the one hand, and as a successful approach on the other hand (Gram-Hanssen et al., 2004; Gram-Hanssen, 2002; Shove, 2003). Secondly, our data is collected from two Venex neighborhoods (satellite towns) in the Netherlands, where education and economical levels of households are quite homogenous. Even if the representation of these characteristics in our sample is in line with the Dutch averages, the homogenous distribution of the variables be the reason for them to come up as not-significant determinants of occupant behavior. Thirdly, the influence of Hawthorne effect (McCarney et al., 2007) must be mentioned, where the survey respondents' awareness of the goal of the survey might have directed them to fill-in the questionnaire different than the reality.

§ 6.6 Conclusions and Future Work

This research aimed to analyze in detail the appliance use in the Dutch housing stock, and define behavioral patterns and profiles of electricity consumption. We analyzed survey data collected from 323 dwellings in the Netherlands on appliance ownership and use; presence; cleaning; household and dwelling characteristics.

First, a descriptive analysis was conducted on the variables related to ownership of appliances, their use, presence, and household and dwelling characteristics, and electricity consumption. We created 4 groups with 'ICE', 'Cleaning', 'Food preparation' and 'Continuously used' appliances. As a second step, correlation analysis was conducted to see the relationship between variables related to occupant behavior and electricity consumption. The outputs of this analysis were used to realize a factor analysis revealing the underlying factors of behavior. Accordingly, we found total appliance use, articulation of technology, presence, (personal) cleaning, and energy conservation as the behavioral factors of electricity consumption. Afterwards, based on the behavioral factors, we defined the behavioral patterns (appliance use, technology/presence, (personal) cleaning/presence, energy conservation). Lastly, we looked for correlations between behavioral factors and household, and dwelling characteristics, from which we found the behavioral profiles (family, techie, comforty, conscious). In the next step, we considered the relationship between behavioral factors, patterns, profiles and electricity consumption. We found statistically significant correlations between different behavioral patterns, as well as between different behavioral profiles in relation to electricity consumption.

In the Netherlands, relationships between behavioral patterns, household and building characteristics in relation to electricity consumption have hardly been investigated. Our work adds to the research by using actual behavior data as well as household and dwelling characteristics, and by driving behavioral factors, patterns, and profiles, and linking them to each other as well as looking for their relationship with electricity consumption.

Determining behavioral profiles could lead to more accurate prediction of electricity consumption in dwellings, as well as planning the targeted energy saving measures, and helping energy companies for better calculations. Considering that occupant behavior might be more visible in the newer dwellings, and that behavior might be revealed more precisely by analyzing 'electricity' consumption, this research might provide more detailed and articulated input on occupant behavior to research and policy, which focus on motivating/encouraging individuals' and households' towards more energy efficient behavior.

In terms of future work, we could think of a couple of directions:

- Every household owning 1 wireless internet router in continuous use and 6 battery charged appliances should be researched further in terms of a mobile 24/7 lifestyle and the addiction to being 'connected'.
- Existing studies showed that large part of household energy use can be explained through repeated daily routines. As follow up work, the causes of daily routines of behavior that are related to electricity consumption should be researched further.
- In relation to the point above, collecting and analyzing longitudinal data on behavior is necessary to confirm the findings from cross-sectional data to overcome methodological limitations.
- Personal cleaning behavior appeared to be an important factor both in the patterns and profiles in this research, which suggests a comfort related aspect of energy consumption. This aspect needs to be investigated in terms of the motivations, frequencies, and consequences of the particular behavior.
- Further research is also needed on the actual household appliance inventory, their powers and energy ratings in much larger samples. This research could be extended by specifically investigating the use of ICE appliances, food preparation (especially freezer, dishwasher) and (personal) cleaning (use of shower and bath, use of dryer and washing machine) based on specific activities like cooking, cleaning, or hobbies. In addition, the stand-by and on/off functions and battery charged appliances must be studied more in detail.

Understanding the occupant behavior will be even more important in future for efficiency of electricity use. Findings from this research could help improving design of objects, systems and architectural design in order to reduce energy consumption by occupants at home.

References

Abreu, J. M., Pereira, F. C., Ferrão, P. (2012). Using profile recognition to identify habitual behavior in residential electricity consumption. Energy and Buildings (49), 479–487.

ADEME (2007). Evaluation and Monitoring of Energy Efficiency in the New EU Member Countries and the EU-25, Intelligent Energy Europe, 2007. http://www2.ademe.fr/servlet/getDoc?sort=-1&cid=96&m=3&id=51262&ref=17618&nocache=yes&p1=111 (last accessed 30.06.14).

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes 50 (2), 179-211.

de Almeida, A., Fonseca, P., Schlomann, B., Feilberg, N. (2011). Characterization of the household electricity consumption in the EU, potential energy savings and specific policy recommendations. Energy and Buildings (43), 1884–1894.

Assael, H. (1995). Consumer Behavior and Marketing Action. South Western College Publishing, Cincinnati.

Assimakopoulos, V. (1992). Residential energy demand modeling in developing
regions. The use of multivariate statistical techniques. Energy Economics 14
(1), 57-63.

Bagge, H. (2007). Energy use in multi-family dwellings: measurements and methods of analysis. Licentiate Thesis, Department of Building Physics, Lund Institute of Technology, Sweden.

Bedir, M., Hasselaar, E., Itard, L. (2013). Determinants of electricity consumption in Dutch dwellings. Energy and Buildings (58), 194–207.

Bourgeois, D. (2005). Detailed occupancy prediction, occupancy-sensing control and advanced behavioral modeling with-in whole-building energy simulation. PhD Thesis, Universite Laval, Quebec.

Calabrese, F., Reades, J., Ratti, C. (2010). Eigenplaces: Segmenting Space through Digital Signatures.

Coleman, M., Brown, N., Wright, A. S., Firth, K. (2012). Information, communication and entertainment appliance use—Insights from a UK household study. Energy and Buildings (54), 61–72.

Darby S. (2006). The effectiveness of feedback on energy consumption. Oxford, United Kingdom. www.eci.ox.ac.uk/research/energy/downloads/smart-meteringreport.pdf (last access: 30.06.2014).

ECN (Energy Research Centre of the Netherlands) (2012). Energy Efficiency Policies and Measures in The Netherlands, Report, 2012.

Field, A. (2009). Discovering Statistics Using SPSS. Sage Publishing, London, p. 627-685

Genjo, K., Tanabe, S., Matsumoto, S., Hesegawa, K., Yoshino, H. (2005). Relationship between possession of electric appliances and electricity for lighting and others in Japanese households. Energy and Buildings (37), 259–272.

Gladhart, P., Morrison, B., Zuiches, J. (1986). Energy and Families, Michigan State University Press, US.

Gram-Hanssen, K., Kofod, C., Nærvig Petersen, K. (2004). Different everyday lives. Different profiles of electricity use. ACEEE Summer Study on Energy Efficiency in Buildings: Breaking Out of the Box.

Gram-Hanssen, K. (2002). Technology and culture as explanations for variations in energy consumption. Proceedings of the American Council for an Energy Efficient Economy Summer Study in Buildings.

de Groot, E., Spiekman, M., Opstelten, I. (2008). Dutch research into user behavior in relation to energy consumption of residence. Proceedings PLEA conference.

Guerra Santin, O. (2010). Actual energy consumption in dwellings: The effect of energy performance regulations and occupant behavior. PhD thesis, TUDelft.

IEA (International Energy Agency) (2008). Statistics for 2008/Energy balances for 2008. www.iea.org (last accessed 20.05.11).

Lutzenheiser, L. (1993). Social and behavioral aspects of energy use. Annual Review of Energy and the Environment (18), 247-289.

McCarney, R., Warner, J., Iliffe, S., van Haselen, R., Griffin, M., Fisher (2007). The Hawthorne Effect: a randomized, controlled trial. BMC Medical Research Methodology 7(30), DOI: 10.1186/1471-2288-7-30
O'Doherty, J., Lyons, S., Tol, R. (2008). Energy-using appliances and energy-saving features: determinants of ownership in Ireland. Applied Energy (85), 650–662.
Ouyang, J., Hokao, K. (2009). Energy-saving potential by improving occupants- behavior in urban residential sector in Hangzhou. Energy and Buildings 41(7), 711-720.
Paatero, J.V., Lund, P.D. (2006). A model for generating household load profiles. International Journal of Energy Research (30), 273–290.
Paauw, J., Roossien, B., Aries, M.B.C., Guerra Santin, O. (2009). Energy profile generator – understanding the effect of user behavior on energy systems. Proceedings 1st European Conference on Energy Efficiency and Behavior.
Papachristos, G. (2015). Household electricity consumption and CO2 emissions in the Netherlands: A model-based analysis. Energy and Buildings (86), 403–414.
Poortinga, W., Steg, L., Vlek, C., Wiersma, G. (2005). Household preferences for energy-saving measures: conjoint analysis. Journal of Economic Psychology (29), 49-64.
van Raaij, F., Verhallen, T. (1983). A behavioral model of residential energy use. Journal of Economic Psychology (3), 39–63.
van Raaij, W.F., Verhallen T.M.M., (1983). Patterns of Residential Energy Behavior. Journal of Economic Psychology (4), 85-106.
Røpke, I. (2012). The unsustainable directionality of innovation—the example of broadband transition. Research Policy (41), 1631–1642.
Shove, E. (2003). Converging conventions of comfort, cleanliness and convenience. Journal of Consumer Policy (26), 395–418.
Tyler, S., Schipper, L. (1990). The dynamics of electricity use in Scandinavian households. Energy 15(10), 841-863.
Wood G., Newborough, M. (2003). Dynamic energy-consumption indicators for domestic appliances: environment, behavior, design. Energy and Buildings (35), 821-841.
Wright, A. (2008). What is the relationship between built form and energy use in dwellings? Energy Policy (36), 4544–4547.
Vringer K., Blok, K. (2007). Household energy requirement and value profiles. Energy Policy (35), 553-566.
Widen, J., Lundh, M., Vassileva, I., Dahlquist, K., Ellegard, E., Wackelgard, E. (2009). Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation. Energy and Buildings (41), 753–768.
Zimmerman, J.P. (2009). End-use metering campaign in 400 households in Sweden: Assessment of the potential electricity savings. ENERTECH.

