EBC

Energy in Buildings and Communities Programme

Annex 66: Definition and Simulation of Occupant Behavior in Buildings

Technical Report:

Occupant Behavior Case Study Sourcebook

November 2017

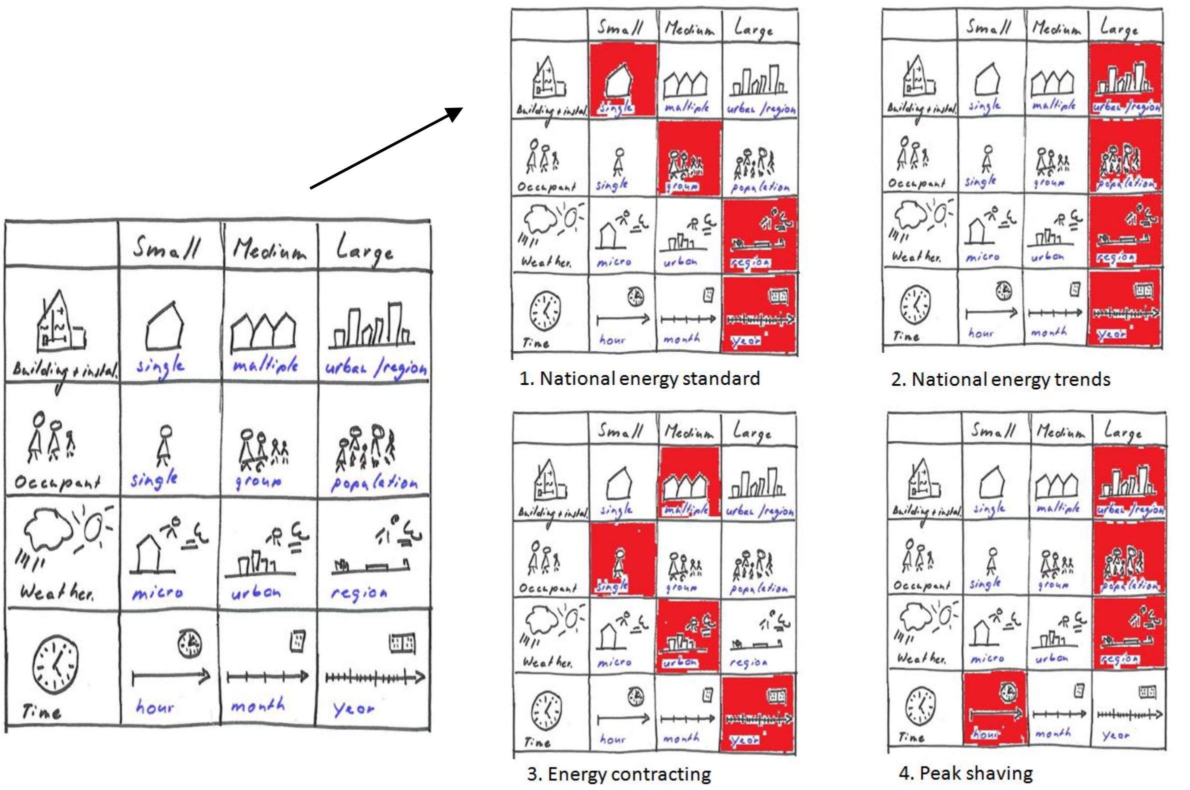

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Table of contents

Preface

The International Energy Agency

The International Energy Agency (IEA) was established in 1974 within the framework of the Organisation for Economic Co-operation and Development (OECD) to implement an international energy programme. A basic aim of the IEA is to foster international co-operation among the 29 IEA participating countries and to increase energy security through energy research, development and demonstration in the fields of technologies for energy efficiency and renewable energy sources.

The IEA Energy in Buildings and Communities Programme

The IEA co-ordinates international energy research and development (R&D) activities through a comprehensive portfolio of Technology Collaboration Programmes. The mission of the Energy in Buildings and Communities (EBC) Programme is to develop and facilitate the integration of technologies and processes for energy efficiency and conservation into healthy, low emission, and sustainable buildings and communities, through innovation and research. (Until March 2013, the IEA-EBC Programme was known as the Energy in Buildings and Community Systems Programme, ECBCS.)

The research and development strategies of the IEA-EBC Programme are derived from research drivers, national programmes within IEA countries, and the IEA Future Buildings Forum Think Tank Workshops. The research and development (R&D) strategies of IEA-EBC aim to exploit technological opportunities to save energy in the buildings sector, and to remove technical obstacles to market penetration of new energy efficient technologies. The R&D strategies apply to residential, commercial, office buildings and community systems, and will impact the building industry in five focus areas for R&D activities:

– Integrated planning and building design
– Building energy systems
– Building envelope
– Community scale methods
– Real building energy use

The Executive Committee

Overall control of the IEA-EBC Programme is maintained by an Executive Committee, which not only monitors existing projects, but also identifies new strategic areas in which collaborative efforts may be beneficial. As the Programme is based on a contract with the IEA, the projects are legally established as Annexes to the IEA-EBC Implementing Agreement. At the present time, the following projects have been initiated by the IEA-EBC Executive Committee, with completed projects identified by (*):

Annex 1: Load Energy Determination of Buildings (*)
Annex 2: Ekistics and Advanced Community Energy Systems (*)
Annex 3: Energy Conservation in Residential Buildings (*)
Annex 4: Glasgow Commercial Building Monitoring (*)
Annex 5: Air Infiltration and Ventilation Centre
Annex 6: Energy Systems and Design of Communities (*)
Annex 7: Local Government Energy Planning (*)
Annex 8: Inhabitants Behaviour with Regard to Ventilation (*)
Annex 9: Minimum Ventilation Rates (*)
Annex 10: Building HVAC System Simulation (*)
Annex 11: Energy Auditing (*)
Annex 12: Windows and Fenestration (*)
Annex 13: Energy Management in Hospitals (*)
Annex 14: Condensation and Energy (*)
Annex 15: Energy Efficiency in Schools (*)
Annex 16: BEMS 1- User Interfaces and System Integration (*)
Annex 17: BEMS 2- Evaluation and Emulation Techniques (*)
Annex 18: Demand Controlled Ventilation Systems (*)
Annex 19: Low Slope Roof Systems (*)

Annex 20: Air Flow Patterns within Buildings (*)
Annex 21: Thermal Modelling (*)
Annex 22: Energy Efficient Communities (*)
Annex 23: Multi Zone Air Flow Modelling (COMIS) (*)
Annex 24: Heat, Air and Moisture Transfer in Envelopes (*)
Annex 25: Real time HVAC Simulation (*)
Annex 26: Energy Efficient Ventilation of Large Enclosures (*)
Annex 27: Evaluation and Demonstration of Domestic Ventilation Systems (*)
Annex 28: Low Energy Cooling Systems (*)
Annex 29: Daylight in Buildings (*)
Annex 30: Bringing Simulation to Application (*)
Annex 31: Energy-Related Environmental Impact of Buildings (*)
Annex 32: Integral Building Envelope Performance Assessment (*)
Annex 33: Advanced Local Energy Planning (*)
Annex 34: Computer-Aided Evaluation of HVAC System Performance (*)
Annex 35: Design of Energy Efficient Hybrid Ventilation (HYBVENT) (*)
Annex 36: Retrofitting of Educational Buildings (*)
Annex 37: Low Exergy Systems for Heating and Cooling of Buildings (LowEx) (*)
Annex 38: Solar Sustainable Housing (*)
Annex 39: High Performance Insulation Systems (*)
Annex 40: Building Commissioning to Improve Energy Performance (*)
Annex 41: Whole Building Heat, Air and Moisture Response (MOIST-ENG) (*)
Annex 42: The Simulation of Building-Integrated Fuel Cell and Other Cogeneration Systems (FC+COGEN-SIM) (*)
Annex 43: Testing and Validation of Building Energy Simulation Tools (*)
Annex 44: Integrating Environmentally Responsive Elements in Buildings (*)
Annex 45: Energy Efficient Electric Lighting for Buildings (*)
Annex 46: Holistic Assessment Tool-kit on Energy Efficient Retrofit Measures for Government Buildings (EnERGo) (*)
Annex 47: Cost-Effective Commissioning for Existing and Low Energy Buildings (*)
Annex 48: Heat Pumping and Reversible Air Conditioning (*)
Annex 49: Low Exergy Systems for High Performance Buildings and Communities (*)
Annex 50: Prefabricated Systems for Low Energy Renovation of Residential Buildings (*)
Annex 51: Energy Efficient Communities (*)
Annex 52: Towards Net Zero Energy Solar Buildings (*)
Annex 53: Total Energy Use in Buildings: Analysis & Evaluation Methods (*)
Annex 54: Integration of Micro-Generation & Related Energy Technologies in Buildings (*)
Annex 55: Reliability of Energy Efficient Building Retrofitting - Probability Assessment of Performance & Cost (RAP-RETRO) (*)
Annex 56: Cost Effective Energy & CO2 Emissions Optimization in Building Renovation (*)
Annex 57: Evaluation of Embodied Energy & CO2 Equivalent Emissions for Building Construction (*)
Annex 58: Reliable Building Energy Performance Characterisation Based on Full Scale Dynamic Measurements (*)
Annex 59: High Temperature Cooling & Low Temperature Heating in Buildings (*)
Annex 60: New Generation Computational Tools for Building & Community Energy Systems (*)
Annex 61: Business and Technical Concepts for Deep Energy Retrofit of Public Buildings (*)
Annex 62: Ventilative Cooling
Annex 63: Implementation of Energy Strategies in Communities
Annex 64: LowEx Communities - Optimised Performance of Energy Supply Systems with Exergy Principles
Annex 65: Long-Term Performance of Super-Insulating Materials in Building Components and Systems
Annex 66: Definition and Simulation of Occupant Behavior in Buildings
Annex 67: Energy Flexible Buildings
Annex 68: Indoor Air Quality Design and Control in Low Energy Residential Buildings
Annex 69: Strategy and Practice of Adaptive Thermal Comfort in Low Energy Buildings
Annex 70: Energy Epidemiology: Analysis of Real Building Energy Use at Scale
Annex 71: Building Energy Performance Assessment Based on In-situ Measurements

Working Group - Energy Efficiency in Educational Buildings (*)
Working Group - Indicators of Energy Efficiency in Cold Climate Buildings (*)
Working Group - Annex 36 Extension: The Energy Concept Adviser (*)
Working Group - Survey on HVAC Energy Calculation Methodologies for Non-residential Buildings

Introduction to Annex 66

Energy-related occupant behavior in buildings is a key issue for building design optimization, energy diagnosis, performance evaluation, and building energy simulation. Actions such as adjusting the thermostat for comfort, switching lights, opening/closing windows, pulling up/down window blinds, and moving between spaces, can have a significant impact on the real energy use and indoor environmental quality in buildings. Having a deeper understanding of occupant behavior, and quantifying their impact on the use of building technologies and building performance with modeling and simulation tools is crucial to the design and operation of low energy buildings where human-building interactions are the key. However, the influence of occupant behavior is under-recognized or over-simplified in the design, construction, operation, and retrofit of buildings.

Occupant behavior is complex and requires a multi-disciplinary approach if it is ever to be fully understood (Figure 1). On one hand, occupant behavior is influenced by external factors such as culture, economy and climate, as well as internal factors such as individual comfort preference, physiology, and psychology; On the other hand, occupant behavior drives occupants' interactions with building systems which strongly influence the building operations and thus energy use/cost and indoor comfort, which in-turn influences occupant behavior thus forming a closed loop.

There are over 20 groups all over the world studying occupant behavior individually. However, existing studies on occupant behavior, mainly from the perspective of sociology, lack in-depth quantitative analysis. Furthermore, the occupant behavior models developed by different researchers are often inconsistent, with a lack of consensus in common language, in good experimental design and in modeling methodologies. Therefore, there is a strong need for researchers to work together on a consistent and standard framework of occupant behavior definition and simulation methodology.

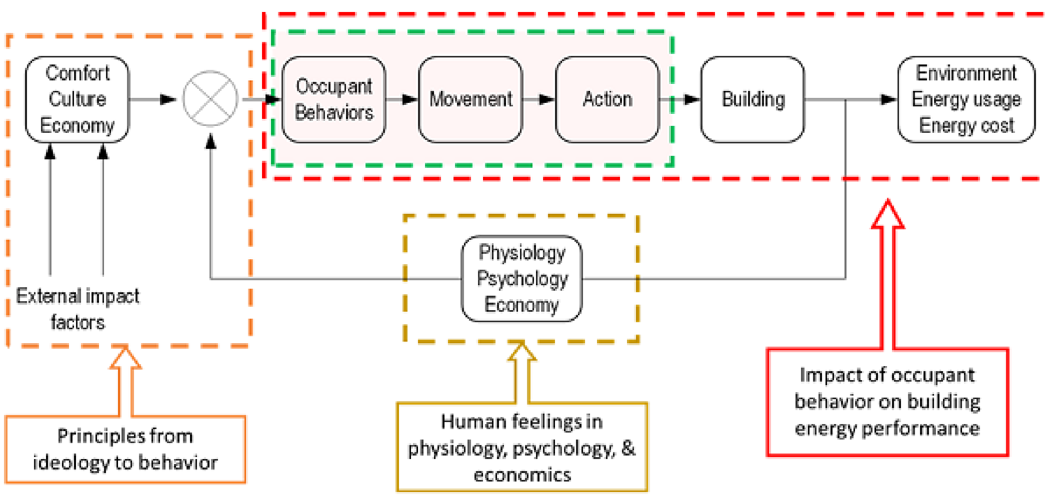

Figure 1: Relationship between occupants and buildings

The Annex 66 project was approved unanimously at the 74th Executive Committee Meeting of the International Energy Agency's Energy in Buildings and Communities Programme, held on 14th November 2013 in Dublin, Ireland. Operating Agents are Dr. Da Yan of Tsinghua University and Dr. Tianzhen Hong of Lawrence Berkeley National Laboratory. The Annex aims to (1) set up a standard occupant behavior definition platform, (2) establish a quantitative simulation methodology to model occupant behavior in buildings, and (3) understand the influence of occupant behavior on building energy use and the indoor environment. The project has five subtasks:

Subtask A - Occupant movement and presence models. Simulating occupant movement and presence is fundamental to occupant behavior research. The main objective of the subtask is to provide a standard definition and simulation methodology to represent how an occupant presents in his/her office and moves between spaces.

Subtask B - Occupant action models in residential buildings. Occupant action behavior in residential buildings affects building performance significantly. This subtask aims to provide a standard description for occupant action behavior simulation, systematic measurement approach, and modeling and validation methodology for residential buildings.

Subtask C - Occupant action models in commercial buildings. Some specific challenges of occupant behavior modeling exist in commercial buildings, where occupant behavior is of high spatial and functionality diversity. This subtask aims to provide a standard description for occupant action behavior simulation, systematic measurement approach, and modeling and validation methodology for commercial buildings.

Subtask D – Development of new occupant behavior definition and modeling tools, and integrating them with current building performance simulation programs. This subtask will enable applications by researchers, practitioners, and policy makers and promote third-party software development and integration. A framework for an XML schema and a software module of occupant behavior models are the main outcomes.

Subtask E - Applications in building design and operations. This subtask will provide case studies to demonstrate applications of the new occupant behavior modeling tools. The occupant behavior modeling tools can be used by building designers, energy saving evaluators, building operators, and energy policy makers. Case studies will verify the applicability of the developed modeling tools by comparing the measured and simulated results.

17 countries and 123 participants from universities, research institutes, software companies, design consultant companies, operation managers, and system control companies participated in this Annex. All parties expressed an interest in developing a robust understanding of energy-related occupant behavior in buildings, via international collaboration on developing research methodologies and simulation tools that can bridge the gap between occupant behavior and the built environment. The Preparation Phase started in November 2013 and continued through November 2014. The Working Phase started in December 2014 and lasted for two and a half years. The Reporting Phase took place from July 2017 to May 2018.

Summary

This sourcebook brings together case studies of building occupant behavior modeling applications from around the world. The purpose is to illustrate the range and types of applications, contribute to a framework for classifying types of applications, and explore which modeling approaches are most appropriate for which contexts. Essential elements of the framework answer the journalist's often-repeated questions about any story: tell us who, what, why, when, and where. In order to determine which model is most fit for which context, three dimensions emerge as being particularly important: the stakeholder and their problem (Who? Why?); the building type, services and provisions (What?); and the process stage and relevant tools (When?).

The case study summaries answer these questions and provide succinct discussions of the modeling strategy that each adopted. The write-ups also include pointers to full publications that provide further details for readers wanting to learn more.

1. Introduction

This report summarizes a set of case studies of occupant behavior in buildings and the associated use of decision support tools including modeling. These cases of occupant behavior modeling innovations provide a "demand-pull" view as seen by the users of such tools to counterbalance the "supply-push" perspective that many who create such models bring to the subject.[1]

Motivation comes from practitioners responding to an international survey who believe occupant behavior is a major source of discrepancy between modeled and measured building energy performance, and that current modeling practice is quite simplistic (O'Brien et al. 2016). A review of nine current building-performance simulation-modeling programs by Cowie et al. (2017) identifies "a widening gap between knowledge and implementation in the field of occupant behavior modeling."

This sourcebook aims to provide a framework for thinking about (1) when occupant behavior becomes important for making decisions about buildings, (2) which tools are most appropriate for specific applications, and (3) what insights emerge from practical experience with these tools. The cases summarized in Table 3 put these concerns into context.

[1] To place the supply-push and demand-pull models of scientific innovation in context, see Godin, B. *Models of Innovation: History of an Idea*. MIT Press, Cambridge, MA, 2017.

2. In what cases does occupant behavior matter? Framework to think about it

PROBLEM STATEMENT

In order to reduce the gap between the predicted energy use and actual building consumption, better understanding of occupant behavior (OB) and assessing the impact of OB on energy use is essential. Other subtasks of Annex 66 deal with an extensive number of energy prediction methodologies, occupant-modeling techniques and advanced dynamic energy simulation models that allow for relatively accurate predictions of energy use by integrating advanced user behavior models in energy simulations. However, in practice, users may not understand the details of the models and may not use them as their creators intended. The “fit-for-purpose” concept introduced in IEA EBC Annex 32 emphasizes the importance of matching product features to their usage context (Warren 2003). The characteristics of building energy performance simulation models incorporating occupant behavior should therefore vary according to application context. Thus, highly complex software tools may not be of much use when the need is for simple energy use estimations. In a detailed building design phase of a project, by contrast, such elaborate features would offer value as long as users doing the energy simulations are provided with sufficient guidance.

Simulation models described in the peer-reviewed literature often incorporate considerable knowledge and evidence regarding the links between occupant behaviors and building energy performance. By contrast, modeling practice shows relatively little or no use of the most advanced developed tools during the design phase due to their complexity and difficulties of use, especially in countries where the relevant regulations are not in place (O’Brien et al. 2016). Many practitioners use simplified tools such as rules of thumb or benchmarking for energy usage estimation. This suggests there is a need for better understanding of behavioral impacts on energy use in order to assess for which situations are certain tools and techniques suitable. In certain buildings, occupants have more impact on the energy use by having direct control over actions leading to energy consumption (light switch on/off, fan on/off, thermostat up/down, and window/door opening/closing and shading positioning). This needs to be recognized before modeling takes place.

The impact of occupant behavior on energy use is typically not well understood and misrepresentation of occupant behavior in simulation inputs can deliver erroneous results. There is building-by-building variation in what occupants can control. In addition, occupant schedules, activities, and adaptive responses to changing comfort conditions vary from person to person. Thus, it is important to distinguish for which cases it is important to analyze occupant behavior more deeply and then to demonstrate and quantify the impact of the occupant behavior on building energy performance. In this way, it can be determined which methodology is most suitable for which case and which occupant behavior models should be applied.

DISCUSSION OF ISSUES

By defining the building design requirements (*what, who, when, why*) first, it becomes easier to recognize the actual needs and purposes of the building occupancy model application. Such a categorization strategy can decrease the mismatch between predicted and actual energy use, increase the usability of suitable developed tools (OB models, energy simulation software) and increase the confidence in using the obtained results. Furthermore, the practitioners can acquire a better understanding of the impact of the occupant behavior on building energy use for different cases. See Figure 1.

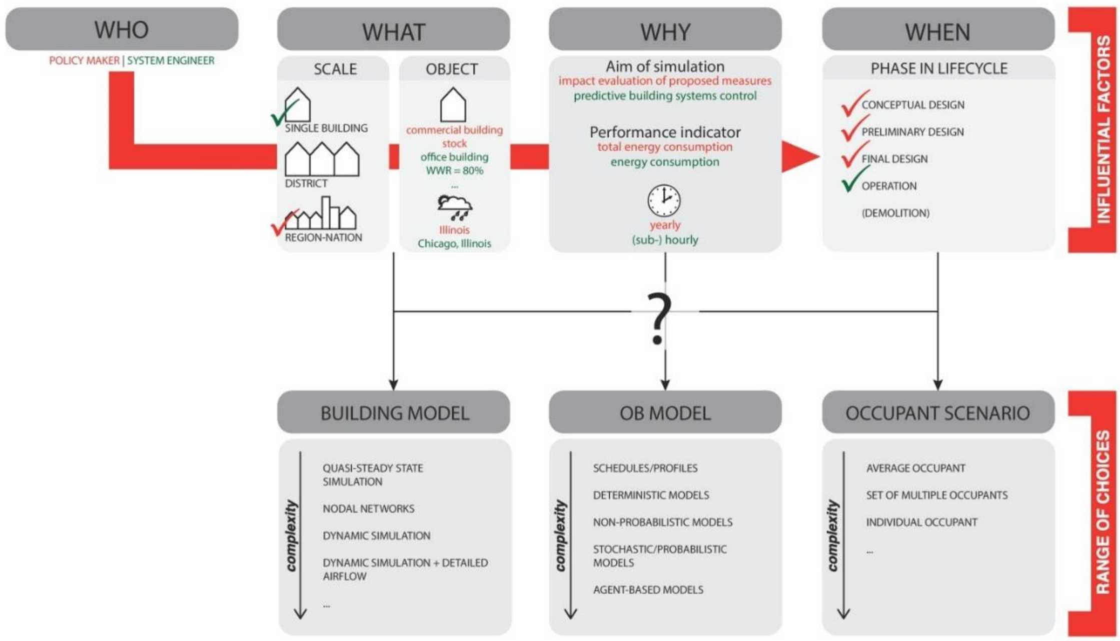

Figure 1: Graphical presentation of the driving factors (who, what, why, when) upon which a suitable energy modeling technique should be elaborated for each specific case (Gaetani, Hoes, and Hensen 2016).

Figure 2 illustrates this categorization process. It assembles specific application scenarios from contextual factors. Sensitivity of energy use to occupant behavior is based on different factors (building scale, typology, occupant type and presence, time period). It illustrates that for different levels, different knowledge needs to be obtained in order to predict the energy usage as accurately as possible (because occupant behavior is not the most influencing factor).

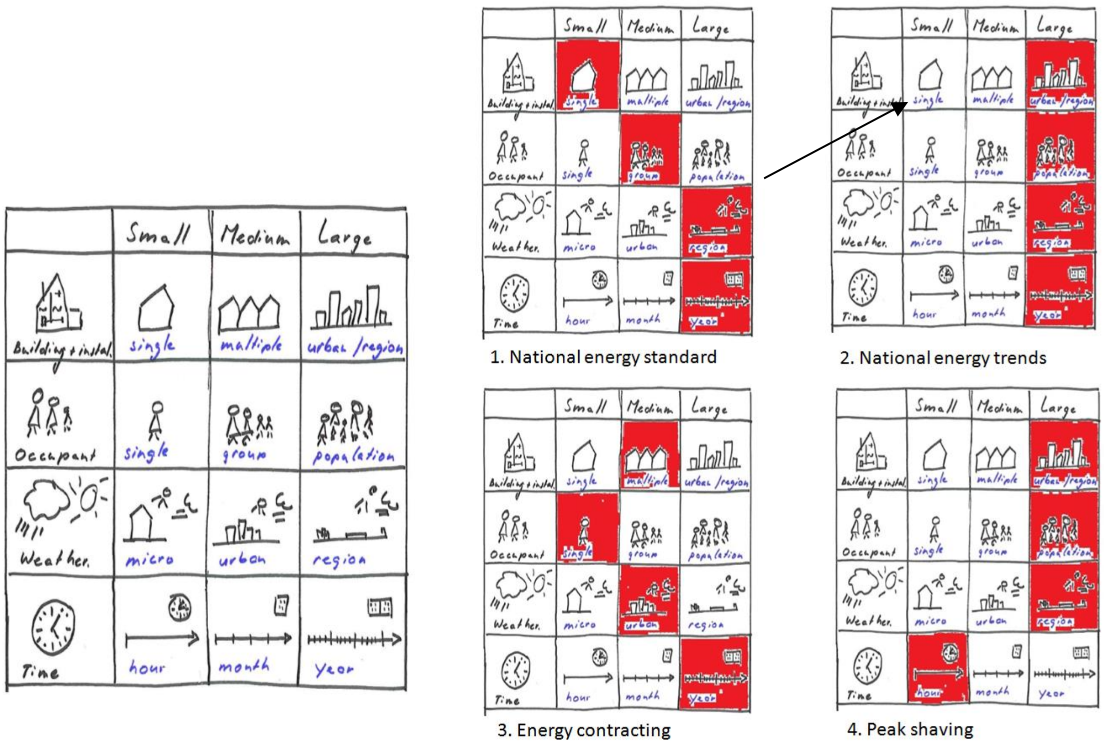

Figure 2: Graphical presentation of correlation between the different variations of building scale, building typology, occupant type and presence, climate and time period according to different scenarios: national energy standard, national energy trends, energy contracting, peak shaving (Polinder et al. 2013)

The driving factors can be reduced to three effective dimensions that define the main objectives of energy modeling:

- Who and why: Stakeholder and problem;
- What: Building type, services and provisions; and
- When: Process stage and tools.

Figure 3 summarizes the three-dimensional classification approach modelers could follow before performing actual energy performance simulations. This approach helps ensure that the main objectives of the simulations are answered. It stimulates and triggers the designer to address the occupant behavior impact and by understanding the occupant behavior impact level (high/low) on energy use, the modeler can choose an occupant behavior model and energy prediction technique that is the most suitable for that case.

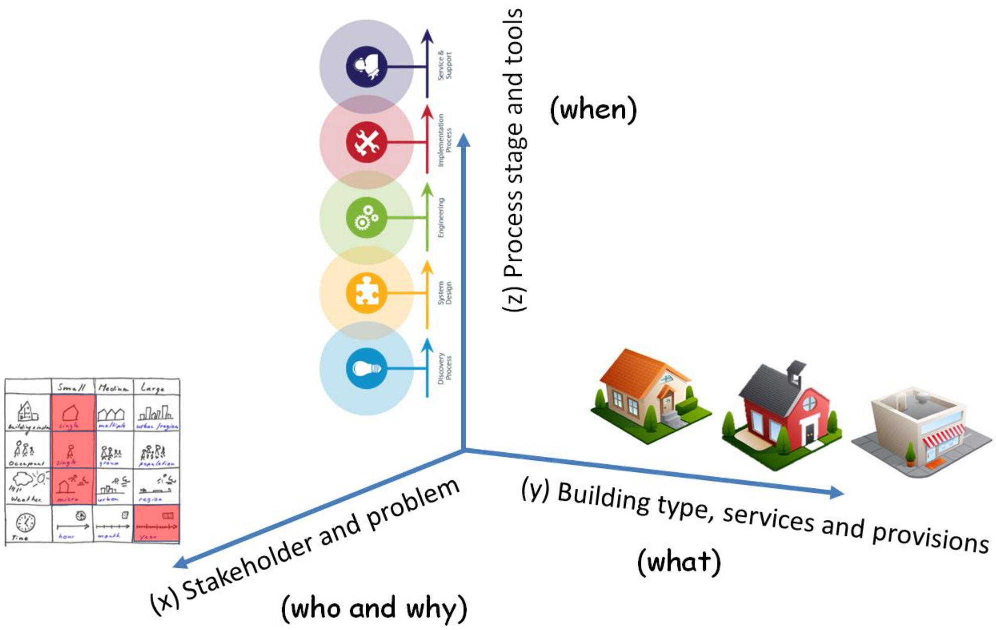

Figure 3: Three dimensions defining main objectives of the energy modeling (Ad van der Aa 2016).

EXAMPLE

An illustration of the categorization process in an office building clarifies how it works. It is helpful first to analyse the different impact levels of occupant behavior on building energy performance. Then the energy modeling techniques and developed tools can be selected according to different representative cases: different building types (*what*) and different user types (*who*).

	Central climate control	Individual climate control
Open plan office	• Presence of people • Equipment	• Presence of people • Equipment • Individual lighting • Openable windows?
Cellular offices	• Presence of people • Equipment • Openable windows • Internal shading	• Presence of people • Equipment • Individual lighting • Temperature setpoints • Openable windows

Figure 4: Influencing parameters of occupant behavior in offices (Ad van der Aa 2016).

For different building types, energy usage caused by occupant actions (using equipment or home appliances) needs to be determined. As illustrated in Figure 4, typically employees in open-plan offices have little influence on energy usage caused by central climate control (cannot open windows or adjust thermostat) whereas an employee in a cellular office having individual climate control can have a greater impact on energy use.

Hence, it is important to distinguish between different building typologies having different occupancy schedules in order to choose an appropriate energy usage prediction technique. For the cases where occupant behavior has a relatively low impact on energy usage, simpler occupant behavior models and energy prediction techniques can be sufficient.

Furthermore, in different design stages (*when*), a different level of accuracy is needed for the energy use prediction. It is important that energy modeling is cost-effective which implies finding a balance between the model accuracy and the simulation aim (including allocated time frame and money expenditure). Depending on the scope and goal of energy modeling (*why*), different energy modeling techniques should be adopted. During the conceptual design process, simple tools should be sufficient, enabling relatively simple estimation of energy consumption for a certain building type (residential, non-residential) and archetypal user profiles (students, family, elderly). In the final design stage, more time-consuming and expensive energy complex software tools should be used in order to increase the accuracy level of energy use prediction.

Moreover, depending on the building scale, different levels of simulation complexity are needed. As described by Gaetani, Hoes, and Hensen (2016), a more detailed and complex simulation model is needed when energy usage for a single building is assessed (design/retrofit). However, using complex tools is not necessarily justified when doing a simple estimation of energy use for a number of buildings in a residential district. Furthermore, a larger error might be obtained when performing simulations where the design parameters are not defined (but instead using the default values) compared to when using simplified methods (rule of thumb or benchmarking). For a single building, occupant behavior needs to be more carefully modeled whereas when predicting energy usage of a multi-building district (residential area), several other factors will influence the total energy use, and therefore detailed and complex modeling of user behavior is not necessarily efficient. Certain occupation profiles and scenarios can be used to estimate an average building usage for that specific area (and can be based on benchmarking).

Overall, the simulation user should choose and critically justify the model complexity and the technique for each individually investigated case. By defining clear objectives for each case, the risk of applying inappropriately complex and time-consuming models is avoided.

3. How to support decision making in different building project phases

Occupant behavior modeling applications belong to specific project phases, governing standards, locations and climates, building designs, vintages, and uses. The Royal Institute of British Architects (RIBA), Honorarordnung für Architekten und Ingenieure (HOAI), International Federation of Consulting Engineers (FIDIC), and Australian Institute of Architects are among the professional organizations that have developed standardized project phase definitions. A brief comparison provides a basis for the definition of phases to be used in this document.

In most countries it is the professional bodies that propose subdivisions of the building process into separate stages to clarify responsibilities, deliverables, liabilities and fee structures. Table 1 provides an overview of the different project stages as defined by the Royal British Institute of Architects, the American Institute of Architects, and the Australian Institute of Architects. It is evident that the overall content of a building process is similar in the three countries, and is likely to be similar in countries not listed in the table. What appears to be country-specific, however, is how the overall building process is subdivided into different project phases. This is likely to be due to differences in country specific building culture, legal and educational systems (Guy and Shove 2000, BDA document). For the purpose of simplification and applicability in countries not mentioned in the table, the last column makes a suggestion how the different country-specific project stages can be summarized into four main phases.

These phases have been established with regard to their relevance to different aspects of occupant behavior in buildings. The early design phase describes the part of the building process where the written or orally presented design brief is analysed and translated into a visual “design narrative” in sketch format that captures the essential characteristics of the proposed building. Depending on the specific project, parameters such as the degree of open vs. closed, indoor vs. outdoor, transparent vs. opaque, light vs. heavy, may be determined at this stage. These parameters are determined at a degree of accuracy sufficient to describe the atmosphere and attitude of the project, but are often not to scale, dimensions not determined and systems and their functionality not defined (Roetzel 2015). Once these qualitative decisions have been made, the following phase of “developed design” develops the sketch design into a set of construction drawings that can be provided to the builder, with detailed specifications about dimensions, materials and functionality of systems and controls (Roetzel 2015). The following construction phase then turns the set of drawings into the physical construction. This is followed by the last phase where the built environment professions such as architects are commonly involved, the handover and operation of the building. While in many countries architects and structural engineers remain liable for 30 years or more, they are commonly not involved in the operational phase and rarely receive feedback such as from post-occupancy evaluation.

Table 1: Sequential stages of a building's design process.

Stages from first to last in sequence	Royal Insitute of British Architects (RIBA)*	Australian Institute of Architects (AIA)**	American Institute of Architects (AIA)***	Simplified summary of stages
1	Strategic definition	Development of Design Brief	Schematic design phase	Early Design
2	Preparation and brief			
3	Concept design	Design phase (analysis of the brief and sketch design)	Design Development phase	
4	Developed design	Design development, documentation and building approvals	Construction document phase	Developed design
5	Technical design		Bid or negotiation phase	
6	construction	Construction	Construction phase	Construction
7	Handover and Close out	Defects liability period		Handover and operation
8	In use			

* https://www.ribaplanofwork.com/PlanOfWork.aspx

** http://architecture.com.au/architecture/national/becoming-an-architect

*** http://www.areforum.org/up/Construction%20Documents%20and%20Services/D200.pdf

In order to establish how decision making around the impact of occupant behavior can be supported in these different stages, Table 2 uses the project phases established in Table 1 and summarises the stakeholders related to each phase as derived from the description of responsibilities by the American, British and Australian Institute of Architects. In addition to that, the types of decisions made at each stage and how they are likely to have an impact on occupant behavior are identified.

Table 2: Stakeholders and decisions made in four main design phases.

Phase	Main stakeholders involved	Key decisions made	Impact of decisions on occupant behavior
Early Design	Client	Budget	Predefines all other parameters, excludes options that exceed budget
	Architect and client	Design narrative, attitude and atmosphere	Basic volumetric and spatial characteristics, e.g., degree of open vs. closed, indoor vs. outdoor, transparent vs. opaque, light vs. heavy. Predefines thermal properties of the building envelope, magnitude of solar heat gains and façade properties.
	Architect and client, specialist consultants	Basic volumetric geometry (building depth and height)	Predefines potential for cross and stack ventilation, predefines percentage of building that can be lit by daylight (indirect impact on lighting control)
	Architect and client	Spatial relationships	Predefines size of spaces and their location towards another. Predefines systems dimensioning, and control opportunities as well as group dynamics around the use of building controls
Developed design	Architect, client, builder, building authorities (permits), building services engineers and specialist consultants	Building services systems (ventilation, heating, cooling, lighting systems)	Predefines use of controls
		Building services controls (complexity, accessibility)	Predefines use of controls
		Façade typology, window opening type	Predefines availability and use of natural ventilation
		Shading systems	Predefines control of shading
		Interior fitout (materiality and acoustic properties)	Predefines space usage
Construction	Architect, builder	Adherence to the design and quality of construction n/a as all decisions are specified in the previous phase	Only applicable if changes are made during the construction phase
Handover and Operation	building operator, building occupants	Type and use of office equipment	Predefines internal heat loads, indirectly influences use of conditioning systems
	facilities manager, building operator	State of systems maintenance	Predefines IAQ and use of systems and controls
	Facilities manager, building operator24	Type of systems	Predefines IAQ and use of systems and controls
	Building occupants	Group dynamics	Influences occupant interaction and use of controls
	Building occupants	Personal attitude	Influences occupant interaction and use of controls
	Building operator, building occupants	Furnishing and occupant density	Influences the amount of occupants who have access to control systems

4. Supporting decision making through occupant behavior modeling and energy simulation

Based on the categorization discussed in previous pages, modelers can choose appropriate occupant behavior modeling strategies based on an inventory of associated profiles. These associated profiles group together cases sharing similar building and occupant characteristics, where occupant behavior can be expected to have a similar effect on energy usage. Figure 5 shows a recent profile development effort. Through statistical analysis, different diversity profiles can be created for different categories (type of occupants, type of building etc.) for each design stage. For early design stages, rules of thumb (representing the central tendency in the distribution) or simplified models (identifying just a few categories) are likely the most plausible ways to support decision-making. In the developed design stage, more rigor may be warranted.

In general, such an inventory helps analysts to choose the most appropriate modeling technique (appropriate level of complexity in occupant behavior modeling) and allows basic determination of the correlation between the occupants and energy usage. For example, Samuelson, Ghorayshi, and Reinhart (2016) show when calibration matters for substantially reducing errors relative to the incremental cost of performing careful calibration. Similarly, D'Oca, Corgnati, and Hong (2015) show the potential for knowledge discovery in databases in order to create an occupancy-schedule learning framework.

