EDITED BY
WILLIAM O'BRIEN
AND FARHANG TAHMASEBI

OCCUPANT-CENTRIC SIMULATION-AIDED BUILDING DESIGN

Theory, Application, and Case Studies

EBC
Energy in Buildings and Communities Programme

ROUTLEDGE

Occupant-Centric Simulation-Aided Building Design

Occupant-Centric Simulation-Aided Building Design promotes occupants as a focal point for the design process. This resource for established and emerging building designers and researchers provides theoretical and practical means to restore occupants and their needs to the heart of the design process.

Helmed by leaders of the International Energy Agency Annex 79, this edited volume features contributions from a multi-disciplinary, globally recognized team of scholars and practitioners. Chapters on the indoor environment and human factors introduce the principles of occupant-centric design while chapters on selecting and applying models provide a thorough grounding in simulation-aided building design practice. A final chapter assembling detailed case studies puts the lessons of the preceding chapters into real-world context. In fulfillment of the International Energy Agency's mission of disseminating research on secure and sustainable energy to all, *Occupant-Centric Simulation-Aided Building Design* is available as an Open Access Gold title.

With a balance of fundamentals and design process guidelines, *Occupant-Centric Simulation-Aided Building Design* reorients the building design community toward buildings that recognize and serve diverse occupant needs, while aiming for superior environmental performance, based on the latest science and methods.

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William O'Brien and Farhang Tahmasebi

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Foreword

Numerous studies and experience from practice have shown that occupants can have a decisive influence on the performance and energy consumption of buildings. On the one hand, energy consumption depends on the use of equipment (e.g., household appliances, IT equipment) and technical systems (e.g., elevators), but there are also comfort-related actions of users which can significantly influence energy performance in both residential and commercial buildings. The latter share depends to a large extent on the needs and expectations of the occupants, the available adaptive opportunities to influence their comfort, and their resulting behavior in terms of any kind of space conditioning.

Despite these factors, occupants are still inadequately represented in building design. It is therefore entirely welcome and, even more, of utmost importance that the authors of this book broached the topic with the aim of promoting a paradigm shift toward considering occupants as active and dynamic participants in buildings and their performance. By presenting and discussing various aspects in this context, the authors provide a highly valuable basis for occupant-centric, performance-based design. This book serves not only as a scientific textbook for graduate students and researchers but also as an application-oriented guidebook for building designers and planners. Much of the content represents the outcome of international research on occupant behavior in buildings over the last 10 years, organized through the International Energy Agency – Energy in Buildings and Communities Annexes 66 and 79.

The book draws a broad picture, from occupant needs with regard to indoor environmental quality and human factors, to methods for planning how to incorporate these needs into the design process, and finally to simulation strategies with ways to choose the most appropriate occupant modeling approach. The book also focuses on building interfaces which play a critical role in human-building interaction for a successful use of adaptive opportunities. And finally, the presented case studies show that occupant-centric, performance-based design does work if implemented properly among the shareholders involved.

Much recognition and thanks are due to the editors and authors, all of them well-known experts in their fields, for addressing this important issue and for raising the quality of building performance for future generations.

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Glossary

Term	*Definition*	*Chapter #*
Action	An interaction event between an occupant and a building system or other system that causes a change in state	**6**
Adaptive behaviors	Occupant behaviors that are triggered by IEQ-related phenomena	**6**
Agent-based model	A modeling technique to represent occupants as autonomous agents who interact with other occupants, building systems, and the building	**6**
American National Standards Institute (ANSI)	An organization responsible for establishing and publishing technical standards spanning a wide range of products, systems, processes, and services	**9**
American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)	A professional association responsible for research, standards, and best practices regarding building mechanical systems and more broadly building performance, design, and controls	**5**
Architecture, engineering, and construction (AEC)	The industry responsible for delivering buildings – from design and occupancy	**9**
ASHRAE Guideline 36	A standard describing best-practice sequences of operation for HVAC systems including certain occupant-centric controls	**10**
Asset management standards	Standards that define the ontology, requirements (of the organization, leadership, planning, support, operation, performance evaluation, and improvement) and management of a built asset	**3**
Aural comfort	A measure of the objective and subjective elements of the satisfaction of the acoustic environment of space	**2**
Binomial model	A common statistical model, also referred to as logistic regression, that is used to predict binary outcomes	**6**