7 Conclusion

In spite of the technological advancement on building design and construction, actual energy use levels of dwellings are different than expected in several cases. Little is known about how occupants interact with their dwellings, what the background to this interaction is, as well as the resulting energy use. This research aimed at revealing the relationship between occupant behavior and energy consumption, both in terms of heating energy and electricity. The determinants of occupant behavior, the sensitivity of dwelling energy consumption to occupant behavior, and defining behavioral patterns/profiles are the main elements of this work. This thesis will help to understand the occupant related factors of energy consumption in dwellings, by this way designing better products, energy management systems, software, and achieving better regulations.

Research on energy consumption of dwellings covers thorough investigation of the behavioral performance during the occupancy process, as well as the aspects that are involved in the design and building processes. There has been extensive progress on the building physics aspects of energy consumption; concerning methods and practices for specification of building geometry, material properties, and external conditions. However, the resolution of input information regarding occupant behavior is still rather low. In order to respond to this, one of the research questions of this thesis has been: what is the sensitivity of dwelling energy consumption to occupant behavior? Secondly, the influence of lighting and appliance use on electricity consumption, as well as the determinants of electricity consumption in dwellings, and lastly, the behavioral patterns of energy consumption are investigated.

This study's methodological approach combined the deductive and the inductive methods, by considering both the determinants of behavior and the actual behavior itself. Deductive methods dissect energy consumption into its factors, such as household characteristics, dwelling characteristics, behavioral aspects, etc. On the other hand, inductive methods model actual behavior from bottom up experimenting and validating energy consumption levels.

In this thesis, occupant behavior was considered as presence patterns in a space, together with the actual heating (thermostat setting and radiator control) and ventilation patterns (operation of windows, grids, and mechanical systems), and the use of lighting and appliances. This research looked at the building and household characteristics that determine occupant behavior, as well as habitual (surveyed) and actual (monitored) occupant behavior.

§ 7.1 Research Questions and Findings

This thesis deals with occupant behavior and actual energy consumption in the Dutch dwelling stock. Here, first the answers to the 4 sub-questions are presented in order to articulate the main research question, and then the response to the main research question is put forward.

§ 7.1.1 Research Q1: What is the sensitivity of a dwelling's heating energy consumption to occupant behavior? (Chapter 3)

- 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?
- How can behavior be modelled in order to assess the robustness of the energy performance in dwellings to occupant behavior?
- What is the weight of each behavioral aspect in terms of its influence on energy consumption?

In Chapter 3, our first hypothesis was proved: sensitivity analysis could be used as a method of evaluating the impact of occupant behavior on heating energy consumption. One important difference of our modeling method compared to existing research was that we did not assume presence as the initiating element of behavior, and nor as a precondition to behavior. There could be occupant behavior that has impact on heating energy consumption, while the occupant is not present in the space, such as preset thermostat and ventilation control behavior, etc.

Investigating our second research question about the weight of each behavior in terms of its influence on energy consumption, and which behaviors are more influential than others, we found that the energy consumption of a dwelling was the most sensitive to thermostat control, followed respectively by ventilation control and presence. We also found that ventilation at night or early in the morning had a great influence on the energy consumption of a dwelling.

Secondly, we found that presence in a space was not as closely related to heating energy consumption, but it was revealed as a strong element of electricity consumption.

Lastly, both heating energy consumption and indoor resultant temperature were the most robust to radiator control. Heating energy consumption was the most sensitive to thermostat settings, and the indoor temperature was the most sensitive to occupant presence. This could be because of the internal heat gain from presence.

§ 7.1.2 Research Q2: What is the influence of lighting and appliance use on the total electricity consumption in dwellings? (Chapter 4)

- What are the main direct and indirect determinants of electricity consumption? (Direct determinant: such as number of appliances and duration of appliance use ... Indirect determinant: such as household size, dwelling size, dwelling type ...)

- How much of the variance in electricity consumption in dwellings can be explained by direct and indirect determinants?

The number and duration of use of general appliances, cleaning appliances, food preparation appliances, and hobby appliances; number of standby appliances, battery chargers, light bulbs, energy-saving light bulbs were found to be significantly correlated to electricity consumption. Presence in room 1 (week – all day), room 2 (week – all day), bathroom (week – morning), room 3 (week – during day) were significantly correlated to electricity consumption.

In terms of household and dwelling characteristics, dwelling type, number of study/hobby rooms, income of the household, yearly gas consumption, household size, years of residence in the current house, hours of working outside, age groups, dishwasher use, washing machine use, number of hot (90 °C) and cold washes, dryer use, number of baths and showers, duration of shower and lastly the heating system type appeared to be significantly correlated to the electricity consumption.

We found no correlation between the location of appliances, the duration of use of ventilation appliances, the number of energy saving light bulbs in the living room, or in the rest of the house, and electricity consumption. In addition, home ownership and electricity-inclusive rent did not emerge as significant predictors of electricity consumption. Gender, education, existence of elderly people and infants in the household, change in household composition in the previous year did not appear to influence electricity consumption either.

Similarly, no correlation was found between electricity consumption and mechanical ventilation systems, probably because these systems were seldom used in our sample (people disabled them or hardly used them at all). Similarly, there was no correlation between the use of extra ventilation appliances and electricity consumption, because their usage was too low (14% of the respondents said they had a fan). Lastly, we could not check the impact of renewable energy because of the insufficient response to the question (10%) in the survey.

Three regression models were built for the direct and indirect determinants, one based on the duration of appliance use (direct) and presence (indirect), one on the number of appliances (direct) and Dwelling, Household, Economic, and Social (DHES) characteristics (indirect), and one on the total duration of appliance use and DHES characteristics. We found that, in the first model, total duration of appliance use alone explained 37% of the variance in electricity consumption. Presence in rooms explained 14% alone and 37% in the combined model. This meant that hourly data on presence did not contribute to modeling electricity consumption in dwellings, when it was considered together with the total duration of appliance use. Study/hobby rooms emerged as important factors in the relationship between presence and electricity consumption, whereas living room and kitchen did not. In the second model, the number of appliances explained 21% of the variance in electricity consumption alone and 42% when combined with DHES characteristics. Household size, dwelling type, the number of showers, use of dryer and washing cycles appeared significant. The final (third) model explained 58% of the variance in electricity consumption, it may be possible to set up a model on occupant behavior and electricity consumption with duration of appliance use and DHES characteristics.

Although we found a strong relationship between number of showers taken per week and electricity consumption, the duration of shower did not appear to be significant. Number of bathing times per week and duration did not appear significant either. ‘Showers taken per week’ gave the clue of a comfort related aspect of electricity consumption, considering the evolution of personal cleaning habits from bathing to showering. It seems like changes in lifestyle preferences might have an increasing influence on consumption patterns.

§ 7.1.3 Research Q3: What are the behavioral patterns and profiles of energy consumption?

- What are the behavioral patterns of thermostat control? How do they relate to the household characteristics, revealing behavioral profiles? (Chapter 5)

We found that most households used Home Energy Management Systems (HEMS) mainly to control their thermostat settings. Also, the most constant thermostat control behavior was at night. This did not change between weekdays and weekends, or in March or April. Most occupants changed their thermostat setting as part of their main daily activities, when they came home, when they got up in the morning, before going to bed, when they left home, etc. It is also worthy to note that we identified the patterns and profiles of behavior, but this did not mean that these were perfectly homogenous. There were always cross-overs between groups. Gadget obsession, care for comfort, and care for control were the main visible characteristics of the three different profiles.

4 occupant groups were identified, where the group of 'no pattern' required detailed investigation of the behaviors, household and dwelling characteristics to understand the context to the behavior. The other three were (1) 'one-off' households with a single set point per time of the day and interval of thermostat use, composed of higher educated males, gadget lovers, and not necessarily interested in energy saving; (2) 'comforty' households with thermostat use of more than one set point and interval with high temperature preferences in different days of the week, composed of home owners with high income, who had bigger size dwellings, not interested in energy saving and preferred higher temperatures; and (3) 'controller' households with single or double set point temperatures and intervals with low temperature preferences in different days of the week, as well as during March and April, composed of households with energy saving in agenda, who are mostly families, and sometimes the elderly, where the parents/couples took energy related decisions together.

7 households with no pattern of thermostat control should be studied much more in detail to understand the particularities of their behavior and characteristics. In these houses, we found evidence that the thermostat might not have been controlled by just one person, which meant that there were more occupant characteristics that were not identified within the current method of data collection/analysis. The other possibility was that there might have been technical issues in monitoring, with calibration or recording the data.

The no-correlation between reported and monitored day time temperature might have meant that people have reported the temperature as they remembered or felt at the time of the questionnaire, however the actual thermostat setting was a different one. This shows the importance of monitoring, i.e. longitudinal data collection in behavioral studies. The same argument could be asserted based on the frequency of touch-screen use, being much more intensive in March and less in April, a fact that was visible with monitoring, but could not have been reported in the questionnaire.

When partners managed heating together, they actually took more decisions towards energy conservation. Also, they checked the current and past energy consumption levels of gas and electricity. Dwellings that were bigger in size, higher in income level of the households, and owner occupied demonstrated more diverse and comfort oriented decisions of thermostat control behavior, which might have been because of the households' less interest in energy saving.

Our findings on the characteristics of households in relation to space heating control, mostly complied with literature in terms of household characteristics, in which age, household size, household composition, income, education, occupation, use of appliances. These characteristics come forward as significant characteristics that determine the behavioral profiles of heating energy consumption. Different than the existing research, in this study we found that even if the household characteristics were used to define different profiles, they didn't appear as the only major elements that determine the variance among groups. For example, 'one-off's were composed of higher educated respondents, but this did not mean that there was no representation of high education in the profile 'controller'; but it meant that education was a defining characteristic for 'one-off's, but not for group 'controller.' Similarly, we saw that 'comforty' group cared more about thermal comfort (as in 15), however, this behavioral attitude was in fact not only in 'comforty.' In this study, behavioral profiles were determined more heterogeneously.

In addition, different than the literature, we found that households with higher education were not necessarily often interested in energy saving, and that the elderly did not necessarily always preferred warmer temperatures.