It also may be useful to provide such information to the occupants so that they understand how their behavior affects the building's energy consumption. This could trigger the users to start behaving in a more energy-efficient way.

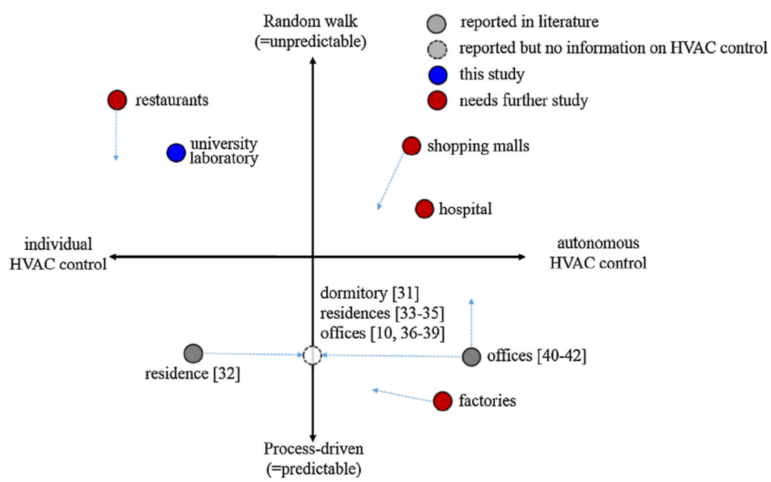

Figure 5: Different types of buildings for occupant behavior study (the arrows indicate that the location can vary) (Ahn and Park 2016)

5. Conclusions and future needs

The development of a framework for classifying applications of occupant behavior modeling is an important and ongoing task. A better framework will allow users to match models to applications more effectively, achieving a “fit for purpose” modeling standard. The case studies summarized in the appendix provide a wealth of illustrations of occupant behavior modeling applications. Tables 3 and 4 summarize the case studies presented in this report.

Table 3. Overview of case studies

Lifecycle	Research focus	Relation to behavior*	Building type	Country	Case study
Design	Impact on space heating	Impacts	Residential	China	13
Design	Impact on AC energy use	Impacts	Residential	China	15
Operation	Occupant satisfaction	Drivers/Systems/Impacts	Office	USA	1
Operation	Building performance	Drivers/Systems	Mixed	USA	2
Operation	Impact on energy use	Drivers/Impacts	Office	USA	3
Operation	Response to load shedding	Actions	Office	USA	6
Operation	Modeling behavior	Actions/Impacts	Office	USA	5
Operation	Occupancy data mining	Actions	Office	USA	7
Operation	Occupancy prediction	Actions	Residential	USA	8
Operation	Impact on energy use	Actions/Impacts	Office	USA	9
Operation	Impact on energy use	Actions/Impacts	Office	USA	10
Operation	Lighting control	Actions/Impacts	Office	USA	11
Operation	Energy behavior drivers	Drivers/Actions/Impacts	Residential	China	16
Operation	Energy use prediction	Impacts	Residential	China	17
Operation	Energy saving operations	Actions/Impacts	Residential	China	18
Operation	Energy behavioral change	Drivers/Impacts	Residential	China	19
Operation	Energy behavioral change	Drivers/Impacts	Educational	China	20
Operation	Air-conditioning system	Actions/Systems/Impacts	Educational	Singapore	21
Operation	Occupants' thermal comfort	Drivers	Office	Singapore	22
Operation	Impact on energy use	Impacts	Office	Singapore	23
Operation	Impact on energy use	Drivers/Impacts	Laboratory	South Korea	24
Operation	Impact on energy use	Impacts	Residential	Italy	25
Operation	Impact on energy use	Drivers/Impacts	Office	Italy	26
Operation	Window opening behavior	Actions/Impacts	Office	Germany	27
Operation	Impact on energy use	Impacts	Office	Netherlands	28
Operation	Occupancy-based energy usage	Actions/Impacts	Office	Finland	29
Operation	Blinds movements	Actions/Impacts	Office	Switzerland	30
Operation	Building performance assessment	Drivers/Systems	Office	Hungary	31
Operation	Occupancy prediction	Actions	Office	Denmark	32
Retrofit	Behaviors to energy-saving retrofit	Actions/Impacts	Office	USA	4
Retrofit	Rebound effect of behaviors	Impacts	Educational	USA	12
Retrofit	Control behavior of heat pump	Actions/Impacts	Residential	China	14

Note: Drivers refer to environment, comfort, psychology and economy factors that impact occupant behavior; Actions refer to occupant movement and actions such as blind operation; Systems refer to building systems such as HVAC; Impacts refer to the impacts of occupant behaviors on various dimensions of buildings such as energy usage

Table 4a. Comparison of case studies

Case studies	Case study 1	Case study 2	Case study 3	Case study 4	Case study 5	Case study 6	Case study 7
Contributors	Jennifer Senick, Clinton J. Andrews, Maren L. Haus, Richard Wener, Michael Kornitas, Mark Bolen, Pinky Samat, UtaKrogmann, and Francis Jordan.	Jennifer Senick, Clinton J. Andrews, Maren L. Haus, Richard Wener, Michael Kornitas, Mark Bolen, Pinky Samat, Francis Jordan, Deborah Plotnik, and Gavin Kwak	Jennifer Senick, Clinton J. Andrews, MaryAnn Sorensen Allacci and Richard Wener	Jennifer Senick, Richard Wener, Irina Feygina, MaryAnn Sorensen Allacci, and Clinton J. Andrews	Steven Malenchak, MaryAnn Sorensen Allacci, and Clinton J. Andrews	Marcelo Figueroa, Handi Chandra Putra, and Clinton J. Andrews	Jie Zhao and Khee Poh Lam
Location	Camden, New Jersey, USA	Maplewood, New Jersey, USA	Philadelphia, USA	Philadelphia, USA	Philadelphia, USA	Philadelphia, USA	Pittsburgh PA, USA
Period	2009-2010	2009 - 2010	2011	2012	2013	2014	2013 - 2015
Objectives	Occupant comfort and satisfaction	Building performance, occupant satisfaction and cost	Effect of occupant behavior on energy use	Occupant response to energy saving technologies and load shedding in a workplace	Evaluation of occupant behavior during load shedding	Learn the impact of incorporating occupant behavior in building energy models	Learn occupancy from power data
Building name	Waterfront Technology Center	Maplewood police and court building	Navy Yard	N.A.	N.A.	Building 101, Navy Yard	Phipps Center for Sustainable Landscapes
Building type	Office	Mixed	Multi-tenant office	Multiple types (i.e. office, laboratory, research and technical shops)	Office	Office multi-tenanted	Office
Building size	9125 m2	3888 m2	7093 m2	Building 1: 7125 m2; Building 2: 70191 m2	N.A.	6982 m2	2137 m2
Owner type	Quasi - governmental	Municipal/government	Liberty property trust/ public	Real estate investment trust/public	Liberty property trust/ public	Philadelphia Industrial Development Corporation	NGO
Occupant type	Office workers	Police and municipal court	Office workers	Office workers	Office workers	Office workers	Office workers
Data collected	N.A.	Indoor environmental quality; occupant satisfaction	Occupant behavior; Assessment of occupant's perception, satisfaction and use of the buildings	Electrical consumption by HVAC and lighting; building system data including HVAC and lighting systems; enviornmental data including Air flow, temperature, light	Building system data including HVAC and lighting systems	Plug load metering data; Site environmental conditions; Occupancy schedule	Power consumptions of office equipment; Occupant data including Fitbit, keyboard and mouse usage.
Models & Analytics	N.A.	Life cycle cost analysis	Life cycle cost analysis	N.A.	Regression analysis	Energy Plus simulation	Data mining algorithms and Energy plus simulation
Primary Contact	Clinton Andrews, Rutgers University. Email: clintonjandrews@gmail.com	Clinton Andrews, Rutgers University. Email: clintonjandrews@gmail.com	Clinton Andrews, Rutgers University. Email: clintonjandrews@gmail.com	Clinton Andrews, Rutgers University. Email: clintonjandrews@gmail.com	Clinton Andrews, Rutgers University. Email: clintonjandrews@gmail.com	Clinton Andrews, Rutgers University. Email: clintonjandrews@gmail.com	Jie Zhao, Delos. Email: jie.zhao@delos.com

Table 4b. Comparison of case studies

Case studies	Case study 15	Case study 16	Case study 17	Case study 18	Case study 19	Case study 20	Case study 21
Contributors	Chuang WANG	Yilong Han and Yujie Lu	Meng Shen and Yujie Lu	Simon Tsui and Allen Yui	Simon Lam, Gary Chiang and Joe Lo	Elizabeth Hio Wa LAI	Lynette Cheah, and Stephen Ross
Location	Beijing, China	Hangzhou, China	Hangzhou, China	Hong Kong, China	Hong Kong, China	Hong Kong, China	Singapore
Period	2015	2016-2017	2016-2017	2014	2016	2016-17	2014
Objectives	Influence of occupant behavior pattern on air conditioning energy consumption in residential buildings	Effectiveness of intervention to change occupant behavior	Energy Prediction Under Behavioral Intervention Strategies	Quantifying impacts on energy reduction with energy forecast facilitates	Quantifying energy savings among similar size households as drivers of behavioral changes	Impact of visualizing energy usage in Hong Kong primary schools	Characterizing user behavior and user-preferences for uncertainty quantification in the life cycle assessment of air conditioning systems
Building name	N.A.	240 residential apartments in three local communities, close to city suburban	240 residential apartments in three local communities, close to city suburban	Park Island	300,000 households	10 local primary schools	University building
Building type	Residential	residential	residential	Residential (Club house)	Residential	School	office
Building size	1764 m2	240 houses	240 houses	500,000 sf	Apartments for ~300,000 households	10 local primary schools with more than 6000 students in total	N.A.
Owner type	Resident	private residence	private residence	Park Island tenants	Residence	Primary schools	University
Occupant type	Residents	residents	residents	Club house exclusive use by tenants	CLP's residential customers (Eco Power 360 users)	Primary school students	university staff
Data collected	Building energy consumption; Building envelope properties; Cooling season data; Occupants' behavior patterns.	monthly home energy consumption; outdoor climate data; occupant behavior measurement data including the frequency of using different appliances; Occupants' personality, quality of life, attitude, and intentions of energy conservation	monthly home energy consumption; outdoor climate data; occupant behavior measurement data including the frequency of using different appliances; Occupants' personality, quality of life, attitude, and intentions of energy conservation	Electricity consumption measured by electric meters; Outdoor temperature and humidity data; Occupants' behavioral changes affected by online energy feedback	Electricity consumption measured by electric meters; Outdoor temperature; Behavioral changes affected by forcasted energy bills.	Electricity consumption - electric meters and add-on sub metering; Outdoor temperature; Occupants behavour of two school groups.	Air conditioning energy consumption; Air conditioning usage data at 5-minute resolution; Environmental data including indoor temperature, humidity, light intensity, and noise; Number of occupancy.
Models & Analytics	Weibull distribution based simulation	Difference-in-difference analysis	Machine learning algorithm	N.A.	N.A.	N.A.	Life cycle analysis
Primary Contact	Chuang Wang, Tsinghua University. Email: Wangchuang02@mails.tsinghua.edu.cn	Yujie Lu, National University of Singapore (NUS). Email: luy@nus.edu.sg	Yujie Lu, National University of Singapore (NUS). Email: luy@nus.edu.sg	Simon Tsui, CLP Power Hong Kong Limited. Email: simontsui@clp.com.hk	Simon Lam, CLP. Email: simonlam@clp.com.hk	Elizabeth Lai, Reconnect Limited. Email: elai@reconnect.org.hk	Lynette Cheah. Singapore University of Technology and Design. Email: lynette_cheah@sutd.edu.sg

Table 4c. Comparison of case studies

Case studies	Case study 22	Case study 23	Case study 24	Case study 25	Case study 26	Case study 27	Case study 28
Contributors	Stephen Siu Yu LAU, and Ji ZHANG	Ruidong Chang and Yujie Lu	Cheol Soo Park and Ki Uhn Ahn	Anna Laura Pisello	Cristina Piselli and Anna Laura Pisello	Karin Schakib-Ekbatan, Marcel Schweiker, and Andreas Wagner	Ad van der Aa, Cristina Jurado López, and Bas Giskes
Location	Singapore	Singapore	Sungkyunkwan University, Suwon, South Korea	Perugia, Italy	Perugia, Italy	Frankfurt, Germany	The Netherlands
Period	2015	2017	2015	2010-2017	2015-2017	2004-2009	2010-2017
Objectives	Learn thermal comfort	Occupant behavior simulation and energy consumption	Correlation between occupants and energy consumption	To analyze indoor occupancy of residential under-occupied single-family buildings	Comparison between monitored and simulated occupants behavior and energy consumption	Monitoring of energy performance and window opening behavior in a German office building	The Influence of Occupant Behavior on the Total Energy Consumption in Offices
Building name	Multiple buildings within National University of Singapore campus	BCA Academic tower	Sungkyunkwan University Campus	house in Perugia	CIRIAF research center	office building	ABT office
Building type	Office	Office	Laboratory	residential	office	office building	office
Building size	N.A.	1944 m2	26.7 m2	513 m2	1808 m2	8585 m2	2040m2
Owner type	Public	public agency	University	Private	University	private	private
Occupant type	Users of different types of learning spaces	office workers	Graduate students	residential	researchers/professors	office workers	office workers
Data collected	On-site measurement of environmental parameters; questionnaire interview of leaning space users.	Floor level total energy consumption, plug load consumption, and HVAC consumption; occupant behavior data measured by onsite sensor with calibration; survey data on occupant behavior.	Electric power consumption of EHP and personal heaters; Building window and door opening ratio; Outdoor air temperature, indoor air temperature and CO2 level; Number of occupants; Measurement of actions such as opening a window, door and controlling EHP.	Energy bills about natural gas for heating and HWP, and electricity for lighting, equipment and cooling; Building envelope and energy systems; Outdoor weather data and indoor microclimate data measured by subhourly monitoring stations; Number, types of occupants and their behaviors; Survey data on occupant behavior.	Sub-hourly power consumptions of office equipment, HVAC and lighting Electrical bills; Building envelope, window and door opening ratio, and energy systems data; subhourly outdoor weather data measured by rooftop monitoring station, and indoor subhourly monitored air quality and illuminance; Number and type of occupants and their behaviors; Survey data on occupant behavior.	Zonal electricity consumption per 10 minutes; Building window status; Environmental data including zonal indoor air and surface temperatures, CO2 concentrations, outdoor solar radiation, light intensities, temperature, relative humidity, wind, CO2 concentration, and rain amounts; Zonal occupancy, and their operation of windows, blinds, and lights.	Monitored and simulated heating, cooling, and plugload energy consumption; building envelop characteristics, lightning zonings, HVAC schedual, and thermal zoning; indoor temperature data; Number of occupancy.
Models & Analytics	N.A.	Regression analysis	Correlation analysis	DesignBuilder simulation	Simulation analysis	Logistic regression and classification algorithms	Energy plus simulation
Primary Contact	Stephen S Y Lau, National University of Singapore (NUS). Email: akilssy@nus.edu.sg	Yujie Lu, National University of Singapore (NUS). Email: luy@nus.edu.sg	Cheol Soo Park, Sungkyunkwan University. Email: cheolspark@skku.ac.kr	Anna Laura Pisello, University of Perugia. Email: anna.pisello@unipg.it	Cristina Piselli, University of Perugia. Email: cristina.piselli@ingpec.eu	Marcel Schweiker. Karlsruhe Institute of Technology. Email: marcel.schweiker@kit.edu	Ad van der Aa, ABT. Email: a.vd.aa@abt.eu

Table 4d. Comparison of case studies

Case studies	Case study 29	Case study 30	Case study 31	Case study 32
Contributors	Ken Dooley	Bernard PAULE, Juline BOUTILLIER, and Samuel PANTET	Zsofia Belafi, Tianzhen Hong, Andras Reith, and Kornel Dome Deme	Fisayo Caleb Sangogboye, Kenan Imamovic, and Mikkel Baun Kjærgaard
Location	Helsinki, Finland	EPFL Innovation Park, Switzerland	Budapest, Hungary	Odense and Vejle, Denmark
Period	2011 - 2016	2013 - 2014	2014 - 2015	2015
Objectives	Normalize consumption by occupancy	Compare benefits of automatic and manual blinds control	Diagnose energy and comfort	Predict time-series occupancy
Building name	N.A.	EPFL Innovation Park	N.A.	University of Southern Denmark & Green Tech Centre
Building type	Office	Office	Office	Office
Building size	6990m2	N.A.	6503 m2	2500 & 4000 m2
Owner type	Private	Public	Private	Public and private
Occupant type	Office workers	Office workers	Office workers	Office workers
Data collected	N.A.	Building system data including blinds position	Electricity and natural gas sub metering data; Building system data including HVAC set points and valve status; Environmental data including outdoor temperature, radiation and indoor thermographic; BMS occupancy data and measurement of occupants' thermal comfort;Comfort and occupant behavior survey, walk-through observation and interview data.	BAS occupancy data
Models & Analytics	Normalization analysis	Simulation analysis	IDA ICE simulation	Multi-label classification algorithms
Primary Contact	Ken Dooley, Granlund. Email: ken.dooley@granlund.fi	Bernard Paule, Estia SA. Email: bernard.paule@epfl.ch	Zsofia Belafi, ABUD. Email: belafi.zsofia@gmail.com	Mikkel Baun Kjærgaard, University of Southern Denmark. Email: mbkj@mmmi.sdu.dk

6. References

Ahn, Ki Uhn, and Cheol Soo Park. 2016. “Correlation between Occupants and Energy Consumption.” *Energy and Buildings* 116. Elsevier B.V.: 420–33. doi:10.1016/j.enbuild.2016.01.010.

AIA. http://www.aia.org/aiaucmp/groups/secure/documents/pdf/aiap026834.pdf

Architecture Australia. http://www.architecture.com.au/docs/default-source/becoming-being-an-architect/becoming-an-architect-brochure.pdf?sfvrsn=0:

BNA. http://www.bna.nl/wp-content/uploads/2015/02/150224-Scope-of-Work-Germany-US-UK-c-BDA-CoFA_Flyer.pdf

Club of Rome Report Limits to Growth, 1972,

Cowie, A., Darakdjian, Q., Feng, X., Hong, T. Usefulness of the obFMU Module Examined through a Survey of Occupant Modeling Functionality in Building Performance Simulation Programs. Building Simulation 2017, San Francisco CA, USA (currently under review).

D’Oca, Simona, Stefano Corgnati, and Tianzhen Hong. 2015. “Data Mining of Occupant Behavior in Office Buildings.” *Energy Procedia* 78. Elsevier B.V.: 585–90. doi:10.1016/j.egypro.2015.11.022.

Gaetani, Isabella, Pieter Jan Hoes, and Jan L M Hensen. 2016. “Occupant Behavior in Building Energy Simulation: Towards a Fit-for-Purpose Modeling Strategy.” *Energy and Buildings* 121. Elsevier B.V.: 188–204. doi:10.1016/j.enbuild.2016.03.038.

Guy and Shove (2000) *A sociology of Energy, Buildings and the Environment*.

“IEA EBC Annex 66.” 2014. http://www.annex66.org/.

O’Brien, William, Isabella Gaetani, Sara Gilani, Salvatore Carlucci, Pieter-Jan Hoes, and Jan L.M. Hensen. 2016. “International Survey on Current Occupant Modeling Approaches in Building Performance Simulation.” *Journal of Building Performance Simulation* 1 (0). Taylor & Francis: 1–19. doi:10.1080/19401493.2016.1243731.

Polinder, Henk, Marcel Schweiker, Ad Van Der Aa, Karin Schakib-Ekbatan, Valentina Fabi, Rune Andersen, Naomi Morishita, et al. 2013. *Final Report Annex 53 - Occupant Behavior and Modeling (Separate Document Volume II)*.

RIBA. https://www.architecture.com/Files/RIBAProfessionalServices/Practice/RIBAPlanofWork2013Overview.pdf

Roetzel, Astrid 2015, Occupant behavior simulation for cellular offices in early design stages—Architectural and modeling considerations, Building Simulation

Samuelson, H.W., A. Ghorayshi, and C.F. Reinhart. 2016. “Analysis of a Simplified Calibration Procedure for 18 Design-Phase Building Energy Models.” *Journal of Building Performance Simulation* 9 (1): 17–29. doi:10.1080/19401493.2014.988752.

UN conference on the human environment 1972, Brundland Report UNEP 2016.

Warren, Peter. 2003. Integral Building Envelope Performance Assessment. Technical Synthesis Report, IEA ECBCS Annex 32. Document A32-TSR-2003, Published by Faber Maunsell Ltd on behalf of the International Energy Agency Energy Conservation in Buildings and Community Systems Programme. ISBN 0-9542670-9-7, pp. 1-16.

7. Appendix: Case Studies

Case 1

Case study title

Occupant comfort and satisfaction performance of energy and water consumption in the NJ Economic Development Authority Building

Contributors

- Jennifer Senick, Clinton J. Andrews, Maren L. Haus: Rutgers Center for Green Building, Rutgers University, NJ, USA
- Richard Wener: Polytechnic Institute of NYU, NY, USA
- Michael Kornitas: Energy Conservation Manager, Rutgers University, NJ, USA
- Mark Bolen, Pinky Samat: Rutgers Center for Green Building, Rutgers University, NJ, USA
- UtaKrogmann and Francis Jordan: Department of Environmental Sciences, Rutgers University, NJ, USA

Contribute to other subtasks

- Subtask C: Occupant action models in commercial buildings
- Subtask E: Applications in building design and operations

When and where

2009-2010, NJ Economic Development Authority's (NJEDA) Waterfront Technology Center, Camden, NJ, USA

Building(s) description

- Owner type: quasi-governmental
- Building type: Business, Office, Commercial-multi tenanted
- Total floor area: 98,225 sf
- Number of stories: 5-story
- Location (city, country): Camden, NJ, USA
- One or two pictures:

Tech Center Building; Source: Ballinger *Entrance lobby;* Source: Ballinger

Occupant type

Workers with varying space needs (from larger build-to-suit tenants to smaller suites for multi-tenants who would share amenities

Methods and Data

The following outline illustrates the phases and actions endeavored by the Rutgers Center for Green Building for conducting a POE (Post Occupancy Evaluation) on the NJEDA Tech Center.

Phase 1: Baseline Research

- **Building Owner Interview -**reviewed overall project details, responsibilities, and expectations.
- **Design, Construction, Engineering Team Interview -** reviewed green features and performance expectations.
- **Facility Manager Interview -** gathered detailed information about the building and FM practices; also used RCGB instruments including an online survey and Building Performance Evaluation (BPE) tool that helps to gather quantitative data in such areas as energy, water, building cost and waste.
- **Tenant Representative Walk-through and Project Briefing** – toured some tenant facilities and explained the study. Solicited tenant participation.

As a result of this step, the study team identified an opportunity to conduct a comparative case study, within the overall study, that would seek to assess similarities and differences in occupant satisfaction. For example, two participating tenants are located on the same side of the building and share a similar line of, but have different office layouts (open-collaborative vs. private-cubicles) which we hypothesize may affect occupant satisfaction in terms of lighting, acoustics, temperature, etc.

- **Follow-up Visit** – the purpose of the second visit was to formalize tenant participation in the study. During this interview the tenant representatives also provided specific information on usage patterns and occupant habits and agreed to have occupant-employees participate in an online survey and follow-up surveys and/or focus groups.

- **Background Survey -** gathered background information about the occupants and their attitude to, and experience of, the building through a brief (10 minute) online survey.

- Rutgers worked with the tenant representative to come up with a communication plan and timeline for inviting occupants to participate in the online survey. An email invitation was sent inviting occupants to participate in the study and they were given two weeks to complete the survey. Incentives were used to encourage participation in the survey (e.g., drawings for a gift certificate to a local restaurant).

- **Building Performance Data Analysis –**performed energy and water analysis and benchmarking and a life cycle cost and infrastructure cost analysis.
- **Survey Analysis –** analyzed and produced the results of the occupant surveys.
- **Case Study Write-up** – completed this draft case study write-up.

Phase 2: Follow-up Research (for consideration under a different grant, from the USGBC)

- **Semi-/Annual Facility Manager Interview -** review utility bills, real-time monitoring results, and repeat/expand participating occupants for survey

- In conjunction with the online survey, the team re-interviewed the facility manager (third site visit) and set up the data logging procedure to collect ongoing data in one hour increments on: Indoor temperature, temperature set points, outdoor air temperature, relative humidity (outdoor and at air handling units), carbon dioxide levels, peak and non-peak hours of the HVAC equipment. Unfortunately, RCGB has been unable to attain this data as it seems the facility manager either cannot or will not provide it.

- **Occupant Focus Group(s)–**occupant focus groups could be used to more finely discern results of the occupant survey(s)

- **Additional Occupant Surveys (optional) –** collect additional feedback on occupant satisfaction and behavior.

Data and models availability

Data and/or models are available to Annex 66 participants. Reports, models, and anonymized data are freely available for download at greenbuilding.rutgers.edu. Please cite this source if you use it.

Summary

This case study analyzes physical performance measures in areas like energy and water consumption, and construction and operation costs, and survey work in the areas of occupant comfort and satisfaction.

Our conclusion as to the role of designing the Tech Center is that the green features did what they were expected to do for electricity use, but were less successful in limiting natural gas use. Factors that may account for the mixed performance we report include a series of design choices relating to the need to maintain optimal performance under partial load conditions. Yet, the actual natural gas usage of the building is higher than expected. Additionally, this building, which has a large outdoor air requirement because it houses potential laboratory, includes a heat recovery system to offset the increased heating and cooling loads. The actual building performance suggests that the heat recovery system is performing less well than intended in the design. We speculate that the outside air may be oversized for current use even while it may play a positive role in occupant satisfaction with building indoor air quality. The heat recovery wheel, which is intended to offset the energy penalty of these fresh air demands, seems not to be off-setting as much natural gas use as anticipated. This is an area that needs further study, as an instance of a more general challenge.

Design decisions that appear to have benefited building electricity performance include lighting and HVAC features. In addition, the building orientation (long axis east to west) in combination with sunscreen systems on the south and west elevations should facilitate reduced heating and cooling loads, as should the light-colored roof (cooling).

In terms of operating practice, we observe that the NJEDA has undertaken a number of measures to benefit the performance of the Tech Center. These include the building commissioning plan that was implemented successfully in five phases – planning, design, construction, acceptance and post-acceptance. Additionally, NJEDA achieved LEED-CI certification for its tenant fit-outs. And yet, it appears that there is more work to be done in promoting the benefits of green building to tenants. Making a further investment in the building’s landscaping and perimeter and/or explaining the nature of xeriscaping might also lead to higher levels of overall satisfaction among occupants. Additionally, when training of maintenance staff is done that as a part of commissioning, the tenants are informed of the enhancements that are made and their role in maintaining these sustainable enhancements.

By way of context, green buildings have demonstrated performance levels that range from 25% below to 30% above predicted energy savings. The authors note that variations in results are likely to come from construction changes, equipment performance and difference in operational practices. This study demonstrates that all three of these factors are in play in considering the performance of the NJEDA Tech Center.

Key Findings

Building Operating Performance

- **Energy Usage:** This building outperforms conventional buildings but falls short of its intended level of performance. The results speak to the complexity of understanding the performance of a multi-tenanted building which is taking a long time to reach full occupancy. Once tenants are fully established, it will be worth revisiting their patterns of energy and water usage.
- **Water Usage:** For the most part water use in the Tech Center is at the same level of magnitude as the LEED design case. However, a more accurate determination of the number of regular occupants is needed for a more accurate

comparison between the predictions for the LEED design case and actual water consumption.

Life Cycle Performance

- **Life Cycle Cost (LCC):** When compared to the budget case modeled building, the reduced energy consumption of the as-built Tech Center results in a positive Net Present Value (NPV) relative to both the design and budget cases.
- **Avoided Infrastructure Analysis – Energy and Water:** We find that typical new buildings are more electricity intensive than the typical existing building, while the natural gas intensity is slightly less, and overall energy intensity is about the same. Regarding water, the typical new green building uses less water than the typical new conventional building, as is the case with the Tech Center.

Building Occupant Satisfaction and Performance

- **Occupant Survey Results:** This facility is viewed very positively, overall, by the limited number of people who completed the survey. A very high degree of satisfaction was expressed about the overall design and appearance of the environment, building views and with the quality of indoor air. There were also some specific areas of concern, namely exterior landscaping, privacy, noise, and thermal comfort. In addition, many respondents were dissatisfied with the location or convenience of recycling containers.

Related publications

- Senick, J., Andrews, C.J., Haus, M.L., Wener, R., Kornitas, M., Bolen, M., Samat, P., Krogmann, U. and Jordan, F. "Waterfront Technology Center Study: A New Jersey Economic Development Authority Building". Prepared by Rutgers Center for Green Building for USGBC – NJ Chapter. 2011. At http://rcgb.rutgers.edu/wp-content/uploads/2013/10/EDA_FINAL.pdf

Case 2

Case study title

Maplewood Police and Court Building: A Post Occupancy Evaluation

Contributors

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- Michael Kornitas: Energy Conservation Manager, Rutgers University, NJ, USA
- Mark Bolen, Pinky Samat: Rutgers Center for Green Building, Rutgers University, NJ, USA
- Francis Jordan: Department of Environmental Sciences, Rutgers University, NJ, USA
- Deborah Plotnik: Rutgers Center for Green Building, Rutgers University, NJ, USA
- and Gavin Kwak: Polytechnic Institute of NYU, NY, USA

Contribute to other subtasks

- Subtask C: Occupant action models in commercial buildings
- Subtask E: Applications in building design and operations

When and where

2009-2010, Maplewood Police and Court Building, Maplewood, NJ, USA

Building(s) description

- Owner type: municipal/government
- Building type: Governmental building, including court, police, detention, office, public meeting areas and other facilities
- Total floor area: 41,850 sf
- Number of stories: 4-story including basement
- Location (city, country): Maplewood, NJ, USA
- One or two pictures:

Maplewood Police and Court Building exterior. *Source: Richard Wener*

Occupant type

- Police department, municipal court

Methods and Data

This study evaluates the Maplewood Police and Court Building on a variety of different parameters including environmental and economic performance, occupant satisfaction, and avoided infrastructure costs (post occupancy evaluation - POE). The following sections provide a detailed analysis of the objectives and outcomes of the Maplewood Police and Court Building from building performance and occupant – user and operator – points of view.

- Descriptions of the building's green features in seven major areas: Site Selection and Planning, Construction Management, Landscaping, Building Design, Building Materials, Building Systems, and Other Features.
- Interviews and questionnaires with the building owner, design team, engineering team, facility manager, and others to gather information on energy and water use, indoor environmental quality, occupant satisfaction, and avoided infrastructure costs.

Occupancy Satisfaction & Performance – Occupant Survey

Information on occupant responses to this building come from a walk-through tour of the facility, individual and group interviews with key personnel including architect, facilities staff, police and court administrators, and patrol officers, and from a self-administered questionnaire distributed to all building personnel. Completed surveys were received from 25 persons representing both the police department and court personnel. This sample represents a cross-section of court and police staff, administrative, clerical and patrol officers, across all shifts, males and females, predominantly between 30 and 50 years of age, most of whom have been on the job for 4 years or more. That said, it is important to note that is a small self-selected sample and therefore must be viewed as suggestive only; the results are most valuable when viewed in context of other observations.

- Analysis of actual energy performance and economic assessment of the building through a Life Cycle Cost (LCC) analysis.

Life Cycle Performance - Life Cycle Cost (LCC) Analysis

To better understand the cost-effectiveness of the new Maplewood Police Station's green features, we performed a Life Cycle Cost (LCC) analysis for the energy-related characteristics and equipment. LCC analysis considers the total costs associated with a building from its construction to its demolition. An LCC analysis is usually comparative, contrasting the as-built, green building with a conventional building or "budget" case. For each scenario, we collected utility consumption data and the capital costs for building features relating to energy consumption (electrical, HVAC, exterior walls, glazing, roof).

For the Maplewood Police Station, utility data and capital cost data were acquired from the township government and the architect, respectively. The costs for the budget case building are modeled using RSMeans CostWorks Online as well as industry-standard building costs, and have been reviewed by engineers and building consultants. Utility consumption estimates for the budget case building come from the energy modeling performed for the LEED submission. Once initial costs and energy consumption costs were obtained for the as-built and budget building designs, they were tabulated in an LCC spreadsheet adapted from one developed by the Rutgers Center for Green Building for prior projects. The budget case building was used as the "base" model for comparison purposes. All analyses are reported on a per-square-foot basis. Finally, we performed several sensitivity analyses. A sensitivity analysis examines the effect that different factors have on the relative NPVs of the represented projects. In this LCC analysis, there are three factors for which we ascribe variable values: future energy costs, the discount rate, and building lifespan. Future energy costs were set to 75% and 150% of their projections from the DOE Annual Energy Outlook 2009. We use three different values for the discount rate. The primary NPV analysis uses a 7% discount rate – arguably pretty generous in today's economic climate, while the low discount rate of 4% represents the low point of the 30-year average mortgage rate with points from Freddie Mac during the recent recession. A more aggressive discount rate of 12% was also employed. Building lifespan for the primary NPV analysis is assumed to be 30 years, and 15-year and 50-year lifespans are considered in the sensitivity analyses.

Data and models availability

Data and/or models are available to Annex 66 participants. Reports, models, and anonymized data are freely available for download at greenbuilding.rutgers.edu. Please cite this source if you use it.

Summary

This case study assessed the Maplewood Police and Court Building. This building was the 33rd LEED certified building in NJ and the first municipal building to be certified by the U.S. Green Building Council's (USGBC) Leadership in Energy and Environmental Design (LEED) green building rating system. This study develops a synthesized analysis on physical performance measures in such areas as energy and water consumption, and construction and operation costs, and survey work in the areas of occupant comfort and satisfaction. This work includes the following:

- Descriptions of the building's green features in seven key areas: Site Selection and Planning, Construction Management, Landscaping, Building Design, Building Materials, Building Systems, and Other Features.
- Interviews and questionnaires with the building owner, design team, engineering team, facility manager, and others to gather information on energy and water use, indoor environmental quality, occupant satisfaction, and avoided infrastructure costs.

- Analysis of actual energy performance and economic assessment of the building through a Life Cycle Cost (LCC) analysis.
- Assessment of environmental impacts of energy and water use.

The combination of the above research provides the basis for this case study write-up that evaluates building performance, occupant satisfaction and cost considerations.

Key Findings

- Daylighting is a valuable and appreciated feature but issues relating to glare that can impact productivity need to be addressed in architecture and interior design;
- Decisions to make use of sophisticated HVAC and control systems need to consider the skill/training level, availability and cost of personnel needed to adequately maintain these systems;
- There are concerns about the accuracy of energy use predictions that were part of the LEED submittal, which may suggest a broader issue about reliance on such models;
- The life-cycle cost effectiveness of a green building is diminished if it suffers from an extended startup period of suboptimal performance; designing for partial and widely variable loads is a challenge of buildings like this and needs to be better addressed;
- The financial viability of adding green features is not a given and in some cases depends heavily on financial subsidies, such as SRECs.

Related publications

- Senick, J., Andrews, C.J., Haus, M.L., Wener, R., Kornitas, M., Bolen, M., Samat, P., Jordan, F., Plotnik, D. and Kwak, G. “Maplewood Police and Court Building: A Post Occupancy Evaluation’. Prepared by Rutgers Center for Green Building for USGBC – NJ Chapter. 2010. At http://rcgb.rutgers.edu/wp-content/uploads/2013/10/Maplewood-Police-final-4_6_11-rev.pdf

Case 3

Case study title

Energy Efficiency and Occupant Behavior-Greater Philadelphia Innovation Cluster (GPIC) for Energy-Efficient Buildings, a U.S. DOE Energy Innovation Hub Repository Case Study

Contributors

- Jennifer Senick, Clinton J. Andrews, MaryAnn Sorensen Allacci: Rutgers Center for Green Building, Rutgers University, NJ, USA
- and Richard Wener: Polytechnic Institute of NYU, NY, USA

Contribute to other subtasks

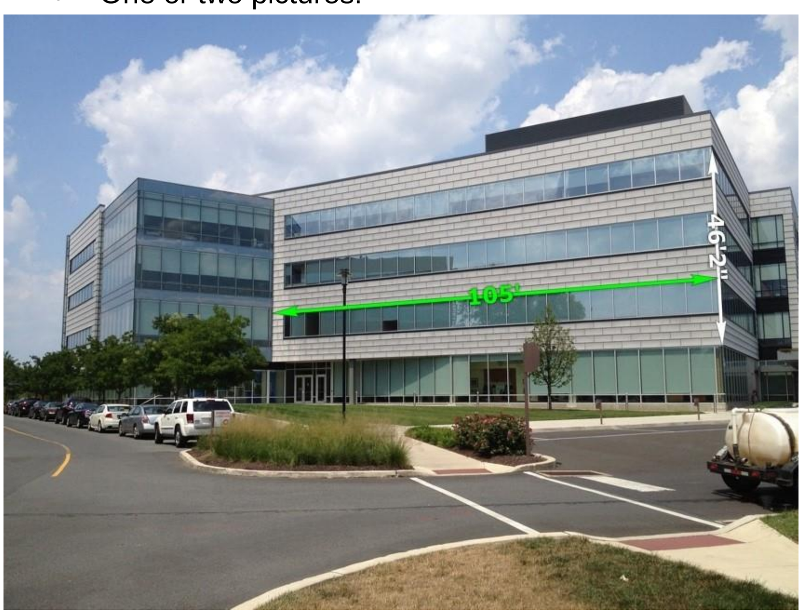
- Subtask A: Occupant movement and presence models in buildings.
- Subtask C: Occupant action models in commercial buildings

When and where

2011, Navy Yard, Philadelphia, PA, USA

Building one description

- Owner: Liberty Property Trust-real estate investment trust/public
- Building type: multi-tenant office
- Total floor area: 76,350 sf
- Number of stories: 4 conditioned + 4-story day-lit atrium
- Location (city, country): Philadelphia, PA, USA
- One or two pictures:



Occupant type of building one

- Typical office workers in a mix of open and private spaces with some ground floor retail

Building two description

- Owner type: Liberty Property Trust-real estate investment trust/public
- Building type: multi-tenant office
- Total floor area: 95,621 sf
- Number of stories: 4 conditioned + 4-story day-lit atrium
- Location (city, country): Philadelphia, PA, USA
- One or two pictures:

Occupant type of building two

- Typical office workers in a mix of open and private spaces with some ground floor retail

Methods

Secondary Data

- Review of Archival Sources: LEED Documentation, ENERGY STAR Portfolio Manager analyses, various consultant reports
- Building Performance Evaluation- utility bill analysis and Building Automation System (BAS) sensor logs

Primary Data

- Walk-through observations of common spaces and a sample of tenant spaces in the two buildings

- Photo documentation of some of these spaces
- Semi-structured interviews with:
- design, construction and engineering team members, representatives of building developer/owner to review design intentions, performance expectations, and features aimed at energy efficiency
- Facility Manager (FM) to gather detailed information about the building and FM practices
- Tenant Representatives for a sample of occupied spaces to understand their expectations and views of the building and any specific office polices regarding energy use
- Focus Groups of:
    - Tenant representatives (also a tenant recruitment strategy)
    - Office occupants for a sample of participating tenants
- Survey of:
    - Building occupants to assess perceptions, satisfaction and use of the buildings such as may impact building energy performance
    - Facility manager in conjunction with a Building Performance Evaluation (BPE) tool to assist in gathering both quantitative and qualitative data in such areas as energy, water, building cost and waste

Data and models availability

Data and/or models are available to Annex 66 participants. Reports, models, and anonymized data are freely available for download at greenbuilding.rutgers.edu. Please cite this source if you use it.