Term	*Definition*	*Chapter #*
Boundary condition	Condition defining how a system (such as a building) interacts with the environment	**7**
Building Automation System (BAS)	The system of hardware and software used to control electrical and mechanical systems in a building	**5**
Building information modeling (BIM)	The process of creating and managing the digital federate model that contains all the information of a project structured according to information containers mirroring the different disciplines involved in the project	**3**
Building operator	The person(s) responsible for the electrical, plumbing, and mechanical operations of a building or facility	**9**
Building Performance	A measure of a building's efficiency or how well it functions; in this context, usually with regard to energy use	**9**
Building performance simulation (BPS)	A software system that employs mathematical models representing buildings to predict various aspects of building performance (energy use, comfort, indoor air quality, etc.)	**5**
Building physics	Application of the principles of physics to the built environment (e.g., acoustics, air movement, thermodynamics)	**9**
Building Research Establishment Environmental Assessment Method (BREEAM)	A sustainability assessment method for master-planning projects, infrastructure, and buildings	**5**
Building Services Research and Information Association (BSRIA)	A UK-based testing, instrumentation, research, and consultancy organization, providing specialist services in construction and building services engineering	**5**
Cognitive load	The amount of effort required to reason and/or process information	**9**
Computational model	A computer-generated model used to simulate and study complex systems using mathematics, physics, and computer science	**7**
Controls-oriented occupant data	Data acquired from sensors or through interactions with control interfaces about a group of occupants' presence, count, identities, and activities	**10**
Cooling degree days (CDD)	A measure of the magnitude and duration of outdoor air temperatures that can be used as an indication of the expected building cooling load	**5**
Data-driven model	A model that is trained or otherwise constructed using measured data	**6**

Term	*Definition*	*Chapter #*
Degree-occupant-hour	Sum of occupied hours multiplied by the number of occupants and derivation of a measurement exceeding a threshold	**5**
Design aims	The set of goals or objectives a given design needs to achieve as specified by the client and all other involved stakeholders	**3**
Design decisions	Any technical decision made by a designer (architect, mechanical engineer, civil engineer, etc.) during the design process	**3**
Design parameter (DP)	A variable used to define an aspect or characteristic of a building or building system	**11**
Design pattern	An abstract design problem-solution pair which appears repeatedly in design contexts and which can be clearly identified and recorded	**3**
Design requirements	The set of requirements established by the project team, with or without the client and other stakeholders, that a given design needs to fulfill	**3**
Design stages	Different stages of project delivery with milestones for information preparation and exchange, client approval, and payments as specified in plans of work from a given accreditation body	**3**
Design workflow	A process for laying out all tasks and processes in a visual map, in order to give team members and stakeholders a high-level overview of each task involved in a particular process	**7**
Deterministic model	A mathematical model that yields the same results, with no randomness, each time it is simulated	**6**
Distributed energy resources (DER)	An electrical power source sited close to customers that can provide all or some of their immediate needs and/or can be used by the utility system to either reduce demand or provide supply to satisfy the energy, capacity, or ancillary service needs of the grid	**5**
Diversity schedule	A series of values (typically ranging from 0 to 1) to indicate the relative intensity of occupant-related phenomena (e.g., occupancy, plug loads)	**6**
Double hermeneutic	A characterization of social science research that acknowledges interactions between researcher and research subject, and the subjectivity inherent in performing such research	**4**
Energy conservation measure (ECM)	A building upgrade designed to save energy	**11**