– What are the behavioral patterns of electricity consumption? How do they relate to the household characteristics, revealing behavioral profiles? (Chapter 6)

This research aimed to analyze in detail the appliance use in the Dutch housing stock, and define behavioral patterns and profiles of electricity consumption. We analyzed survey data collected from 323 dwellings in the Netherlands on appliance ownership and use; presence; cleaning; household and dwelling characteristics. Descriptive, correlation and factor analyses were used to conduct the study. We created 4 groups with 'ICE', 'Cleaning', 'Food preparation' and 'Continuously used' appliances.

Most appliances were used in the morning (07:00-09:00) and the evening (18:00-20:00). Every household owning a dryer, an individual freezer pointed to the habits of cleaning and food preparation/ conservation. In addition, every household owning on average 2 TVs, 1 desktop computer, 1 laptop, 1 stereo system and 1 DVD player; some households 1 TV and 1 laptop per person; the total daily hours spent watching TV being 4 hours on average, PC use per day being approximately 2 and a half hours, and laptop use 3 hours suggested how central ICE appliances, especially TVs and computers were to our lives, and the importance of the improvement of energy efficiency of these appliances. As for cleaning appliances, a dryer was used 2 times per week and a washing machine 5 times. These numbers showed that almost every item of clothing was worn only once before it is washed. When this was considered together with the 17 minutes use of the iron per day and the once or twice showers per person per day, it might be telling about the occupations and/or the cleaning comfort preferences of the households. In terms of food preparation appliances per household (on average), the fact that there was a freezer in continuous use tell about food storing/eating habits. Perhaps less fresh food was being consumed and/or households might have been preserving food for winter/summer. The grill and microwave oven being used 24 minutes in total per day suggested that the main meals consisted of easy-to-prepare food. Lastly, a dishwasher was used 42 minutes per day on average, which meant that either the dishwasher was used on the quick cycle every day or the long cycle nearly 4 times a week. The numbers of ownership and duration of use in our sample were similar with the Dutch averages.

In order to derive the behavioral factors, patterns and profiles, first we conducted a correlation analysis between electricity consumption and the variables of occupant behavior, household and dwelling characteristics that could be related to electricity consumption. We selected the variables based on a literature review and our former paper (2). We found that total daily duration of use of continuously active, food preparation, (personal) cleaning, and ICE, battery charged appliances, as well as the number of stand-by appliances, and energy saving and halogen lamps (appliance use behavior); total weekly number of hot laundry cycles, baths, and duration of showers (behavior); total weekly hours of presence in rooms, kitchen, and bathroom (presence); household size, years of residence in the same house, presence of children or elderly in the household, monthly household income (household characteristics), type of dwelling and number of bedrooms (dwelling characteristics) were significantly correlated to electricity consumption. The variables of ownership of PV or solar panels, a member of the household having university or higher education, and hours spent outside the house for work were not found significantly correlated to electricity consumption, however they were still included in the factor analysis, since they might reveal insight about occupant behavior and electricity consumption and might contribute to building the behavioral patterns and profiles.

By using exploratory factor analysis, we found the behavioral factors and their underlying variables as total appliance use (total duration of use of continuous, cleaning, and food appliances), articulation of technology (duration of use of ICE, stand by and battery charged appliance use), spatial presence (active presence in rooms, bathroom, and living room and kitchen, number of halogen lamps), (personal) cleaning behavior (duration of shower, number of baths, number of hot washes, duration of use of dishwasher, number of dryer loads), and energy conservation (ownership of PV/solar panel, less use of dryer, hot washes, douche, and more number of energy saving lamps). In the following step, the 4 behavioral patterns were derived as the use of appliances, presence/ (personal cleaning), presence/technology, energy conservation.

While the use of ICE appliances created enough factor score to relate to a separate behavioral factor and pattern, the behavioral factor of presence appeared in two different behavioral patterns ((personal) cleaning and technology). The positive or negative behaviors of (personal) cleaning and use of halogen or energy saving lights also lead to two different patterns ((personal) cleaning and energy conservation). The correlation analysis revealed that the behavioral factors and patterns were significantly correlated to electricity consumption, and there was statistically significant difference between different factors and patterns. This might be explained by almost all variables (except for the ownership of PVs) being correlated with electricity consumption.

In terms of the behavioral profiles, we found that the behavioral factor 'appliance use' related to the profile 'family' considering the characteristics of dwelling typology (row house or middle level), household size (couple), higher working hours outside the house in some cases, and elderly household in some cases, slightly lower income (not statistically significantly correlated to the factor). The behavioral factor 'technology' related to the profile 'techie' considering the characteristics of higher income level, higher education level, and less hours of working outside in some cases. The behavioral factor '(personal) cleaning' related to 'comforty' considering the characteristics of dwelling typology (corner or freestanding), higher income level, bigger household size, and less hours of working outside. Lastly the behavioral factor 'energy conservation' related to the profile 'conscious' considering the characteristics of higher education level, working more hours outside, smaller household size, and top floor apartment or corner house in some cases. The factor of 'spatial presence' did not relate to a specific behavioral profile.

The higher or lower values of household size, income, education, working outside, number of bedrooms, and dwelling type were found to be related to different behavioral factors. For instance, the 'comforty' profile had bigger household size, higher income and number of bedrooms compared to 'family,' while it had lower working outside hours. The 'conscious' profile was found to have more hours of working outside, smaller household size, and higher education, compared to 'techie,' and was found to live in a house that gets more day light. The profile 'conscious' didn't necessarily correlate to income, but it had more income than profile 'family,' less income than 'comforty.' In our sample, considering the electricity consumption, the behavioral profiles did not relate to particular household stereotypes such as single, couple, elderly, etc., but to variables such as working hours, household size, education, and income.

We found that electricity consumption is closely related to occupants' presence. Besides, appliance use based on specific activities like cooking, washing, lighting, TV and PC use could be a good way to model occupant behavior and electricity consumption, and the related profiles. The use of ICE appliances (articulation of technology) determined a behavioral pattern on its own. Younger householders had the most appliances but also the most energy saving appliances (ESA). In our sample, the two groups had the most number of appliances were young singles, couples or families. Economic affluence had a strong influence in grouping the households according to electricity consumption. Income was one of the household characteristics that we used to determine the behavioral profiles, as well.

Finally, the overall question of this research is:

How much does the occupant behavior influence the energy consumption of dwellings in the Netherlands, and how could we identify the determinants of consumption, as well as the behavioral patterns and profiles?

The literature review shows that not achieving the calculated energy performance levels and significant energy consumption differences are observed in dwellings even with similar building characteristics. The variances between the calculated energy performance and the actual energy consumption of dwellings in energy efficient housing, i.e. energy performance gap, could stem from several reasons, such as unexpected occupant behavior, lack of comprehensive data of the whole building process, calculation drawbacks, the construction defects/mistakes in building construction. This thesis has been interested in determining occupant behavior in relation to energy consumption, claiming that the buildings' energy consumption can be validated in total, only during occupancy, when the design is tested on actual use.

This thesis brought together the occupant behavior that is habitual (questionnaire), and that is dynamic (monitoring). In addition, occupant behavior was included in this research both regarding presence, and regardless of it. Occupant behavior was considered as (presence patterns in a space, together with) the actual heating, i.e. thermostat setting and radiator control; and ventilation patterns, i.e. operation of windows, grids, and mechanical systems; and the use of lighting and appliances.

This thesis collected more detailed data on the determinants, and actual occupant behavior, both cross-sectional (surveyed) and longitudinal (monitored), and looked at the determinants of behavior, i.e. building and household characteristics that determine occupant behavior, as well.

Referring to the lack of research, this study combined the deductive (cross-sectional, macro data, macro level statistics) and the inductive methods (longitudinal data, detailed high frequency data, performance simulation), by considering both the determinants of behavior and the actual behavior itself. We found that deductive methods are much faster in calculating and dissecting energy consumption into its factors, such as household characteristics, dwelling characteristics, behavioral aspects, etc; and inductive methods model actual behavior from bottom up experimenting and validating energy consumption levels.

Applying sensitivity analysis in a large sample size of households/dwellings in relation to heating energy consumption, this research has found that the heating energy consumption of a dwelling is the most sensitive to thermostat control, followed respectively by ventilation control and presence. Both heating energy consumption and indoor resultant temperature are the most robust to radiator control. Calculating a regression model on the determinants of electricity consumption, this research has found that using the total duration of appliance use and parameters of household size, dwelling type, number of showers, use of dryer and washing cycles, and presence in rooms. This explained 58% of the variance in electricity consumption.

Introducing behavioral profiles and patterns contribute to the modeling of energy consumption and occupant behavior, this research revealed that household composition, age, income, ownership of dwelling, and education are the most important elements of behavioral profiling.

This research will help understanding the occupant related factors of energy consumption in dwellings, as well as the more accurate representation of occupant behavior, which will contribute to the better design of products, systems, dwellings, and achieving more advanced regulations.

§ 7.2 On the Limitations of the Research

One limitation of Dataset 1 (OTB dataset) was the low response rate to the questionnaire (5%). This might have been partly because the inhabitants were uncomfortable with personal questions about their lifestyles and income levels. It might have been related to the number and intricacy of questions, as well. The returned questionnaires being filled in completely showed that the interest/awareness of inhabitants in the subject matter was high.

In terms of the representation power of the dataset, general characteristics found to be representative of the Netherlands (validation dataset: WoON Database), except for the parameters of income and education, which were higher than the national average. In terms of heating and ventilation systems, the OTB dataset had a small number of dwellings with balanced ventilation and solar boilers; and no dwellings with heat pumps. The WoON Database included dwellings with heat recovery ventilation. One aspect to pay attention is the year of construction of the dwellings in these neighborhoods. The neighbourhoods were chosen on purpose, with the aim of working on new buildings with low EPC values. Potential deviations from the national averages might be caused by focusing on these two recently built neighborhoods. Here, it must be noted that similar sample sizes were observed in previous work on occupant behavior and energy consumption in dwellings (e.g. Jeeninga, 2001; Uitzinger, 2004). These studies claimed that a low response rate might not influence the accuracy of the results. Many results from early research are similar to the later ones (Curtin et al., 2000; Keeter et al., 2006).