Summary

Multi-tenanted buildings typically accommodate diverse groups of tenants with various energy needs, while additional complexity emerges from their interaction with building systems and design. Factors such as fragmented responsibilities/locus of control issues, split incentives along with inadequate flow of information, and other related issues, such as luck of coordination between building design and interior design each may be especially relevant to a multi-tenanted context, given its heterogeneous population. These factors can make energy management in multi-tenanted buildings highly challenging and help explain shortfalls in realization of building performance objectives. Conversely, successful resolution of those could lead to joint benefits for building developer/owners and tenants/occupants.

These case studies investigate direct and indirect effects on energy use based on aspects as developer/owner requirements, building design and systems, construction outcomes, and building operator and occupant behavior. They provide valuable insights into the challenges that confront the goal of achieving a 50% energy reduction in commercial buildings in the Greater Philadelphia region by 2014. Research design and methods are based on POE research and entail primary and secondary data collection via semi-structured interviews of tenants and members of the developer/owner team, an occupant survey, building walk-throughs, focus groups, utility bill and building automation system sensor log analyses, and building performance benchmarking.

Key Findings

- **Disconnect between core and shell design/construction and interior fit-out of tenanted spaces**

An alternative approach is needed that can simultaneously satisfy energy objectives and occupants workplace preferences. This could be accomplished through increased coordination between core and shell and interior fit-out in a manner that takes the mediating role of occupant behavior more fully into account, at all levels of organization. From a policy perspective, GPIC investigators can then take this knowledge about occupant behavior and tie it into the development of better, more integrated design process and best practices that are incorporated into building programs within the GPIC region and nationally. Performance-based codes and tying incentives for energy efficiency to actual performance would also be expected to advance the GPIC energy agenda.

- **Diffused and confused locus of control**

A level of cooperation among building developer/owner, manager, and tenants/occupants is required to meet energy efficiency and related objectives. Additionally, some level of confusion exists regarding control over key building functions such as lighting and HVAC. A variety of remedies may be available ranging from a program of tenant/occupant education to new design approaches and operating systems that help to assuage the inherent tension between centralized and local control. GPIC investigators of building occupant behavior can assist in finding solutions by formalizing the results of POE into models of more realistic occupant behavior that the building and real estate industries can, in turn, use in designing, construction and operating buildings with more predictable performance.

- **The role of direct feedback and a new view of split incentives; is economic motivation sufficient?**

While direct feedback on energy use remains an important tool in promoting energy efficient behavior, other approaches could be made available to building occupants that would capture their interest and bond them to a mission of steep energy reduction. Developers/owners of buildings already comprehend the importance of direct feedback even while costs to sub-meter a multi-tenanted building can be prohibitive and technically complicated for a mix of tenants such as represented in this study. Next in line for GPIC research in Year 2 is an exploration of the effects of customized feedback mechanisms (individual dashboards) in conjunction with serious games/social media-like interventionist approaches in these or similar buildings. This is an undertaking to be executed at all levels of organization – developer/owner, building manager, tenant, and employee/occupant.

Related Publications

- Senick, J., Andrews, C.J., Sorensen Allacci, M., Wener, R.E., Niyogi, I. and Brooks, J. "Energy Efficiency and Occupant Behavior". Prepared by the Rutgers Center for Green Building for at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA. 2012. At http://rcgb.rutgers.edu/wp-content/uploads/2013/11/report_Energy_Efficiency_and_Occupant_Behavior.pdf

Case 4

Case study title

Occupant Behavior in Response to Energy-Saving Retrofits and Operations

Contributors

- J.A. Senick: Rutgers Center for Green Building, Rutgers University, NJ, USA
- R.E. Wener, I. Feygina: Polytechnic Institute of NYU, NY, USA
- M. Sorensen Allacci, and C.J. Andrews: Rutgers Center for Green Building, Rutgers University, NJ, USA

Contribute to other subtasks

- Subtask C: Occupant action models in commercial buildings
- Subtask E: Applications in building design and operations

When and where

2012, Philadelphia, PA, USA

Building one description

- Owner: a real estate investment trust/public
- Building type: single-tenanted office
- Total floor area: 76,692 gross sf
- Number of stories: 3 story
- Location (city, country): Greater Philadelphia, PA, USA
- Not available

Occupant type of building one

Office, some private, some open work areas

Building two description

- Owner type: a real estate investment trust/public
- Building type: 35 buildings including office, laboratories, experimental research and technical shops
- Total floor area: 755,540 sf
- Number of stories: 3 story
- Location (city, country): Philadelphia, PA, USA
- Not available

Occupant type of building two

Offices, some private, some open work spaces

Methods

This study employed a quasi-experimental research design using data collected through a series of participant surveys to assess building occupants' reactions to energy-saving technologies in their work environment. Each of the buildings underwent a series of load-shed events in which cooling and lighting were decreased by a preset amount.

- In Building 1 the decreases ranged from 5 to 15 %.
- In Building 2 the decreases entailed switching to weekend lighting in the hallways, and turning the HVAC system off.

Participants were surveyed on days when the building was operating under the normal energy load (control days) and during load shed days, and these measurements were compared to detect changes in responses.

Participants also completed a comprehensive survey which assessed their satisfaction with and concerns about environmental factors in the workspace, including air flow, temperature, and light, ability to alter and control the environment, choice of adaptive behaviors resorted to when environmental features do not meet needs, as well as perceived productivity and overall job satisfaction. The survey was completed during the shoulder season, in the early Fall, and again during the Winter in a shorter follow-up format.

Data and models availability

Data and/or models are available to Annex 66 participants. Reports, models, and anonymized data are freely available for download at greenbuilding.rutgers.edu. Please cite this source if you use it.

Summary

This study addresses occupant response to energy-saving technologies and load shedding in the workplace. Two case studies of office buildings are presented in which occupant response to environmental conditions is tracked. The load shedding involved planned reduction of electrical consumption within each building, through reductions to both HVAC and lighting systems. The research questions asked whether these changes produced noticeable responses from the occupants in how they felt about ambient conditions in the workplace.

The study's findings are suggestive about the characteristics of buildings that are more conducive to load shedding that is acceptable or even viewed positively by building occupants, and the extent to which typical office buildings may be overcooled during the summer and shoulder months.

Also, the degree to which the load shedding causes a significant change in the perceived quality of environmental conditions appears to be a function of 1) how big the change in conditions (percentage change in lighting levels and temperature/airflow) - small changes may be beneath the threshold of detection and have minimal impacts; and 2) how satisfactory existing conditions were prior to load shedding. Therefore, larger changes in conditions, in terms of percentage of decrease in power to HVAC and lighting, are likely to be detected and may affect comfort, satisfaction, productivity, and stress. The strength of the effect and the direction of change depends on qualitative factors of building systems and nature of the load shedding, as well as prior levels of satisfaction.

These grounded hypotheses, resulting from this work, will be tested on additional buildings in BP3 en route to producing a roadmap with our industry partners regarding how to scale up successful energy efficiency interventions in commercial buildings. The data collection associated with the current effort should be viewed as a pilot, as conditions for and timing of the load shedding were evolving even as instruments were being developed and tested on site. This resulted in in data collection from a relatively small number of testing days and research subjects.

Key Findings

In drawing conclusions we need to be careful to take into account the differing contexts of these buildings. First, they have different functions and populations. Building 2 is owner-occupied by employees of a scientific research organization. Building 1 is occupied by a single tenant whose employees are mostly engineers. Building 1 has much more sophisticated control systems and a superior building envelope, allowing it much better control over internal conditions, whereas Building 2 consists of a series of interconnected buildings of various ages, different envelopes, and varying control systems, over which operators have much less control, reducing their ability to adjust for changing conditions, areas with different kinds of sun exposure, etc.

- All load shedding is not the same. Load shedding may be much better suited for buildings that have sophisticated controls and high-tech envelopes, in which operators can tailor adjustments at a fine-grained level so that the load shedding is not seen as a drastic change. Load shedding may be a more risky strategy in buildings with older systems and less control over operations.
- A second important finding relates to the extent to which these (and many other) buildings may be over-cooled in summers. Especially given that occupants preferred somewhat warmer temperatures (Building 1), reducing the extent of over-cooling, where it occurs, could save energy – not only during load-shedding events but on a regular basis.

Related Publications

- Senick, J.A., R.E. Wener, I. Feygina, M. Sorensen Allacci, and C.J. Andrews. 2013. Occupant Behavior in Response to Energy-Saving Retrofits and Operations. Prepared by the Center for Green Building at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA. 2103. At http://rcgb.rutgers.edu/wp-content/uploads/2013/10/Subtask-6.4-No30-Attachment-Occupant-Behavior-and-AERs_resubmitted.pdf

Case 5

Case study title

Preliminary experimental evaluations of occupant behavior during load shedding

Contributors

Malenchak, S., Sorensen Allacci, M., and Andrews, C.J: Rutgers Center for Green Building, Rutgers University, NJ, USA

Contribute to other subtasks

- Subtask C: Occupant action models in commercial buildings
- Subtask E: Applications in building design and operations

When and where

2013, Greater Philadelphia region, PA, USA

Building(s) description

- Owner: Liberty Property Trust-real estate investment trust/public
- Building type: commercial office-9 buildings
- Total floor area: Not applicable
- Number of stories: Not applicable
- Location (city, country): Greater Philadelphia region, PA, USA
- One or two pictures: Not available

Occupant type

Typical office workers in open office spaces in an office building (enclosed offices and cubicles)

Methods and Data

The study seeks to answer multiple questions. The first has to do with advanced energy retrofits spread throughout the designated buildings. The second question addresses the effects of partial load shedding on occupant behavior and satisfactions in the buildings. Based on an agreement with their local energy provider, the company agreed to participate in simulated load shedding events throughout peak periods during the summer of 2013; the sheds took place once a week for six weeks. The events consisted of a reduction in energy consumption to the buildings' heating, ventilation, and air conditioning (HVAC) and lighting systems, of differing percentages. Their goal was to see how this would affect their tenants.

This was to be accomplished in several ways, the first being field interviews and observations. During load shed events, the research team conducted intercepts interviews among tenants, attempting to uncover any perceived differences noticed during the events. Also collected were observations on occupant behavior, such as the use of personal fans, lights, etc., as well as temperature and lighting measurements throughout the building. The last measure came in the form of tenant surveys, which are the focus of this paper.

This quasi-experiment took the form of an interrupted time series program evaluation. To evaluate the effects of load shedding, data were collected from occupants in each building using online surveys conducted both before the program took place (baseline surveys), as well as in the mornings and afternoons of both load-shed and separate control days, during which there were no changes to the building systems (daily surveys). The baseline survey consisted of a comprehensive questionnaire about the participant's background information as it pertains to this study, such as location in the building, ratings on general building performance, age, etc. The daily surveys were shorter, and intended to only observe current behaviors and satisfactions. There were 81 baseline and 554 daily surveys completed during the course of this program. The majority of the independent, or explanatory, variables used for this analysis came from the baseline survey, which were then matched to the participants of the daily surveys.

Data and models availability

Data and/or models are available to Annex 66 participants. Reports, models, and anonymized data are freely available for download at greenbuilding.rutgers.edu. Please cite this source if you use it.

Summary

Load shedding has become increasingly popular across the industrialized world in recent years. This is the practice of reducing some or all of a building's energy consumption for a period of time, usually during hours of peak energy demand, in order to reduce stress on the power grid and reduce the chances of total system collapse. There is a large and growing body of literature on the effects and benefits of load shedding in regards to controlling energy demand and supply, but there is virtually no research done on the behavioral effects this practice may have on occupants of buildings undergoing the treatment.

This report describes the methods and results of an interrupted time series quasi-experiment used to try to capture these results. To do so, we employed a series of occupant surveys during both load shedding (of both HVAC and lighting systems, at several levels of intensity) and control (normal) conditions across nine multi-tenanted commercial buildings owned by a real estate investment trust in Greater Philadelphia and analyzed the results using a variety of statistical techniques, most notably linear regression models.

Our results suggest that there is no impact from these instances of load shedding on occupants in this set of buildings, or in some cases a slight positive effect, with the latter being counterintuitive when considering the program. This leads to two potential conclusions: either 1) the effect of the load shedding on occupants is slight enough that it goes unnoticed, or 2) that the buildings were operating inefficiently under normal conditions. In either case, there is the potential that permanent changes in operating

practices may be a viable option. The results also suggest that organizational learning is taking place as the building owner gains experience with this technology.

Key Findings

- There is either no impact from load shedding on occupants, or a positive effect, which is counterintuitive when considering the program.
- The buildings are perhaps not operating at their optimal levels, at least in terms of the HVAC systems. The effect of load shedding on occupants is minor, at least in the percentages used in this experiment.
- It may be possible to shed certain amounts of loads permanently without loss of utility to building occupants.
- Reductions in required electricity production may be possible on a fairly large scale, should these results prove robust.

Related publications

- Malenchak, S., Sorensen Allacci, M., and Andrews, C.J. 2014. Preliminary Experimental Evaluations of Occupant Behavior during Load Shedding. Prepared by the Center for Green Building at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA. At http://rcgb.rutgers.edu/wp-content/uploads/2014/05/LoadSheddingReport20140131.pdf

Case 6

Case study title

Preliminary Report: Incorporating Information on Occupant Behavior into Building Energy Models

Contributors

- Figueroa, M., Putra, H.C., and Andrews, C.J.: Rutgers Center for Green Building, Rutgers University, NJ, USA

Contribute to other subtasks

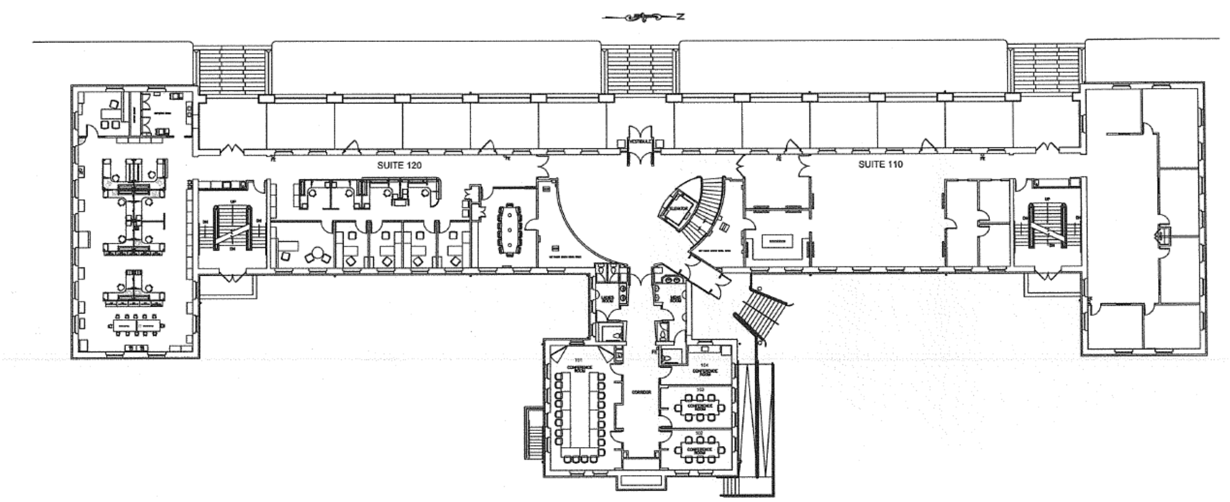
- Subtask C: Occupant action models in commercial buildings
- Subtask E: Applications in building design and operations

When and where

2014, Building 101, Philadelphia, PA, USA

Building(s) description

- Owner: Philadelphia Industrial Development Corporation (PIDC)
- Building type: commercial office-multi tenanted
- Total floor area: 75,156 sf
- Number of stories: 3 floors and basement
- Location (city, country): Philadelphia, PA, USA
- Floor plan:



FIRST FLOOR

Occupant type

Typical office workers in open office spaces in an office building

Methods and Data

Data Collection

The approach followed was multi-method to record independent observations and self-report by tenant representatives and occupants of leased office space at Building 101.

- An initial walk-through guided by facilities personnel incorporated initial observations and contacts with tenants as perspective participants in the study.
- Upon return, consenting tenants were engaged in in-depth interviews that developed information including the organization's mission, number of employees, their schedules in the office, and overall lighting and temperature fit with office needs.
- Short intercepts were conducted with tenant employees and included questions asking individuals to compare the typical lighting and temperature they have compared to their preferred levels.
- Photo documentation and spot measurements of temperature and light levels were taken in conjunction with interview comments.
- An online building-wide anonymous survey focusing on occupancy patterns and uses of space and equipment was also distributed through facilities management.
- Finally, targeted plug load metering was implemented in tenanted and some common spaces where their measurements could be used to compare appliance use and energy consumption to inform future strategies toward energy efficiency.

EnergyPlus building physics model & calibration process

EnergyPlus is a US DOE supported energy analysis and thermal load simulation program (see http://apps1.eere.energy.gov/buildings/energyplus/energyplus_about.cfm). The program is capable of calculating and integrating details of heating and cooling loads, conditions from HVAC and coil loads, and energy consumption of primary plant equipment in text format.

Agent-Based model

This paper modeled occupants' thermal comfort actions (adjusting thermostat set points, turning on/off space heater, opening/closing the windows and door, and changing winter/summer clothes) and their influence on airflow rate entering their thermal zone by using set points and infiltration schedules. Occupants' lighting comfort actions (turning on/off headlights, turning on/off task lights, opening/closing windows blinds) were modeled using equipment schedule. In modeling the occupant behavior that updates the schedule, this study adopts two paradigms to specify theories and processes of human behavior. Agent-Based modeling (ABM) provides a paradigm of simple entities, called by agents that respond respectively to the environment. ABM is widely used in the ecological domain, but not very straightforward in representing human-like behavior (Epstein 2006; Axelrod 1997). Belief, Desire, Intention (BDI) is a paradigm of agents that are based on a psychological view of how people behave. BDI characterizes the process of human decision-making, such that autonomous agents follow five procedural steps in making behavioral decisions: establishing beliefs, desires, and intentions, developing plans, and deciding to carry out a particular plan of action (Rao and Georgeff, 1998). NetLogo (Wilensky and Rand 2013) is used to develop an integrated model of the two paradigms. Calibration is done using survey and interview data from individual building occupants, plus building-wide performance data for building 101. The model is validated by using it to predict outcomes (expressed as usability metrics) for an additional building. The complete modeling logic contains a building performance sub model that updates the state of the indoor environment over time. It contains a human agent sub model that simulates individual and shared decisions of occupants as they experience and react to changing environmental conditions. It also includes a file populated with information about the current state of controllable and uncontrollable building features. A building performance sub model has inputs such as building site conditions and design choices. Inputs for human agent model include occupancy schedule, occupant preferences and capabilities. Outputs include the usability measures of effectiveness, efficiency, and satisfaction (Andrews et al. 2011).

The Building 101 simulation study consists of three main components: the building energy model, the occupant behavior model, and the integrating model.

The building energy model, using EnergyPlus, incorporates occupant behavior component within it at a very limited level. The picture of having the building physics and the building occupants to perform an active-reactive interaction drives the overall goal of this simulation study. The building energy model does not allow users to modify the input variables. It also does not receive values exogenously for all the input variables. The integrated model runs in two-step for each simulation-hour. The model calls the building energy sub-model and the occupant behavior sub-model alternately. Initially, the integrated model runs the building energy sub-model in order to create the building environment. The model, then, runs the occupant behavior model in order to simulate building occupants' sensation and adaptive behavior towards the surrounding building environment. The occupant behavior model will consider the building environment conditions, resulted from the building energy model run at the previous time period, and the occupants' physiological preference towards the environment.

The integrated model has not yet completed to perform calibration for both comfort and satisfaction simulations on Building 101. The model, however, successfully follows the logic of occupants' comfort and satisfaction (Andrews, Chandra Putra, and Brennan, 2013). In the thermal comfort scenarios, occupants perceive the environment as Too Hot, Thermally Neutral, or Too Cold. The set of adaptive behaviors occupants perform range from Do Nothing, Adjust the Thermostat, Turn On/Off a Personal Fan, Turn On/Off a Personal Space Heater, and Add/Remove Clothing. In experiments simulating illumination levels, occupants perceive Too Bright, Illumination-Neutral, or Too Dim. Occupants can respond such sensations with the following adaptive behaviors: Do Nothing, Adjust Window Blinds, Turn Task Light On/Off, and Turn Overlight On/Off.

Data and models availability

Data and/or models are available to Annex 66 participants. Reports, models, and anonymized data are freely available for download at greenbuilding.rutgers.edu. Please cite this source if you use it.

Summary

Accepted practice absolves building energy modelers with responsibility for capturing many of the effects of occupant behavior by assuming fixed comfort targets and ignoring "unregulated" loads. This paper asks what we can learn by incorporating more detailed information about occupant behavior into models. It compares results of three approaches: conventional practice, an augmentation incorporating detailed occupancy patterns, and an augmentation incorporating detailed behavioral responses of occupants to evolving comfort conditions. We apply these models to a highly-instrumented commercial building in Philadelphia, PA, USA, using EnergyPlus and extensions based on Markov chain modeling and agent-based modeling. We share preliminary findings only because the project schedule was disrupted.

Key Findings

- Better occupancy data greatly improves energy model accuracy
- Standard assumptions about occupant schedules are often wrong so that a more sophisticated representation is warranted
- Better data about occupants' adaptive responses only marginally improves energy model accuracy
- Yet such data are quite valuable for predicting occupant satisfaction
- EnergyPlus needs additional hooks for incorporating occupant behavior.

Related publications

- Figueroa, M., Putra, H.C., and Andrews, C.J. 2014. Preliminary Report: Incorporating Information on Occupant Behavior into Building Energy Models. Prepared by the Center for Green Building at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA. At http://rcgb.rutgers.edu/wp-content/uploads/2014/05/ModelingReport20140131.pdf

Case 7

Case study title

Occupant individual behavior and group occupancy schedule data mining through office appliance power consumptions

Contributors

- Jie Zhao & Khee Poh Lam, Center for Building Performance and Diagnostics, Carnegie Mellon University

Contribute to other subtasks

Subtask A: Occupant movement and presence models in buildings

When and where

2013 – 2015, Phipps Center for Sustainable Landscapes, Pittsburgh, PA, USA

Building(s) description

- Owner type: NGO
- Building type: commercial office
- Total floor area: 23,000 sf
- Number of stories: 2 conditioned + 3rd floor atrium
- Location (city, country): Pittsburgh, PA, USA
- One or two pictures:

Occupant type

Typical office workers in open office spaces in an office building

Description of the datasets

Data points	Collection frequency	Collection period	Format
power consumption data of office appliances	5 minutes	3 months	Plugwise API -> Web-based MySQL -> CSV
Fitbit connection data	Whenever Fitbit is connected, about 6 seconds while it is connected	3 months	Python script -> CSV
Keyboard and mouse movement	5 minutes	3 months	Java program -> CSV

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Not available, protected by IRB agreement.

Summary

This case study developed a practical data mining approach using office appliance power consumption data to learn the individual occupant behavior and group occupancy schedule. All-in-one wireless electrical outlet meters/switches Plugwise® were installed to meter office appliance power consumptions. Fitbit® pedometers were used to record occupants "ground truth". The method was implemented in a medium office building. A total of 15 volunteers participated in the study over three months. The individual occupant behavior was categorized as “computer-based work”, “non-computer-based work”, “remote work”, and “absence”. The group schedule was defined as a percentage of occupied to the total number of occupants in a time series.

Decision tree, linear regression, support vector regression, locally weighted learning, and several other algorithms were tested and compared. The data mining results showed that using power consumption data of office appliances, the average percentage of correctly classified individual behavior instances was 90.29%. The average correlation coefficient between the predicted group schedule and the ground truth is 0.94. The experimental results also showed a fairly consistent group occupancy schedule, while capturing the diversified individual behavior in using office appliances.

Compared to the occupancy schedule used in the Department of Energy prototype medium office building models, the learned schedule had a 36.67–50.53% lower occupancy rate for different weekdays. The heating, ventilation, and air conditioning (HVAC) energy consumption impact of this discrepancy was investigated by simulating the prototype EnergyPlus models across 17 different climate zones. The simulation result showed that the occupancy schedules’ impact on the building HVAC energy consumption had large variations for the buildings under different climate conditions.

The learned occupancy schedule also contributed to two different studies. In publication [2], the learned occupancy schedule was used to calibrate an EnergyPlus model. In publication [3], the learned occupancy schedule was used to develop a new behavior-oriented metric to quantify the plug load energy savings due to occupant behavior change.

Key Findings

- Computer power consumptions can accurately predict office workers' presence and working behavior
- The occupancy schedule of this case study building is significantly different from the occupancy schedules in the DOE's prototype building models
- Group occupancy schedule is fairly consistent throughout the experiment period
- Individual occupant working behavior is very diversified
- Passive HVAC energy impact from occupant presence varies by climate zones

Related publications

- Zhao, J., Lasternas, B., Lam, K.P., Yun, R., Loftness, V. (2014). Occupant behavior and schedule modeling for building energy simulation through office appliance power consumption data mining. Energy and Buildings, 82, 341-355.
- Lam, K.P., Zhao, J., Ydstie, E.B., Wirick, J., Qi, M., Park, J. (2014). An EnergyPlus whole building energy model calibration method for office buildings using occupant behavior data mining and empirical data. Proceedings of 2014 ASHRAE/IBPSA-USA Building Simulation Conference, 160-167, Atlanta, GA.
- Lasternas, B., Zhao, J., Yun, R., Zhang, C., Wang, H., Aziz, A., Lam, K.P., Loftness, V. (2014). Behavior-Oriented Metrics for Plug Load Energy Savings in Office Environment. Proceedings of 2014 American Council for an Energy-Efficient Economy (ACEEE) Summer Study on Energy Efficiency in Buildings, 7, 160-172, Pacific Grove, CA.
- Zhao, J., Yun, R., Lasternas, B., Wang, H., Lam, K.P., Aziz, A., Loftness, V. (2013). Occupant Behavior And Schedule Prediction Based on Office Appliance Energy Consumption Data Mining. Proceedings of CISBAT 2013 International Conference - Clean Technology for Smart Cities and Buildings from Nano to Urban Scale, 1, 549-554, EPFL, Lausanne, Switzerland.

Case 8

Case study title

A Framework including a unique test data to predict the Residential Occupants' Presence for Model Predictive Control in Residential Environment

Contributors

Bing Dong, Zhaoxuan Li,
Mechanical Engineering Department
University of Texas at San Antonio, USA

Contribute to other subtasks

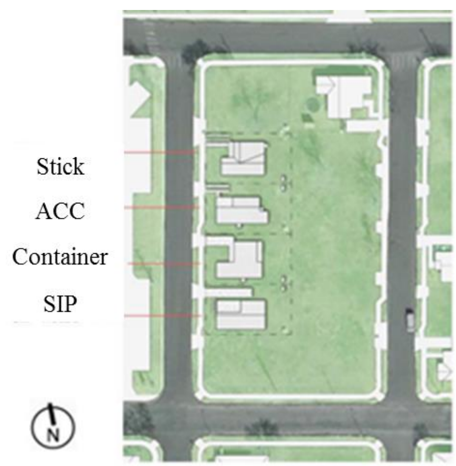
Subtask A

When and where

Four residential houses, at downtown San Antonio, U.S.A.

Building(s) description

- Building type: residential building
- Total conditioned floor area: 2000 ft^2 (185 m^2)
- Number of samples: 4
- Location (city, country): San Antonio, USA
- One or two pictures:



Occupant type

- To represent the diversity of occupants and their presence in residential building environment, occupant spaces are first categorized at room level: rest areas, living areas, and cooking areas:
  - The rest areas represent guest bedrooms and master bedrooms
  - The living areas represent living rooms
  - The cooking areas represent kitchens
- Occupancy presence is also categorized at house level.

Description of the datasets

Information of the investigated office building

- Room types and functions
- Room-level occupancy presence detection
- Family types (single, couple, couple with children, etc.)
- Income level

Investigated the stochasticity of occupant presence patterns at both the room-level and house-level:

- Presence differences among different houses
- Presence differences at room level for the same house
- Presence similarity at room level for each space types for different houses
- Variances difference for the presence rates of individual rooms and individual houses
- Typical patterns of the occupancy presence

The predictive abilities are evaluated at four prediction windows:

- 15-min ahead
- 30-min ahead
- 1-hour ahead
- 24-hour ahead

Inputs of the model:

- Occupancy binary historical data

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request. More information is available in the published conference and journal articles.

Summary

This study provides a unique test dataset for residential occupancy and develops the appropriate algorithms to predict occupancy presence for a residential building that allow a better control and optimization of whole building energy consumptions. The residential houses are usually simulated based on Time User Survey data. This study focuses on providing a unique data set of four residential houses collected from occupancy sensors within one year period in the U.S. Periods are varied within the year 2014 and not continuously available. A new inhomogeneous Markov model for occupancy presence prediction is proposed and compared to three other models: Probability Sampling, Artificial Neural Network, and Support Vector Regression. Training periods for the presence prediction are optimized based on change-point analysis of historical data. The study further explores and evaluates the predictive power of the models by various temporal scenarios, including 15-min ahead, 30-min ahead, 1-hour ahead, and 24-hour ahead occupancy presences forecasts. The spatial-level comparison is additionally provided by evaluating the prediction accuracy at both room-level and house-level. The final results show that the proposed Markov model outperforms the other methods in terms of an average 5% correctness with 11% maximum difference in one time step ahead forecast of the occupancy presence. In day ahead prediction, not much difference could be observed among the models.

This study observes a significantly lower performance in 24-hour ahead prediction scenario compared to the other prediction windows (e.g., 15-min to 1-hour ahead). It is challenging to improve the forecast accuracy in this case even with the changes of temporal resolution (sampling rate) between 15-min and 1-hour resolution. The seasonal or other time-related factors are not identified owing to the difficulties to continuously collect the data. As this study sole focuses on a proposed prediction model of the residential occupancy and provides a unique data set for the test at first, the longer and more general data set is rather a necessary part to be investigated in future for general studies and applications. Further investigation on improvements of the day ahead predictions on more general and abundant data pool could be conducted by the more advanced time series analysis and more house samples to detect the irregular dynamics of the occupancy pattern.

Key Findings

- The residential occupancy has large dynamics in terms of the presence. Residential presence pattern is highly different because of the family type, the income level, and the life style.
- Onsite collection of residential data is extremely difficult owing to the residents can actually replace and relocate those sensors. The data set collected through occupancy sensor contains large uncertainty. Future smart residential homes with hidden and untouchable sensors may provide more insights on how the residential occupancy real looks like.
- Occupancy presence prediction is possible and accurate for extremely short and short time step ahead cases. Day-ahead case is really difficult and hard to improve considering the randomness especially in residential environment.
- Many more occupancy models need to be validated for prediction purpose not only for building simulations.

Related publications

- Li, Z., Dong, Bing. A new modeling approach for short-term predictions of occupancy presence in residential buildings. Building and Environment (accepted), 2017.
- Li, Z., Dong, Bing. Investigation of a short-term prediction method of occupancy presence in residential buildings. IBPSA 2017 (accepted).

Case 9

Case study title

A simulation approach to estimating potential energy savings of occupant behavior measures

Contributors

Kaiyu Sun, Tianzhen Hong, Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, USA

Contribute to other subtasks

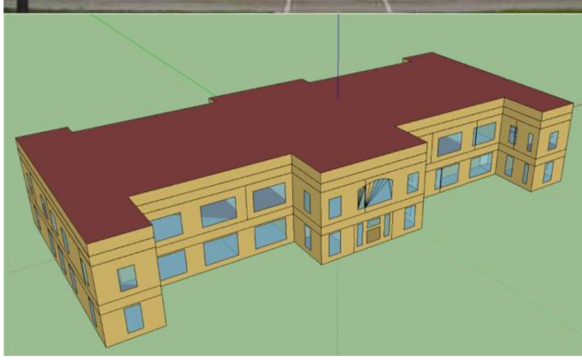
Subtask D

When and where

An office building in four U.S. climates and two vintages

Building(s) description

- Building type: office building
- Total conditioned floor area: 18,550 ft^2 (1,723 m^2)
- Number of stories: 2
- Location (city, country): four cities (Chicago, Fairbanks, Miami, and San Francisco), USA
- One or two pictures:



Occupant type

- Typical office workers in open and private office spaces

- Three prevailing types of work schedules on weekdays: 8am–5pm, 7am–6pm, and 6am–11pm. The occupants don't work on weekends.

Description of the datasets

Information of the investigated office building

- Room function
- Realistic zoning
- Number of occupants in each zone
- Lighting schedule, plug-load power density and schedule

Investigated five occupant behavior measures:

- Lighting control, two scenarios:
    - Occupants turn on lights when they enter the room and turn off lights when they leave the room.
    - Occupants turn on lights when they are in the room and feel that it is dark; they turn off lights either when they leave the room or feel that the room is bright enough.
- Plug-load control: when the zone is occupied, the electric equipment is 100% on; when the zone is unoccupied, the electric equipment will be reduced by 30%.
- Thermal comfort criteria: considers a theoretical situation where all the occupants have a broader thermal comfort acceptance range defined by either:
    - ASHRAE Standard 55 comfort zone limits
    - ASHRAE Standard 55 adaptive comfort criteria
- HVAC control: two scenarios:
    - Occupants turn on HVAC when they are in the room and turn off HVAC when they leave the room.
    - Occupants turn on HVAC when they are in the room and feel hot (in cooling mode) or cold (in heating mode), and turn off HVAC either when they leave the room or feel cold (in cooling mode) or hot (in heating mode).
- Window control: Natural ventilation is taken as the priority to provide cooling for perimeter zones, and mechanical systems pro-vide supplementary cooling when natural ventilation alone is not enough to meet cooling setpoints.

The saving potentials of the five occupant behavior measures were evaluated in four climate zones:

- Chicago (Hot summer cold winter)
- Fairbanks (Cold winter)
- Miami (Hot and Humid)
- San Francisco (Mild)

and two vintages:

- 1989 (existing buildings)
- 2010 (new buildings)

Inputs of the baseline model:

- Stochastic occupancy schedules generated by the Occupancy Simulator (occupancysimulator.lbl.gov)
- Efficiency inputs based on ASHRAE Standard 90.1 of the 1989 and 2010 editions, including lighting power density, envelope properties, and HVAC equipment efficiencies.

Data and models availability

Are data and models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request. More information is available in the published journal article.

Summary

The case study developed a methodology to estimate the potential energy savings of occupant behavior measures. First, this study defines five typical occupant behavior measures in office buildings (covering lighting, plug-load, comfort criteria, HVAC control and window control), simulates and analyzes their individual and integrated impact on energy use in buildings. A real office building was investigated and modeled. The energy performance of the five occupant behavior measures was evaluated in four typical U.S. climate zones (Chicago, Fairbanks, Miami and San Francisco) and two vintages (1989 and 2010) representing existing and new buildings. The Occupancy Simulator, a web-based App developed by LBNL, was used to simulate the realistic occupant movement and generate occupant schedules in each zone with inputs from the site survey of the case building.

Based on the simulation results, the occupant behavior measures can achieve overall savings as high as 22.9% for individual measures and 41.0% for the integrated measures. Although actual energy savings of occupant behavior measures depend upon many factors, the presented methodology is robust and can be adopted for other studies aiming to quantify occupant behavior impact on building performance.