Term	*Definition*	*Chapter #*
Energy efficiency (EE)	A measure of the ability for a building to use energy effectively compared to the service it provides	**5**
Energy management system (EMS)	A building tool used to analyze and process building energy data to monitor energy use and efficiency	**9**
Energy modeling	The process of building computer models of energy systems to analyze and predict a building's energy use over time	**9**
EnergyPlus	A comprehensive building performance simulation tool	**5**
Epistemology	The study of knowledge; that is, how we know what we claim to know	**4**
eQuest	A building performance simulation tool	**9**
Factor, contextual	A circumstance in a building that influences occupancy or behavior; this factor can be categorized as physical environment, psychological, social, or physiological	**2**
Factor, personal	A factor related to the personal characteristics of the occupant, like age, weight, and personality.	**2**
Factor, physical environmental	The physical circumstances of a space, such as the building envelope and availability of adaptive opportunities, that affect an occupant's behavior	**2**
Factor, physiological	The physical circumstances of an occupant that affect behavior and comfort such as their demographics and level of health	**2**
Factor, psychological	The mental circumstances of an occupant that affect behavior and comfort, such as preferences, expectations, and perceived control.	**2**
Factor, social	The influence of other people (e.g., in a shared room) on one's behavior or presence	**2**
Fit-for-purpose model	A model that generates the required results to the necessary level of accuracy within a manageable amount of time and effort	**7**
Formative evaluation	Evaluation activities designed to specify directional targets, monitor progress, and provide ongoing feedback	**4**
Grid-interactive efficient building (GEB)	An energy-efficient building that uses smart technologies and on-site DERs to provide demand flexibility while co-optimizing for energy cost, grid services, and occupant needs and preferences, in a continuous and integrated way	**5**
Haptics	Electronically or mechanically generated movement or vibration, often felt through the sense of touch	**9**

Term	*Definition*	*Chapter #*
Heat index (HI)	The temperature feels like to the human body when relative humidity is combined with the air temperature (AKA apparent temperature)	**5**
Heating degree days (HDD)	A measure of the magnitude and duration of outdoor air temperatures that can be used as an indication of the expected building heating load	**5**
Hidden Markov model (HMM)	A statistical model to predict a series of events, based in part on indirect observations	**6**
Human–building interactions (HBI)	The study of the interactions between occupants and a building's physical space and the interfaces within it	**9**
Human Factors and Ergonomics Society (HFES)	A society representing professionals who work in the field of human factors and ergonomics	**9**
Human information processing (HIP)	A model that describes how people receive, use, and act upon information provided to them based on attentional resources and inputs	**9**
Indoor environmental quality (IEQ)	A holistic measure of comfort and healthiness of an indoor space for human occupants, which comprises four main components: thermal comfort, visual comfort, aural comfort, and indoor air quality	**2**
Information delivery plans	The information deliverables for each task in a project, including their format and who is responsible for delivering them	**3**
Information management	The process of producing, collecting, storing, curating, distributing, using, archiving, etc. all the information related to a design project	**3**
Information management standards	Standards which define information management concepts, principles, organization, functions, delivery cycles and planning, team capability and capacity, common data environments, and workflows for built projects	**3**
Information management systems	Processes designed to store, organize, retrieve, and distribute information to be used in decision-making	**3**
Institute of Electrical and Electronics Engineers (IEEE)	A professional organization representing electrical and electronics engineers	**9**

Term	Definition	Chapter #
Integrated design process (IDP)	A design approach which involves all stakeholders of a project from the early design stages (i.e., from the specification of design requirements and objectives) so that integrated and optimum design solutions are developed through common agreement and interdisciplinary methods	**3**
Integrated Project Delivery (IPD)	A project delivery model that embraces a collaboration between stakeholders to distribute the risk and reward of the project	**3**
International Electrotechnical Commission (IEC)	An international organization that publishes standards for electrical and electronic equipment	**9**
International Organization for Standardization (ISO)	International Organization for Standardization	**9**
Leadership in Energy and Environmental Design (LEED)	A green building certification program with a set of rating systems for the design, construction, operation, and maintenance of green buildings, homes, and neighborhoods	**5**
Lighting load	The installed power of the luminaires in a building	**9**
Markov chain model	A stochastic model to predict a series of events, whereby the transition of state probability only depends on the previous state	**6**
Model complexity	Level of detail in a model, which in turn depends on its size and resolution	**7**
Model resolution	Number of variables in the model and their precision or granularity	**7**
Model size	Number of components in a coupled model	**7**
NABERS Building Standard	A rating system that measures the operational environmental performance of buildings and tenancies, e.g., the energy efficiency, water usage, waste management, and indoor environment quality of a building or tenancy and its impact on the environment	**7**
Non-adaptive behaviors	Occupant behaviors that are related to habits, tasks, and other phenomena that are not triggered by IEQ-related phenomena	**6**
Objective data	Data that is directly observable by reliable instruments or people	**4**
Objective function	A mathematical construct of building performance metrics in a design optimization problem that is to be maximized or minimized	**8**