Thirdly, even if the questions on presence and behavior are detailed on a weekly basis, respondents might have filled in the information based on remembering their habits, but not actual behavior. This could be a limitation on the one hand, but also a successful approach to obtain data on habits, on the other hand. The influence of Hawthorne effect (McCarney et. al., 2007) must also be mentioned, where the survey respondents' awareness of the goal of the survey might have directed them to fill-in the questionnaire different than the reality.

Another limitation of Dataset 1 was related to the tracking and recording system of electricity consumption in the Netherlands. Electricity providers ask occupants to send in their meter readings once a year. These providers actively check the meter readings as well, but they have different schedules. If the occupant fails to send in the meter readings, the electricity consumption is calculated based on the previous reading by the provider, which may be up to three years ago (more than 3 years is not allowed under the Dutch regulations). This reality could have created a bias in the accuracy of the electricity consumption data.

Dataset 2 had limitations resulting from monitoring. The real-time energy consumption figures recorded by the HEMS were not used, because of the inconsistency of the data. The most precise thermostat control data was collected in March and April 2011, out of 6 moths that the monitoring was made. Besides, there was a probability that thermostat behavior had not changed significantly in March and April, because of little outside temperature change.

45 households' monitoring data was used over the sample size of 61. 8 households did not provide reliable data in March and April, and 8 cases for either March or April. Besides, 4 April and 12 April 2011 were the days that monitoring was problematic for all households. Another limitation was that the data was collected from the consumers of one energy company. Being the subscriber of this company might have brought in essential differences between this group and the rest of the households in the country, in terms of awareness and lifestyle. In order to overcome this, the 61 households were chosen according to their characteristics matching with Dutch averages. Additionally, they did not have any specific affinity with energy consumption through their work at home. In addition, to decrease the impact of the limitations of the research on the quality of the outputs, other published research was consulted to compare and validate the results. .

§ 7.3 Relevance of This Research and its Contributions

The scientific contribution of this research is characterized by the combination of several domains, i.e. design for sustainability, policy and building regulations for energy efficiency, construction and management of buildings (developers, contractors, housing associations…), management of energy supply (energy companies) and behavioral studies. This research has sought for explaining heating energy and electricity consumption of dwellings in Dutch context, in relation to determinants of energy consumption, actual behavioral patterns, and the household behavioral profiles in detail.

Relationships between behavioral patterns, household and building characteristics in relation to electricity consumption have rarely been investigated in the Netherlands. However, there is no work on profiling households by their electricity consumption.

Our work contributes to the literature by (1) using (partially) continuous data on actual behavior as well as household and dwelling characteristics, (2) driving behavioral factors, patterns, and profiles, and linking them to each other, as well as looking for their relationship with electricity consumption.

Determining behavioral profiles could lead to more accurate prediction of electricity consumption in dwellings, as well as planning the targeted energy saving measures, and helping energy companies for better calculations. Considering that occupant behavior might be more visible in the newer dwellings, and that behavior might be revealed more precisely by analyzing 'electricity' consumption, this research might provide more detailed and articulated input on occupant behavior to research and policy, which focus on motivating/encouraging individuals' and households' towards more energy efficient behavior.

Our work on thermostat control behavior in 61 Dutch dwellings in detail, using an applied questionnaire on household and dwelling characteristics, and behavioral attitudes, as well as the HEMS recording data on chosen thermostat settings in March and April 2011, revealed the thermostat control patterns and profiles of the households, and evaluated monitoring as a method for understanding the relationship between occupant behavior and energy consumption.

This identification is valuable because it combines several methods of data collection and analysis, and it provides a representation for this group of occupants and suggests directions on the more energy efficient use of thermostat control systems. However, this research does not have a high capacity of representation, since the sample size is rather small. However, they provide deeper insight into behavior, and they create the possibility to validate/compare the results of other research.

This research has provided a better understanding of thermostat control and relevant behavioral patterns. By considering these insights, energy performance regulations could be articulated, better design of thermostat control devices could be achieved, more efficient infrastructural implementations could be developed by energy companies, the targeted energy saving measures could be better planned.

In particular for the design and engineering industry, and energy companies, this research means support for designing systems that are effective in reducing energy consumption, as well as influencing occupants towards energy efficient behaviors. Findings from this research could help in improving design of objects, systems and architectural design in order to reduce energy consumption by occupants at home.

The results presented in this thesis suggest directions on the more energy efficient use of thermostat control and appliances. Using the behavioral patterns, designers can facilitate and create opportunities for embedding thermostat control and home energy management systems in daily life and for better consideration of occupants' behaviors, practices and goals for a more efficient human–machine interaction in saving electricity.

For product and systems design, considering the heterogeneity of the behavioral patterns and profiles, and the possibility that more than one person might be managing thermostat, HEMS could be designed flexible enough to suit various possible activities/ conditions at home. In this respect, this research could be followed up in a way that the field work includes all individuals that possibly use the HEMS. Using the behavioral patterns, designers could facilitate processes for embedding HEMS in daily life. Energy management systems could be integrated more with thermostat control. This kind of combination might provide more efficient use. The technical issues in measuring and monitoring, as well as calibrating data remain as obstacles to deal with. It is important to emphasize that more consideration should be given to occupant behavior, for a more efficient user–machine interaction, and energy preservation.

For construction industry and design informatics (particularly simulation based energy performance assessment and design tools), this research illustrates the benefit of considering the occupant behavior in early phases of design in renovating existing housing stock and for new housing.

Claiming that changes in lifestyle preferences will have an increasing influence on consumption patterns, every household owning 1 wireless internet router in continuous use, on average 6 battery charged appliances in an average household emphasize the importance of improving these technologies. Through studying behavioral determinants and patterns, opportunities for embedding thermostat control behavior in design stage calculations can be explored.

Several studies display the 'energy performance gap' between the calculated and actual energy consumption levels of buildings, and explore the reasons to it. There is significant evidence to suggest that buildings do not perform as well when they are completed, as was anticipated when they were being designed. It's important to identify the source(s) of energy performance gap and bridge them, such as issues of communication, building commissioning, issues of calibration, accuracy, energy management systems development, metering in relation to weather data and occupant behavior.

This research focuses on occupant behavior and energy consumption in dwellings, and understanding how behavioral patterns relate to energy consumption. Sensitivity analysis as a methodology could contribute in the calculations and calibrations of energy performance and consumption of households, as well as in communication and commissioning of buildings. Sensitivity analysis would also contribute to the efforts of policy making (mentioned below) and energy companies (mentioned above).

For policy, this research could help in improving the models and calculations of occupant behavior in building regulations; hence the theoretical consumption levels could be more realistic. The behavioral patterns identified in this study could also contribute to more dynamic calculation and integration of occupant behavior in building regulations and policies.

Further research could utilize the knowledge produced in this research to increase the energy efficiency of dwellings. For a coherent and intact description of the occupants' thermostat control behavior and the significant differences among them, behavioral patterns were identified in this thesis. This study proves that exploring patterns requires a combination of deductive and inductive methodologies.

§ 7.4 Recommendations for Future Work

Recommendations on future work to this research are threefold. In subsection 4.1, the possible follow up research on occupant behavior and energy performance has been reported in short term and further, where the former could partially be realized with the same data set, and the latter requires new research proposals. Subsection 4.2 deals with recommendations for architectural and energy management systems and product design practice drawn from important findings regarding the role of occupant behavior in energy consumption. While household characteristics such as household size, number of children and elderly, their socio-economical and educational level have an indirect influence on energy consumption, presence, lighting and appliance use, and the use of energy management systems have a direct influence. Subsection 4.3 presents the recommendations for policy from the conclusions of the sensitivity analysis (Chapter 3), monitoring (Chapter 5) and determinants analysis (Chapter 6). In building the regulations, the energy performance of a building is calculated based on a standard formula of occupant behavior. More dynamic calculations are necessary to include occupant behavior in energy performance regulations, which can help to predict energy savings and performance more accurately.

§ 7.4.1 Research

Potential further research topics are listed below and some of them are addressed further in: '4.2. Energy management systems.'

- Modeling thermal comfort and indoor air quality could lead to results that would evaluate and explain the sensitivity of our model further. (Chapter 3)
- Further research is needed on the actual household appliance inventory, their powers and energy ratings in much larger samples. This would improve the regression model we set up in Chapter 5. The significant connection that was identified between electricity consumption and ground-floor dwellings points to the need for a detailed study on lighting.
- We have not collected enough data on stand-by appliances' energy consumption. Further research is needed on this topic using (Chapter 5). Understanding lighting and appliance use based on monitoring could reveal much more about electricity consumption.
- Every household owning 1 wireless internet router in continuous use and 6 battery charged appliances should be researched further in terms of a mobile 24/7 lifestyle and the addiction to being 'connected'. (Chapter 5-6)
- Personal cleaning behavior appeared to be an important factor both in the patterns and profiles in this research, which suggests a comfort related aspect of energy consumption. This aspect needs to be investigated in terms of the habits, motivations, frequencies, and consequences of the particular behavior.
- This research could be extended by specifically investigating the use of ICE appliances, food preparation (especially freezer, dishwasher) and (personal) cleaning (use of shower and bath, use of dryer and washing machine) based on specific activities like cooking, cleaning, or hobbies.
- Methodologies regarding monitoring occupant behavior need to be improved in terms of data collection frequency, calibration, modelling method, sampling of behavior data (is data size of 60 better to understand intricacies of household and behavior characteristics (as in Dataset 1), 300 (Dataset 2), or sample size of Dataset 3 (more than 4000 sample size representing the Dutch housing stock)?
- Whether we work with cross-sectional (questionnaire) or longitudinal data (monitoring), the research is still time-bound, meaning that there is a big possibility that different behavioral patterns will appear in a year, two years, and longer, depending on the changes in lifestyle, household composition, etc. Further research could explore longer time spans in monitoring and modelling in residences.

§ 7.4.2 Energy management systems and design

Energy efficiency of dwellings is influenced by climate, building, systems, lighting and appliances characteristics as well as household characteristics and behavioral patterns. There has been much advancement of building elements such as thermal insulation, fenestration, energy distribution system and their air tightness quality, which have significant direct impact on the energy consumption of dwellings. However, the same cannot be claimed considering occupant behavior. While household characteristics such as household size, number of children and elderly, their socio-economical and educational level have an indirect influence on energy consumption, presence, lighting and appliance use and energy management systems have a direct influence.