Future studies can expand to cover: (1) a larger scale with more population, such as the city, state, and country scales; (2) other occupant behaviors such as the operation of window shades; (3) other building types, such as residential and retail. Future work can also look for opportunities to implement the occupant-behavior measures in real buildings. If the actual energy savings from occupant-behavior measures are available, the method of quantifying the energy savings potential can be verified, and necessary enhancements to the method can be implemented to improve its accuracy.

Key Findings

- Occupancy schedules have a significant impact on the energy savings of occupant based measures. When estimating the potential energy savings of occupant-related measures, it is crucial to apply the occupancy schedules reflecting the realistic characteristics of the occupancy variations in time and space.

- The main energy savings captured by the occupant behavior measures come from the avoidance of energy waste in the unoccupied rooms, especially for the energy use of lighting, plug-load and HVAC systems.
- Based on the simulation results, the occupant behavior measures can achieve considerable energy saving potentials as high as 22.9% for individual measures and 41.0% for the integrated measures.
- This study confirms the human dimension is as significant as the use of advanced building technologies for low- or net-zero energy buildings.

Related publications

- Sun, K., Hong, T. A simulation approach to estimate energy savings potential of occupant behavior measures. Energy and Buildings 136 (2017) 43–62.

Case 10

Case study title

A Framework for Quantifying the Impact of Occupant Behavior on Energy Savings of Energy Conservation Measures

Contributors

Kaiyu Sun, Tianzhen Hong, Building Technology and Urban Systems Division, Lawrence Berkeley National Laboratory, USA

Contribute to other subtasks

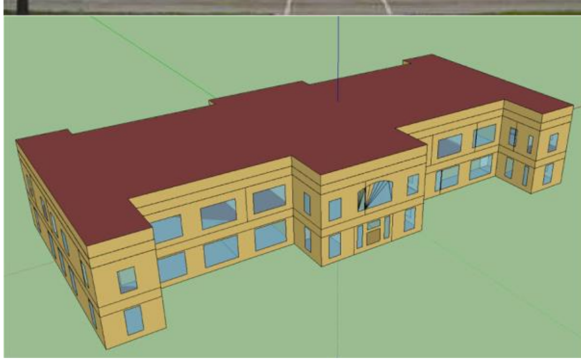
Subtask D

When and where

A 15-year-old office building, in four U.S. climates

Building(s) description

- Building type: office building
- Total conditioned floor area: 18,550 ft^2 (1,723 m^2)
- Number of stories: 2
- Location (city, country): four cities (Chicago, Fairbanks, Miami, and San Francisco), USA
- One or two pictures:



Occupant type

- To represent the diversity of occupants and their behaviors in building performance simulation, occupant energy-use styles are first categorized into three distinguished attitudes: austerity, normal, and wasteful, regarding their energy consciousness during interactions with building energy systems, including HVAC, windows, lights, and plug-in equipment:
  - The normal behavior represents the typical design assumptions of occupant behavior in a building
  - The austerity behavior represents the ideal conditions of energy savers
  - The wasteful behavior represents the ideal conditions of energy spenders

Occupant Behavior	Austerity	Normal	Wasteful
Cooling Setpoint (°C)	26	24	22
Heating Setpoint (°C)	18	21	22
Control of lights	Dim lights if unoccupied	Follow standard schedule	Always on during working hours
Control of plug-loads	turn 30% off if unoccupied	Follow standard schedule	Always on during working hours
HVAC occupancy control (For VRF ECM only)	Off if unoccupied	Off if unoccupied	Always on
HVAC startup control (For VRF ECM only)	Turn on HVAC only when occupants feel hot, based on a probabilistic model of HVAC operation	None	None
Window operation (For natural ventilation ECM only)	Concurrent HVAC and natural ventilation	Either HVAC or natural ventilation	HVAC and natural ventilation both on all the time

- Three prevailing types of work schedules on weekdays: 8am–5pm, 7am–6pm, and 6am–11pm. The occupants don't work on weekends.

Description of the datasets

Information of the investigated office building

- Room function
- Realistic zoning
- Number of occupants in each zone
- Lighting schedule, plug load power density and schedule

Investigated the impact of occupant behaviors on the energy savings potential of seven individual energy conservation measures (ECMs) and one packaged ECM:

- Reducing lighting power density
- Reducing plug-in electric equipment power density
- Improving envelope performance
- Improving HVAC system efficiency
- Daylighting control
- Variable refrigerant flow system
- Natural ventilation coupled with the VRF system
- The integrated ECM: the integration of the above individual ECMs

The impact on saving potentials was evaluated in four climate zones:

- Chicago (Hot summer cold winter)
- Fairbanks (Cold winter)
- Miami (Hot and Humid)
- San Francisco (Mild)

Inputs of the baseline model:

- Stochastic occupancy schedules generated by the Occupancy Simulator (occupancysimulator.lbl.gov)
- Efficiency inputs based on ASHRAE Standard 90.1-2001, including lighting power density, envelope properties, and HVAC equipment efficiencies.

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request. More information is available in the published journal article.

Summary

This study presents a framework for quantifying the impact of occupant behavior on ECM energy savings using building performance simulation. First, three occupant behavior styles (austerity, normal, and wasteful) were defined to represent different levels of energy consciousness of occupants regarding their interactions with building energy systems (HVAC, windows, lights and plug-in equipment). Next, a simulation workflow was introduced to determine a range of the ECM energy savings. Then, guidance was provided to interpret the range of ECM savings to support ECM decision making. Finally, a pilot study was performed in a real building to demonstrate the application of the framework. Simulation results show that the impact of occupant behavior on ECM savings varies with the type of ECM. Occupant behavior minimally affects energy savings of ECMs that are technology-driven (the relative savings differ by less than 2%) and have little interaction with the occupants; for ECMs with strong occupant interaction, such as the use of zonal control variable refrigerant flow (VRF) system and natural ventilation, energy savings are significantly affected by occupant behavior (the relative savings differ by up to 20%).

The zero-net energy (ZNE) technologies are successful and growing today as energy performance requirements are becoming more and more stringent. ZNE technologies, such as natural ventilation, HVAC control, and demand response, tend to need more interaction with occupants. Therefore, they are more sensitive to occupant behaviors and reactions to stimulations, which makes occupant behavior a significant uncertainty factor for the technology’s performance. In other words, occupant behavior may significantly change the way technologies are designed and expected to perform. The proposed framework provides a novel, holistic simulation approach enabling energy modelers to calculate the ECM savings as a range rather than a single fixed value considering the variations of occupant behaviors in buildings, which provides a critical input to the risk analysis of ECM investments, enabling stakeholders to understand and assess the risk of adopting energy efficiency technologies for new and existing buildings.

Recommended future work include: (1) developing more realistic occupant behavior styles based on a large-scale survey of occupants in various climates, (2) pilot testing the methodology in a real design or retrofitting project, and (3) extending the study for other building types and building technologies.

Key Findings

- The occupant behavior style has a significant influence on building energy use. Buildings occupied by energy spenders could consume more than twice the energy of the energy savers.
- For occupant-independent ECMs, which are purely technology-driven and have little interaction with the occupants, such as reducing LPD, reducing EPD, improving envelope properties, and improving HVAC system efficiency and daylighting control, energy saving percentages are minimally affected by occupant behavior styles. For occupant-dependent ECMs, which have strong interactions with the occupants, such as the VRF system and natural ventilation, energy saving percentages are significantly affected by occupant behavior styles.
- The wasteful behavior style generally achieves the greatest absolute energy savings while its saving percentages are close to or even lower than those of the austerity and normal behavior. This is important information for decision makers in retrofit planning.
- The occupant schedules have certain impacts on the simulated results of ECM savings, especially for the occupant-dependent ECMs coupled with the austerity behavior style. Adopting realistic occupant schedules rather than normalized ones would help improve the accuracy of ECM saving evaluation.

Related publications

- Sun, K., Hong, T. A Framework for Quantifying the Impact of Occupant Behavior on Energy Savings of Energy Conservation Measures. Energy and Buildings (under review), 2017.

Case 11

Case study title

Lighting Energy Consumption in Ultra-Low Energy Buildings: Using a simulation and measurement methodology to simulate occupant behavior and lighting controls

Contributors

- Panyu Zhu, Tsinghua University, Beijing, China
- Michael Gilbride, University of Washington, Seattle, WA, USA
- Da Yan, Tsinghua University, Beijing, China
- Hongsan Sun, Tsinghua University, Beijing, China
- Christopher Meek, University of Washington, Seattle, WA, USA

Contribute to other subtasks

Subtask D

When and where

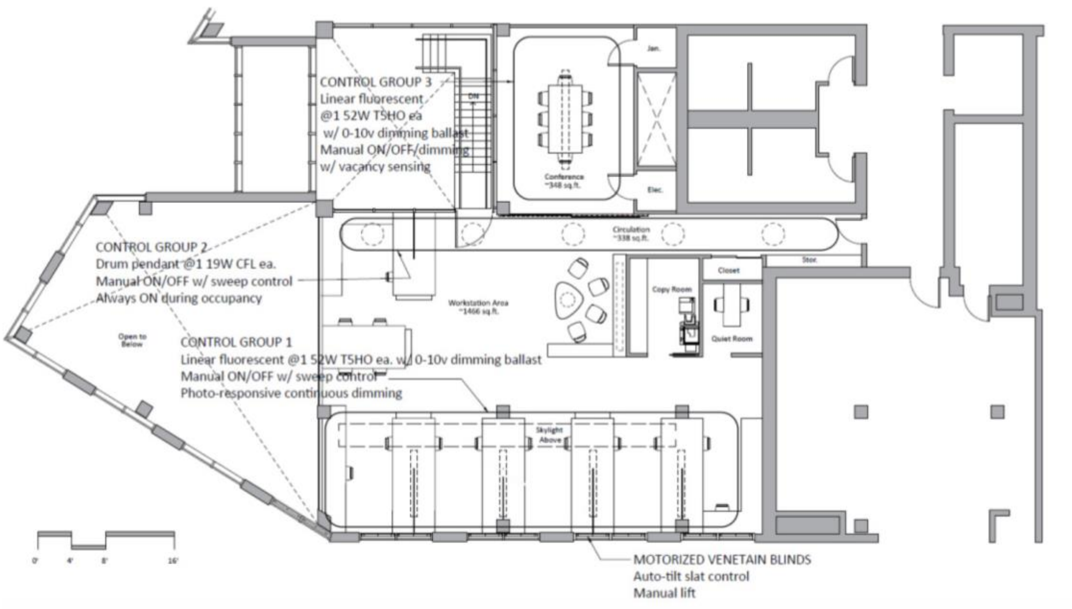
- 2016-2017
- An open office on the 2nd floor of a six-story 4831 m² (52,000 ft²) office building (The Bullitt Center) in Seattle, WA, USA

Building(s) description

- Building type: office building
- Total conditioned floor area: 52,000 ft^2 (4,831 m^2)
- Number of stories: 6
- Location (city, country): in Seattle, WA, USA
- One or two pictures:

Investigated Office description

- Office type: open office
- Total conditioned floor area: about 300 m^2
- Number of occupants: 22
- Location: on the 2^{nd} floor in The Bullitt Center
- Floor plan:

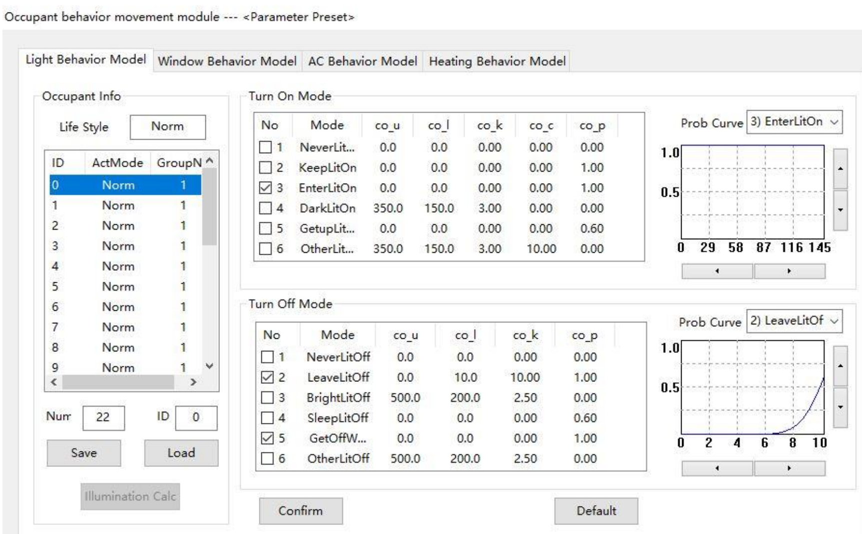


Occupant type

- The office is equipped with IP enabled “smart” plug strips that measure device-level consumption (monitors, computers, task lighting, etc.) at two-second intervals at the receptacle level and report data through a wireless connection to an online database. Occupancy patterns were derived from these measurements with the assumption that most people at work use computers. There are four occupancy patterns:

	Occupant ID	Start time	End time	Working days / year
occupancy-1	A	09:00	17:00	171
occupancy-2	B-H	09:30	17:30	239
occupancy -3	I-P	09:00	17:00	256
occupancy -4	Q-W	10:00	17:00	120

- Lighting-control actions were modeled in DeST, where probability curve is used to describe each action. The probability curve for lighting behavior is defined by four parameters, which are threshold (u), range (l), curve shape (k), and probability (p).



Description of the datasets

Information of the investigated offices in that building

- Room function
- Realistic zoning
- Number and affiliation of occupants
- Layout of desks
- Layout and capacity of lamps and lanterns
- Device-level plug load
- Office-level lighting load

The impact of control strategy on lighting energy consumption was compared in four scenarios:

- Scenario-1: “Enter –ON; leave – OFF”
- Scenario-2: “Enter –ON; leave – OFF, automatically dimming” (baseline)

- Scenario-3: "Dark –ON; leave – OFF, automatically dimming"
- Scenario-4: "Dark –ON; leave – OFF"

Inputs of the baseline model:

- Occupancy schedules derived from measurements
- Lighting control patterns

Data and model's availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request. More information is available in the published journal article.

Summary

This research proposed a simulation methodology that incorporates measured energy use data to generate occupant schedules and control schemes with the ultimate aim of using simulation results to evaluate energy-saving measures that target occupant behavior. Hourly lighting and plug load circuit data from the office space was gathered from June 2015 to July 2016. Occupancy patterns were derived from these measurements with the assumption that most people at work use computers. The lighting control pattern of "enter-ON, leave-OFF, with dimming effect" was modeled in DeST. The simulated lighting load and energy consumption were compared with the measured data as calibration. Then the calibrated model was considered as the baseline (scenario 2) in the scenario analysis. Four scenarios with different lighting control patterns including the baseline were simulated and compared to show their impact on lighting energy consumption. According to simulation results, lighting energy could be largely reduced by installing dimming control. Occupant behavior also showed its influence on energy saving. By changing the turn-ON-light action from the "enter -ON" pattern to the "dark-ON" pattern, the lighting energy could be further reduced.

Ultra-low energy buildings, such as the Bullitt Center, demonstrate the centrality of occupant behavior to achieving low energy use and improving energy performance. The proposed methodology in this research can be valuable in testing the sensitivity of occupant behavior and energy outcomes in buildings such as the Bullitt Center, where occupant behavior can significantly impact overall performance. As occupants interact with the building and with how much or little control they have over their own environment quantifying the savings can help occupants understand the importance of controls and further their adoption.

Recommended future work include: (1) energy saving potential of sub-controlled overhead lighting system; (2) plug load control strategies with the aim of energy saving; (3) predicting energy impacts of changes in occupancy

Key Findings

- Occupant behavior has a great impact on energy consumption, especially in Ultra-low energy buildings, such as the Bullitt Center.
- From evaluating lighting energy performance and occupant behavior in the four scenarios, it is clear that dimming through controls is the most effective energy-saving strategy.
- When there is no automatic dimming function, the impact of occupant behavior becomes much greater.
- The combination of using measured energy use data to understand occupant schedules and activities with the predictive potential of computer simulations can be a useful tool in improving the energy performance of ultra-low energy buildings.

Related publications

- Panyu ZHU, Michael Gilbride, Da Yan, Hongsan Sun, Christopher Meek. Lighting Energy Consumption in Ultra-Low Energy Buildings: Using a Simulation and Measurement methodology to Simulate Occupant Behavior and Lighting Controls. Building Simulation (under review), 2017.

Case 12

Case study title

Understand and manage occupant rebound behavior and its influence on decision-making of energy retrofitting projects

Contributors

Yujie Lu and Nan Zhang, Department of Building, National University of Singapore, Singapore

Contribute to other subtasks

Subtask E: Applications in building design and operations

When and where

- Maryland, United States
- Simulation was performed and analyzed during Jan 2016 – Dec 2016

Location description

- Owner type: University
- Building type: campus; educational facilities
- Total floor area: N.A.
- Location (city, country): Maryland, United States
- Buildings' conditions: Around 75% of buildings are older than 25 years, average age 40 years

Occupant type

University staffs and students

Description of the datasets

Key parameters in the energy retrofitting decision:

- Projects characters: *Capex*(I_c), *O&M cost* (I_{OM}), *Energy Savings (R(t))*
- Contract: *Guaranteed amount of energy saving (G), sharing percentage (%) of between ESCOs and owners (α & β)*
- End Users: *max rebound effect of end users (ϕ), shared percentage between end users and owners (θ)*
- Net Present Value (NPV) of the retrofitting project and various parties involved
- Optimal contract period (*n*) of ESPC*

Methodology used for analysis

- Simulate end users' rebound effect and the influence on the actual energy savings by considering three different scenarios in the ESPC: 1) Renters do not have rebound effect; 2) renters have rebound effect but do not have shared incentives; and 3) renters have rebound effect and can share part of monetary incentives from the energy savings.

- Monte Carlo Simulation of occupant behavior and the influence to the retrofit project performance under different parameters inputs
- Sensitive analysis and impact analysis on the proposed decision-making model
- The relationship among all stakeholders involved in energy retrofit project is indicated in the following figure.

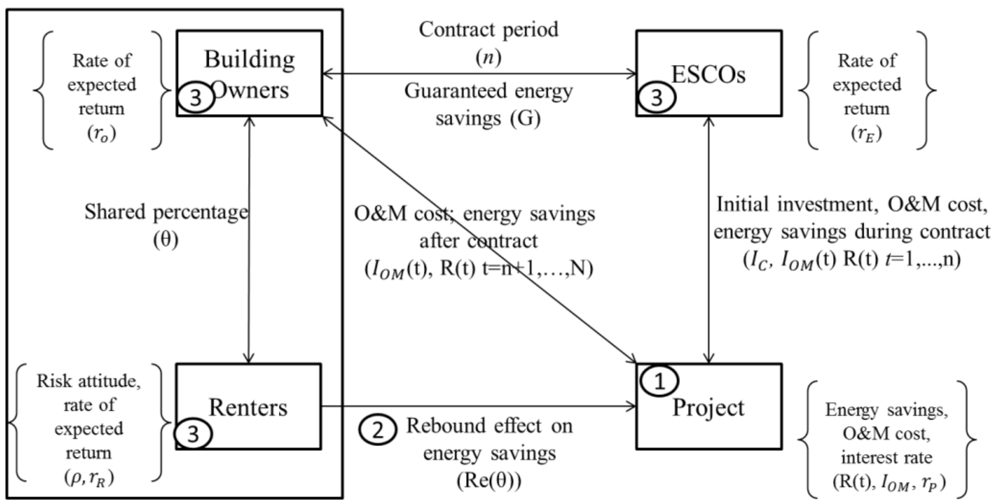


Figure 1. Overall relationship among all stakeholders in EPC project considering renters' rebound effect

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request.

Summary

Energy Savings Performance Contracts (ESPCs) are a business model that aims to promote building energy efficiency through retrofitting with minimal or zero upfront costs for owners. Many studies show that occupants tend to use more energy than expected after retrofits (referred as rebound effect), which results in underestimated retrofitting costs. However, end users' energy-using behaviors and their relationship to the ESPCs decision-making process have seldom been studied. This study aims to propose such a behavior-based model to assist the contract decision-making among the major stakeholders in a building's retrofit, including building owners, Energy Service Companies (ESCOs), and renters. The proposed model incorporates renters' rebound effect (consuming more energy than expected after the retrofit) and investigates the impact that major variables have on the rebound effect. To validate and evaluate the performance of the proposed model, a real retrofitting project in Maryland, United States, was examined. The results show that the rebound effect can significantly increase the payback period of ESPCs contracts by up to 4 years. The contract duration is also subject to renters' risk attitudes toward shared energy savings. The findings of this study can help ESCOs and building owners predict the potential energy savings, design proper EPC strategy, and maximize the potential savings from building retrofits.

Key Findings

This study introduces a behavior-based decision-making model for evaluating and designing ESPCs contracts in rented properties. Renters' rebound effect, a significant but frequently ignored phenomenon, is incorporated in this model to better estimate potential energy savings. The result shows that renters' rebound effect would cause up to a 4-year difference of acceptable ESPCs contract length in the case study (17-year contract with 15% rebound effect, 13-year contract without rebound). In order to mitigate and eliminate renters' rebound effect, a shared incentive strategy between owners and renters was proposed. The major associated variables with rebound effect were discussed to assess their impacts on the profitability and duration of ESPCs projects, such as renters' risk attitudes, expected rates of return, and sharing strategy variables. Main findings include as follows.

- The baseline case (scenario 1) does not consider the rebound effect of renters on energy savings and this scenario results in the optimal contract period of 13 years.
- However, the renters' rebound effect is common in the energy retrofit projects (scenario 2). With users rebound effect, if no actions have been taken to control the rebound effect, the optimal contract period would be 17 years, which is apparently too long for building owners.
- When providing the money incentives to the renters ---Owners share part of energy savings to the renters (scenario 3), the optimal contract period is shortened to 14 years. Compared with the second scenario, contract period of this case is three years shorter, which contributes to the success of EPC in energy retrofit project.

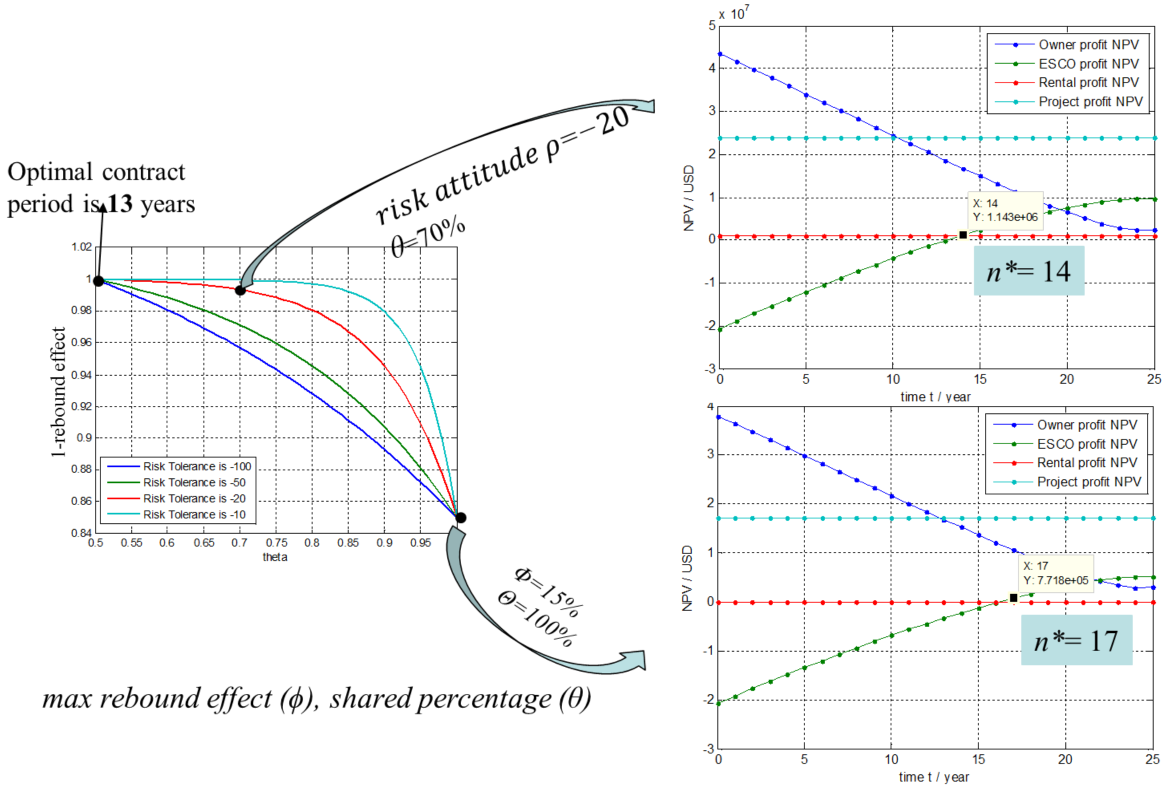
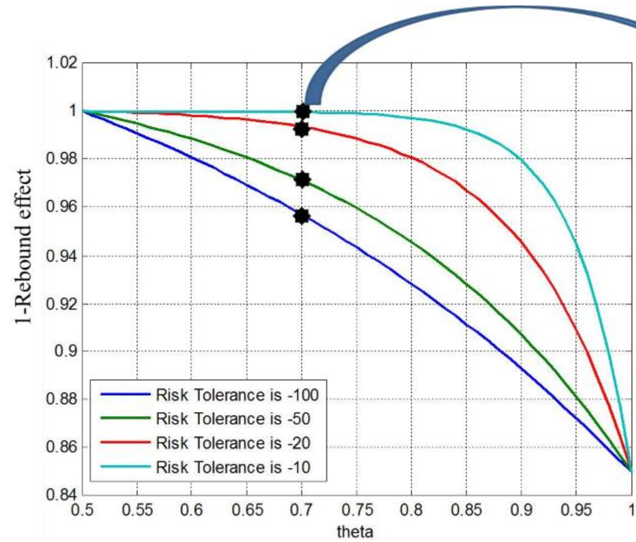


Figure 2. Optimal contract periods at different scenarios

Risk attitude (ρ) reflects the renters' energy conservation behavior response to incentives and affects their rebound effect. For example, sensitive renters (i.e., schools with tight budgets) are more easily motivated by shared incentives since the shared amount is negligible compared to the building O&M cost. These "sensitive renters" can be represented by the shallow curve (ρ=-100) in Figure 3. The other type of renters (i.e., schools with abundant budgets) may be insensitive to shared incentives, and they (as "insensitive renters") can be represented as the steep curve (ρ=-10) in Figure 3.

As indicated in Figure 3, when the sharing percentage is fixed (i.e., 0.7), renters with different attitudes can yield different actual savings and result in different projects' NPVs and contract periods. For example, the insensitive renters ($\rho = -10$) resulted in a 9.06% increment in a project's NPV and in a 1-year decrease in the contract period (from 14 years to 13 years) compared to the sensitive renter ($\rho = -100$).



Risk attitude	NPV of Project (million USD)	Change in percentage	Contract period
ρ =-100	22.18	0%	14
ρ =-50	22.84	2.98%	14
ρ =-20	23.85	7.53%	14
ρ =-10	24.19	9.06%	13

Figure 3. Rebound effect under different risk attitudes

This proposed case study contributes to the body of knowledge in two aspects. First, it incorporates renters' energy rebound effect into ESPCs contract assessment for rented properties. The rebound effect was found to dominantly determine the contract period in our result. Second, the shared saving scheme proposed in our decision model enables a feasible "joint saving mode" that can mitigate the renters' rebound effect via shared monetary incentives from the saved energy cost. The results suggest the effectiveness of shared saving strategies in intervening and managing occupant behavior for education and institutional buildings to achieve occupant energy efficiency.

Related Publications

- Yujie Lu, Nan Zhang and Jiayu Chen (2017), A Behavior-based Decision Making Model for Energy Performance Contracting in Building Retrofit. Vol 156, Dec 1 2017, page 315-326. Energy and Building, Elsevier. [DOI: 10.1016/j.enbuild.2017.09.088]

Case 13

Case study title

Analysis on the influence of occupant behavior patterns to building envelope's performance on space heating in residential buildings in Shanghai

Contributors

Siyue GUO, Da YAN, Ying CUI, Building Energy Research Center, Tsinghua University

Contribute to other subtasks

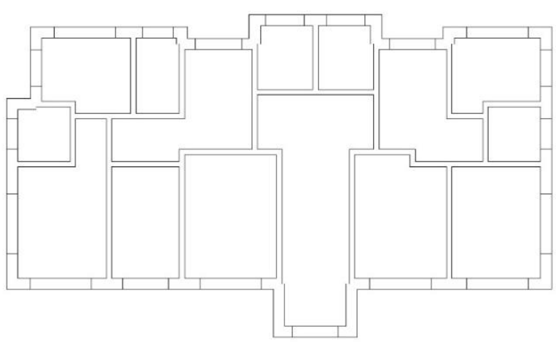
Subtask B: Occupant action models in residential buildings.

When and where

Simulation, Shanghai, CN

Building(s) description

- Owner type: Resident
- Building type: Residential Building
- Total floor area: 23,000 sf
- Number of stories: 12, 2 households in each floor
- Location (city, country): Shanghai, CN
- Plane Figure:



Occupant type

Three member family, 2 adults& 1 children, in one apartment.

Description of the model

- Window-wall ratio

orientation	east	south	west	north
WWR	0.35	0.4	0.35	0.4

- Heat transfer coefficient of building envelope (W/(m2·K))

	Wall	Roof	Window
Below national codes	2	1.7	4.7
Current national codes	1.5	1	3.2
Above national codes	1	0.6	2.7

- Occupant behavior patterns

Pattern 1	Heating for 24h, all the room maintain 18℃ above
Pattern 2	Heating as long as anyone come back home, maintain 18℃ above
Pattern 3	Heating only when residents feel cold, maintain 15℃ above
Pattern 4	Heating only when residents feel cold and stop heating when sleep, maintain 15℃
Pattern 5	Heating only when residents feel cold and stop heating when sleep, maintain 12℃

- Shape coefficient: 0.24;
- Coefficient of heat transfer of the enclosure: recording to national code "Design Standard for Energy Efficiency of Residential Building in Hot Summer and Cold Winter Zone",
- The indoor heat gain is set to 4.3W/m^2
- The heating season is December 1st to following February 28th.

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

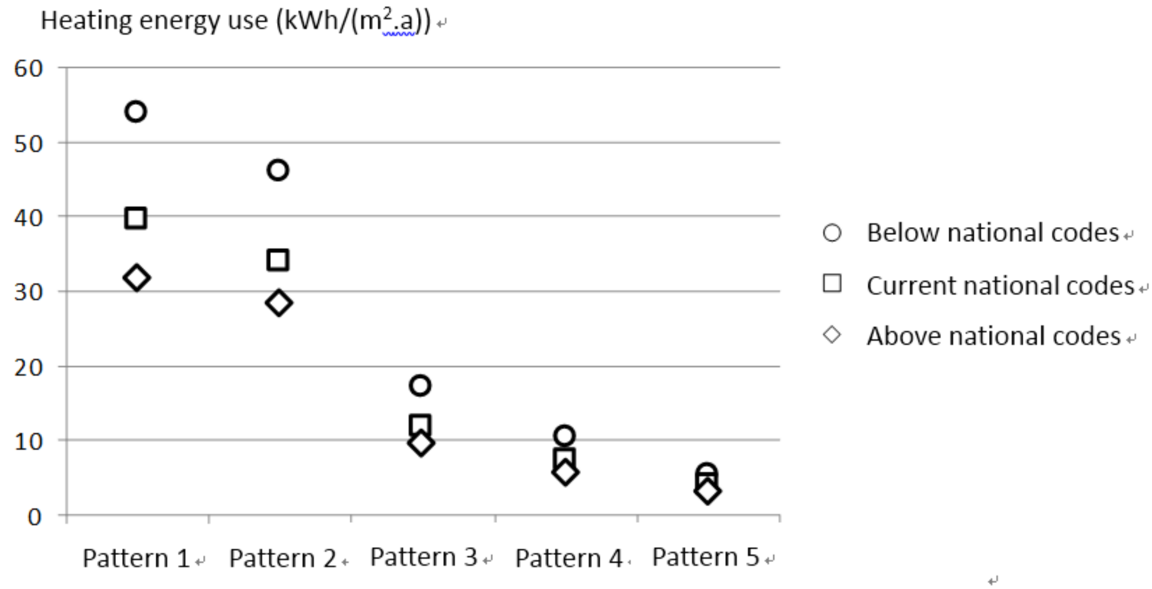
- Not available.

Summary

In this Case study, using building energy consumption simulation software DeST, different occupant behavior patterns and the life cycle energy consumption of external wall insulation were taken into account to help set an appropriate standard of the heat transfer coefficient of building envelope in residential buildings.

It was found that the energy-saving potential of building envelope improvements could be significantly reduced under the "part-time, part-space" heating modes than "full-time, full-space" heating modes. Considering the life cycle energy consumption, it's necessary to increase external insulation to a suitable thickness rather than blindly increasing insulation since energy consumption of insulation materials manufacturing could not be ignored.

The figure below revealed that the energy-saving potential of building envelope improvements differ a lot because of the various living patterns. In pattern 1, which might be called “full time, full space” heating patterns, strengthening the building envelope could lead a large amount of energy saving, however, the heating energy use varies slightly between the below national codes case and the above national codes case in pattern 5 which might be call “part-time, part-space” heating patterns.



Key Findings

- Because of behavior pattern, the households might have ten times difference in heating energy use.
- The energy saving amount of different building envelope insulation level varies from different occupant behavior patterns.
- Considering the life cycle energy consumption, it’s necessary to increase external insulation to a suitable thickness rather than blindly increasing insulation and seldom think about living patterns.

Related publications

- Siyue Guo, Da Yan, Ying Cui. Analysis on the influence of occupant behavior patterns to building envelope's performance on space heating in residential buildings in Shanghai[C]. Proceedings of the 2nd Asia conference of International Building Performance Simulation Association (ASim), Nagoya, Japan, November 28-29, 2014.

Case 14

Case study title

Occupant control behavior of low-temperature air source heat pump (ASHP) in Chinese rural housing

Contributors

- Dr. Rongjiang Ma, Department of Building Science, Tsinghua University, China
- Prof. Xudong Yang, Department of Building Science, Tsinghua University, China

When and where

2014 – 2016, 10 houses in Erhezhuang village, Beijing, China

Building(s) description

- Owner type: rural residents
- Building type: rural housing
- Total floor area: 70-140 m^2
- Number of stories: 1
- Location (city, country): Beijing, China
- One or two pictures:

Occupant type

- Typical rural residents living in Beijing for decades

Description of the datasets

Data points	Collection frequency	Collection period	Format
Operation status and continuous power consumption data of each air source heat pump	1 minute	2 months	CSV
Indoor and outdoor temperature data	2 minutes	2 months	CSV

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Summarized data will be available; models are yet to be developed.

Summary

Currently, China has more than 600 million people, occupying 24 billion m^2 (about 258 billion sf) of building space, in vast rural areas. Approximately 317 million tons of coal equivalent (tce), equaling 9.3×10^9 GJ, is consumed by the rural residential sector each year. Among which, about 120.3 million tons of coal (raw coal, ball-shaped coal, honey coal, etc.) and 82.8 million tons of raw biomass (wood branches, firewood, straw, etc.), equaling 131.3 million tce or 3.8×10^9 GJ, is consumed for household heating. These solid fuels significantly contribute to both indoor and regional emissions of pollutants such as carbon monoxide and fine particulate matter ($PM_{2.5}$).

This case study presents the first results from an intervention study currently conducted in Beijing suburb, China. The purpose of this particular effort is to quantify the effectiveness of using a split-type, low-temperature air source heat pump (ASHP) as an alternative way of clean heating in rural households. Ten (10) rural houses with floor areas between 70-140 m^2 were tested, and detailed field measurements were conducted in two typical houses that represent general operating behavior patterns.
Temperature loggers were used to record the indoor and outdoor temperatures. Smart power meters were installed to meter power consumption of ASHPs, and record the operating status of the heat ASHP. The temperatures and time-varying electricity consumption for nearly two months were monitored.

Three "typical" occupant control modes can be summarized, all based on residents' own use pattern without much instruction.

- Occupant control behavior 1: "USED EVERYDAY & CONTINUOUS OPERATION". This occurred in one of the master bedrooms where and the ASHP was on all the time. Indoor temperature setting of ASHP was medium (~18 ℃) and seldom changed. This temperature setting was considered as sufficient to meet the local rural residents' comfort need.
- Occupant control behavior 2: "USED EVERYDAY & INTERMISSIVE OPERATION". This occurred in one of the bedrooms, where ASHP was on at night only (9.4 hours/day on average) when the room was occupied for sleep. And indoor temperature setting was high (~20 ℃) at night.
- Occupant control behavior 3: "USED IRREGULARLY". This occurred in irregularly occupied living rooms, where the ASHP was on only when the room is occupied (2.1 hours/day on average). And indoor temperature setting varied greatly (15-25 ℃) depending on guests' comfort demand & clothing level, but in general higher than continuously occupied rooms.

The corresponding energy consumption of the three occupant control modes (rooms) are summarized in the following table.