Term	*Definition*	*Chapter #*
Object-oriented structures	Structures composed of clearly defined and identifiable objects or building blocks	**3**
Observational measure	Measure that provides an objective view of occupant behavior in a space, such as behavior tracking, mapping, instrument-based data collection, photography, and videography	**4**
Occupancy	The presence of occupants, which can be defined as a binary state (occupied or unoccupied/vacant), number of occupants present, and/or details on present occupants (e.g., demographics)	**1**
Occupant behavior	The actions or resulting states caused by the interactions between occupants and buildings/building systems	**1**
Occupant discomfort hours (ODH)	The sum of the product of the number of occupants present and the number of hours that they suffer from discomfort	**11**
Occupant preference learning	Inferring occupant preferences through algorithms assimilating occupant activity data concerning adaptive behaviors	**10**
Occupant-centric control (OCC) variables	Occupant-related variables defined within a building controller which are used in control sequences. An example of an occupant-centric control variable is the latest expected arrival time. It can be used in a sequence to switch an HVAC zone's mode of operation to unoccupied, when the current time exceeds the latest expected arrival time in a vacant space	**10**
Occupant-centric controls (OCC)	Occupant-centric controls (OCC) is an indoor climate control approach whereby occupancy and occupant comfort information are used in the sequence of operation of building energy systems	**10**
Occupant-centric metrics	Building performance metrics that capture the quality of services occupants receive and the degree of buildings' flexibility to accommodate occupants' interactions with building systems which influence building operations and thus resource usage and environmental performance	**5**
Occupant-hour	Sum of hours multiplied by the number of occupants in corresponding hours	**5**
Occupants	Human inhabitants of buildings	**1**
Occupants distribution scenarios (ODS)	Set of assumptions about how occupants are distributed within a building	**11**
Offline learning for OCC variables	Algorithms used to transform occupant data from sensors or control interfaces to OCC variables using archived historical data	**10**

Term	*Definition*	*Chapter #*
Olfactory	The sense of smell of occupants, referring to their ability to perceive odor of indoor air	**2**
Online learning for OCC variables	Algorithms used to transform occupant data from sensors or control interfaces to OCC variables in an online fashion. It is broadly categorized as recursive or batch online learning algorithms	**10**
OpenStudio	A cross-platform collection of software tools to support whole building energy modeling using EnergyPlus and advanced daylight analysis using Radiance	**5**
Parallel coordinates plot	A graph used in parametric simulation to illustrate the performance of an individual or multiple design variants in terms of multiple metrics, whereby each metric is represented by a separate axis and the axes are equally spaced and parallel to each other	**8**
Participatory measure	A method that allows occupants to participate directly in research, such as a design charrette or crowd-sourced data collection effort	**4**
Perceived control	Level of subjectively perceived control over one or more of the IEQ factors via building systems or other adaptive opportunities. This may differ from objectively available control, e.g. when a person is not aware of a control opportunity or considers it ineffective	**2**
Performance indicator	In the context of building simulation, a quantitative measurement by which the performance, efficiency, etc. of a building can be assessed, stand-alone or by comparison with a defined target	**7**
Persona	A fictional or nonfictional set of characteristics that define a representative occupant for design and modeling purposes	**6**
Personalized control	A control strategy that provides individual control opportunities to an occupant to control the IEQ factors of its immediate personal surrounding without affecting the IEQ factors of other occupants in the same room	**2**
Plan of work	Document issued by professional accreditation body to provide a road map for the building industry on design process management	**3**
Post occupancy evaluation (POE)	The process of objectively or subjectively measuring the comfort level of a building after users have begun occupying it	**5**