Our results showed that occupant behavior is very dynamic in terms of the duration and chosen thermostat setting, and occupants' use of spaces and HEMS may differ considerably, hence individualization and decentralization of energy management systems should be investigated. The individual and local comfort requirements could be responded by using demand-controlled, user centered energy management systems.

There is improvement in terms of research and design of climate and energy management products and occupant interaction; however, the user aspects of how the climate control systems integrate in architectural design has not been investigated at all.

Variation in the distribution of light, temperature and humidity generate microclimate zones. Indoor comfort management devices with different focus of field, capacity and effect could be used individually or in-combination in different rooms, in order to create the desired indoor climate in relation to energy performance. Indoor comfort and energy management systems could be controlled locally by devices with individual focus; this way these systems could independently be installed in dwellings for refurbishment purposes. These devices could be modular design and scalable.

Integrating large centralized climate/energy management systems may not be easy, especially in renovating existing buildings. However, if a decentralized, adaptive/responsive system is considered, different spaces and demands could be addressed separately. This possibility could help reducing consumption levels considerably.

Many studies agree on the key aspects of indoor climate and energy management and automation systems as: occupant being in control; enhanced information visualization and decision support; intuitive, interactive and upgradeable user interfaces & reliable automation. The findings of this research also support the arguments of the occupants being in control of the systems and products, and the interactive feedback systems.

The communication protocols among individual devices and/or systems could be designed in such a way that both the users and the control devices are active determinants of the indoor comfort and energy management. The internal heat gain from the occupants and the devices could be sensed by different sensors and stored in a dynamic dataset, where all energy management devices are connected real time. Our work on sensitivity analysis could hold a basis to develop such intelligent systems. Intelligence may include time schedules, occupancy control, feedback mechanisms, and demand response by automatically increasing/decreasing its capacity, or switching on/off.

Consequently, energy consumption control, management of active occupant (operation), smartness (sensor/automatic/simulation), comfort (air quality, thermal, acoustic, visual), decentral vs central, network (actively communicate with their immediate neighbours and environment), integrated into building compotents (wall, floor and skin), multiple sensors, distributed intelligent climate control could help to overcome problems such as unhealthy indoor climate, energy inefficiency and environmental impact.

§ 7.4.3 Building regulations and energy policies

The Energy Performance Building Directive (EPBD) demands all EU member states to apply performance-based energy requirements and label certification schemes towards lowering the building energy consumption levels since 2006. Energy consumption here covers space heating, cooling, ventilation; lighting; and water heating.

The EPC (energy performance coefficient) in the building regulations in the Netherlands is used as a constant displaying the overall building-related energy consumption; its calculation considers water heating, ventilation and lighting. These calculations mainly include the size of the dwelling, and then envelope quality, systems characteristics, etc. as well as, standard calculations for occupant-related parameters (indoor temperature, presence, air change). Better modeling of occupant behavior would improve the calculation of EPC. In addition, our results of sensitivity analysis and monitoring showed that occupant behavior is rather dynamic, especially in terms of the duration of a chosen setting. Therefore, an important future work on EPC would be to be able model this dynamism in the calculation, such as integrating a simulation software that could update the formula in a more dynamic way based on occupant behavior.

Another field of improvement could be to develop user profiles for energy use and use this as part of EPC formula, or the regulation. Precise energy prediction is not one of the goals of energy performance regulations in the Netherlands, but a better prediction of energy performance could help in understanding the capacity of energy saving of a building, as well as realizing the actual energy savings expected from the housing stock.

§ 7.5 Final Words

One of the goals of sustainable design is to maintain indoor comfort levels while reducing energy consumption and environmental impact. In addition to advanced research and labeling implementations in the field, building regulations on environmental impact and energy consumption both nationally and in EU level present the optimum thresholds that need to be achieved.

Understanding occupant behavior will be even more important in future for efficiency of electricity use. Findings from this research could help improving design of objects, systems and architectural design in order to reduce energy consumption by occupants at home. Including occupant behavior articulately in the product and system designs, as well as in the calculation tools and methods of building regulations will help in reaching the aimed energy performance levels. Unless done so, the levels set as goals might stay as abstract figures. Occupants' preferences and needs have an important influence on the energy efficiency of the buildings, but there is still little known about this, especially in terms of the actual behavior and the determinants of it.

Lastly, research efforts in this field are also important for the occupants to realize, and further understand how significant the impact of their decisions at home to its energy performance, through which their energy consumption expenses as well as their environmental impact could be reduced.

Appendix A Hems Protocol

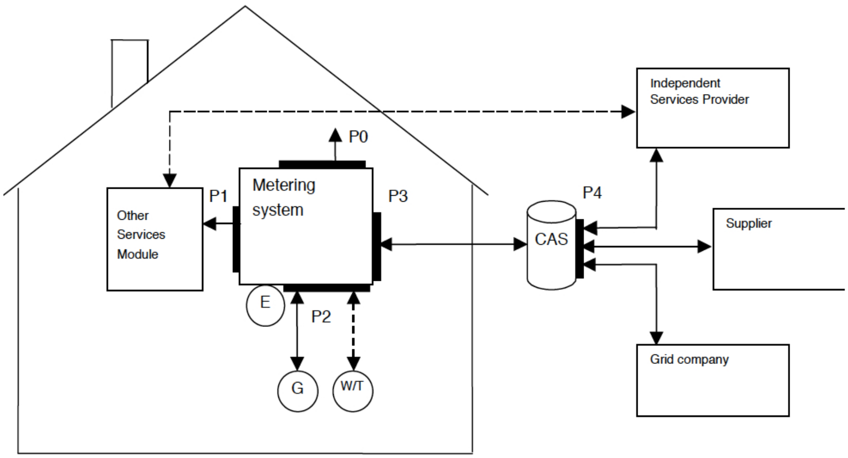


FIGURE APP.A.1 Communication ports belonging to the metering installation according to Dutch smart meter requirements (DSMR) source: KEMA

Smart meter information (P1 port)

The following information can be found in the KEMA (37) report on smart metering:

“As well as the displays on various parts of equipment, the metering installation has the following communication ports:

Port P0 for communication with external devices (e.g. hand-held terminal) during installation and on-site maintenance of the metering installation. This is a local port used for installation and maintenance purposes by personnel that is on-site. A typical implementation of this port is an optical connector for laptops or hand-held terminals. The local port is an integrated part of the E meter and gateway.

Port P1 for the communication between the metering installation and auxiliary equipment (a maximum of 5 appliances can be connected). P1 is a read-only interface, i.e. it cannot be used for sending data to the metering system. Port used for the communication between the metering installation and one or more other service modules. This port is a read-only port and can therefore not be used for sending data to the metering installation.

Port P2 for the communication between the metering system and one to four metering instruments and/or grid company equipments. Port used for the communication between the E meter and other M&S equipment installed at the same connection.

Port P3 for the communication between the metering installation and the Central Access Server (CAS). In version 2.0 of this document this appendix was not yet finished. Important to note is that the P3 interface will be based on the international DLMS/COSEM standard. Port used for the communication between the metering installation and gateway on the one hand and the CAS on the other.

Port P4 is the port on the CAS with which independent service providers, suppliers and grid companies gain access to the CAS. Note that P4 is outside the scope of this document.

Source: KEMA Consulting. (2008). Smart Meter Requirements - Dutch Smart Meter specification and tender dossier. v2.1 final Main. KEMA Consulting. By order of EnergieNed. Retrieved: http://www.netbeheernederland.nl/DecosDocument/Download/?fileName=ME9LdQVsZjHwTjd0nEEAZrYPlkwxcT7vuIfV0_y_Df8HZQIRp4H7sKD7gXLBnDn9&name=DSMR2.2-Main-Document

Appendix B OTB questionnaire

CHARACTERISTICS HOUSEHOLD

HOUSEHOLD

We would like to know some facts about your household. Fill in the following table, start with yourself (respondent) and continue with the rest of your family.

1. What is the year of birth and the gender of you and your relatives/housemates?

↓ Mark the persons of your household here	Year of birth	Gender (M/F)
☒ Respondent		
☐ Person 2		
☐ Person 3		
☐ Person 4		
☐ Person 5		
☐ Person 6		
☐ Person 7		

Remember the order you gave your family members above, and use this order along the rest of the questionnaire.

2. Was there change in the composition of your household, by e.g. childbirth or living in lodging, in the past year?

☐ Yes, explanation: ____________________

☐ No

MAIN OCCUPATION

3. What is the main occupation of the household members? Mark the category of the main occupation of each family member. Multiple marks per person are possible.

	Main occupation (Tick where appropriate)				
	Works outside the home	Works at home	Household activities	Pupil/Student	Other
☒ Respondent					
☐ Person 2					
☐ Person 3					
☐ Person 4					
☐ Person 5					
☐ Person 6					
☐ Person 7					

4. In general, how many hours do you (and your family members) work or study outside the house?

	Hours a week outside work and/or study (excluding travelling time)
☒ Respondent	
☐ Person 2	
☐ Person 3	
☐ Person 4	
☐ Person 5	
☐ Person 6	
☐ Person 7	

BACKGROUND

5. Did someone of your household ever lived outside the Netherlands? If so; for how long, and where? If there were multiple periods outside the Netherlands, please add up the total years.

	Lives in the Netherlands since (fill in the year)	Total number of years residential outside the Netherlands	Country (with multiple countries, the country where one lived the longest time)
☒ Respondent			
☐ Person 2			
☐ Person 3			
☐ Person 4			
☐ Person 5			
☐ Person 6			
☐ Person 7			

6. Mark the highest level of education programme for every household member, including current education and not completed education.

	None	Elementary school	Low vocational training (LBO/VMBO)	MAVO	HAVO	VWO	Middle vocational training (MBO)	High vocational training (HBO/Bachelor)	University (Masters/WO)	Postgraduate (WO+)	Other, viz:
☒ Respondent											
☐ Person 2											
☐ Person 3											
☐ Person 4											
☐ Person 5											
☐ Person 6											
☐ Person 7											

2

DWELLING CONDITIONS

CURRENT DWELLING

7. In what type of dwelling do you live?
- ☐ Apartment; Pleas answer this next question →
- ☐ Maisonette (apartment with two floors); Answer this→
- ☐ Corner house (house in the corner of the block)
- ☐ Row house (sharing both walls with other houses)
- ☐ Semi-detached house (sharing a wall with a house)
- ☐ Detached house (no houses next to it)

If you are living in an apartment or maisonette, pleas mark in this figure how your dwelling is located.
E.g. At ground floor with neighbours at one side is E, at the top floor with at both sides neighbours is B, and so on.