Table 1 Energy consumption of the three occupant control modes

Occupant control mode	**Room**	**Average running time per day (hours)**	**Average indoor temperature when running (℃)**	**Energy consumption of heating season per unit area (kWh/m^2)**
USED EVERYDAY & CONTINUOUS OPERATION	Master Bedroom	23.2	18.2	36
USED EVERYDAY & INTERMISSIVE OPERATION	Second Bedroom	9.4	19.7	37
USED IRREGULARLY	Living Room	2.1	21.0	11

After careful comparison, the results indicate that allowing for occupants' own and flexible control of the ASHP can meet the various thermal comfort needs, and have significant energy saving implications.

Key Findings

- Continuously monitored ASHP power consumptions and indoor temperatures can accurately reflect residents' occupational and control behaviors, beyond understanding the indoor comfort conditions and corresponding energy consumption.
- Three representative occupant control behaviors related to ASHP use were identified.
- The key energy-related occupant behaviors in residential buildings had a strong influence on energy consumption.
- Actual building energy use could not be reasonably estimated without fully understanding and taking into account the possible occupant behaviors.
- ASHP is an alternative way of clean heating to meet various thermal comfort needs in rural households.

Related publications

- Tsinghua Building Energy Research Center, 2016 Annual Report on China Building Energy Efficiency, China Building and Architectural Press.

Case 15

Case study title

Influence of occupant behavior pattern on air conditioning energy consumption in residential buildings

Contributors

Chuang WANG, Building Energy Research Center, Tsinghua University

Contribute to other subtasks

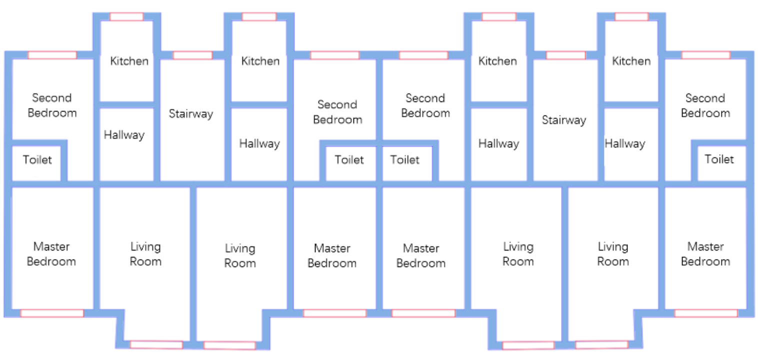
Subtask B: Occupant action models in residential buildings.

When and where

Simulation, Beijing, CN

Building(s) description

- Owner type: resident
- Building type: Residential building
- Total floor area: 1764m^2
- Number of stories: 6, four households in each floor
- Location (city, country): Beijing, CN
- Plane Figure:



Occupant type

- Three-member family, 2 adults& 1 children, in one apartment.

Description of the model

- Heat transfer coefficient of building envelope (W/(m^2·K))

Wall	Window
0.622	2.8

- Window-wall ratio: South:0.5, North 0.3;
- The lighting power density in each room is 5 W/m^2

- Equipment consumption(W/M^2)

Master Bedroom	Second Bedroom	Living Room
6.3	7.9	9.8

- Every main room has a split air conditioner.
- The cooling season is from June 1st to September 30th.
- The Step of the simulation is 5 mins.
- Occupant behavior patterns

Pattern 1	Cooling and open the window for 24h, all the room maintain 26℃
Pattern 2	Open window all the time & Cooling as long as anyone is in the room, maintain 26℃
Pattern 3	Open window when get up or feel stuffy & Close the window before sleep and open the air conditioner. Cooling as long as anyone is in the room, maintain 26℃
Pattern 4	Open window when get up or feel stuffy & Close the window before sleep and open the air conditioner. Cooling only when residents feel hot (28℃) and stop cooling when leaving home, maintain 26℃
Pattern 5	Open window when get up or feel stuffy & Close the window before sleep and open the air conditioner. Cooling only when residents feel hot (29℃) and stop cooling when leaving home, maintain 26℃
Pattern 5	Open window when get up or feel stuffy & Close the window before sleep and open the air conditioner. Cooling only when residents feel hot (29℃) and stop cooling when leaving home, maintain 27℃

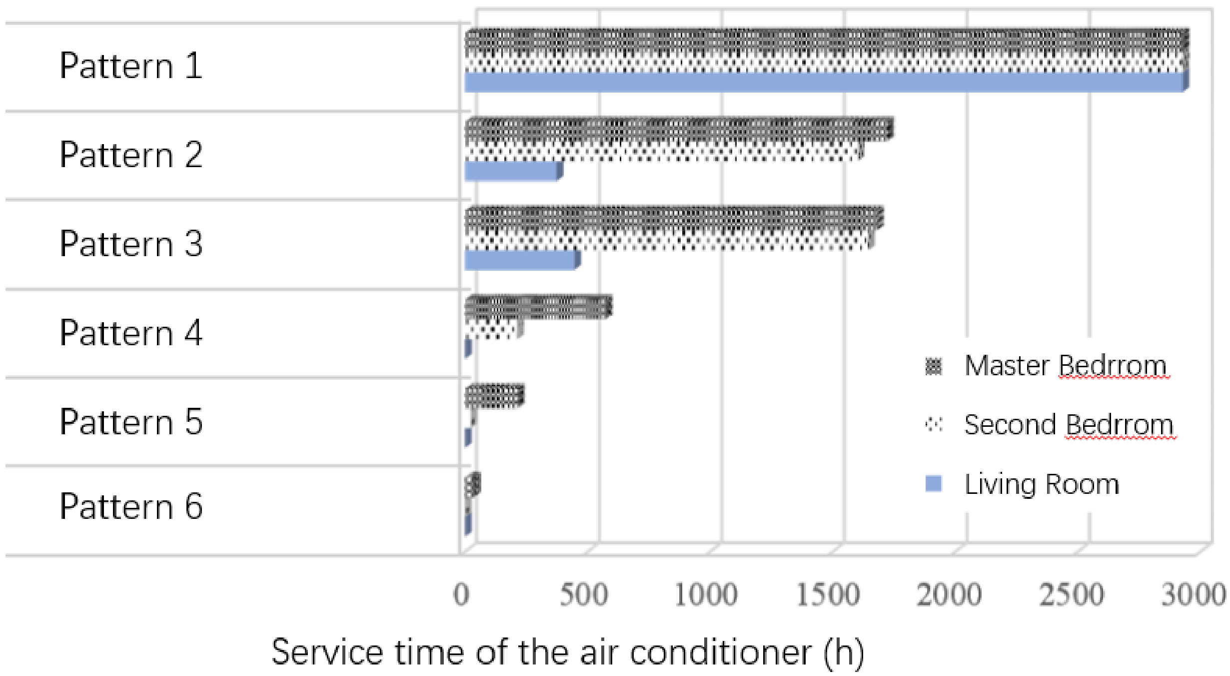
Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

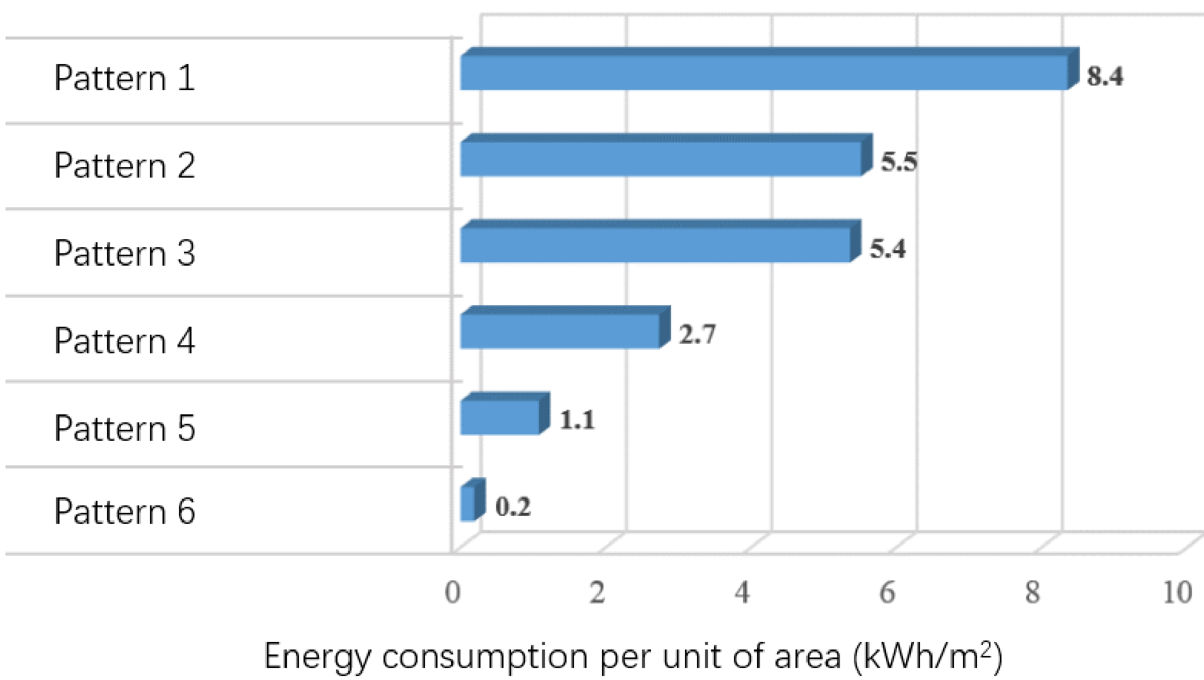
- Not available.

Summary

This case study defines six different patterns of the residential. And by compare the service time of the air conditioner and the final energy consumption of each pattern, it can be seen that even when use the same kind of HVAC system (in this case, split air-conditioner) and in the same building, different patterns of the occupant's behavior will cause great difference between the energy consumption. After defining different patterns using the three-parameter Weibull distribution and other probability value, the simulation could give the energy consumption of each patterns.



The figure above shows the service time of the air conditioner. It can be seen that the service time under pattern 1 could be about 3000 hours, while pattern 2 and pattern 3 is 1700h, which is half of pattern 1. And the pattern 4 \5\6 only use the AC for 600h\200h\40h.



This result reveals the great difference between different patterns. And it is the great gap in the service time that causes the large difference in energy consumption.

Key Findings

- Different patterns of the occupant behavior will cause a great gap in the energy consumption.
- When people reduce the opening time of the AC, change the using pattern from using 24h per day to open only when in the room, the energy consumption of the AC could be reduced.
- When raising the tolerant temperature, the service hour and the energy consumption of the AC would be reduced too.

Related publications

- Chuang WANG. Research of energy-consumption-related occupant behavior. Ph.D. Thesis, Tsinghua University, 2015.

Case 16

Case study title

Effectiveness of Information Conveying Means in Energy Behavior Interventions

Contributors

Yilong Han, Yujie Lu, Department of Building, National University of Singapore, Singapore

Contribute to other subtasks

Subtask E

When and where

- Hangzhou, China
- April 2016 – July 2016

Location description

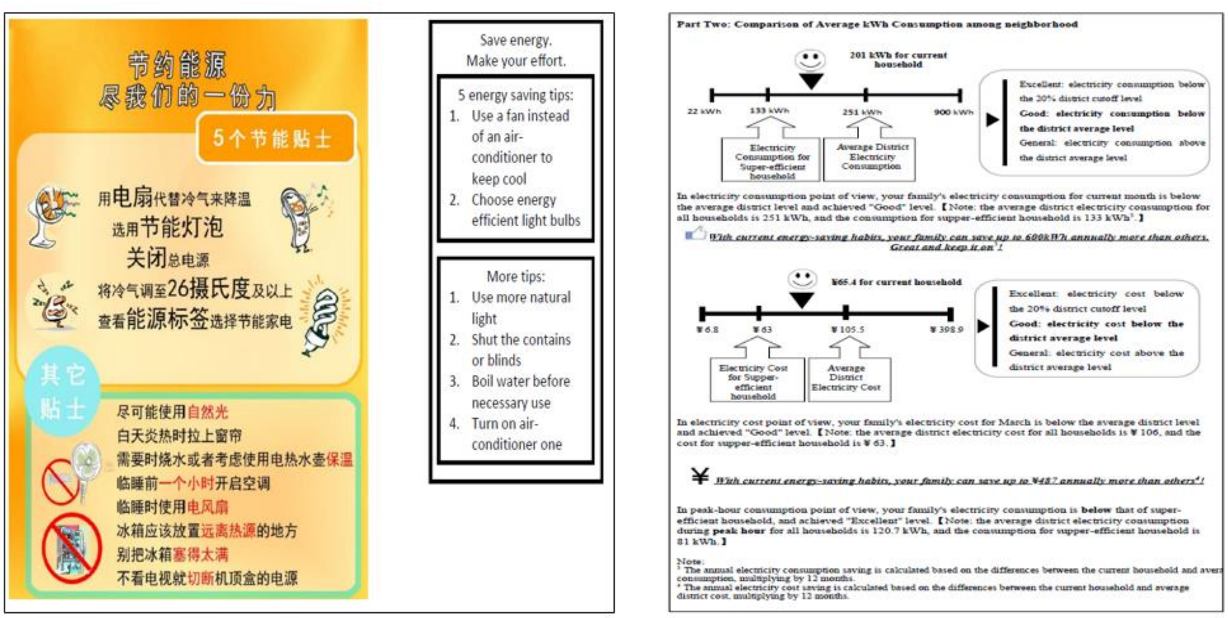
- Building type: residential building
- Location (city, country): Hangzhou, China
- Changmu Community, Qinfeng Community
- Total Households: 2000+; Sample households 240-
- One or two pictures

Occupant type

- Typical household in Changmu Community and Qinfeng Community
- A total of 2000+ households lives in the studied communities. Among them, 240 households are recruited to participate in this household behavior intervention study.

Types of intervention strategy

- Energy saving tips
- Eco-feedback



(a) (b)

Figure 1. (a) Example message of energy saving tips; (b) example template of eco-feedback information.

Description of the datasets

Information of occupancy:

- Demographic information
- Self-reported energy consumption behavior, including the usage of main appliances
- Quality of life perception

Information of energy consumption:

- Monthly household electricity bill
- Historical energy data from the previous year

Models for analysis:

- Pearson and Spearman correlation analysis, paired-sample t-test and Wilcoxon signed-rank test
- Simple and multiple linear regressions

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request.

Summary

Efforts have been made to explore the best ways to present information and feedback in order to maximize energy savings. Karjalainen (2011) examined different ways of presenting feedback on electricity consumption and user interface prototypes systematically. He found that presentations of cost, appliance specific breakdown, and historical comparison are key preference features of feedback on household electricity consumption that are valued most by occupants. The impact of real-time energy monitors and in-home display on energy consumption in residential settings are also studied in several metropolitan cites. Researchers also used different types of messages and message conveying means in behavior intervention experiments. Delmas and Lessem (2014) tested the efficacy of detailed private and public information on electricity conservation in a unique field experiment context in university residence halls. Private information that contains energy usage information was delivered through an online dashboard coupled with weekly emails, while public information was presented in the form of posters. Kamilaris et al. (2015) employed a case study on the individual energy use of personal computers in an office setting and assessment of various feedback types toward energy savings. A Sweden study (Vassileva et al. 2012) that included more than 2000 households evaluated the effects of the different ways of presenting feedback used for different intervention groups. Web-based feedback resulted in being the more effective compare to direct display and paper-based and achieved approximately 15% electricity savings in different neighborhoods. Feedback via TV channel was found to be the most interesting way to receive information.

Although participating occupants' preferences are accessed via questionnaires during the development of the intervention strategies, preference does not necessarily mean effective in real life. We still lack empirical studies to understand the roles of communication means in conveying energy-related messages in behavior intervention programs. Thus, this case study aims to evaluate whether information conveying means have an impact on the effectiveness of behavior interventions, and if so, what is the best strategy to maximize the outcomes. There are five treatment groups consisting of a combination of different information conveying means (paper-based, electronic-based, or in-person interaction) and intervention strategies (eco-feedback and/or energy saving tips), referring to Table 1. A sixth group (control group) is used to calculate household electricity consumption variations of each treatment groups. Household electricity data was collected over a span of two years (January 2015 - December 2016), and the monthly behavior intervention last for four months (April 2016 – July 2016).

Key Findings

Table 1. Group settings and household energy performance after the first month's intervention

Group	**# of Households**	**Information Conveying Means**	**Behavior Intervention Strategies**		**Household Electricity Consumption Variations**
			Eco-feedback	Energy Saving Tips	
1	37	Leaflets & Stickers	✓	✓	-12.1%*
2	35	Leaflets & Stickers		✓	-0.1%*
3	37	WeChat	✓	✓	-5.7%
4	30	WeChat		✓	-6.6%
5	25	Consultation	✓	✓	+0.6%
Control	37	-	-	-	-

Note: *Household energy consumption variation difference between group 1 and group 2 are statistically significate, p<0.05.

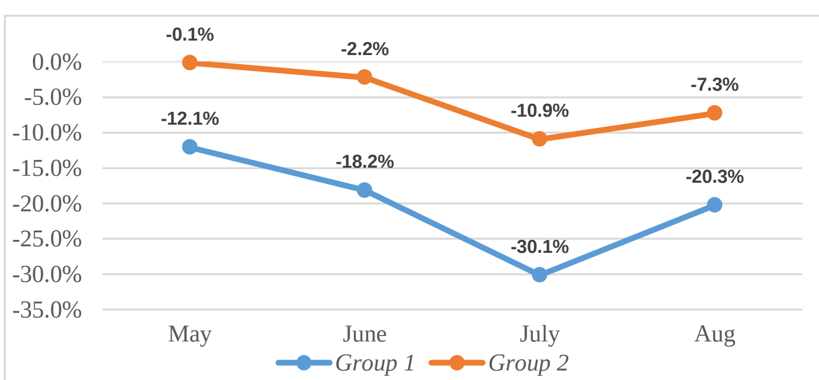


Figure 2. Household energy consumption variations of group 1 and group 2

- During the treatment period, households consumed less electricity energy compared to the same time last year. In other words, the positive impact of this behavior intervention experiment was exhibited in most groups (except the consultation group).

- Referring to group 2 and group 4, electronic-based information conveying means (WeChat) is more effective, achieving 6.6% energy savings, compared to paper-based means (Leaflets & Stickers), when only “energy saving tips” is provided. Electronic-based delivery is more effective when the message is short, in figure format, and entertaining.

- Referring for group 1 and group 2, more intervention strategies (eco-feedback + energy saving tips vs. energy saving tips) resulted in more household electricity reductions in paper-based delivering means, but similar evidence cannot be identified in electronic-based delivering means (compare group 3 and group 4). The information containing both eco-feedback and energy saving tips is quite lengthy, thus is not effective for cell-phone display. This finding is consistent with finding 2). However, we find that paper-based method may be more effective in a long run.

- In this study, the results show that behavior interventions are hard to execute through in-person interaction/consultation, as more people drop off from group 5 and the households of group 5 did not show better energy performance. Future behavior intervention programs that involve in-person interaction should be treated and designed more carefully.

- The longitudinal study (in Figure 2) revealed that our behavior intervention became more effective over the course of the study period in group 1 and group 2. The performance rebounded after the last intervention ended in August.

This study contributes the understanding and exploration of targeted and tailored feedback in behavior intervention programs in buildings. Proper message conveying means may help promote intrinsic motivation and energy behavior, and change the individual’s energy performance, leading to a long-term benefit. The effectiveness of the message conveying depends on the way it is delivered and the information it contains. The potential delaying of paper-based leaflet messages make them easy to be ignored at the first place. However, leaflets are relatively easy to access over time, thus can exert multiple stimulations over and after the intervention period. Quite oppose to the long-term nature of leaflets messages, electronic-based instant messages can convey information real-time and in a timeliness manner. However, our results showed that instant messages need to be short and entertaining to be effective. This is reasonable since mobile users easily get bored with lengthy and user-unfriendly messages. Another disadvantage of instant messages is they are easy to forget and hard to retrieve. Paper-based leaflet messages may promote the persistence of behavior intervention programs, but proper electronic-based instant messages could result in significant short-term benefits.

This study suggests future research to include a combination of message delivering means based on the nature and the purpose of messages. The implementation of smart meters may help better reveal the underlying energy behavior profiles. Future study should focus on promoting in-person interaction in such interventions to eliminate human-induced misinterpretation, as it is considered one of the effective underused strategies. The platform of WeChat demonstrated its own advantages in this study. However, we did not explore its social media features. The use of social networks and peer educations could potentially escalate the effectiveness of behavior intervention strategies.

Related Publications

- Yujie Lu, Harn Wei Kua, Lin Xu, and Maoliang Ling (2017). Is Instant Messaging Effective in Promoting Household Energy Saving? A Household Intervention Study in Hangzhou, China. *Working paper*.
- Yujie Lu, Harn Wei Kua, Lin Xu*, Yilong Han, Maoliang Ling, Yong Wang Lee (2017). Effectiveness of Delivering Eco-Feedback to Reduce Household Energy Consumption. *Working paper*.

Case 17

Case study title

Household Electricity Consumption Prediction Under Multiple Behavioural Intervention Strategies

Contributors

Meng Shen, Yujie Lu, Department of Building, National University of Singapore, Singapore

Contribute to other subtasks

Subtask E

When and where

- Hangzhou, China
- April 2016 – July 2016

Location description

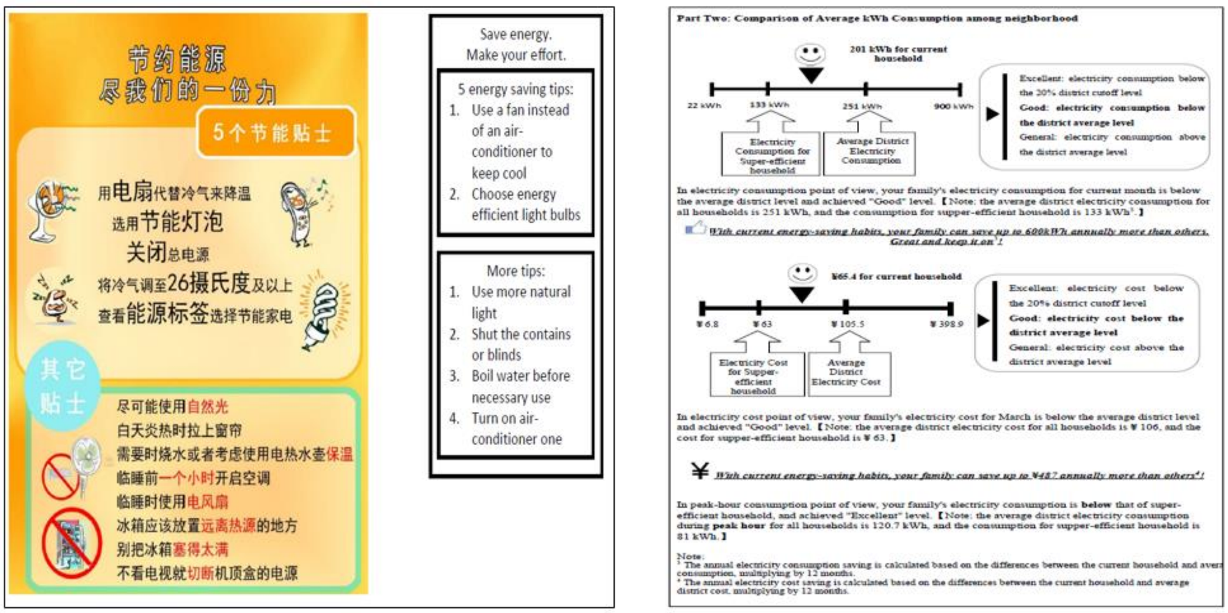
- Building type: residential building
- Location (city, country): Hangzhou, China
- Changmu Community, Qinfeng Community
- Total Households: 2000+; Sample households 240-
- One or two pictures

Occupant type

- Typical household in Changmu Community and Qinfeng Community
- A total of 2000+ households lives in the studied communities. Among them, 240 households are recruited to participate in this household behavior intervention study.

Types of intervention strategy

- Energy saving tips
- Eco-feedback



(a) (b)

Figure 1. (a) Example message of energy saving tips; (b) example template of eco-feedback information.

Description of the datasets

Information of occupancy:

- Demographic information
- Self-reported energy consumption behavior, including the usage of main appliances
- Big five personality traits

Information of energy consumption:

- Monthly household electricity bill
- Historical energy data from the previous year

Models for analysis:

- Support vector regression (SVR)
- Akaike information criterion (AIC)

- Simple and multiple linear regressions
- Monte Carlo simulation

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request.

Summary

Residential buildings contribute to 13.6% of the electricity use in China. According to National Energy Administration of China, the amount of electricity consumption expanded quickly by 10.8% in 2016, and therefore the residential sector is considered as the key sector for energy savings. It appears to us that a recent trend of calling for investigating the potential occupant behavior driven energy reductions in buildings (Khosrowpour et al., 2016), showing that the tremendous faith is no longer only being placed on the innovative energy-efficient technology. Since household energy-related behavior itself can significantly bear on energy use (Schakib-Ekbatan et al., 2015), it leaves the room for further discovering the great potential of achieving cost-effective energy efficiency in buildings through introducing multiple behavioral intervention strategies to change occupant behaviors (Stern, 2011).

However, as existing studies failed to consider and quantify the impact of changes in occupant behaviors and other characteristics on the household electricity consumption, the effectiveness of behavioral interventions may not be assessed and predicted accurately (Shen et al., 2016). There is a growing need to identify key energy behaviors for predicting the household energy consumption accurately through different intervention strategies, in particular targeting the residents' with heterogeneous characteristics. It is undisputed that the energy-related behaviors are not easily to be measured as they are influenced by a wide range of factors. Moreover, the majority of the behavioral intervention studies aimed to improve the households' performance on energy conservation has focused on conducting a statistical analysis of a field or laboratory experiment, or carrying out a system simulation experiment. The impacts of monthly usage feedback delivering via different medias on electricity consumption are still unclear. In addition, prior research on the linkage between personal characteristics (such as demographic factors etc.) and the intervention effects rarely explained the underlying logic of why uniform intervention may have different impacts on occupants, which personality traits actually lead to observed differences (Shen & Cui, 2015; Shen et al., 2015). That is, personality being an important motivation of our attitudes, values, and beliefs, may be a significant predictor of the energy behavior and energy consumption (Milfont & Sibley, 2012). With this in mind, this paper starts with the following questions: Can we use household energy-related behaviors and their personality traits to predict their energy consumption through various behavioral intervention strategies? How to measure the interaction effect between behaviours and other personal characteristics on consumption prediction? Can we optimize the intelligent solution approach such as Support Vector Regression (SVR) to accurately predict the electricity consumption for each household?

Therefore, based on an experiment conducted to infer the effects of feedback via different delivered methods on household monthly electricity consumption in Hangzhou, China, this paper presents a variable selection approach to determine the optimal set of household electricity consumption predictors. Moreover, an optimal SVR model is proposed for predicting household consumption under multiple intervention strategies. The aim of the model development is to choose the best-fit intervention strategy which can generate the maximum electricity savings for every single household. The improved model is designed to incorporate energy-related behaviors, personality traits, demographic/building features and the weather data, into behavioral interventions to predict electricity consumption for the households. In particular, the interaction effect between behaviors and other variables has been introduced to the household electricity consumption prediction.

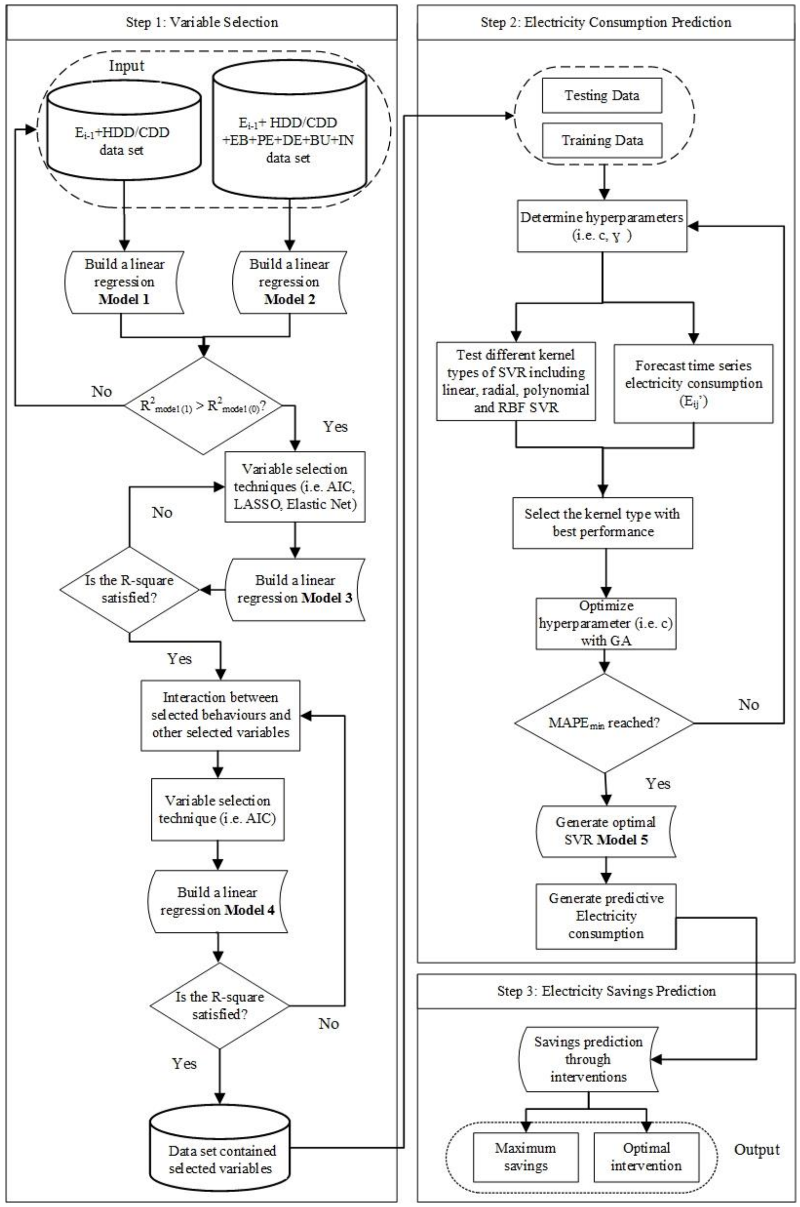


Figure 2. Flow chart in developing an optimal SVR prediction model

Key Findings

Table 1. Performance of SVR on the household energy consumption forecasting measured by Mean Absolute Percentage Error (MAPE; %).

Model	Next-month prediction		Time-series forecasting				
	Training data	Testing data	February	March	April	May	June
OLS Regression	28.11	22.75	36.22	35.28	44.54	40.88	38.41
SVR-Linear	26.1	18.89	38.89	34.06	42.20	35.20	33.51
SVR-Radial	7.00	25.09	6.63	51.32	67.59	58.94	42.82
SVR-Polynomial	14.88	13.80	16.67	30.66	45.99	41.87	55.31
SVR-RBF	9.42	10.65	11.58	26.77	37.81	33.41	34.98
SVR-GA RBF	8.42	9.28	6.55	25.53	36.27	27.71	29.68

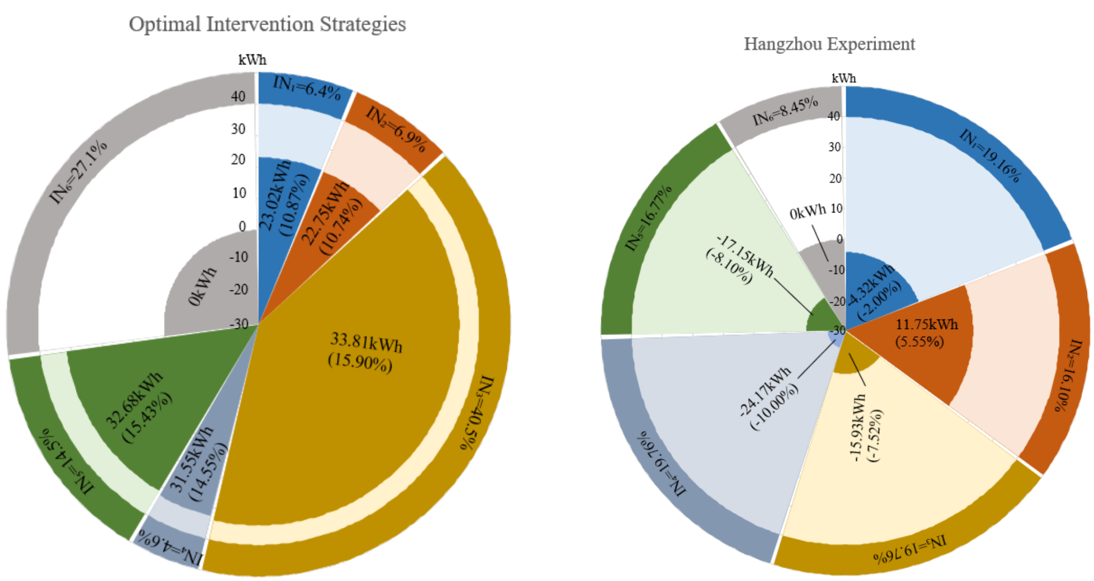


Figure 3. Variation of the maximum electricity savings (kWh) with saving percentage (%) shown in brackets, and the household proportion (%) under each intervention strategy (from IN_1 to IN_6). The saving percentage is relative to the control condition.

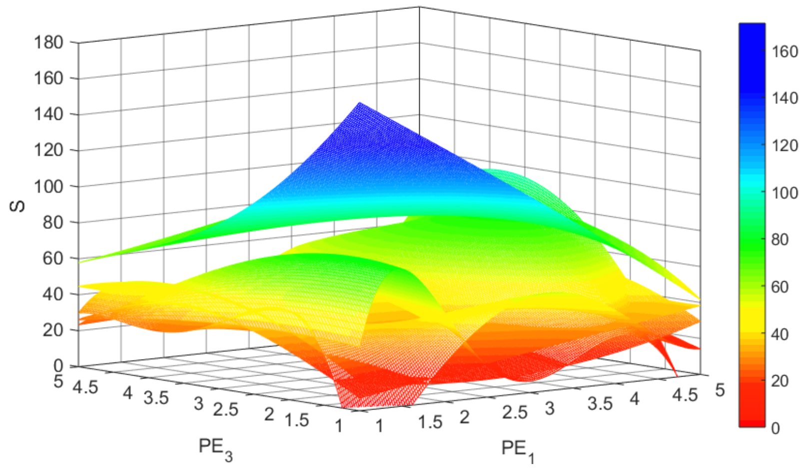


Figure 4. The relationship between the maximum electricity savings (S), the personality traits of extraversion (PE_1) and conscientiousness (PE_3), with the optimal intervention strategies (IN_1-IN_5) presented in five surfaces respectively.

- Based on the experiment conducted in Hangzhou, China, this study has proposed a variable selection approach to determine the best subset of consumption predictors by implementing AIC. This approach is vital to find the optimal set of variables for prediction which assist in increasing the accuracy of household electricity consumption prediction. Among the initial 48 variables, 18 of them have been considered as the critical predictors including energy behaviors, personality trait, demographic information, building features and weather indicators in this research.
- This study improves the accuracy of prediction by introducing the interaction effect between the selected five behavior predictors and other variables to the prediction model. The proposed GA RBF SVR is capable to predict household electricity consumption under multiple intervention strategies. The result shows that the proposed model exhibit the best and robust performance in both next-month prediction and time-series forecasting (see Table 1).
- The proposed model is able to act as a decision-making tool to predict the electricity savings accurately through each intervention strategy and to choose the most appropriate intervention strategy for different households (in Figure 3). According to the proposed approach, we calculated the most appropriate treatment strategy for each of the households in all experiment groups. This new customized approach generated from the improved SVR model can overall lead to an additional 12.1% reduction in households energy consumption than the experiment setting. Specifically, the result demonstrated that the intervention strategy of WeChat with feedback and without feedback achieved the highest (15.97%) and second highest (15.43%) electricity savings compared to other strategies, followed by the consultation strategy (14.9%). The sticker strategies showed the smallest reduction in electricity consumption during the experiment period. Importantly, all of the feedback intervention presented a slightly more electricity savings comparing to non-feedback intervention.
- To examine the effect of personality traits, including extraversion and conscientiousness, on the maximum predictive electricity savings, we simulated

10,000 households by using the Monte Carlo method and illustrated the results in a 3D surface plot (see figure 4), in which the predicated maximum energy savings in WeChat with feedback condition was much more than any other intervention strategies, reinforcing the previous predictive results. Further, we identified five types of people (i.e., E^LC^H, E^LC^L, E^HC^H, E^MC^L and E^LC^M) based on their extraversion and conscientiousness that response very distinctively to the optimized intervention strategy. The plot presented that the residents with a high rate of conscientiousness while a low rate of extraversion only has a small saving potential. Nevertheless, those who are disorganized and introverted showed polarized behaviors that this type of person could either save massive electricity consumption with the help of the WeChat with feedback intervention or save little.

The first contribution of this study is the effort to design a predictive tool that with the aim of selecting the optimal intervention strategy and predict the maximum of electricity savings potential for each household, along with extracting the most critical subset of all candidate characteristic variables of households. Furthermore, the proposed prediction model considered the households' characteristics including the energy use behaviors and personality traits can further improve the accuracy of the electricity consumption prediction. Last but not least, the results would gain knowledge about the design of behavioral intervention strategy in terms of the demand-side management, and more importantly, would lead to considerable energy savings in the aggregate.

Given the contributions above, this study has two limitations that require for the future study. The current work was conducted in one city of China. However, residents' behaviors and living habits may be different from in other countries. To generalize the prediction model, it needs to be applied to and tuned by different scales and culture. In addition, the prediction model is developed by monthly household consumption. To further improve the accuracy of prediction with the proposed model, future work should use minute-based energy data to reduce the value of MAPE in the residential sector.