Term	*Definition*	*Chapter #*
Practitioners	Professionals who apply skills and knowledge to one or more phases of the building life cycle (design, operations, management, etc.)	**1**
Project information requirements	The information required by each party at key decision points throughout the life of a building project (from building design to building in use)	**3**
Reversal function	In the context of occupant behavior modeling, a function indicating the returning of a building component in the position prior to the action (e.g., closing a window or opening a shading system)	**7**
Self-report measure	A method that allows researchers and designers to understand how users perceive a space and their own needs, such as questionnaires, interviews, focus groups, and diaries	**4**
Sequences of operation	A specification defining how each building system, subsystem, and device shall interact with each other to deliver building services	**10**
Simulation-aided building design	An approach to building design in which the design process is informed by building performance simulation and analysis	**8**
State	The resulting condition after an occupant has acted or a building system has changed (e.g., window is open, light is on)	**6**
Stochastic model	A model that introduces randomness such that the output varies each time it is simulated	**6**
Subjective data	Data that is not directly observable in the same way by all instruments and people	**4**
Summative evaluation	Evaluation activities designed to measure how well the building works	**4**
Task illuminance	The total amount of light falling on a surface, in this case, the amount of light needed to perform a task such as reading and writing.	**9**
Technology acceptance model (TAM)	A model that illustrates how users accept and use new technologies	**9**
Test-Reference Year (TRY)	Datasets with a sequence of 8,670 hourly data values of typical meteorological variables for a specified location	**5**
Theory of planned behavior (TPB)	A psychological theory that attempts to predict human behavior based on expressed intentions, attitudes, beliefs, given perceived controllability of environmental features	**4**

Term	*Definition*	*Chapter #*
Thermal comfort	A measure of occupants' satisfaction with thermal conditions, which is frequently defined as "That condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation." according to ANSI/ASHRAE Standard 55-2020	**2**
Triangulation	Use of multiple sources of data to see whether results point in the same direction, thereby increasing confidence in the validity of outcomes.	**4**
Trigger	External event or circumstance that causes an occupant to initiate an action or relocate	**6**
User experience (UX)	An area of research and industry that focuses on how people interact with devices, controls, or products	**9**
User journey	A technique mimicking a person's experience during one session of using a building, consisting of the series of actions performed to achieve a particular goal (e.g., typical day of a facility manager in an office building)	**7**
Variable air volume – air handling unit (VAV AHU) system	A widely used air-based HVAC approach in commercial and institutional buildings whereby the centrally-supplied air supply rate is varied at the zone level to control the heating and cooling rate	**10**
Visual comfort	A measure of the objective and subjective elements of the satisfaction of the luminance from electric lighting and daylight in space	**2**
WELL Building Standard	A performance-based system for measuring, certifying, and monitoring features of the built environment that impact human health and well-being, through air, water, nourishment, light, fitness, comfort, and mind	**5**
Window-to-wall ratio (WWR)	The fraction of a building's facade area that comprises windows	**9**

1 Introduction

William O'Brien and Farhang Tahmasebi

We shape our buildings; thereafter they shape us.

— Sir Winston Churchill.

Building designers have a responsibility to ensure that people are provided with safe, comfortable, and healthy buildings. At one extreme, designers are liable if their buildings endanger the lives of occupants; however, there are in fact many scales of impact that buildings and their design can have on occupants, from appropriate illuminance and thermal neutrality to the psychological benefits of pleasant views and soundscapes. While extreme risks to human occupants are tightly regulated and carefully designed for fear of liability, indoor environmental quality and occupant well-being are often overlooked and misunderstood. In particular, the wide-ranging role of building designers and operators in addressing occupants' needs came to light in the recent context of COVID-19, where conversations about such topics as indoor air quality, aerosols, and ventilation became commonplace, even among laypeople.

In this book, we guide building design practitioners and researchers on how to elevate occupants as a major consideration in the building design process, from conception to operation. In principle, buildings are designed to provide safe, healthy, comfortable, and functional spaces for human occupants to live, work, play, learn, and sleep. One might assume that occupants' physiological, psychological, and behavioral needs would be examined and then translated into design decisions. Yet, this primary purpose of buildings (i.e., to meet occupant needs) is too often taken for granted, forgotten, or neglected. Practitioners and researchers often describe making *buildings* healthy and comfortable (in very coarse terms, such as temperature setpoints), while forgetting that the real goal is to promote *occupants'* health and comfort (O'Brien *et al.*, 2020).