A ☐	B ☐	A ☐
C ☐	D ☐	C ☐
E ☐	F ☐	E ☐

8. For how many years have you been living in this house?
- ☐ Less than 1 year
- ☐ ______ years

9. Do you rent or own your dwelling? And what are the living expenses every month?

☐ Rental home: what is the monthly rent?
- ☐ Less than € 300,-
- ☐ Between € 300,- and € 500,-
- ☐ Between € 500,- and € 700,-
- ☐ Between € 700,- and € 900,-
- ☐ More than € 900,-

Rental home: Is water included in the rent?	☐ Yes	☐ No
Rental home: Is heating included in the rent?	☐ Yes	☐ No
Rental home: Is electricity included in the rent?	☐ Yes	☐ No

☐ Owner-occupied home: what is the gross monthly mortgage?
- ☐ Less than € 300,-
- ☐ Between € 300,- and € 500,-
- ☐ Between € 500,- and € 700,-
- ☐ Between € 700,- and € 900,-
- ☐ Between € 900,- and € 1100,-
- ☐ Between € 1100,- and € 1300,-
- ☐ More than € 1300,-

PREVIOUS DWELLING

10. Before moving to this house, in what type of house you were living? Multiple answers possible, e.g. when you and your partner did not cohabited before the current house.
- ☐ Apartment
- ☐ Maisonette (apartment with two floors)
- ☐ Corner house (house in the corner of the block)
- ☐ Row house (sharing both walls with other houses)
- ☐ Semi-detached house (sharing a wall with a house)
- ☐ Detached house (no houses next to it)

PRESENCE AT HOME

Here we are going to ask about the use of de different rooms in your dwelling. Similar dwellings are being used in different ways by different occupants, and that is why we would like you to fill in the table below, marking how you are using your rooms.

11. Mark how you use your rooms, multiple marks per room are possible.

↳ Here you mark which rooms exist in your dwelling.	Baby's bedroom	Nursery	Bedroom	Hobby room	Study	Guest room	Living room	Storage
☐ Living room								
☐ Attic								
☐ Bedroom 1								
☐ Bedroom 2								
☐ Bedroom 3								
☐ Bedroom 4								
☐ Bedroom 5								

Remember the order you gave your rooms, and use this along the rest of the questionnaire. (E.g. did you fill in that Bedroom 2 is used as a study this will be your study along the whole questionnaire)

12. What kind of kitchen do you have?

☐ An open kitchen
☐ A closed kitchen

Fill in tables 13 and 15 according to the example below; example A:

This respondent leaves home at 8:30 o'clock, takes lunch at home between 12:00 and 14:00, than collects the children of school and arrives with them (persons 3 and 4) at home at 15:30 o'clock. Person 2 leaves every morning at 8:00 and returns home at 18:00. Person 3 leaves home at 8:30 o'clock, and returns at 15:30.

	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☒ *Respondent*	X	X	X	X	X	X	X	/				X	X		/	X	X	X	X	X	X	X	X	X	
☒ *Person 2*	X	X	X	X	X	X	X											X	X	X	X	X	X	X	
☒ *Person 3*	X	X	X	X	X	X	X	/							/	X	v								
☒ *Person 4*																									

Fill in tables 14 and 16 according to the example below; example B:

In general there are 2 persons in the kitchen between 7:00 and 8:00, 1 person is in the bathroom, and 1 in Bedroom 1. In general 3 people have breakfast in the kitchen between 8:00 and 8:30 … Diner is at 18:00 o'clock with 4 people in the Living room, and one stays here until the children leave for bed at 21:00. Than there are 2 persons in the Living room, and they go to bed at 23:00 o'clock (Bedroom 1).

	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☒ *Living room*												1	1			3	2	4	4	4	2	2			
☒ *(Open) kitchen*							2	3									1								
☒ *Bathroom*							1																		
☐ *Attic*																									
☒ *Bedroom 1*	2	2	2	2	2	2	1																		

We would like to know how much family members are at home during the **WINTER** and in which room they generally stay. Please fill this in as accurate as possible at the next page.

4

ENERGY

With these important questions the energy efficiency of your dwelling is being evaluated.

ELEKTRICITY

17. Do you have an overview of your consumption of electricity?
☐ No. Please make an estimation as accurate as possible.
☐ Yes; How much electricity (in kWh) did you consume according to this last overview?

☐ Double rate	Low rate (rate or meter I)	____________	kWh
	High rate (rate or meter 2)	____________	kWh
☐ Single rate	Electricity:	____________	kWh

18. From when till when is the period of this overview? (day/month/year)
From: ____ / ____ / ____ Till: ____ / ____ / ____

19. In the above mentioned period, was there a long time no one at home, e.g. because of holidays?
__________ weeks nobody was at home.

20. The company that supplies your electricity is: ____________

21. Do you check your use of electricity by taking the meter reading frequently?
☐ No
☐ Yes. Please send copies of this in the return envelope?

22. Do you own solar panels (PV cells for electricity production)?
☐ No
☐ Yes; __________ m^2 PV cells

GAS

23. Do you have an overview of your gas consumption?
☐ No, I do not use gas. Continue with question 28, below.
☐ No. Please make an estimation as accurate as possible.
☐ Yes; How much gas (in m^3) did you consume according to this last overview?
Gas consumption: __________ m^3

24. From when till when is the period of this overview? (day/month/year)
From: ____ / ____ / ____ Till: ____ / ____ / ____

25. The company that supplies your gas is: ____________

26. Do you check your consumption of gas by taking the meter reading frequently?
☐ No
☐ Yes; Please send copies of this in the return envelope?

27. Do you own solar collectors (a solar boiler for hot water)?
☐ No
☐ Yes; __________ m^2

HEAT SUPPLY

28. Do you have an overview of your heat supply?
☐ No, I am not connected to heat supply. Continue with question 31, at the next page.
☐ No. Please make an estimation as accurate as possible.
☐ Yes; How much heat was supplied to you according to this last overview?
Heat supply: __________ GJ / kWh (circle the correct unit)

29. From when till when is the period of this overview? (day/month/year)
From: ____ / ____ / ____ Till: ____ / ____ / ____

30. The company that supplies your heat is: ____________

6

ENERGY

With these important questions the energy efficiency of your dwelling is being evaluated.

ELEKTRICITY

17. Do you have an overview of your consumption of electricity?

☐ No. Please make an estimation as accurate as possible.
☐ Yes; How much electricity (in kWh) did you consume according to this last overview?

☐ Double rate	Low rate (rate or meter I)	________	kWh
	High rate (rate or meter 2)	________	kWh
☐ Single rate	Electricity:	________	kWh

18. From when till when is the period of this overview? (day/month/year)
From: ___ / ___ / ___ Till: ___ / ___ / ___

19. In the above mentioned period, was there a long time no one at home, e.g. because of holidays?
________ weeks nobody was at home.

20. The company that supplies your electricity is: ________

21. Do you check your use of electricity by taking the meter reading frequently?

☐ No
☐ Yes. Please send copies of this in the return envelope?

22. Do you own solar panels (PV cells for electricity production)?

☐ No
☐ Yes; ________ m^2 PV cells

GAS

23. Do you have an overview of your gas consumption?

☐ No, I do not use gas. Continue with question 28, below.
☐ No. Please make an estimation as accurate as possible.
☐ Yes; How much gas (in m^3) did you consume according to this last overview?
Gas consumption: ________ m^3

24. From when till when is the period of this overview? (day/month/year)
From: ___ / ___ / ___ Till: ___ / ___ / ___

25. The company that supplies your gas is: ________

26. Do you check your consumption of gas by taking the meter reading frequently?

☐ No
☐ Yes; Please send copies of this in the return envelope?

27. Do you own solar collectors (a solar boiler for hot water)?

☐ No
☐ Yes; ________ m^2

HEAT SUPPLY

28. Do you have an overview of your heat supply?

☐ No, I am not connected to heat supply. Continue with question 31, at the next page.
☐ No. Please make an estimation as accurate as possible.
☐ Yes; How much heat was supplied to you according to this last overview?
Heat supply: ________ GJ / kWh (circle the correct unit)

29. From when till when is the period of this overview? (day/month/year)
From: ___ / ___ / ___ Till: ___ / ___ / ___

30. The company that supplies your heat is: ________

6

HEATING

We are interested in the way you use your heating system during the **WINTER** months. Consider a winter day not very warm or cold, in the last winter the temperature was 5˚C on an average day.

TEMPERATURE REGULATION

31. Mark how you control the **central** temperature at home:

- ☐ With radiator taps

- ☐ Manual thermostat

- ☐ Automatic thermostat

- ☐ No thermostat. Continue with question 33, at page 9.

ADJUST TEMPERATURE

If you are not able to adjust the temperature because you do not have a thermostat, please continue with question 33 at page 9.

We would like to know when you adjust the central thermostat a regular day during the **winter**. See example below.

***EXAMPLE**: When they get up out of bed at 7:00 the thermostat is set at 20°C, when they leave home it is adjusted to 15 degrees at 8:30. About 13:00 o'clock the thermostat is set again at 20°C, and at 22:00 it is adjusted to 15. This happens every weekday, except at Fridays.*
In the weekend the thermostat will be set at 20°C an hour later, and at 22:00 again adjusted to 15°C.

	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00	Same as previous day
Monday	15	15	15	15	15	15	**20**	**20**	15	15	15	15	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	15	15	15	15	
... day																										**X**
Friday	15	15	15	15	15	15	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	15	15	15	15	
Saturday	15	15	15	15	15	15	15	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	**20**	15	15	15	15	
Sunday																										**X**

32. Fill in how and when the thermostat in your house is adjusted:

	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00	Same as previous day
Monday																										
Tuesday																										
Wednesday																										
Thursday																										
Friday																										
Saturday																										
Sunday																										

RADIATOR USE

33. What settings are available at your radiators? (e.g. 0/1/2/3/4/5, of on/of)

____

Weekdays

We would like to know when you turn on/of your radiators in different rooms on **weekdays**. At general when is the radiator turned on in the specified room? Use the settings as given in the previous question (nr. 33). For the settings on/of, write ++ for 'on', and write 0 for 'of'. If your radiators do not have any indications than write down ++ for open (turned on), + for half open, and 0 for closed (turned of).