Related Publications

- Meng Shen, Huiyao Sun, Yujie Lu* (2017). Household electricity consumption prediction under multiple behavioral intervention strategies using support vector regression. Energy Procedia. *Forthcoming*.
- Meng Shen, Yujie Lu*, Lin Xu, Huiyao Sun (2017). Prediction of Households Electricity Consumption and Concerted Intervention Strategies Based on Occupant Behaviour and Personality Traits. *In preparation*.

Case 18

Case study title
Energy Forecast Facilitates Greener Clubhouse Environment

Contributors
Simon Tsui & Allen Yui, CLP Power Hong Kong Limited

Contribute to other subtasks
N/A

When and where
Since 2014, New Territories, Hong Kong

Building description
- Owner: Park Island tenants
- Building type: Residential Clubhouse
- Total floor area: over 500,000 sf
- Number of stories: three 2-conditioned-story Clubhouses
- Location (city, country): Hong Kong, China

Occupant type
- 3 deluxe clubhouses, exclusive use by the tenants of Park Island, with catering facilities, swimming pools, ball courts, etc.

Methods
- Meter Online (MOL) mapped the 9-day hourly weather forecast temperature and humidity data of the 13 weather stations of Hong Kong Observatory with CLP's nearest 126 customer supply regions to forecast the energy consumption for individual customers in coming 9 days.
- The Clubhouse Manager drives behavioral changes of his team to reduce the electricity consumption by making use of the forecast information from MOL. As a

result, 5% electricity consumption was reduced monthly during the summer period. Total electricity of 7000kwh saved.

Data and models availability

The customer does not agree to disclose the consumption data.

Summary

The MOL service is widely adopted by CLP's commercial & industrial customers such as hotels, shopping malls, officer towers, clubhouses and factories, etc. Energy saving achieved ranges from 1% to 6% of the total consumption. The saving is significant because it is merely by behavioral change without any capital investment by the customers.

Key Findings

[1] Raising the air conditioning temperature set-point of a clubhouse could be a quite common way to save electricity, but less comfort for the clubhouse users is a price to pay and thus it is difficult to get all the clubhouse users' support.

[2] MOL consumption forecast function provides a scientific data to support the decision of energy saving actions. Both technical and non-technical staff can refer to the same standard of MOL forecast information. Like the Clubhouse Manager, in this case, he reduced the air conditioning supply for every MOL high consumption forecast day.

[3] Simple and standardized energy-saving operations enable direct involvement of all staff to support the energy saving actions. It brought a successful behavioral change.

[4] The success case was shared with other customers through CLP's e-newsletter published in June 2015 that has further driven energy saving behavioral change.

Related Publications

- CLP Green Plus e-Newsletter, CLP Power Hong Kong Limited, Issue June 2015
- CLP Meter Online Energy Management System, APIGBA Intelligent Green Building Forum, 2016
- The Meter Online Service - Application of weather information in support of CLP electricity consumption forecast for customers, CEPSI International Conference, 2016
- Meter Online Energy Management System, IET Annual Power Symposium, 2016
- Meter Online - Information Drives Behavioural Change to Save Building Energy, World Sustainable Built Environment Conference, 2017

Case 19

Case study title

Information Drives Behavioural Changes for Residential Customers with Eco Power 360

Contributors

Simon Lam, Gary Chiang, Joe Lo, CLP Power Hong Kong Limited

Contribute to other subtasks

N/A

When and where

2016, Kowloon and New Territories Areas, Hong Kong

Building description

- Building type: Residential households with majority of apartments in high-rise buildings

Occupant type

- Over 300,000 residential customers' households
- Location (city, country): Hong Kong, China

Methods

- Eco Power 360 provided residential customers with required information to drive the behavioral change to adopt energy efficient living style. The information includes consumption projection, energy usage benchmarking, and consumption distribution analysis.
- Consumption project provided a comprehensive analysis of electricity consumption based on previous 12-months of consumption data and the projected consumption of the next billing period, for understanding the customer behaviors in energy usage.

- Energy usage benchmarking compared customers' electricity usage with similar households and drive the customers' behavioral changes
- Consumption distribution analyses customers' electricity consumption distribution and provide directions for energy saving to customers
- Eco Power 360 drives behavioral changes for the residential customers and also influences their family members to reduce the electricity consumption by making use of the analysis information from Eco Power 360.
- As a result, Eco Power 360 supported Power Your Love 2016 programme to save energy again. The participant was saved more than 10% of energy compared to other customers in summer (June to August) of 2016

Data and models availability

Residential customers' consumption data are not disclosed.

Summary

Eco Power 360 is widely adopted by CLP's residential customers. Energy saving result was achieved especially in the summer period. The saving is engaging. It could drive the energy saving by behavioral change for the Eco Power 360 users and also their family members.

Key Findings

- During summer 2016 (Mid June to Mid August), the ~300,000 participants of the Power Your Love program and Eco 360 users saved around 3GWh of electricity.
- The average temperature of that period was 0.8% higher than the same period in 2015.
- The saving percentage of the Eco 360 users is 10% better than the saving percentage of all other residential customers.
- Based on customer services experience, customers found it difficult to perform energy saving actions without the information of appliances distribution and also the energy saving advice.
- Customers found it hard to engage and motivate their family members to participate in energy saving. Simple gamification, e.g., energy saving tips may help to encourage customers' commitment and involvement in sustaining long-term energy saving behaviors.
- Analytic results with consumption projection and benchmarking results could influence behavioral change in a continuous manner
- Simple and easy to understand energy saving tips enabled the residential customers to adopt energy saving actions and also share with their family members. It brought a successful behavioral change.

Related Publications

- CLP Light magazine, CLP Power Hong Kong Limited, Issue 14, 12.2016

Case 20

Case Study Title

Investigate the effectiveness of providing energy usage feedback system coupled with education intervention on energy saving for Hong Kong primary students

Contributor

Elizabeth Hio Wa LAI, Reconnect Limited

Contribution to other subtasks

N/A

When and where

Hong Kong
15 December 2016- 14 December 2017

Building(s) description

10 Primary Schools in Hong Kong

Occupant type

Students of 10 primary schools in Hong Kong

Methods and data

One of the project objectives is to evaluate the effectiveness of having both energy usage feedback system and energy saving education on primary schools students in Hong Kong. 10 local primary schools are chosen randomly out of the 571 primary schools in Hong Kong[2]. It is anticipated that this control study will contribute to the knowledge concerning the magnitude of the impact of education intervention, together with the use of feedback tool on energy usage, on inducing behavioral change in students in relation to energy conservation. The aim is to investigate the changes in the students' behavior concerning energy usage, with an expectation that they will adhere to the energy-saving principles outside of the school premises, by bring such good practices to their home and beyond.

[2] Education Bureau (2015), Primary schools figures and statistics, http://www.edb.gov.hk/en/about-edb/publications-stat/figures/pri.html., Accessed 13 April 2016.

This curriculum was delivered over an eight-month intervention period designed to establish 'good behaviors' pertaining to energy saving. The Reconnect team held a series of activities with participating schools covering education, smart energy metering feedback system, and energy saving competitions, such as 'five-minute shower challenge', 'no air-con days', and 'eat locally think globally'.

During the intervention phase, the 10 schools will be divided into 2 groups with the following structure (Table 1 and Figure 1).

- **Group A Experimental School Group (With Feedback)** - students will receive both education intervention and energy usage feedback by accessing real-time information on their energy usage through the interactive screen at schools and web-based interfaces;
- **Group B Control School Group (With No Feedback)** - this is the control group which only receives education intervention and no real-time feedback on energy usage.

Table 1 Research groups

	Education	Monitoring	Real-time Feedback
Group A Experimental School Group (With Feedback)	•	•	•
Group B Control School Group (With No Feedback)	•		

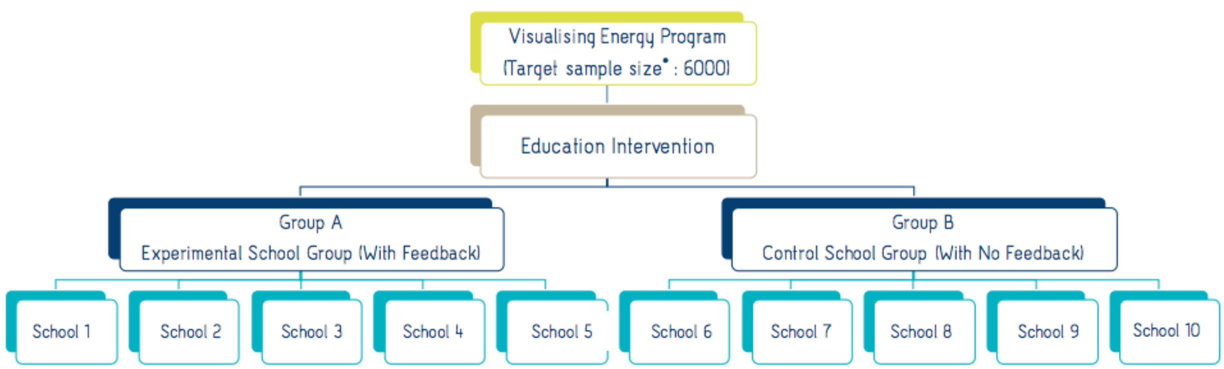


Figure 2 Experimental schools and control school groups

Data and models availability

- Not available.

Summary and key findings

The program is divided into three phases as shown below:

- **Phase 1 Baseline** – The baseline for both Control School Group and Experimental School Group were was based on the historical energy data collected from the schools. The information collected from the historical data analysis provide the necessary database for comparison during Phase 2 and Phase 3. In addition, data collected throughout the baseline period (including building information, site observations) were analysed.

- **Phase 2 Intervention** – a 8-month intervention period is designed to instill good behaviour pertaining to energy saving. A series of activities will be held covering education, smart energy metering feedback system and competition.
- **Phase 3 Post-intervention** – to ensure that the students uphold to the good behaviour instilled from the previous year, a 1-month post-intervention will be held to observe students behaviour without the series of intervention activities being held.

The following results were obtained thus far half way into the program.

- Overall - a **10% reduction** in actual energy consumption (kWh) was recorded across all 10 schools thus far from January to June 2017. However, one of the participating schools increased 39% in student intake in 2017 compared to 2016 (**Table 3**) thus using the normalised figures by the number of students would be more appropriate in this case for the rest of the discussion. As such a **13% reduction** in actual energy consumption (kWh) normalised by student number was achieved from January to June 2017 (**Table 2**).
- Comparison - Experimental School Group achieved a **14% reduction**

Table 2 Results

2016 vs 2017	All (Experimental + Control) (kWh)	All (Experimental + Control) (kWh/student)	Experimental School (kWh/student)	Control School (kWh/student)
Jan – Mar 2017	+4%	0%	-1%	2%
Apr – Jun 2017	-15%	-19%	-19%	-18%
Jan – Jun 2017	**-10%**	**-13%**	**-14%**	**-12%**

Table 3 Changes in Number of students from 2015-2016 to 2016-2017 per participating school

School	2015-2016		2016-2017		% Student No.
	No. of Class	No. of Student	No. of Class	No. of Student	
School 1	11	270	15	375	39%
School 2	25	682	25	715	5%
School 3	24	659	24	660	0%
School 4	12	283	12	301	6%
School 5	25	729	26	712	-2%
School 6	26	700	26	690	-1%
School 7	30	956	30	953	0%
School 8	24	600	24	603	1%
School 9	30	949	30	954	1%
School 10	26	608	24	630	4%
Overall	233	6436	236	6593	2%

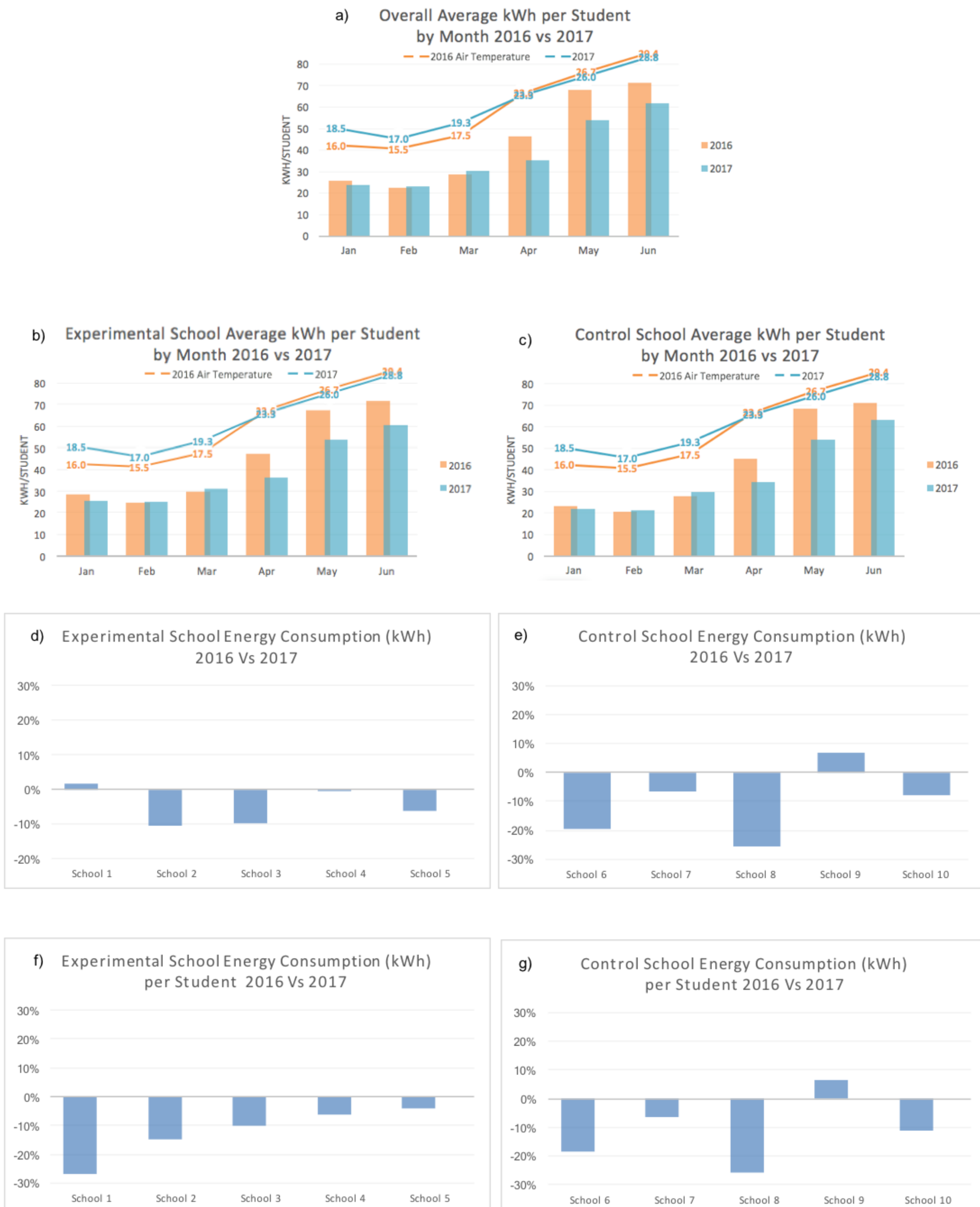


Figure 2 Results

The following aspects are highlighted for discussions of the results:

- **Periods –** the project took place thus far was characterised by the following two periods: o
- **January – March 2017** – A relatively low reduction rate was achieved during the first 3 months of the program because the smart metering system was only completed in March / April 2017. In addition, the education intervention during the first 3 months were not too intensive (Let's Get Active, 5-minute shower challenge at home, Earth Hour), thus the energy saving was not significant during this period (All 0%, Experimental School Group -1%, Control School Group +2%) (**Table 2**, **Figure 2a, 2b, 2c**).
- **April – June 2017** – The visualising smart metering system was completed during this period and also a more intensive education program took place during the period (Easter Energy Bunny Competition), hence, the energy saving was more significant during this period (All -19%, Experimental School Group -19%, Control School Group -18%) (**Table 2**, **Figure 2a, 2b, 2c).**

  1.
- **Weather** – The temperature difference was higher in the early months of 2017 (January – March) in comparison to the later months (April – June), thus under similar temperature situation, the energy savings achieved in April – June was a solid prove to suggest that the program was successful in reducing energy usage (**Figure 2a, 2b, 2c**).

- **Student number** – As mentioned earlier, referencing the absolute energy consumption without taking into account the number of student intake fluctuation could distort the picture considering the case with School 1 with 39% increase in student intake. A slight increase in School 1's energy consumption (kWh) as shown in Figure 3d but a significant drop when the energy consumption (kWh) is normalized by the number of students as shown in Figure 3f21. Thus, the number of student intake should be taken into account when considering the changes in School's energy consumption.

- **Experimental vs. Control School Group** – Experimental School Group (-14%) slightly excel in energy reduction compared to the Control School Group (-12%) (**Table 2**), suggesting having the visualising feature creates a positive impact in energy reduction and the program was on track thus far achieving the -15% reduction target.

- **Consistency** – Across the 10 schools, the majority of the schools achieved energy reduction except for School 9 (**Figure 2d, 2e, 2f, 2g**) suggesting the energy reduction is consistent across schools. The credit goes to the education intervention that took place.

- **School feedback** - Through informal face to face discussion with the participating schools' principals and teachers, most schools were pleased with the electricity bill reduction and students' behavioural change thus far. Upon further discussion with the Principals and Teachers, it was found that most Schools wished more could be done apart from energy saving. Energy saving is recognised as only one segment of the more holistic personal carbon emission.

> The Schools wish to see campaign that can mobilise the students to do furthermore with their personal carbon emission, extending into their daily routine.

The program thus far proved to be successful in mobilising behavioural change to achieve realistic energy reduction in the participating primary schools as a case study. However, it should be noted that the case study was still half way through the program, as such, no conclusive fact can be drawn at this stage to suggest if the provision of visualising data indeed affects behavioural change. Furthermore, there were multiple factors which could have affected the results including student number, difference in school culture in advocating for behavioural change, school's micro-climate which could have affected the need to use energy. Therefore, a further study is warranted to examine other factors which could have affected behavioural change apart from the provision of visualising energy feature.

Related Publications

Case 21

Case study title

Characterizing user behavior and user-preferences for uncertainty quantification in the life cycle assessment of air conditioning systems

Contributors

- Lynette Cheah, Singapore University of Technology and Design (SUTD), Singapore
- Stephen Ross, Singapore University of Technology and Design (SUTD), Singapore

Contribute to other subtasks

Subtask A, C

When and where

- 2014
- University staff offices in the former SUTD campus, Dover Road, Singapore

Building(s) description

- Building type: university office building
- Total conditioned floor area: (unknown)
- Number of storeys: 4
- Location: Singapore – tropical climate

Investigated Office description

- Office type: single occupant closed office rooms

- Fifteen comparable offices investigated, each measuring about 12 m^2
- Each office incorporated one identical 2.5-kW rated inverter-type air-conditioning (AC) system with outdoor compressor and indoor mounted wall unit
- Location: on the ground to 4th floor of the former SUTD Dover Campus building

Occupant type

- University staff with variable occupancy hours
- Integrated sensor units were deployed, each measuring the internal environmental conditions of a single office
- Measurements recorded at 5-minute intervals, 24 hours per day for a period of 5 months (July – November 2014)
- Recorded variables that represent proxy measurements of office users' behavior
- Patterns in occupancy, AC use and user preferences were determined from these proxy measurements

Description of the datasets

Recorded information on internal environmental conditions:

- Temperature
- Humidity
- Light intensity
- Noise
- Motion

The course of a day was divided into four states of user behavior based on cooling system usage and occupancy of the room:

- on & in - system cooling and room occupied
- on & out - system cooling and room unoccupied
- off & in - system idle and room occupied
- off & out - system idle and room unoccupied

States of user behavior were characterized by fitted probability distributions to be employed in a stochastic life cycle assessment model

Behavioral inputs of the product life cycle use-stage model:

- Probability of users being in 4 distinct states of behavior
- Users' preference for office internal temperature

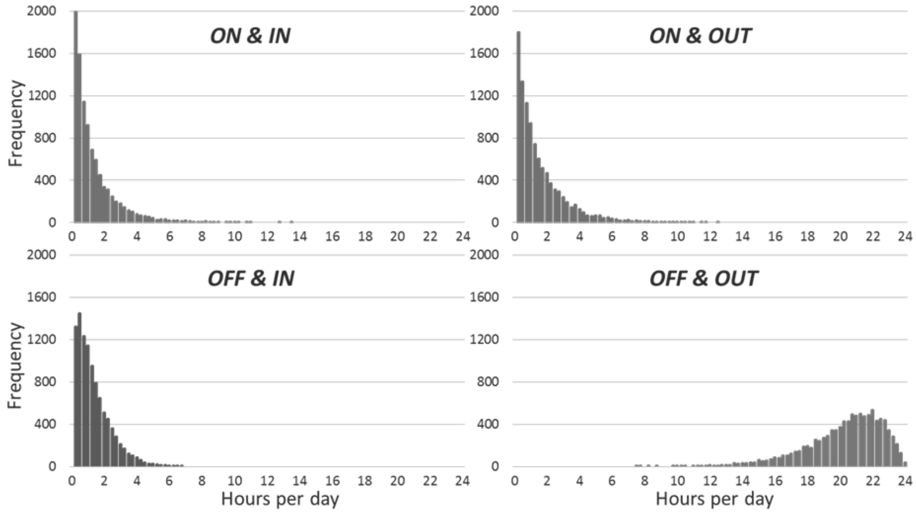


Figure 1: Probability distributions characterizing time spent by office users in four behavioral states combining occupancy and air-conditioning use

Data and model's availability

Data might be available upon request. More information is available in the published journal article and masters student thesis.

Summary

The life cycle environmental profile of energy-consuming products, such as air conditioning (AC), is dominated by the products' use phase. Different user behavior patterns can therefore yield large differences in the results of a cradle-to-grave assessment. Although this variation and uncertainty is increasingly recognized, it remains often poorly characterized in life cycle assessment (LCA) studies. Today, pervasive sensing presents the opportunity to collect rich data sets and improve profiling of use-phase parameters, in turn facilitating quantification and reduction of this uncertainty in LCA. This study examined the case of energy use in building cooling systems, focusing on global warming potential (GWP) as the impact category. In Singapore, building cooling systems or air conditioning consumes up to 37% of national electricity demand. Lack of consideration of variation in use-phase interaction leads to the oversized designs, wasted energy, and therefore reducible GWP.

High-resolution data on air-conditioning usage patterns and user behavior were collected from university staff offices in Singapore, spanning a period of 5 months from July to November 2014. Fifteen single-occupancy offices of comparable size were assessed, each incorporating one 2.5-kilowatt (kW) rated inverter-type air-conditioning system with outdoor compressor and indoor mounted wall unit. Data were collected from the 15 offices using integrated sensor units measuring internal environmental conditions of one individual office. Sensor measurements recorded at 5-minute intervals included: room

temperature, humidity, lighting, motion, and noise. Usage of the cooling system and room occupancy were determined by analysis of trends in the proxy measurements collected. Observed trends indicated rapid response in the recorded variables to changes in cooling system usage and office occupancy, validating the robustness of the data.

Occupants' time was characterized by probabilistic distributions in four states of user behavior. The quantified interindividual variability and other use-phase variables were propagated in a stochastic model for the life cycle of air-conditioning systems. Simulation was conducted by way of Monte Carlo analysis. Analysis of the generated uncertainties identified plausible reductions in energy use and thus global warming impact through modifying user interaction.

Key Findings

- *Occupants relied on automated thermostat control to manage cooling throughout working hours, regardless of occupancy time*
- *Overall 27% of the total life cycle emissions generated, and 33% of the use stage emissions, occurred from energy spent cooling air when there was no occupancy*
- *Although the 'off & out' state accounted for by far the largest period of time, and the largest proportion of GWP, the low power drawn by the system while idle resulted in a very low contribution to uncertainty in results.*
- *If time residing in the 'on & out' state could be minimized and transferred to the 'off & out' state, the potential exists in this case for up to 24% reduction in overall life cycle GWP. Furthermore, users adjusting their behavior to raise preferred office temperature setting by 1°C could result in further life cycle emissions reduction of 8%.*

Designers concerned about the environmental profile of high energy products and systems in the building environment need better representation of the underlying variability in use-phase data to evaluate the impact. This study suggests that user behavior can be reliably inferred through proxy measurements of environmental conditions and the proliferation of pervasive sensing.

Related publications

- Ross, S. and Cheah, L. (2016) Uncertainty quantification in life cycle assessments: interindividual variability and sensitivity analysis in LCA of air-conditioning systems. *Journal of Industrial Ecology.* doi:10.1111/jiec.12505
- Feng, J., (2015), Variation in User Behavior and its Impact on the Electricity Demand of Air Conditioner Use, Masters thesis, Singapore University of Technology and Design.

Case 22

Case study title

Thermal Comfort in Different Types of Learning Spaces in Tropical University Campus

Contributors

- Stephen Siu Yu LAI, Department of Architecture, School of Design and Environment, National University of Singapore
- Ji ZHANG, Solar Energy Research Institute of Singapore, National University of Singapore

Contribute to other subtasks

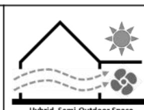
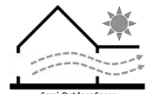
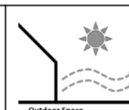
Subtask E: Integration of occupant behavior models with BEM programs

When and where

Feb-Apr of 2015, 2016 and 2017, Multiple buildings within National University of Singapore campus

Building(s) description

- Owner type: University
- Building type: education institution
- Total floor area: N.A.
- Number of stories: varies
- Location (city, country): Singapore
- One or two pictures: The types of spaces, locations of survey and number of respondents for each year are illustrated in the table below.

Year	Type of Space							
	 Indoor Space (Air-conditioned)		 Hybrid Indoor Space (Mechanical + Natural Ventilation)		 Hybrid Semi-Outdoor Space (Mechanical + Natural Ventilation)	 Semi-Outdoor Space (Natural Ventilation)		 Outdoor Space (Natural Ventilation)
2015	Central Library Foyer (30) 	Business School Atrium (69) 	Stephen Riady Centre (60) 	The Deck Canteen (58) 	U-Town Education Resource Centre (51) 	Central Library Forum (90) 		Business School Porch (10) 
2016	Central Library Foyer (30) 	SDE design studio (30) 	Stephen Riady Centre (30) 		U-Town Education Resource Centre (30) 	Central Library Forum (30) 		Plaza outside CREATE building (30) 
2017	Central Library Foyer (108) 	SDE design studio (108) 	Stephen Riady Centre (108) 		U-Town Education Resource Centre (108) 	Central Library Forum (108) 	seating area in front of SDE Co-Op (108) 	

Occupant type

- Users of different types of learning spaces in university campus, such as fully air-conditioned indoor space, hybrid indoor space, hybrid semi-outdoor space, and naturally ventilated semi-outdoor space.

Description of the datasets

Data points	Collection frequency	Collection period	Format
On-site measurement of environmental parameters and questionnaire interview of leaning space users using thermal comfort-related indices	Each interview lasts 5-8 minutes	2 months	Excel data -> Tableau and SPSS

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Not available for public access at the time being,

Summary

The environmental quality of learning spaces has a significant impact on users' health, productivity and psychology. Studies have shown that conducive and comfortable learning environment can promote active learning which may eventually enhance conceptual understanding of the learners. Thermal discomfort such as overheated or too cold classrooms can be associated to physical stress (thermal stress) and therefore be responsible for illnesses and poor performance of the students.

Nowadays, facilitated by information technology such as internet and web-based virtual teaching and learning, spaces for intensive and prolonged study are no longer bounded primarily by interior spaces and are extended to semi-outdoor and outdoor spaces within a campus. Whereas users in this diverse environment are in closer contact with the natural environment, they are also prone to the fluctuation of climatic conditions, and this poses new challenges to architectural designer and researchers dedicated to creating flexible yet conducive learning environment.

Given the characteristics of the tropical climate which is typically hot and humid throughout the whole year, how to create a comfortable learning environment for these different types of spaces, especially through passive design strategies, becomes thus not only necessary but also crucial. This study examined the thermal comfort of users of various types of learning spaces within a tropical university campus with different types of cooling and ventilation strategies, such as centralized air-conditioning, hybrid of natural and mechanical ventilation and natural ventilation. The difference in users' thermal sensation, thermal expectation and thermal satisfaction across different types of spaces are compared. The relationship between thermal sensation and predicted thermal comfort using the PMV model and the adaptive model was also examined.

Key Findings

(Based on the data collected in 2015)

- Hybrid space with a mixture of natural and mechanical ventilation has greater potential be provide comfortable thermal environment for users as compared to air-conditioned spaces and naturally ventilated spaces in the tropical climatic context.
- The relatively higher neutral operative temperature and the relatively wider acceptable operative temperature range for both types of hybrid spaces imply that users in hybrid spaces may have a higher thermal tolerance level and a wider range of temperature for adjustment than those in purely air-conditioned or naturally ventilated spaces.
- PMV had the lowest predictive power for thermal sensation vote for naturally ventilated semi-outdoor space, implying the inappropriateness of applying the PMV model for naturally ventilated space.
- PMV tends to overestimate thermal sensation and predicts a result that is relatively warmer, especially for hybrid spaces.
- As compared to adaptive model, PMV model tends to overestimate the percentage of respondents who may feel thermally neutral for both hybrid and naturally ventilated spaces.
- In comparison, adaptive model also seems to produce overestimation for hybrid indoor space. However, adaptive model produces quite accurate predictions for hybrid semi-outdoor space using the according to the 80% acceptance range of

operative temperature, and it also produces an accurate prediction for naturally ventilated semi-outdoor space according to the 90% acceptance range. This suggests that adaptive model might be a more appropriate model to be implemented in thermal comfort study for hybrid or naturally ventilated spaces than the PMV model.

(The data collected in 2016 and 2017 is in the process of analysis.)

Related publications

- Lau, S. Y., Zhang, Ji; (2016) Thermal Comfort in Different Types of Learning Spaces in Tropical University Campus. Paper accepted by the International Workshop on Implications of Occupant Behaviour for Building Operation & Design, Vienna University of Technology, Vienna, Austria.

Case 23

Case study title

Impact of Occupancy on Energy Consumption in Office Buildings

Contributors

Ruidong Chang, Yujie Lu, Department of Building, National University of Singapore, Singapore

Contribute to other subtasks

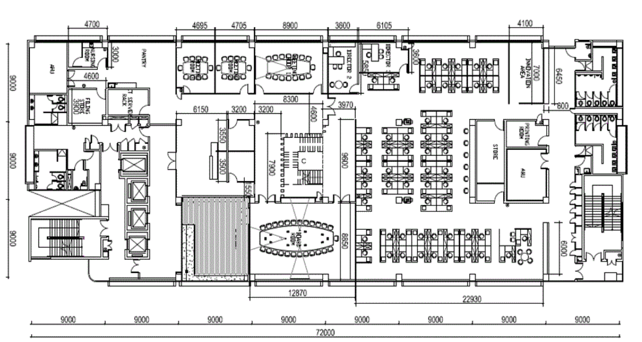
Subtask D

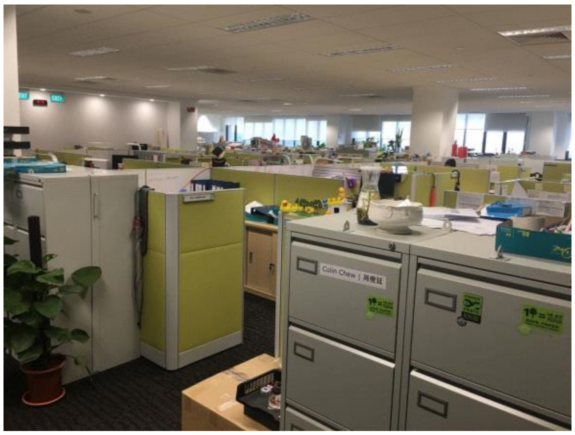
When and where

Floor 9 of a 1.5-year-old institutional building

Floor description

- Building type: institutional building (Floor 9 and 10 are office spaces)
- Floor area: (1,944 m^2)
- Location (city, country): Singapore
- One or two pictures





Occupant type

- Typical office workers in open and private office spaces
- Office workers can opt to select flexible working hours. Four prevailing types of work schedules on weekdays: 9am–6:45pm, 8:30am–6pm, 8am-5:30 and 7:30am–5pm. The occupants don't work on weekends.

Description of the datasets & models

Information of the investigated floor

- Room function
- Realistic zoning
- Lighting, plug load and ACMV schematic diagram layout

Information of occupancy:

- Observations (counting) on occupancy at 30-minutes interval from 8:00 am to 7:00 pm were conducted on one week (April 11-17, 2017) including four working days (April 11, 12, 13, 17, 2017) and three holidays (April 14 of public holiday and April 15-16 of weekend). The counted occupancy during only four working days form real occupancy schedules.
- A questionnaire was developed to capture key parameters of occupant behaviors including first arriving time, last departure time, and meeting duration. These parameters were subsequently used as inputs in Occupancy Simulator

(occupancysimulator.lbl.gov), to generate simulated occupancy schedules on the same days.

Information of energy consumption:

- Plug load at 15-minutes interval
- Lighting energy consumption at 15-minutes interval
- HVAC energy consumption at 15-minutes interval
- Total energy consumption at 15-minutes interval

Models for analysis:

- Occupancy Simulator (occupancysimulator.lbl.gov)
- Pearson and Spearman correlation analysis, paired-sample t-test and Wilcoxon signed-rank test
- Simple and multiple linear regressions

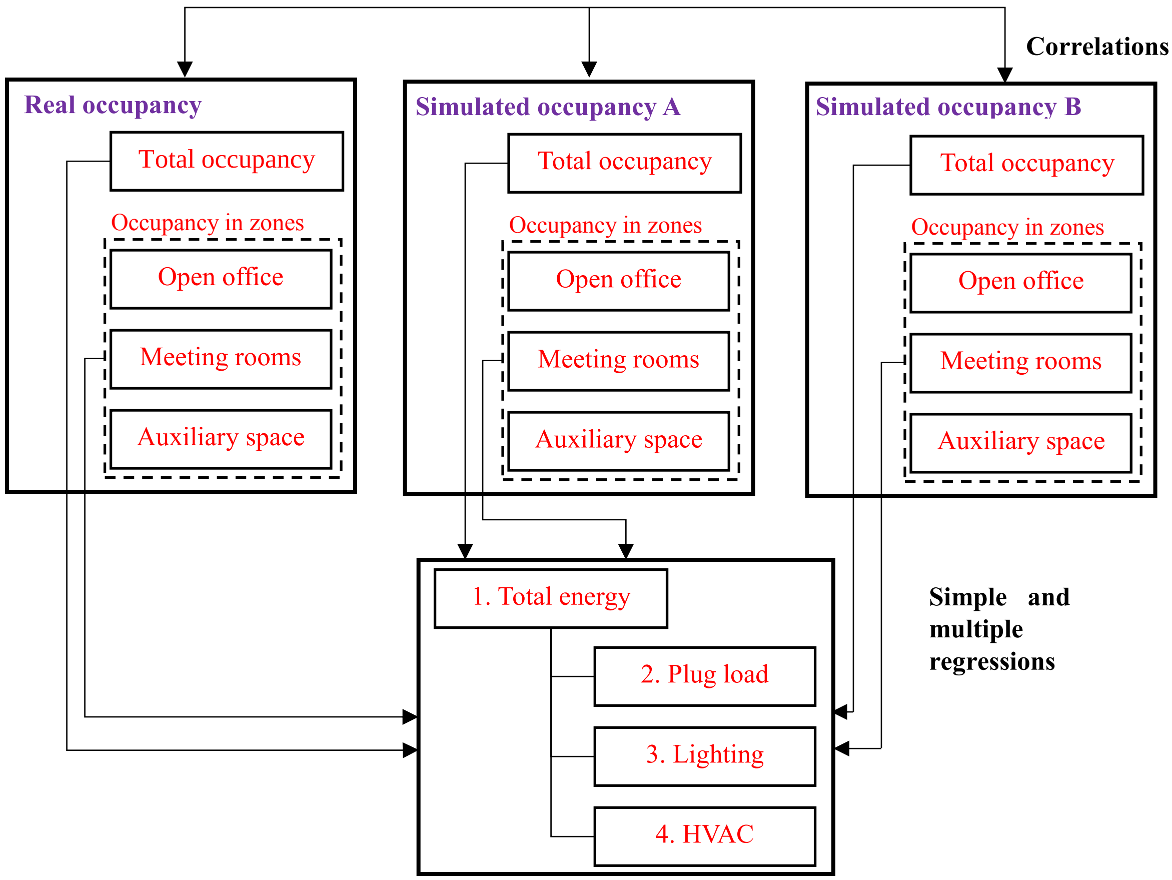
Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request.

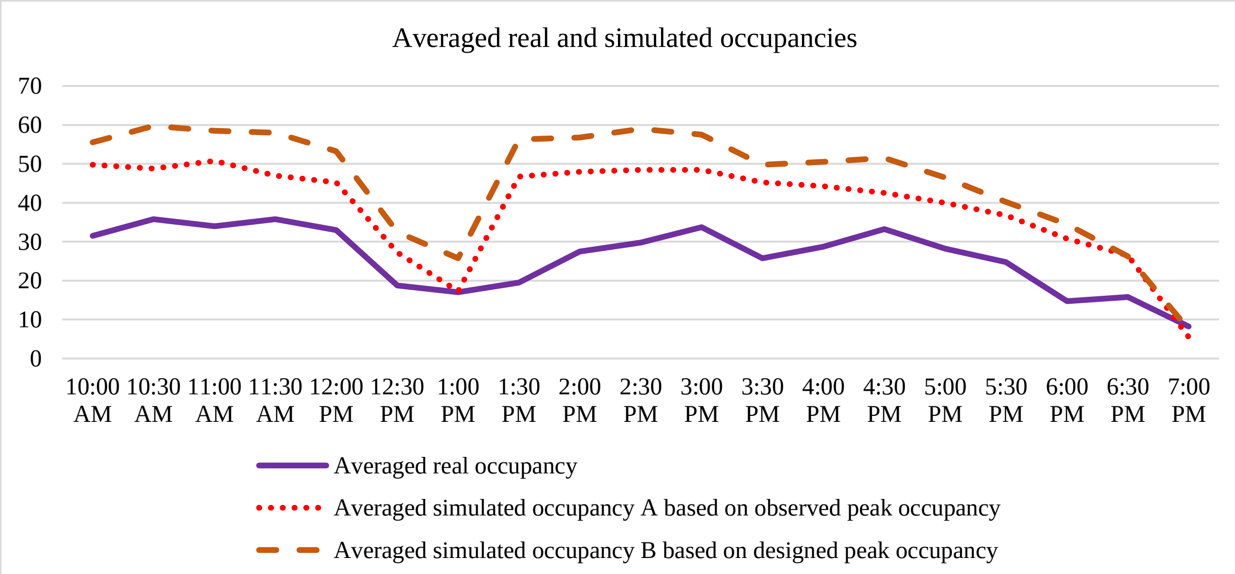
Summary

Currently, the dominant approach of the environmental impact assessments of buildings, including comparing the energy consumption of buildings, is to normalize the impacts by building size, typically defined as gross floor area. However, this approach neglects the impacts of occupancy on building energy consumption, and there is a growing need to develop occupancy patterns-based indicators to assess the sustainability performance of buildings. Unfortunately, real occupancy is highly stochastic and could be significantly different from the designed occupancy schedule. This calls for a holistic understanding of how occupancy patterns impact the environmental performance of buildings, and whether real occupancy in buildings could be accurately simulated. This study provides a holistic examination of the associations among the real/simulated occupancy and building energy consumption, enabling developers and researchers to further improve the Occupancy Simulator (occupancysimulator.lbl.gov), and to develop occupancy patterns-based sustainability assessment indicators of buildings.



Based on a case office building in Singapore, this study tests the accuracy of Occupancy Simulator developed in Subtask D in predicting the real occupancy in a building, and examines the impacts of occupancy on building energy consumption. First, the designed and observed peak occupancy were inputted in the simulator, with other key parameters remaining the same, thereby generating two simulated occupancy schedules. The two simulated schedules were compared with each other and, with the real occupancy, to assess the accuracy of the simulated occupancy. Then, the impact of occupancy on building energy consumption was evaluated through two linear regression models, including simple linear regression using total occupancy data, and multiple linear regression using occupancy data of different zones. The two linear regression models were utilized to assess the impact of occupancy on four types of energy consumption, namely plug load, lighting, HVAC and total energy consumption, thereby generating 8 scenarios. The three datasets of occupancy schedules, namely the real occupancy schedule, the simulated schedule based on designed peak occupancy, and the simulated schedule based on observed peak occupancy, were used as inputs in the 8 scenarios, thereby generating 24 regression equations. By comparing the 24 regression equations and the associate R^2 statistics, the different degrees of impacts of both real and simulated occupancy on various forms of building energy consumption were revealed.

Key Findings



- The simulated occupancy schedule has a fairly high correlation with real occupancy schedule (R^2:0.6-0.7). However, when differentiating the occupancies in various zones, the correlations become weaker. Specifically, the correlation coefficient between real and simulated occupancy for open office is 0.5-0.6, and for meeting room is 0.3-0.4. The simulator also achieves high consistency, as the correlation coefficient between the two simulated occupancies based on design and observed peak occupancy achieves 0.9.
- In reality, unpredictable variations to occupancy i.e., stochastic events, such as department retreat and guest visitation, currently could not be captured by Occupancy Simulator, which prohibits the simulated occupancy to have an even higher correlation with real occupancy.
- Many buildings suffer from the low occupancy levels during their use. In this study the observed peak occupancy, which is only around 80% of the designed peak occupancy, only appears at a few time points during the observation. Thus, both the simulated occupancy schedules based on the designed and observed peak number of occupants overestimate the occupancy. The Occupancy Simulator (occupancysimulator.lbl.gov) may have overestimation issues.
- The regression analysis reveals that occupancy has a larger impact on plug load (R^2 around 0.4) than the energy consumption of lighting (R^2 around 0.1) and HVAC (R^2 around 0.1) because in this case building occupants have little interactions and/or control over the building systems such as lighting and HVAC that follow daily routine. The results clearly show that the impact of occupancy on building energy consumption is strongly moderated by different functions of building spaces. The variance of HVAC energy consumption is explained more by occupancy in the area of the open office, while the variance of lighting energy consumption is more explained by occupancy in meeting rooms. Even in

buildings with minimum interactions with occupants, like the building in this study, the regression results show occupancy in different zones could explain around 40% variance of total energy consumption of buildings.

- Because the simulator could not capture all stochastic events in reality, the R^2 between the simulated occupancy and energy consumption in most cases is lower than that between real occupancy and energy consumption. But interestingly, the regression of simulated occupancy and HVAC energy consumption has higher R^2 in this case study. Reasons behind this need further exploration.

Despite above findings, it could be a challenge for office users to determine the input parameters needed for Occupancy Simulator, such as the first arrival and last departure time of occupants, and the meeting times and durations for different meeting rooms. As many buildings do not have occupancy sensors, questionnaire surveys or interviews become the only viable approaches to obtain these parameters. However, surveying occupants does not necessarily generate credible information, as this study reveals the real arrival time of some occupants in the office is significantly later than their reported time in the survey. A more reliable way of collecting data so as to improve the applicability of the simulator needs to be further explored.

Recommended future work include: (1) improving the Occupancy Simulator through considering the low occupancy levels of many buildings during their actual use and subsequently overcoming the overestimation issue, (2) conducting large-scale investigation of installing occupancy sensors on buildings so as to run data mining and machine learning, thereby generating more realistic occupancy schedules, (3) extending the study for whole building analysis and other building types with different countries/cultures and (4) exploring the development of occupancy patterns-based sustainability assessment indicators of buildings.

Related Publication

- Ruidong Chang and Yujie Lu (2017). Calibration and advancement of occupant simulator used in high density institutional and office buildings. In preparation.

Case 24

Case study title

Correlation between occupants and energy consumption

Contributors

Cheol Soo Park, Ki Uhn Ahn, School of Civil and Architectural Engineering, Sungkyunkwan University, South Korea.

Contribute to other subtasks

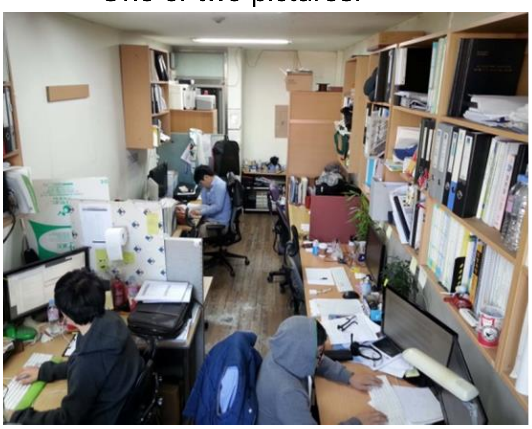
Subtask A: Occupant action models in commercial buildings

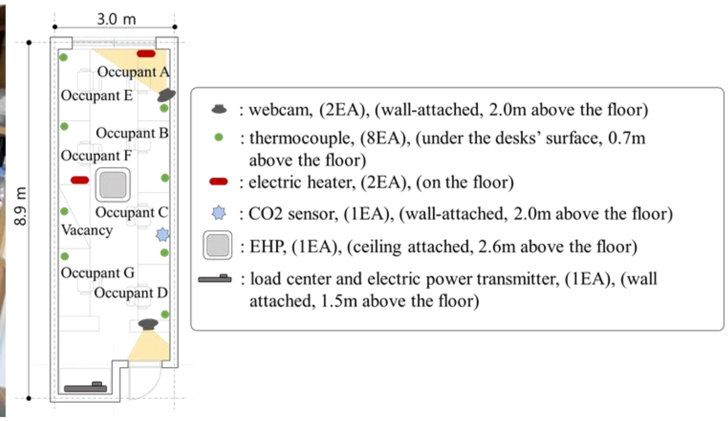
When and where

2015, A laboratory room in the Sungkyunkwan University, Suwon, South Korea

Room description

- Owner type: University
- Room type: A laboratory room in the University
- Total floor area: 287.4 sf
- HVAC: A ceiling-mounted electric heat pump (EHP)
- Location (city, country): Suwon, South Korea
- One or two pictures:





Occupant type

- Seven people (MS and Ph.D. students)
- Occupants are free to enter/leave and control the indoor condition according to their preferences.

Description of the datasets

Data points	Collection frequency	Collection period	Format
The number of occupants	1 minute.	2 weeks	JPG (the room is captured as an image file)
CO_2 level	1 minute	2 weeks	XLS
Window opening ratio	1 minute	2 weeks	JPG
Action of occupant's opening a window	1 minute	2 weeks	JPG
Door opening ratio	1 minute	2 weeks	JPG
Action of occupant's opening a door	1 minute	2 weeks	JPG
Electricity power consumption of EHP	1 minute	2 weeks	JPG
Action of occupant's controlling EHP	1 minute	2 weeks	JPG
Air temperatures at each occupant's desk	1 minute	2 weeks	XLS
Electricity power consumption by personal heaters	1 minute	2 weeks	XLS
Outdoor air temperature	1 minute	2 weeks	XLS

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Not available. The data will be used for the follow-up study and publication.

Summary

Although it is widely acknowledged that occupants play a critical role in building energy consumption, the characteristics of occupants are not well-represented in building simulation. Many statistic and data-mining technologies have been applied to develop a reliable occupant model. In contrast, rather than attempting to develop the occupant

model, this study aims to investigate the correlation between the occupant behavior and energy consumption based on a series of experiments.
First, this study dealt with the randomness of the occupants' presence and behavior. The degree of randomness was verified using a Normalized Cumulative Periodogram (NCP) based on a random walk hypothesis. In addition, the correlation between occupant and energy consumption was investigated using the wavelet coherence.
In this study, while the occupants' presence had a randomness, it was not strongly correlated to the energy consumption. The occupants' active action to control a heating/cooling system (turn on/off) was correlated to the energy consumption. In contrast to the occupant's presence, the occupants' active action did not follow the random walk, and it had no particular frequency. This means that it is difficult to predict the control action of occupants with a specific time interval.

Key Findings

- There is a significant difference in individual preference with respect to the indoor condition.
- Occupants' presence in a university laboratory has a randomness, but it is not strongly correlated to the energy consumption.
- Occupants' active action is more correlated to energy consumption than occupancy.
- Occupants' action does not follow the random walk, but it has no particular frequency that can be predicted.

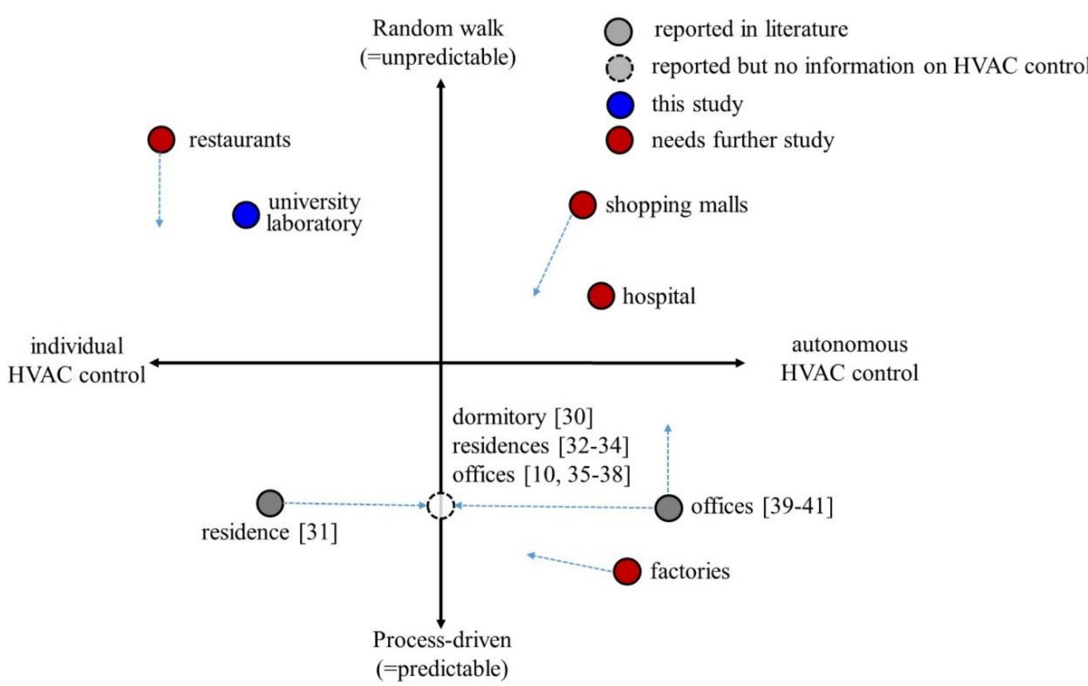


Figure 1 Different types of buildings for occupant behavior study (the arrows indicate that the location can vary) (excerpted from [2])

Related publications

- Ahn, K.U., Park, C.S. (2015). Time series correlation between occupants and energy consumption, Proceedings of the 14th IBPSA Conference, December 7-9, Hyderabad, India
- Ahn, K.U., Park, C.S. (2016). Correlation between occupants and energy consumption, Energy and Buildings, In press

Case 25

Case study title

A Framework for Quantifying the Impact of Occupant Behavior on Energy performance of single-family detached houses

Contributors

Anna Laura Pisello, Department of Engineering – CIRIAF Interuniversity research centre on pollution and environment Mauro Felli – University of Perugia, Italy

Contribute to other subtasks

Subtask D

When and where

A 40/50-year-old residential building, in central Italy temperate climate

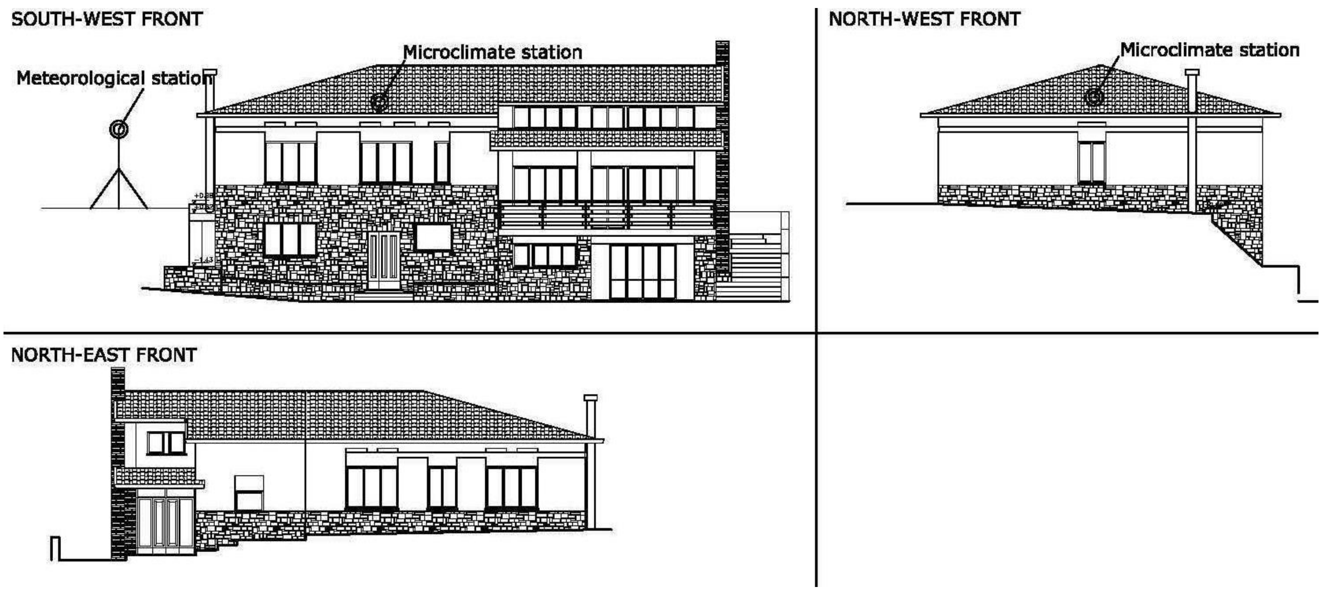
Building(s) description

- Building type: single family residential building
- Total conditioned floor area: 513 m^2
- Number of stories: 3
- Location (city, country): Perugia, Italy
- One or two pictures:

Occupant type

- In order to realistically characterize building occupancy, dedicated attitudes survey was elaborated and submitted to all the occupants of the house. As expected, such survey highlighted the very weak and discontinuous occupancy schedule of the indoor thermal zones, compared to classic building simulation schedules which would overestimate building energy consumption prediction. The survey campaign by means of questionnaire was also carried out together with field microclimate indoor-outdoor monitoring campaign and bills assessment about electricity and natural gas for cooling-lighting and heating, respectively.

- The occupancy profiles were firstly assumed to be consistent to standard occupancy and therefore, they were fitted according to the survey results, highlighting the relatively much weaker energy need and internal gain characterizing the real occupancy compared to classic ones used in this case study at preliminary stage (i.e. UK's National Calculation Method).



Description of the datasets

Information of the investigated residential building

- HVAC systems details and operations
- Field survey about thermal zone function: realistic zoning
- Number of occupants in each zone and weekly agenda with varying season during the year
- Lighting schedule according to occupancy field analysis
- Indoor microclimate parameters as monitored in the attic thermal zone (non-occupied), such as air temperature, relative humidity, superficial temperature of roof, ceiling, walls, air velocity, mean radiant temperature.
- Outdoor microclimate parameters as monitored in the house garden (non-shaded area), such as air temperature, relative humidity, global solar radiation above a horizontal plane, global solar radiation reflected by the roof, air velocity and main direction.

- Thermal transmittance values measured in all the opaque walls, ceilings and roof.

Investigated the impact of real occupancy in low-density buildings on the energy consumption:

- Elaboration of the baseline model
- Calibration and validation of the model according to data collected through field surveys, (i) indoor microclimate monitoring survey and (ii) real occupancy survey
- Quantitative analysis of the energy requirement overestimation imputable to classic occupancy schedules, in low-density occupied houses (e.g. about 1 person per 150 m^2)

Inputs of the baseline model:

- UK's National Calculation Method implemented in DesignBuilder simulation engine for residential spaces.
- Physical characterization of the building in order to minimize possible sources of prediction errors not imputable to occupancy.

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Available upon request. More information is available in the published journal article.

Summary

This study presents a framework for quantifying the impact of family-specific occupant behavior in detached house, where the occupancy is typically less dense and less repetitive than classic office buildings or multifamily residential buildings, where thermal zones are characterized by high level of occupants' density and the actions carried out within these spaces are in general more repetitive and better predictable.

In this view, a building dynamic simulation model has been elaborated thanks to a variety of field experimental analysis such as indoor microclimate, outdoor meteorological conditions, HVAC system information, envelope component thermal transmittance measurements, energy bills analysis and finally indoor occupancy surveys. Occupancy schedules framed thanks to these field surveys highlighted the single-family schedule in a variety of thermal zones, which occupancy is very time depending and personal attitude depending, since the spaces at the disposal of each occupant (i.e. a member of the family) is much larger compared to classic residential buildings. Therefore, such case studies may not be effectively identified through typical residential schedules by simply defining a dynamically variable thermal power per square meter, since these values overestimate the energy need of single-family detached houses.

Recommended future work includes: (1) developing more realistic occupant behavior styles based on large-scale survey of occupants in detached houses in suburban areas, (2) investigating the energy intensity related to occupancy with varying climate conditions, by correlating energy need with occupancy intensity per square meter or other building-design-dependent variables, (2) pilot testing the methodology in real design or retrofitting projects of detached houses.

Key Findings

- The occupant behavior style of single-family large-surface houses needs particular attention when modeling thermal-energy behavior of detached house, since it hugely differs with respect to classic building occupant simulators.
- The space at the disposal of each occupant is typically larger than classic residential buildings, meaning that the house tends to be less energy intense and energy needy per square meter.
- Building occupancy should be modelled after investigating real occupancy in case of Post-Occupancy Assessment campaigns, or by means of predictive models which take into account this building peculiarity.
- As further development of the study, field surveys are therefore recommended in order to develop a reliable wide database of occupancy models identifying this building typology, which represents a non-negligible category in both Europe and other countries in suburban areas.

Related publications[3]

- Pisello, A.L., Cotana, F. The thermal effect of an innovative cool roof on residential buildings in Italy: Results from two years of continuous monitoring (2014) Energy and Buildings, 69, pp. 154-164. DOI: 10.1016/j.enbuild.2013.10.031
- Pisello, A.L., Rossi, F., Cotana, F. Summer and winter effect of innovative cool roof tiles on the dynamic thermal behavior of buildings (2014) Energies, 7 (4), pp. 2343-2361. DOI: 10.3390/en7042343

[3] The mentioned publications concern the case study characterization for energy retrofit purpose. The detailed post-occupancy study is still under development for journal submission.

Case 26

Case study title

How peers' personal attitudes affect indoor occupancy in office buildings: Results from a continuous monitoring campaign

Contributors

Cristina Piselli, Anna Laura Pisello, CIRIAF – Interuniversity Research Centre, Department of Engineering, University of Perugia, Italy

Contribute to other subtasks

Subtask D

When and where

A 9-year-old research office building, in the temperate climate context of Perugia, in central Italy

Building(s) description

- Building type: research office building
- Total conditioned floor area: 19,461 ft^2 (1,808 m^2)
- Number of stories: 2
- Location (city, country): Perugia, Italy
- One or two pictures:

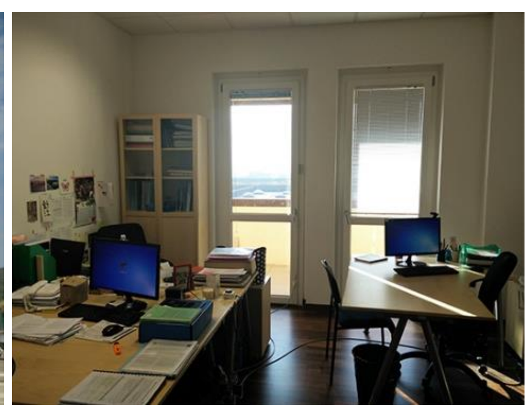



Figure 3. View of the building from the East side, and typical office indoors.

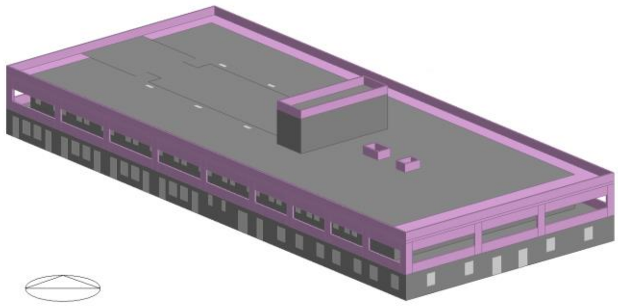


Figure 4. Building model layout.

Occupant type

- A group of peer employees working in different rooms of a research center building characterized by the same end-use, i.e. researchers' office rooms, were considered. The occupants are represented by peers performing the same job, with similar age (i.e. from 25 to 35 years old) and educational level, and theoretically the same working schedule on weekdays, i.e. 9am–1pm and 3pm–7pm. The occupants don't work on weekends.
- The building hosts around 30 office rooms. Occupancy of 5 rooms out of 30 have been monitored for one whole year. The 5 monitored offices are all located on the first floor and are on the same South-West oriented side of the building. They are all almost rectangular shaped with the same size. They are provided with two big windows on the South-West side and are equipped with the same HVAC system and lighting system. Heating and cooling systems operate between October, 15th –April, 15th and June,1st –September, 30th, respectively. Additionally, each office is equipped with a dedicated thermostat, which is set up by the occupants in terms of desired ambient temperature and mechanical ventilation rate, according to their personal needs and thermal perceptions. Each office room is also equipped with two or three computers and hosts two or three people.

Table 4. Summary of the five office rooms monitored.

Room number	Occupancy level [people per room]	Monitored appliances
1	3	3 desks with personal computer
2	2	2 desks with personal computer
3	2	2 desks with personal computer
4	3	3 desks with personal computer
5	2	2 desks with personal computer

Description of the datasets

Information of the investigated office building

- Room function
- Realistic zoning
- Building envelope systems
- Air-conditioning system operation
- Number and type of occupants in each zone
- Lighting and plug load power density

Monitoring of four energy and thermal comfort-related parameters influenced by occupants' behavior inside five office rooms, through a wireless sensor network system (Figure 3):

- Indoor air temperature
- Level of illuminance on the work plane
- Electricity consumption of the appliances
- Opening/closing of door and windows

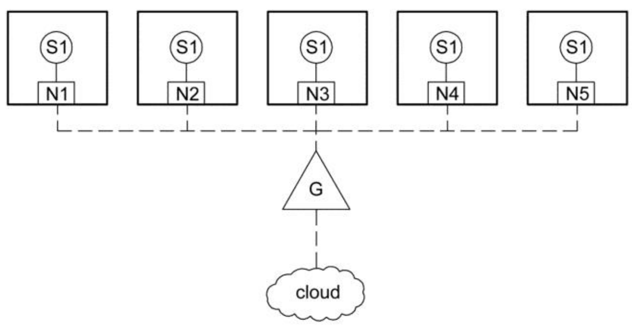


Figure 5. Architecture of the monitoring system.

Peer occupants' behaviors were evaluated in the temperate climate context of Perugia, in central Italy and the following meteorological parameters were continuously monitored at the same time:

- Outdoor dry-bulb temperature and air relative humidity
- Wind velocity and main direction
- Global and direct solar radiation over a horizontal plane
- Rain fall rate

Inputs of the building simulation model:

- Standard occupancy schedules for office buildings according to the EnergyPlus database (UK's National Calculation Method for Non-Domestic Buildings standard, http://www.uk-ncm.org.uk/)
- Building fabric components, air-conditioning and lighting system according to the real building characteristics
- TMY weather file for the city of Perugia according to the database by the U.S. Department of Energy, Energy Efficiency and Renewable Energy (https://energy.gov/eere/office-energy-efficiency-renewable-energy)

Data and models availability

Are data and/or models available to the Annex 66 participants?

- Available upon request. More information is available in the published journal article.

Summary

Occupants' behavior significantly affects building thermal-energy performance, and its prediction may become particularly hard in those buildings occupied by a wide variety of users. In fact, human attitudes and habits in interacting with system controls and building envelope influence indoor microclimate and energy needs. In this view, peer occupants are usually assumed to have an identical response to similar environmental conditions and in determining building thermal-energy performance. However, different peer occupants' personal attitudes and habits can affect the indoor environmental behavior of buildings. In fact, despite most of the occupants can be identified as "peers" in terms of age, educational background, working schedule, indoor thermal perceptions, and control capability, they present substantially different behavior. This leads to significant discrepancies in the thermal-energy performance of different areas situated even in the same building position (same façade, orientation etc.). Therefore, peers' personal attitudes represent a key variable to be considered while predicting the overall thermal-energy behavior of buildings in dynamic conditions. In this view, the purpose of this case study description is to:

- identify the different attitudes and energy behaviors of occupants typically considered as peers,
- define how such divergent habits can influence the thermal-energy performance of the indoor building environment, and
- compare the real behavior of peer occupants with the standard occupancy model usually considered in building dynamic simulation.

To this aim, a group of peers working in a university office building was examined. In particular, five office rooms characterized by the same orientation, architectural layout, size, construction technology, and HVAC system were selected for the continuous monitoring of occupants' attitudes during the course of one year. Key indoor microclimate indicators, i.e., indoor air temperature and illuminance over the work plane, and data about occupants' daily attitudes in terms of electricity use, switching on/off of lights, and opening/closing of doors/windows were collected. Additionally, a survey among all the building occupants was carried out to support the experimentally collected data in identifying the different habits of the peers. Finally, the case study office building was investigated by means of thermal energy dynamic simulation while assuming the standard occupancy model for an office building (UK's National Calculation Method for Non-Domestic Buildings standard, http://www.uk-ncm.org.uk/). Therefore, the real monitored occupants' habits were compared with physical parameters simulated according to the standard schedules. In this perspective, the case study analysis wants to demonstrate how peers behave differently in their offices, despite their clear theoretical similarities. Moreover, the standard occupancy model is neither representative of specific occupants' attitudes nor of their averaged behavior.

All these components should be more carefully evaluated for elaborating reliable prediction models or post-occupancy assessment in buildings. Therefore, recommended future work include: (1) extending the study for other buildings (same and different typologies), (2) extending the study to different climate and cultural contexts, (3) developing more realistic occupant behavior schedules based on a large-scale survey of occupants specific for each climate and cultural context.

Key Findings

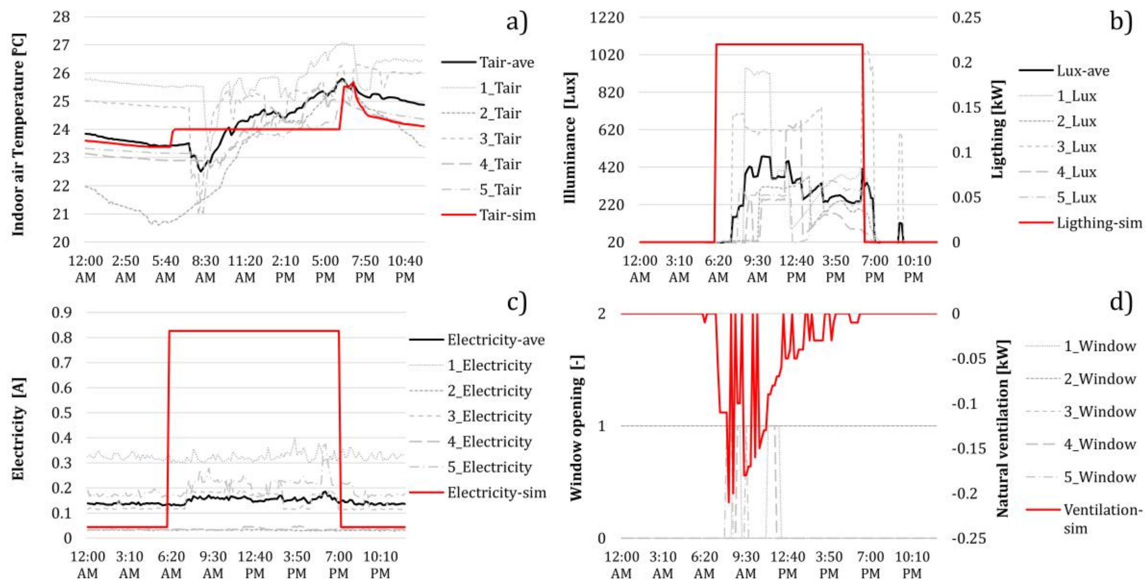


Figure 6. Occupants' behavior simulation (red lines) results vs. monitored data in terms of a) indoor air temperature, b) illuminance over the working plane, c) equipment electricity consumption, and d) windows opening.

- Occupants' individual behavior represents a key variable affecting building management of large buildings even if the occupants can be theoretically assumed to be "peers".
- Significant discrepancies were found between the monitored rooms, demonstrating that typical peers do not behave the same, but require differential energy needs that should be considered while predicting thermal-energy and lighting behavior of massive institutional buildings.
- Simplified standard models do not predict any occupant's peak energy demand or individual preference. Moreover, the standardized implemented procedure is not even representative of the average occupants' behavior and tend to overestimate energy needs (Figure 4).

- Peers' door opening profiles seem to be related to personal preferences about working style, while window opening profiles completely change their trend, even for single offices, with varying the seasonal conditions. The simulated trend of natural ventilation entering the offices in summer appears to be rather consistent with the detected windows opening for some offices (Figure 4d). However, it is not generally representative of the random occupants' habits.

Related publications

- Pisello, A.L., Castaldo, V.L., Piselli, C., Fabiani, C., Cotana, F. How peers' personal attitudes affect indoor microclimate and energy need in an institutional building: Results from a continuous monitoring campaign in summer and winter conditions. Energy and Buildings, Volume 126, 2016, pages 485-497.
- Pisello, A.L., Castaldo, V.L., Piselli, C., Fabiani, C., Cotana, F. Can we assume that peers behave the same? Results from a continuous monitoring campaign in an office building. CLIMA 2016 Conference. Aalborg, May 22-25, 2016.

Case 27

Case study title

Monitoring of energy performance and window opening behavior in a German office building

Contributors

Karin Schakib-Ekbatan, Marcel Schweiker, Andreas Wagner – Karlsruhe Institute of Technology, Germany
Fatma Zehra Çakıcı - Ataturk University, Turkey

Contribute to other subtasks

Subtask D

When and where

An office building in Frankfurt, Germany, built in 2002

Building(s) description

- Building type: office building
- Total conditioned floor area: 8585 m^2 heated floor area
- Number of stories: 2-level underground car park + 4 office floors + 1 floor apartments on top
- Location (city, country): Frankfurt, Germany
- One or two pictures:

Figure 1. Exterior view of the KfW Ostarkade building from the South-East

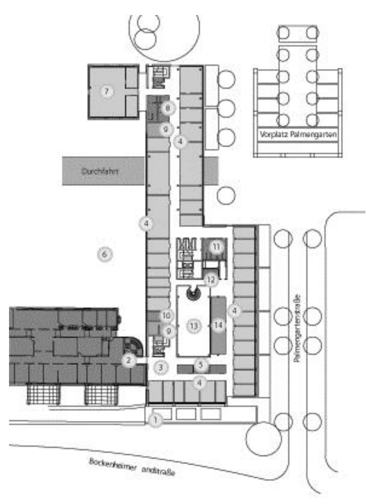


Figure 2. Ground floor plan of the building

Occupant type

- Office workers, working as employees of the KfW bank

Description of the datasets

The dataset comprises three types of data which can be grouped with respect to outdoor conditions, indoor conditions, and actions of occupants or events. Table 1 summarizes the monitored data for all conditions as follows.

Table 1. Monitored data

Outdoor	Indoor	Behaviour
Solar radiation [W/m^2] Rain – amount [l/m^2] Rain – event [yes/no] Light intensity– horizontal [lx] Light intensity - South [lx] Light intensity - East [lx] Light intensity - North [lx] Light intensity - West [lx] Outdoor temperature [°C] Wind – velocity [m/s] Wind – direction [°] CO_2 content in air [ppm] Outdoor humidity [%rH]	Room air temperature [°C] Surface temperature [°C] Ceiling slab temperature [°C] CO_2 concentration [ppm]	Occupancy [0/1]* Window contact [0/1 ; Reed contacts]* Top light control [0/1 ; Reed contacts]* Sun protection [% of closure: 0% = open to 100% = closed] Electricity consumption [kWh]

*for analyses aiming at duration in terms of daily means, data were transformed from 10-minute intervals to minutes

A weather station is located on the top of the building, providing data regarding the outdoor conditions for all offices, such as temperature. However, the microclimate close to the different façades can differ, e.g., depending on the intensity and direction of wind.

The office rooms can be grouped in four types; standard offices, traders' offices, large offices and others with a special function in use. Due to this diversity it was decided to only analyze standard offices in terms of occupant behavior. Standard offices all have the same size (~20m^2), facing mostly east and west (one is facing south). They have one fixed and two operable windows, internal top light windows above the doors (to allow for night ventilation through the atrium) and sun protection elements (operated both manually and automatically). They are occupied by one or two persons.

Since the building was completed and started to be monitored in 2003, the starting year for the analysis was selected as 2004. The analysis period was from January 1st, 2004 to December 31st, 2009.

Besides the data of outdoor conditions, there are several data indicating changes, behaviors and events in the building. Among indoor conditions data, five data is available for all offices, which are presence of the occupant(s), window contact, top window control, room air temperature and use of sun protection, while others are not available for all offices, including CO_2 concentration, surface temperature, component temperature and electricity consumption. A summary of the variables for monitored standard offices is shown in Table 2. For the analysis presented below, we concentrate only on data, which are available for all 16 rooms of the sample; therefore CO_2-concentration and surface temperature are not included.

Table 2. Variables for monitored standard offices

	Room ID	**Occupancy**	**Window control**	**Top window control**	**Room air temperature**	**CO_2-Concen-tration**	**Surface temperature**
East	E01	•	•	•	•		
	E02	•	•	•	•		
	E03	•	•	•	•		•
	E04	•	•	•	•	•	•
	E05	•	•	•	•		
	E06	•	•	•	•		•
	E07	•	•	•	•	•	•
	E08	•	•	•	•		
	E09	•	•	•	•		
	E10	•	•	•	•		
	E11	•	•	•	•		
West	W01	•	•	•	•		•
	W02	•	•	•	•		•
	W03	•	•	•	•		
	W04	•	•	•	•		
	W05	•	•	•	•	•	•
	W06	•	•	•	•		

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Data are available upon request from Marcel Schweiker or Andreas Wagner.