34. Where and when do you turn on the radiator(s) on **weekdays**?

	Radiator(s) present	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☐ Living room																										
☐ (Open) Kitchen																										
☐ Bathroom																										
☐ Attic																										
☐ Bedroom 1																										
☐ Bedroom 2																										
☐ Bedroom 3																										
☐ Bedroom 4																										
☐ Bedroom 5																										
☐ Entrance																										

Weekend

We would also like to know how you use the radiators on days of the weekend**.**

35. In comparison with weekdays, how is the use of radiators on the weekend?

☐ About the same on weekends as on weekdays; you do not have to fill in the next table, continue with question 37 at page 11.

☐ Different on weekends than on weekdays, please fill in the next table.

8

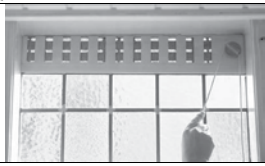
36. Where and when do you turn on the radiator(s) on **the weekend**?

	Radiator(s) present	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☐ Living room																										
☐ (Open) Kitchen																										
☐ Bathroom																										
☐ Attic																										
☐ Bedroom 1																										
☐ Bedroom 2																										
☐ Bedroom 3																										
☐ Bedroom 4																										
☐ Bedroom 5																										
☐ Entrance																										

VENTILATION

Ventilation at home occurs by windows, grids and ventilators. With ventilators one speaks of mechanical ventilation. There are two kinds of mechanical ventilation: With balance ventilation both input and output of the air occur mechanical. If only the output/exhaust of air is mechanical one speaks of mechanical exhaust ventilation, with this the input of air occurs by natural way (e.g. grids). Natural ventilation is possible by means of windows or grids.

37. Mark what kind of ventilation is present at your **current dwelling**. Multiple marks are possible.

☐	Windows without grids	
☐	Grids	 
☐	Mechanical exhaust ventilation	An exhaust system which sucks with a ventilation motor via air pipes and exhaust valves air out of the kitchen, the bathroom and the toilet. Most of the times there are grids in the windows. The device as shown under 'balance ventilation' is NOT present.  exhaust valve
☐	Balance ventilation	  input valve Sometimes hidden in a closet: 
☐	I don't know	

38. What kind of ventilation was present in your **previous dwelling**?

☐ Windows without grids
☐ Grids
☐ Natural pipes in kitchen and sanitary rooms
☐ Bathroom ventilator (possible connection with lightning)
☐ Mechanical exhaust ventilation
☐ Balance ventilation
☐ Other, viz: ____________
☐ I don't know

WINDOWS

39. Why do you open the windows in general? (Multiple marks possible).

☐ To get fresh air
☐ Cooling down (adjust temperature)
☐ To remove condensation
☐ To dissipate dirty air (e.g. smoke, cooking smells)
☐ Other reason, viz: ____________

10

40. Why do you close the windows in general? (Multiple marks possible).

☐ Against draft
☐ Against the cold (adjust temperature)
☐ To block sounds from outside
☐ To block smells from outside
☐ For safety reasons
☐ Other reason, viz: ____________________________

Winter

Now will follow some questions about the use of the windows during the winter (average temperature of about 5 °C, not to much wind, no rain, no snow). Where and when do you open and close your windows on an average day during the **WINTER**?

If you use doors for ventilation (like doors to the garden or balcony) please consider these doors as windows.

41. Where and when do you open your windows in the **WINTER**? Mark with a cross if the windows are open.

		01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☐ Living room																										
☐ (Open) Kitchen																										
☐ Bathroom																										
☐ Attic																										
☐ Bedroom 1																										
☐ Bedroom 2																										
☐ Bedroom 3																										
☐ Bedroom 4																										
☐ Bedroom 5																										
☐ Entrance																										

There are two ways for windows to be considered open:

Open (wide or semi)
A cantilever window or top- and side-hinged window at the tip setting is considered open. See both pictures below.

At a chink
(maximum 1 cm space between window and frame)

11

42. In what way are your windows positioned during the **WINTER** in general?

	Number of windows in room	Number of windows open	Number of windows at a chink	Number of windows closed
☐ Living room				
☐ (Open) Kitchen				
☐ Bathroom				
☐ Attic				
☐ Bedroom 1				
☐ Bedroom 2				
☐ Bedroom 3				
☐ Bedroom 4				
☐ Bedroom 5				
☐ Entrance				

43. If there is nobody at home, does this change the number of windows opened during the **WINTER**?
- ☐ Yes, I will close all windows
- ☐ Yes, I will close some windows
- ☐ Yes, I will open some windows
- ☐ No, it stays the same

44. If the heating is turned on, does this change the number of windows opened?
- ☐ Yes, I will close all windows
- ☐ Yes, I will close some windows
- ☐ Yes, I will open some windows
- ☐ No, it stays the same

45. Does weather circumstances (snow, rain, wind) change the number of windows opened?
- ☐ Yes, I will close all windows
- ☐ Yes, I will close some windows
- ☐ Yes, I will open some windows
- ☐ No, it stays the same

SUMMER

Now the same questions will follow about the use of windows, but than during the **SUMMER** (consider last SUMMER, with no extreme conditions, no rain, no hard wind).

46. Where and when do you open the windows in the **SUMMER**? Mark with a cross if the windows are open.

		01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☐ Living room																										
☐ (Open) Kitchen																										
☐ Bathroom																										
☐ Attic																										
☐ Bedroom 1																										
☐ Bedroom 2																										
☐ Bedroom 3																										
☐ Bedroom 4																										
☐ Bedroom 5																										
☐ Entrance																										

47. In what way are your windows positioned during the **SUMMER** in general?

	Number of windows in room	Number of windows open	Number of windows at a chink	Number of windows closed
☐ Living room				
☐ (Open) Kitchen				
☐ Bathroom				
☐ Attic				
☐ Bedroom 1				
☐ Bedroom 2				
☐ Bedroom 3				
☐ Bedroom 4				
☐ Bedroom 5				
☐ Entrance				

48. If there is nobody at home, does this change the number of windows opened during the **SUMMER**?

☐ Yes, I will close all windows
☐ Yes, I will close some windows
☐ Yes, I will open some windows
☐ No, it stays the same

49. Does weather circumstances (rain, wind) change the number of windows opened?

☐ Yes, I will close all windows
☐ Yes, I will close some windows
☐ Yes, I will open some windows
☐ No, it stays the same

GRIDS

Now some questions about the use of grids (attached to windows) will follow.
If you do not own these kinds of ventilation grids, please continue with question 54, page 15.

50. Why do you open the grids? Multiple marks possible.

☐ To get fresh air
☐ Cooling down (adjust temperature)
☐ To remove condensation
☐ To dissipate dirty air (e.g. smoke, cooking smells)
☐ Other reason, viz: ______________________

51. Why do you close the grids? Multiple marks possible.

☐ Against draft
☐ Against the cold (adjust temperature)
☐ To block sounds from outside
☐ Because of the sounds of the grid
☐ To block smells from outside
☐ Because of the smells of the grid
☐ For safety reasons
☐ Other reason, viz: ______________________

Winter

52. Where and when do you open the grids at a normal day during the **WINTER**? Consider last winter (average temperature of 5 °C, not much wind, no rain, no snow).
Mark with a cross when the grids are open.

	Number of grids in room	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☐ Living room																										
☐ (Open) Kitchen																										
☐ Bathroom																										
☐ Attic																										
☐ Bedroom 1																										
☐ Bedroom 2																										
☐ Bedroom 3																										
☐ Bedroom 4																										
☐ Bedroom 5																										
☐ Entrance																										

SUMMER

53. Where and when do you open the grids at a normal day during the **SUMMER**?
Mark with a cross when the grids are open.

	Number of grids in room	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
☐ Living room																										
☐ (Open) Kitchen																										
☐ Bathroom																										
☐ Attic																										
☐ Bedroom 1																										
☐ Bedroom 2																										
☐ Bedroom 3																										
☐ Bedroom 4																										
☐ Bedroom 5																										
☐ Entrance																										

MECHANICAL VENTILATION (exhausts ventilation and balance ventilation)

Do you not own mechanical ventilation, or is it impossible for you to adjust this, please continue with question 62, at page 17.

54. Why do you turn up your ventilation system? Multiple marks possible.
☐ To get fresh air
☐ Cooling down (adjust temperature)
☐ To remove condensation
☐ To dissipate dirty air (e.g. smoke, cooking smells)
☐ Other reason, viz: ______________

55. Why do you turn down your ventilation system? Multiple marks possible.
☐ Because of the sounds of the system
☐ Because of the smells of the system
☐ Other reason, viz: ______________

56. How much settings are possible with your system? (e.g. 2 or 3 settings) ____________________

57. What is the indication at your system? (e.g. 0/1, or 1/2/3, or high/low) ____________________

58. Do you sometimes disconnect the plug from the power socket?
☐ Yes, namely _____ days a year
☐ No

Winter
We would like to know in what way you use the mechanical ventilation during the WINTER (consider last winter, with an average temperature of 5 °C, not to much wind, no rain, no snow). With this question think about what you did last winter with the mechanical ventilation system while you were cooking diner, went to be, get up in the morning, and so on.

59. Fill in at what time, and to what setting, you adjusted the ventilation in the **WINTER** in the table below. (With settings like 'high' and 'low' use the first letters; H and L):

	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
Settings on weekdays																									
Settings on weekends																									

(possible) comments:
____

SUMMER

60. Fill in at what time, and to what setting, you adjusted the ventilation in the **SUMMER** in the table below. Consider a day without rain and without hard wind.