Summary

This study is based on simple statistics as well as logistic regression analyses in order to evaluate how much the occupants interact with their building in a manner suitable to the building concept with natural ventilation. The findings show that behavior profiles of window opening give helpful hints regarding the interaction between building and occupants. The window opening times in winter are too long in 10 - 25% of the days. In 10 - 40% of the times during summer the window opening does not support the building concept due to windows being opened while the outdoor temperature is higher than the indoor air temperature. These non optimal behaviors could be linked directly to an increased energy consumption in winter. In the summer case, prolonged window opening at high outdoor temperatures does not lead directly to a higher energy demand, because no cooling system exists. However, the increased heat gain leads to a higher demand for night ventilation, which in some cases is facilitated by an electrical fan. In such a way, the auxiliary energy demand is increased.

In a recent study the data was taken to train and evaluate several classification algorithms for detecting occupant’s interactions with windows, while taking imbalanced properties of the available data set into account. The tested methods include support vector machines (SVM), random forests, and their combination with dynamic Bayesian networks (DBN). The results show that random forests outperform all alternative approaches for identifying the window status in office buildings.

Key Findings

- Study 1: If occupants are not informed about the building energy concept their behavior might cause higher energy consumption or longer periods of discomfort as their interactions do not match the designed usage patterns.
- Study 2: Random forests appear to be an appropriate classification algorithm for detecting occupant’s interactions with windows, when the available data set shows imbalanced properties.

Related publications

- Schakib-Ekbatan, K.; Zakici, F. Z.; Schweiker, M. & Wagner, A. (2015). Does the occupant behavior match the energy concept of the building? - Analysis of a German naturally ventilated office building, Building and Environment, 84, pp. 142 - 150.
- Markovic, R.; Wolf, S.; Cao, J., Spinnräker, E.; Wölki, D.; Frisch, J. & van Treeck, Ch. (2017). Comparison of different classification algorithms for the Detection of User’s Interaction with Windows in Office Buildings, Energy Procedia, under peer-review by the scientific committee of the CISBAT 2017 International Conference

Case 28

Case study title

The Influence of Occupant Behaviour on the Total Energy Consumption in Offices.

Contributors

- Ing. A. van der Aa, MSc. C. Jurado López, ABT, Delft, The Netherlands.
- MSc. B. Giskes, TU Eindhoven, The Netherlands

Contribute to other subtasks

N/A

When and where

- ABT office at Delft, The Netherlands.

Building(s) description

- Building function: office
- Building style: industrial, flexible and demountable
- Automation level: lighting presence controlled. Thermal acclimation regulated by thermostat. Ventilation constant according to opening schedule (no CO_2 controllers). Automatized sun shadings.
- Total conditioned floor area: 2,040 m^2
- Number of floors: 3
- Location (city, country): Delft, The Netherlands
- One or two pictures:

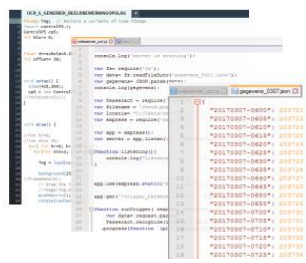
Analysis occupancy

The occupant influence on the energy demand is studied by analyzing the breakdown of the total energy consumption. Measured and simulated data sets are used for this purpose.

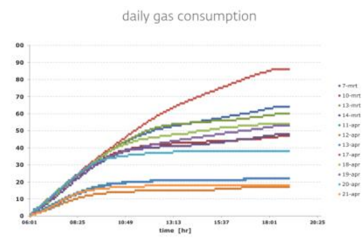
In the first place, the total electricity, heating and cooling consumption are monitored/simulated as follows:

- The total electricity consumption of the building is monitored by smart meters.
- The total heating consumption is monitored by an automated gas-metering reading. The existing analogue gas meter is monitored by a camera which reads the total gas consumption every 10 minutes. The readings are translated and recorded via an Application Programming Interface (API).

(a) Data reading



(b) Data processing

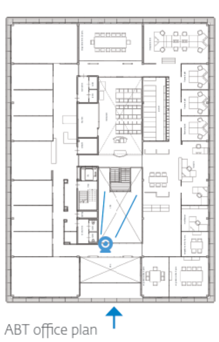


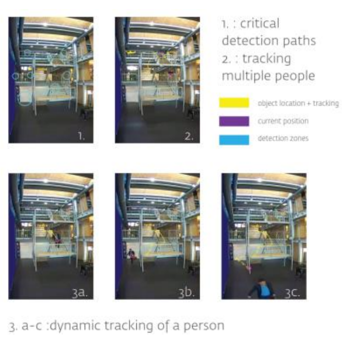
(c) Data analysis

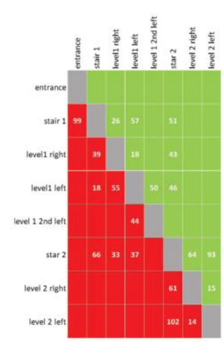
- The total cooling consumption is calculated by law-driven software (EnergyPlus) and monitored for few days.

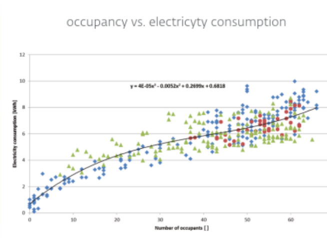
In the second place, the energy related to different purposes is monitored/simulated as follows:

- Control of workspace: plug-load meters are installed in different workspaces in order to study the electrical consumption related to the usage of the workspace.
- Occupancy: the occupancy of the building is monitored by a camera which detects and tracks the motion of the building's occupants. The entry or exit of an occupant to the building and different floors is recorded.









- Data reading

(b) Data processing

(c) Data analysis

- Indoor temperature set points: the indoor temperature set points are monitored.
- Control of lightings: the occupant influence on the lighting system is simulated according to the case study (presence based).
- HVAC operating hours: based on building operating data.

Description of the datasets

Information of the investigated office building

- Building characteristics
    - Envelop characteristics
    - Room function
    - Thermal zoning
- System characteristics
    - Lighting zonings
    - HVAC schedule
- Occupant behavior (use & operation of the building)
    - Occupancy
    - Opening hours
    - Manipulation capability on building operation (windows and partially sun shadings)

Variables studied to analyze the impact of occupant behaviors on the energy consumption in offices:

- Lighting power density (presence in areas with lighting sensors)
- Plug-in electric equipment power density
- Occupancy

Inputs of the baseline model:

- Envelop properties and equipment inputs based on an inventory of case study and ASHRAE Standard 90.1-2004.
- Climate file created for this case study (Delft) extracting weather data from KNMI (2010-2016).
- Occupancy schedules based on actual occupancy of the building.
- Lighting power density and internal heat gains based on ASHRAE Standard 90.1-2004.

Data and models availability

Measured data set available

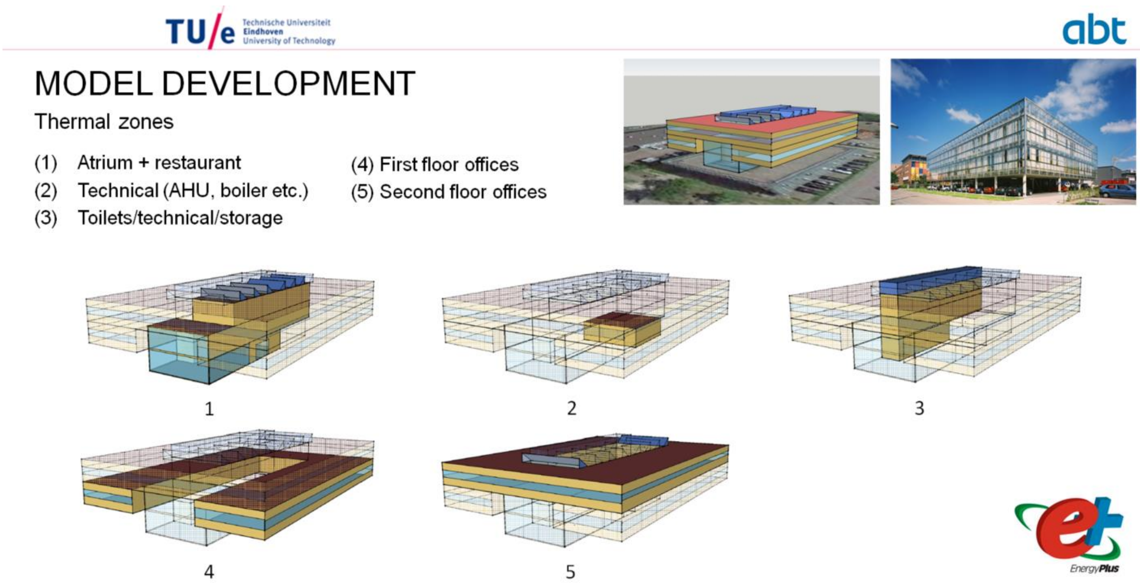
Measured data set available upon request.

	Source	Time resolution	Measurement period
Electricity	Utility bills	monthly	2010 - 2016
	Smart meters (incl. generation)	15 minutes	September 2016 - today
	Plug load meters	10 minutes	January - March 2017
Gas	Utility bills	annually	2010 - 2016
	Automated gas-metering reading	10 minutes	March 2017 - today
Thermal energy*	Heating	hourly	April 2016 - today (daily) January 2017 - today (hourly)
	Cooling	hourly	September 2016 - today (daily) January 2017 - today (hourly)
Temperatures (indoor air, inlet/outlet flows)	Building Management System	hourly	March 2016 - today
Occupancy	Movement detection and tracking	Continuous (every time there is a change)	March 2017 - today

*Estimated heating and cooling demand assuming constant flow.

Model available

Energy Plus model available upon request.



Summary

The case study of the ABT office (Delft) aims at designing advance energy simulation models, energy monitoring and failure detection in offices and public buildings. In order to reach this goal, a better understanding of the actual energy consumption (electrical and thermal energy) in offices and public buildings is needed.

The existing energy prediction models show large differences between actual and simulated data. This mismatch is due to different influencing parameters in predicted and actual energy demands. These parameters can be classified in 3 different groups: (1) physical characteristics of the building & systems, (2) weather data, and (3) occupant behavior (use & operation of the building). Several studies indicate that the occupant behavior is the dominant factor of the mismatch between predicted and actual data (responsible for 80% of the performance gap). Therefore, this research focuses on the influence of occupant behavior on the total energy consumption of offices.

The goal of this study is to get a fundamental understanding of the influence of occupant behavior on the total energy consumption (electricity, heating and cooling) of the ABT office by using measurement and simulated data. The building is heated by gas boilers and cooled by an electrical chiller. The Building Management System (BMS) regulates the heating and cooling delivered to the building according to the indoor air temperature set points.

Measured and simulated data sets are used to analyze information about actual energy consumption and how it is influenced by the occupant. The influence of the occupant behavior on the electrical energy is explained by ‘breaking down’ the measured electricity consumption by performing experiments that involve varying the settings of the installations in the BMS. The heating and cooling demand are studied by using simulated and measured data. The simulated data are obtained by using a law-driven

building energy simulation software to generate a fully calibrated simulation model of the ABT office.

In contrast with previous studies, the results of this research show that the influence of the occupant behavior on the electrical and heating demand is minimal in offices with building operating system (indoor temperature sensors and limited manipulation of the users) and lighting sensors. The results show that the occupant behavior has an influence on the electrical energy up to 12% hourly, 4.7% monthly and 8% annually. The influence on the heating demand is estimated to have an hourly variation up to 17% and an annual variation up to 10%. The occupancy influence on cooling needs to be further analysed when more measured data are available. Figure 6 shows the electricity consumption breakdown and consumption variation due to occupant behavior or presence.

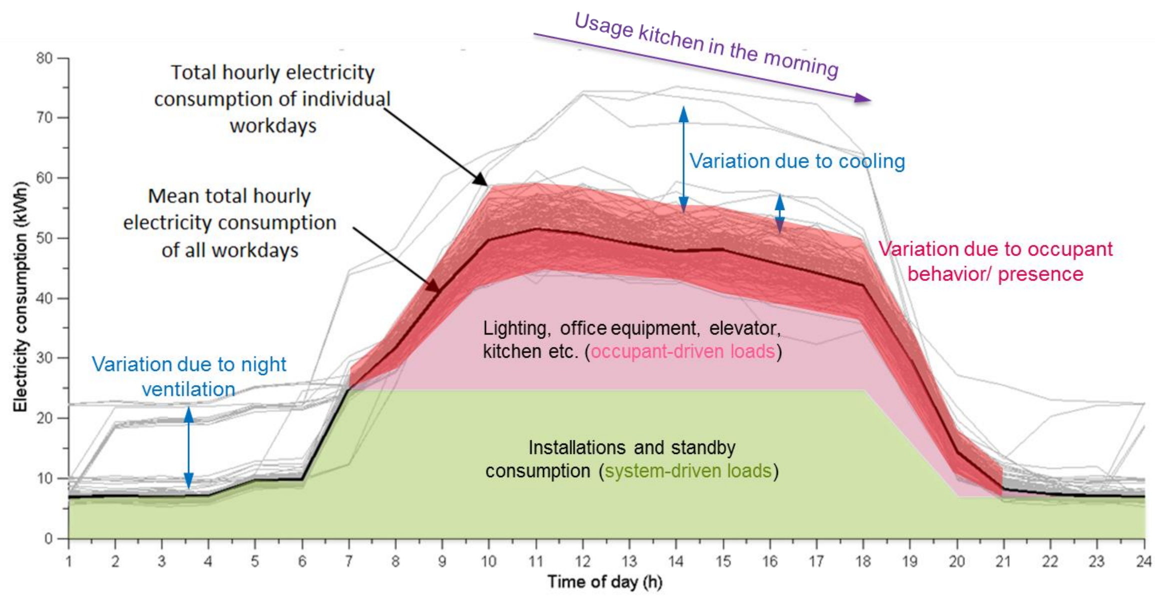


Figure 7 Breakdown electricity consumption based on measured hourly electricity consumption and the mean consumption for occupied days.

Recommended future work include: (1) Analysing occupancy influence on cooling demand based on electricity measurements, (2) studying the occupancy influence on heating demand based on hourly gas measurements, and (3) extending this study to other building types and building technologies.

Key Findings

- The occupant behavior has a minimal influence on building energy use in office buildings with BMS (semi-automated building). This influence is expected to be higher in non-automated buildings and lower in fully-automated buildings.
- The influence of the occupant behavior on the electricity consumption can be estimated by analyzing the actual electricity demand. The profile variations of the

electricity demand can be explained based on information collected related to the operation and use of the building.

- Quantifying uncertainty in energy predictions (in the design phase) allows decision makers to take better choices. The uncertainty due to the occupant behavior could be quantified by performing a sensitivity analysis with the building performance simulation software.

Related publications

Case 29

Case study title

Measurement of total person-hours per year in order to normalize consumption by occupancy

Contributors

Ken Dooley, Granlund Consulting and Aalto University, Helsinki, Finland

Contribute to other subtasks

Subtask E: Applications in building design and operations

When and where

1. 2011 [1]

   a. Energy consumption was simulated with 9 different occupancy profiles which were based on combining 3 population densities (m^2/person) and 3 different working hours per day (h).

2. 2012 [2]

   a. Occupancy measurements using Bluetooth low energy RFID tags
   b. Occupant Surveys
   c. Walkthroughs and observations

3. To be completed in 2016

   a. New techniques of people counting such as:
      i. People counting cameras
      ii. Occupancy measurements by recording the number of connections to the internet server
      iii. Smartphone tracking by monitoring wifi, Bluetooth low energy or by iBeacons
      iv. Occupant Surveys

Building(s) description

- Owner type: Private company
- Building type: commercial office
- Total floor area: 6,990 m^2
- Number of stories: 3 conditioned + 1 small floor with a large conference room
- Location (city, country): Helsinki, Finland
- Picture:

Occupant type

- Office workers with their own desk in open office spaces in an office building

Description of the datasets

Data points	Collection frequency	Collection period	Format
Simulated data with 9 different occupancy profiles	continuous (simulated)	1 year (simulated)	CSV
Survey	15 minutes	1 week	.xls
Walkthroughs	3-4 per day	1 week	.xls
RFID tags	continuous	1 week	.xls

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Not available, protected by privacy agreement with building owner

Summary

The current method of benchmarking the environmental impact of buildings is to normalize the building consumption with gross floor area. Buildings are first divided into categories that represent the building function and once this has been done they are compared and normalized based on building size. Typically, building size is defined by gross floor area. This practice is reinforced by national building regulations which aim to reduce energy consumption in buildings as they also present their target criteria in the format of energy per unit area such as kWh/m^2. However, if energy efficiency is measured by normalizing consumption with area then we argue that this practice is encouraging the inefficient use of the existing building stock which leads to an increase in the total energy consumption of the building stock.
In order to explain the previous point, let's consider a building with two identical office zones that have the same floor area. In office zone A there are 5 desks and the employees typically work a 9 hour day and in office zone B there are 10 desks and the

employees typically work an 11 hour day. If these two identical office zones are benchmarked for energy or water consumption then office zone A is considered more efficient. This is due to the fact that fewer people consume relatively less energy and water. It doesn’t necessarily mean that zone A has been designed more efficiently or that it has more efficient control systems or management practices. The biggest driver of the perception of energy efficiency is that it has less people and that these people also work a shorter day.

There an increasing focus on reducing energy consumption and the environmental impact of buildings in the real estate industry, yet this seems to be contradicted by building regulations that encourage buildings to have low population densities and short hours of operation. Buildings should be encouraged to maximise population density and hours of operation per day as this makes the most efficient use of the embodied emissions of the building stock and reduces total energy consumption as buildings consume energy even when they are unoccupied.

This approach is enhanced by two societal trends which have emerged in recent years which are the “future of work” and the “sharing economy”. The future of work suggests that office employees are spending less time in the workplace and more time working at home or in public spaces such as coffee shops. It also suggests that working hours are becoming more flexible and that less and fewer people are rigidly sticking to the traditional working hours of 9am to 5pm. In many countries this has resulted in a movement away from the one desk per person model towards flexible desk policies and in coworking spaces. However, it must be noted that normalization by area discourages companies from more space efficient working methods. The trend towards sharing is typified by Uber and AirBnB which focus on reducing excess capacity. For example, if a car is only used by its owner for 20% of the hours in the year then sharing aims to use the car for as much of the spare 80% as is possible. If we apply this concept to workspaces then future offices will be closer to coworking spaces than the one desk per person offices of the past. However, once again these practices are inhibited by benchmarking that normalizes consumption by area.

We propose an alternative to benchmarks that normalize with area which is to normalize consumption with area and <u>total annual person hours</u> [1]. Total person annual hours is the sum of the hours that all occupants have spent in the building during the year in question. A key question is how to measure building occupancy and our next phase of our research aims to measure occupancy using emerging technology such as:

1. Low cost and highly accurate people counting cameras
2. Server connections as a method of measuring occupancy
3. Smartphone tracking by monitoring wifi, Bluetooth low energy or by iBeacons

The forthcoming research will form part of the NewTREND (New integrated methodology and Tools for Retrofit design towards a next generation of ENergy efficient and sustainable buildings and Districts) research project which is funded by the European Union. This examination of total person-hours per year aims to add to the literature on: (a) new approaches for building data collection and (b) sub-optimal practices in the operations phase.

Key Findings

So far

- Benchmarking that normalize with area encourage occupancy profiles that are suboptimal with regard to best practices in energy efficiency and environmental impact reduction.
- Benchmarks that normalize with the area and total annual person hours encourage occupancy profiles that are suboptimal with regard to best practices in energy efficiency and environmental impact reduction.
- It is challenging to find solutions that can accurately calculate occupancy rates and can measure total person-hours per year.

Anticipated

- People counting cameras are a realistic method of people counting when high accuracy is required
- Server connections is a consistent method for measuring occupancy when low accuracy is needed
- Smartphone tracking is a consistent method for measuring occupancy when low accuracy is needed.
- Smartphone tracking is a realistic method of people counting when high accuracy is required but only if all employees have enabled the relevant indoor mapping application on their phone.

Related publications

- Dooley, K., 2011 **New Ways of Working: Linking Energy Consumption to People**, in: The REHVA European HVAC Journal, Volume 46, Issue 6, November 2011 also in 6th World Sustainable Building (SB) Conference, Helsinki, Finland, 18-21 October 2011
- Huovila, A., Tyni, A. & Dooley, K., 2013 **Building Occupancy as an aspect of Energy Efficiency,** in: Proceedings of SB13 Conference in Dubai, UAE, December 8-10 2013.

Case 30

Case study title

Global lighting performance: Annual survey of blinds movements of 3 office buildings in Lausanne Switzerland.

Contributors

Bernard PAULE, Julien BOUTILLIER, Samuel PANTET, Estia SA, Lausanne, Switzerland

Contribute to other subtasks

N/A

When and where

- 02.01.2013 – 01.31.2014 EPFL Innovation Park, CH 1015 Lausanne, Switzerland

Building(s) description

- Owner type: NGO
- Building type: office buildings
- Total floor area: Not applicable
- Number of stories: 4 (+ground floor)
- Location (city, country): Lausanne, Switzerland
- One or two pictures:



Occupant type

- Typical office workers in single and open office spaces in an office building

Description of the datasets

Data points	Collection frequency	Collection period	Format
Blinds position	60 minutes	12 months	webcam full HD

Data and models availability

Are data and/or models available to the Annex 66 participants? If yes, where to download them? License agreement to use.

- Not available, protected by ESTIA agreement.

Summary

This project focused on the effective use of movable shading devices in offices, and on the impact on the indoor daylighting.
The first part of the project consisted in the observation of the actual use of sunscreens when the command is not automated (administrative buildings, operating webcams from 01-02-2013 to 31-01-2014 over 125 openings, e.g., more than 500'000 individual blind positions analyzed). The main information is that sunscreens are very few and poorly used (less than two movements blinds / week) regardless of the orientation or season. Furthermore, the average position of the blinds leads to a significant obstruction. With an average of 57% of the window surface covered by the blinds, the use of electric lighting is almost mandatory for the back part of the room. The consequence of this misuse is that the contribution of natural light is far from being optimized.

Thus the implementation of automation system to control the blinds position is of high interest. This study has shown that such systems can achieve performance comparable to those observed in the case of very “tolerant” users. In Switzerland, where the implementation of Venetian blinds is widespread, the issue of automation is particularly important and this information should be disseminated among designers and building owners.

The second part of the project focused on the simulation of the actual contribution of daylight in each of the observed rooms (Simulations DIAL + / Radiance). This allowed us to compare the results with those that would have been achieved with automated blinds. The results of these simulations were then used to estimate the electricity consumption for lighting. This study shows that the energy savings associated with automated blinds can reach several kWh/m^2 per room and per year. Comparison with SIA 380/4 (Swiss standard) calculations shows that the actual version of the Swiss Standard underestimates the potential related to blinds automation and also tends to overestimate the effects of artificial lighting automated control.
The main conclusion of this study is that the implementation of automatic blinds can significantly increase the number of hours during which the use of artificial lighting is not necessary, while preserving the visual comfort and freedom of choice for users. The other conclusion is that the Swiss Standard should better promote the use of daylight by imposing specific targets on this topic.

Key Findings

- <u>Without automation</u>: The calculation according to the Swiss Standard is very pessimistic in the absence of automation. We observed that the users would not switch on the lights until the light level is very low. The predicted consumption without automation should, therefore, be reduced by 20% to 35%.

- Automation on lighting only: An on/off automation on artificial lighting is probably counter-productive because it increases considerably the number of hours 'lights on' when the blinds are not automated, as a consequence of the poor operation of the blinds just mentioned.
- Automation on blinds only: the energy savings potential from automating the blinds is very high, even without automating the artificial lighting.
- Automation on both lighting and blinds: the Swiss Standard calculation is pessimistic to very pessimistic for this scenario. The cases auto/off and continuous dimming with automation of the blinds shows a big gap between the calculations to the Standard and the simulations based on our observations.

Related publications

- Paule, B. Boutillier, J. & Pantet, S. (2014): Global lighting performance, Annual report 2013-2014. Project 81 0083: Swiss Federal Office for Energy, Lausanne, 2014.
- Paule, B. Boutillier, J. & Pantet, S. (2015): Shading device control: Effective impact on daylight contribution, Proceedings of the CISBAT'15 Conference, Lausanne, Sept. 2015.
- Schneeberger, J.-L.: Automatische Storen sparen Energie (2015), Bundesamt für Energie, Bern 2015.

Case 31

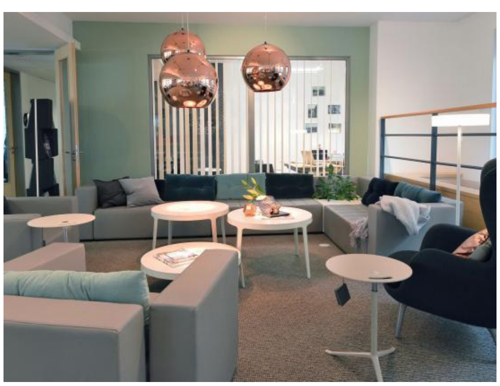
Case study title
Smart Building Management vs. Intuitive Human Control

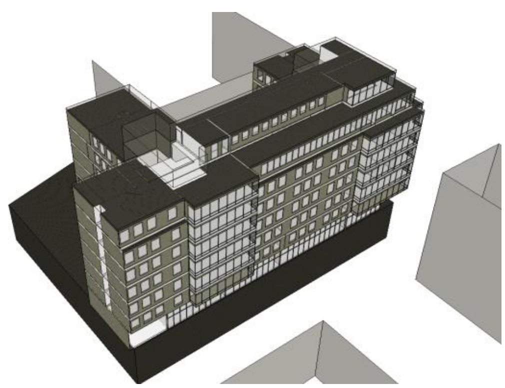
Contributors
- Zsofia Belafi, Tianzhen Hong: Lawrence Berkeley National Laboratory, Berkeley CA, USA
- Andras Reith, Kornel Dome Deme: Advanced Building and Urban Design (ABUD). Budapest, Hungary

Contribute to other subtasks
N/A

When and where
2014 – 2015: Office Building, Budapest, Hungary

Building(s) description
- Owner type: private
- Building type: commercial office
- Total floor area: 70,000 sf
- Number of stories: 8 conditioned + 3 garage
- Location (city, country): Budapest, Hungary
- Year of construction: 2008
- Occupants: 450
- Pictures:





Occupant type
- Typical office workers in open and private office spaces

Description of the datasets

Data points	Collection frequency	Collection period	Format
Electricity, natural gas submetering (BMS data)	1 month	5 years	csv
HVAC setpoints, valve status, room temperatures, weather data: temperature, radiation (BMS data)	5 mins	16 months 11/18/13-3/11/15	csv
Occupancy Y/N (BMS data)	15 mins	1 year 6/10/13-6/10/14	csv
Comfort and OB survey (212 answers out of 450 workers)	Once	Once in March, 2014	Google sheet
Thermal comfort measurement (code-compliance)	Once	Once in March, 2014	Report
Walk-through, interview	Once	Once in April, 2014	xls
Thermographic camera check	Once	Once in February, 2014	Report, pictures

Data and/or models availability

Unfortunately, data are not available to the Annex 66 participants as the owner of this private office building did not agree to share the data.

Summary

The owner of a large office building was facing high utility bills and low user comfort in his building which is located in Budapest, Hungary and was built in 2008. The office building was designed and built according to state-of-the-art design and energy management principles. Therefore, the causes of the poor operation were not quite clear. The objective of the project was to evaluate the energy performance and comfort indices of the building, to identify the causes of malfunction and to elaborate a comprehensive energy concept.

In the first phase of the project, current building conditions and operation parameters were evaluated with special regard to building management systems, occupant control behavior and user comfort. The evaluation tools used include: an online survey of 450 occupants, indoor comfort measurement, and on-site walk-through, thermographic camera check, and analysis of the energy consumption patterns, HVAC operation and indoor climatic conditions recorded by BMS system. As an outcome of the preliminary analyses, our investigation found that the state-of-the-art building management system is in good condition but it is operated by building operators and occupants who are practically not aware of the building management processes.

The energy consumption of the building was simulated by the zonal building energy modeling software, IDA ICE. The baseline model was calibrated to the annual measured energy consumption of the building. The behavior and presence of the building occupants were modeled based on the survey results and occupancy signals of the office sensors. As a result, we proposed intervention measures that would increase indoor thermal comfort and/or decrease energy consumption of the building. A parametric study was carried out to evaluate the energy and comfort yield of each measure proposed. In addition to this, cost estimations were prepared and simple return on investment (ROI) was calculated. Based on the ROI value of each measure, intervention packages were put together with 3, 6 and 12 years of ROI and a package containing all solutions. It was found that the all solutions package achieve 23% of annual cost savings. Soft solutions were also prepared for the owner, which included suggestions to provide a comprehensive training for building operators and occupants on building operation and adaptability [1].

In the final phase of the project, indoor HVAC operation conditions (setpoints), control schedules and principles were optimized for four different office types with different orientation and façade type ensuring highly energy-efficient operation and high comfort levels [2]. Simulation-based optimization assisted the process and helped us to undertake building management system fine-tuning tasks. The method applied includes the use of the IDA ICE model supplemented with optimization plugin using the NSGA-II genetic algorithm.

Key Findings

- Occupants are dissatisfied (54-64%) with the indoor comfort conditions. Comfort problems are permanent as the occupants installed additional equipment to improve their thermal comfort (17-34%).
- Occupant dissatisfaction is higher in those offices where there is no operable window or intelligent room thermostat while indoor parameters are the same. Therefore, better user control options result in higher occupant satisfaction.
- The fan-coil units are able to operate in heating and cooling mode on the same day.
- Smart BMS system is capable of controlling and operating the building in an energy efficient way with high user comfort, but the onsite personnel and the owner's representatives are not trained to use such system effectively.
- 20% of electricity consumption is not submetered. It is not known where this energy is consumed.
- Control setpoints are adjusted by onsite personnel in an intuitive way (lighting, shading). This results in uncontrollable setpoint changes and low energy efficiency.
- Air supply duct of the fan-coil units is not installed properly, exhaust air is recirculated into the offices and constant sewer smell is observed throughout the building.
- By means of the HVAC operation setpoint optimization user comfort can be increased by 31.2% and 9.5% in winter and summer conditions respectively while consuming the same level of energy.

Related publications

- Z. Belafi, A. Reith: Smart Building Management vs. Intuitive Human Control – a Case Study - , Nottingham, UK, Occupant Behaviour Symposium, 2014 - presented in Berkeley, CA, ANNEX66 meeting, 2015
- (http://www.nottingham.ac.uk/research/groups/environmental-physics-and-design/ob-14-and-annex-66/index.aspx)
- K.D. Deme, Z. Belafi, A. Gelesz, A. Reith, Genetic Optimisation of Indoor Environmental Parameters for Energy Use and Comfort - A Case Study for Cool-Humid Climate, Build. Simul. Conf. (2015).

Case 32

Case study title

Improving Occupancy Presence Prediction Via Multi-Label Classification

Contributors

Fisayo Caleb Sangogboye, Kenan Imamovic, Mikkel Baun Kjærgaard, Center for Energy Informatics, University of Southern Denmark, Denmark

Contribute to other subtasks

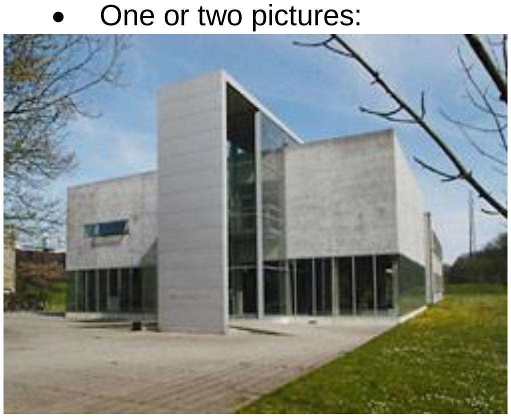
Subtask A: Occupant movement and presence models in buildings

When and where

- 2015, Maersk McKinney Møller Institute, University of Southern Denmark, Odense
- 2015, Green Tech Centre, Vejle

Building(s) description

- Owner type: University and Commercial
- Building type: commercial office
- Total floor area: 2500m2 and 4.000m2
- Number of stories: 2 & 3 story buildings respectively
- Location (city, country): Odense and Vejle, Denmark
- One or two pictures:



Occupant type

1. Typical office workers in closed office spaces in office buildings

Description of the datasets

Data points	Collection frequency	Collection period	Format
Occupancy presence data	30 seconds	14 weeks	KNX Protocol -> sMAP -> OccURE Platform -> Time series Data & Metadata

Data and models availability

Not available.

Summary

The case study utilized multi-label classification algorithms for occupancy presence prediction and analyzed various factors that influence prediction accuracy. The presence data utilized for modeling the classification algorithms were obtained from two case buildings (the Maersk McKinney Møller Institute Building at the University of Southern Denmark, Odense and the Green Tech, Vejle, Denmark). The office buildings mainly consist of 1, 2, 3, 4 and 6-persons offices, and the offices considered for the university building and the Green Tech includes 1, 2 and 4-person offices and 2, 3, 4, and 6-person offices respectively. The occupants of these offices do not work on fixed schedules and all offices are equipped with motion sensors that report occupancy status through a KNX protocol to a building operation system in the form of sMAP. From sMAP, we extract the data for each office and we distinguish three kinds of occupancy frequency (low, moderate and high). The data used for this analysis are from periods
August 16th to November 22nd, 2015, and this comprises 14 weeks of motion sensor data sampled every 30 seconds.

Obtained occupancy data were used to formulate occupancy prediction as an MLC problem to determine occupancy for a single day. We partition each day into subintervals of equal lengths and a subset of the intervals represents the predictable labels. In our implementation, we partition each day into 10-minute intervals to generate occupancy vector of 144 elements. Each label in the feature model is called a "Slot," which takes a value of 1 if an area is occupied during an interval and 0 if otherwise. The aim is to predict unknown and future timeslots and to investigate factors that influence the performance of identified classifiers. To obtain a broad overview, the following machine learning classifiers, Support Vector Machine (SVM), Random Forest, Multi-label k-Nearest Neighbour (MLkNN), and Decision Tree were chosen for evaluation. All selected classifiers except SVM provides an adaptation for ML classification, and thus a baseline approach (binary relevance with one-vs-all method) for problem transformation and algorithm adaptation was used in this case. We compare the MLC algorithms to an implementation of the PreHeat [1] algorithm with k equal to five as presented in the original implementation. For evaluation, predictions of 3-hours and rest-of-the day horizons were conducted for time periods 07:00, 09:00, 11:00, 14:00 and 18:00 which corresponds to slots 42, 54, 66, 84 and 108 respectively. This implies that the model used for predicting any slot were trained with data of slots preceding them. For example, a model predicting from slot 42 over a specified prediction horizon will be trained with features DayName, DayType, Season, Holiday and Slot 1 - Slot 41. Also the inclusion and exclusion of holiday feature was examined for each presented scenario.

In total, 20 scenarios were investigated for each office space and each scenario presents the performance (F-measure and prediction accuracy) of each model for all investigated scenarios.

The evaluation results indicate that the F-measure of PreHeat and SVM on the average are significantly higher than that of other classifiers in most cases. However, the instances at which other classifiers outperform SVM and PreHeat are where the rooms have low occupancy frequency. We can also deduce that in all cases that the F-Measure of PreHeat is slightly higher than that of SVM in rooms with high occupancy frequency. This is because SVM uses more similar instances in the training dataset that belongs to the same hyperplane as the sample, while PreHeat uses only five most similar previous instances. Also the classifier with most counts for highest accuracy score for the observed cases was SVM with count 40 followed by PreHeat with 29, Random Forest with 28, Decision Tree with 26 and lastly, MlKNN with 16.

Thus, we can conveniently conclude that SVM provides a more robust performance than other classifiers. By presenting more accurate algorithms for occupancy prediction, we hope to foster the development of more energy-efficient HVAC scheduling systems to reduce the overall energy consumption of buildings. Results from this study are published in [2].

Key Findings

- PreHeat and SVM outperforms other classifiers in rooms with high occupancy frequency while other classifiers outperform both PreHeat and SVM in rooms with low occupancy frequency.
- The reason for this observation is because PreHeat simply selects and computes the mean of the five closest occupancy schedules to the currently observed

schedule. While the selected schedules may be representative of the currently observed occupancy schedule for spaces with high occupancy frequency, these are usually not the case for spaces with low occupancy frequency.

- In the case of SVM, SVMs create slack variables to accommodate the classification exceptions and given that these exceptions are minimal for high occupancy frequency, the resulting model is usually representative of newly observed occupancy schedules. However, for spaces with low occupancy frequency, several slack variables are created to accommodate the several prediction exceptions. And these exceptions are usually not representative of newly observed occupancy schedules.
- A comparison between PreHeat and SVM indicates that SVM has a better performance than PreHeat in terms of prediction accuracy.

Related publications

- J. Scott, A. Bernheim Brush, J. Krumm, B. Meyers, M. Hazas, S. Hodges, and N. Villar. Preheat: controlling home heating using occupancy prediction. In Ubicomp, pages 281–290. ACM, 2011.
- F. C. Sangogboye, K. Imamovic, and M. B. Kjærgaard. Improving occupancy presence prediction via multi-label classification. In Proceedings of the Second IEEE Workshop on Pervasive Energy Services (PerEnergy), 2016, IEEE.