	01:00	02:00	03:00	04:00	05:00	06:00	07:00	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	00:00	01:00
Settings on weekdays																									
Settings on weekends																									

(possible) comments:
____

61. Sometimes there is a summer setting in balance ventilation, is this present at your system?
☐ Yes, my balance ventilation system does have a summer setting, I use this _____ days a year.
☐ No, my balance ventilation system does not have a summer setting.
☐ I do not know if my balance ventilation system does have a summer setting.

HOUSEHOLD APPLIANCES

We would like to know more about the use of appliances. This is important to know because some appliances will heat up during use, and with that it influences the temperature in your dwelling.

APPLIANCES INVENTORY

62. Mark which and how much of the following appliances is present at your home, and how many hours a day **OR** a week these appliances are turned on. Count the total amount of hours. ***E.g.**: you have two TV's, one is turned on 21 hours a week, the other 3 hours a week, totally this is 24 hours a week.*

Appliance	Number	Minutes a day turned on (total)	Hours a week turned on (total)	Mark if this appliance is used in the living room/open kitchen.
Television set				
Computer monitor				
Computer and/or laptop				
Video game console				
Stereo and/or radio				
Home Cinema set				
Wireless internet				
DVD player				
Hard Disc Recorder				
Video recorder				
Video camera				
Wireless home phone				
Food processor				
Coffee maker				
Electric kettle				
(Sandwich) toaster				
Electric grill or oven				
Microwave				
Induction hob				
Electric hot plate				
Gas cooker / gas oven				
Cooker hood				
Fridge				
Freezer				
Dishwasher				
Washing machine				
Drier				
Iron				
Vacuum cleaner				
Lights at front door or in garden				
Extra heating appliances (e.g. garden heating or electric radiator)				
Sun bed				
Jacuzzi				
Sauna				
Water bed				
Aquarium				
Terrarium				
Close in-boiler (little kitchen boiler)				
Fireplace				
Air conditioning unit				
Fan (ceiling / standing)				
Other, viz: ____________________				

16

CHARGERS

63. How many appliances with chargers or batteries do you charge regularly at home? Consider mobile phones, cameras, laptops, loose batteries, and so on.
I own ____ appliances with chargers, and in total I charge ____ hours a week appliances with chargers. Count all the hours of all the chargers together!

HOUSEHOLD APPLIANCES
Of some of the household appliances there is more information needed.

64. If you own (more than) one **fridge**, what is its energy label?
Fridge 1: ____ Fridge 2: ____
What is the content in litres of your fridge(s)? Fridge 1: ____ Fridge 2: ____

65. If you own (more than) one **freezer**, what is its energy label?
Freezer 1: ____ Freezer 2: ____
What is the content in litres of your freezer(s)? Freezer 1: ____ Freezer 2: ____

66. If you own a **dishwasher**, what is its energy label? ____
What is the content in covers of your dishwasher? ____
And how often do you use your dishwasher every week? ____ times a week.

67. If you own a **washing machine**, what is its energy label? ____
What is the maximum content in kg of your washing machine? ____
And how often do you do your laundry every week? ____ washings a week.
At what temperature you usually do your laundry?

	Number of washings a week
cold	
30°C	
40°C	
50°C	
60°C	
90°C	

68. If you own a **drier**, what is its energy label? ____
What is the maximum content in kg of your drier? ____
And how often do you dry a load every week? ____ loads a week.
How much time (in minutes) does it take in general before your clothing is dry?
(on average for one drying load) ____ minutes.

LIGHTING

69. How much low-energy light bulbs are being used in your living room?
____ low-energy light bulb in the living room
And in the rest of the dwelling? ____ low-energy light bulb in the rest of the dwelling

70. How much normal light bulbs or halogen lights are being used in your living room?
____ normal or halogen light bulbs in the living room
And in the rest of the dwelling? ____ normal or halogen light bulbs in the rest of the dwelling

71. How much electronic/electric appliances are in stand-by in the living room?
____ appliances in stand-by in the living room
And in the rest of the dwelling? ____ appliances in stand-by in the rest of the dwelling

SANITARY

SHOWER AND BATH

72. How many showers and baths are present in your house?

_______ shower(s)
_______ bath(s)

SHOWER

73. Write down per person how many showers are taken in your house and how much time these showers take approximately:

	Number of showers taken a week	Number of minutes a shower takes
☒ Respondent		
☐ Person 2		
☐ Person 3		
☐ Person 4		
☐ Person 5		
☐ Person 6		
☐ Person 7		

BATH

74. Write down per person how many baths one takes a week:

	Number of baths taken a week
☒ Respondent	
☐ Person 2	
☐ Person 3	
☐ Person 4	
☐ Person 5	
☐ Person 6	
☐ Person 7	

OTHER

PETS
The keeping of pets can correlate with the ventilation needs and the temperature at a dwelling.

75. If you own pets, how many and what kind of pet(s) do you own? And where are these pets in general accommodated? Multiple answers are possible.

	Number	Accommodation		
		Inside, whole house	Inside, part of the house	Outside
Dog				
Cat				
Rodent				
Bird				
Fish or turtle				
Other, viz: ___________				

HOBBIES

76. Mark if you or one of your family members practices one of the specified hobbies at home. With that write down the number of hours this hobby is been practiced **inside** the house.

	No	Yes, that is been practiced … hours a week inside the house
Do you practice hobbies with what it is necessary to open the windows (by smell, gas or dust) Namely: ______________________		
Do you practice hobbies with what you use more energy (special electrical machines) Namely: ______________________		

SMOKING

77. Does someone in your household smoke?
☐ Yes, namely: ______________ (fill in which one, respondent/person…)
☐ No

78. Is there being smoked inside the house? (except for unique parties)
☐ Yes; What is being smoked, and how much?
_____ cigarettes a day.
_____ cigars a day.
_____ pipe a day.
_____ a day other smoking materials, namely: ______________
☐ No

HEALTH

79. How is your health and that of your family members?
Mark how everyone is doing in general.

	Very good	Good	Mediocre	Bad	I don't know
☒ Respondent					
☐ Person 2					
☐ Person 3					
☐ Person 4					
☐ Person 5					
☐ Person 6					
☐ Person 7					

80a. Mark if someone has one of the following complaints in the last year:
Mark if this complaint is decreasing considerable during long stays outside the house, like when one is on holidays.

	Allergies (pets, dust)	Complaint decreases when outside the home	Stuffed up or runny nose	Complaint decreases when outside the home	Common cold	Complaint decreases when outside the home	Wheezy breathing	Complaint decreases when outside the home	Tightness of the chest	Complaint decreases when outside the home	Shortness of breath	Complaint decreases when outside the home	Asthma-attacks	Complaint decreases when outside the home	Hay fever	Complaint decreases when outside the home	Sore throat	Complaint decreases when outside the home	Weary or runny eyes	Complaint decreases when outside the home
☒ Respondent																				
☐ Person 2																				
☐ Person 3																				
☐ Person 4																				
☐ Person 5																				
☐ Person 6																				
☐ Person 7																				

20

80b.Mark if someone has one of the following complaints in the last year:
Mark if this complaint is decreasing considerable during long stays outside the house, like when one is on holidays.

	Irritation of contact lenses	Complaint decreases when outside the home	Migraine	Complaint decreases when outside the home	Headache	Complaint decreases when outside the home	Completely worn-out	Complaint decreases when outside the home	Concentration problems	Complaint decreases when outside the home	Multiple times waking up every night (if crying baby is the cause, than do not mark!)	Complaint decreases when outside the home	Skin problems (dry or itchy skin)	Complaint decreases when outside the home	Muscular pain (not because of sports)	Complaint decreases when outside the home	Joints ache	Complaint decreases when outside the home	Other, namely:	Complaint decreases when outside the home
☒ Respondent																				
☐ Person 2																				
☐ Person 3																				
☐ Person 4																				
☐ Person 5																				
☐ Person 6																				
☐ Person 7																				

INCOME

If we know your income we might make a correlation between income and energy consumption.

81. What is the total gross income of your **whole** household per year?

- ☐ Minimum; less than € 9500,-
- ☐ Below average; between € 9500,- and € 28500,-
- ☐ Average; between € 28500,- and € 34000,-
- ☐ Between 1 and 2 times average; between € 34000,- and € 56000,-
- ☐ 2 times average or more; more than € 56000,-

SATISFACTION

82. How satisfied are you with the indoor climate (temperature distribution, humidity)?
- ☐ Very satisfied
- ☐ Satisfied
- ☐ Not t satisfied, not dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

83. How satisfied are you with the indoor air quality?
- ☐ Very satisfied
- ☐ Satisfied
- ☐ Not t satisfied, not dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

84. How satisfied are you with the indoor sound level (sound sources, isolation)?
- ☐ Very satisfied
- ☐ Satisfied
- ☐ Not t satisfied, not dissatisfied
- ☐ Dissatisfied
- ☐ Very dissatisfied

Curriculum Vitae

Merve Bedir studied architecture at Middle East Technical University (METU), Ankara. Following her bachelor degree obtained from the Department of Architecture at METU (2003), She started working in design and construction firms in Turkey, among which were a hotel and holiday village in Antalya by Atelier T and Limak, as well as the new airport terminal in Ankara by EDDA and TAV.

At the end of 2004, she started her master's degree in Institute of Science and Technology, connected to the Faculty of Architecture and Engineering of Gazi University, Ankara. She worked on her master's research, simultaneous to her professional work in Antalya and Ankara. Her master's research was focused on the use of simulation programs in calculating the energy performance of dwellings, and her case study was a single-family house in Ankara. She started working as a research assistant in the Department of Architecture of the same university in 2005. Bedir obtained her master's degree in 2007.

Bedir started her PhD research at the end of 2008 at OTB Research Institute. Most of her research was already completed during her 4 years in the institution, however it was mostly published later. Her research was presented in journals like Energy and Buildings, Journal of Architecture and Planning Research, as well as conferences such as PLEA, IBPSA, MISBE, and Sustainable Buildings.

Merve Bedir is the founder and partner of design and research firm L+CC (2013), based in Rotterdam. Her work at L+CC was supported by Future Architecture Platform, Creative Industries Fund NL, Prins Claus Funds, European Cultural Foundation, European Union Creative Program, United Nations' UNHabitat, UNDP programs, Embassy and Consulates of the Netherlands in Turkey, Germany, Bulgaria, and China, Goethe and French Cultural Institutions, Heinrich Boll Foundation, among others.