In building design and research, occupants are often presented as a barrier to high performance. After all, occupants are a major source of uncertainty and often behave in unexpected and complicated ways that contradict the expectations or aspirations of designers and researchers (Day and O'Brien,

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2017; Janda, 2011). During the building design process, it is rarely known who will occupy the space in the first year, let alone in the next decade (Van Dronkelaar *et al.*, 2016). Unlike the weather, which is imposed on buildings without the designer's control, building design can be used to positively influence occupants and improve the occupant experience (O'Brien and Gunay, 2015). Consider the likelihood that an occupant chooses to take the stairs instead of the elevator in the following scenarios: (1) the stairwell is hidden away, dimly lit, and filled with stale air; or (2) the stairwell is open to a brightly lit, multi-story atrium with tropical plants. Ultimately, designers' decisions can greatly affect occupant comfort, health, and behavior—despite the temptation to sidestep this responsibility.

Indoor environmental quality (IEQ), which is largely a function of building design and operations, can have a profound impact on occupants' health and productivity (Fisk and Rosenfeld, 1997; Newsham *et al.*, 2009; Wyon and Wargocki, 2013). In commercial buildings, the cost of occupant salaries can average approximately two orders of magnitude higher than energy costs and an order of magnitude higher than rent (Yudelson, 2010). In other words, the value of a 1% decrease in worker productivity can rival energy costs. Moreover, the spillover effect of IEQ cannot be understated. For example, lighting and daylighting quality at work can affect sleep quality (Figueiro and Rea, 2016), while student learning and hospital patient recovery have been found to be profoundly affected by IEQ (Hsu *et al.*, 2012; Issa *et al.*, 2011; Joarder and Price, 2013; Ryan and Mendel, 2010; Wargocki *et al.*, 2020). IEQ is not only an objective measure, but also a subjective one that should be evaluated by the occupants themselves. Subtle aspects of building design, such as interface accessibility and feedback, can contribute greatly to the way occupants perceive and control IEQ (Ackerly and Brager, 2013; Brager *et al.*, 2004; Karjalainen, 2009).

It is by now widespread knowledge that buildings impact occupants and building design can positively affect occupants' behavior and empower them to improve their personal comfort. Still, many buildings significantly underperform in these regards (Bordass *et al.*, 2001; Leaman and Bordass, 2001; Tamas *et al.*, 2020). This book is motivated by the need to rethink the way buildings are designed for occupants, with a focus on quantitative and simulation-based methods. Consider the following statements that are implied by building standards, codes, and rating systems (note: the references below provide evidence *against* these common assumptions):

- The best way to deal with uncertain occupancy is to make conservative, worst-case assumptions (Gilani *et al.*, 2016; Hoes *et al.*, 2009; O'Brien *et al.*, 2019). (It is often building codes that lead designers down this path).
- Building occupancy has regular, clockwork-like schedules and nominal, near-capacity occupancy (D'Oca and Hong, 2015; Duarte *et al.*, 2013).

- Occupants are merely recipients of the indoor environmental conditions and do not actively respond to improve these conditions for their benefit (Brager *et al.*, 2004).
- IEQ is a purely physical and physiological phenomenon such that we can accurately predict occupant comfort from direct measurements of indoor environmental parameters (Schweiker and Wagner, 2015).
- If standard recommended indoor environmental conditions are provided to occupants, there is no need to provide them with affordances to improve their comfort (Heerwagen and Diamond, 1992; Kim *et al.*, 2018; Li *et al.*, 2017).
- The four domains of IEQ—indoor air quality and thermal, visual, and aural comfort—are independent from each other and have equal roles in occupant comfort and well-being (Kim and de Dear, 2012; Schweiker *et al.*, 2020).
- Occupants do not understand how buildings work and will often waste energy relative to design intent, and so their control over the indoor environment and building systems should be restricted (Gilani and O'Brien, 2018; Gunay *et al.*, 2018).
- Automating building systems and eliminating the possibility of occupant overrides can ultimately minimize the negative impact that occupants have on buildings (Boerstra *et al.*, 2013; Bordass *et al.*, 1993; Hellwig, 2015).

By and large, the leading literature and we, the authors of this book, hold that the above statements are either incorrect or at least counterproductive when thinking about occupant-centric design. With this book, we aim to equip designers with state-of-the-art knowledge about occupants and occupant modeling and simulation practices so they can design superior buildings.

While there are existing books focused on IEQ and healthy buildings (Allen and Macomber, 2020; Bluyssen, 2013; Bluyssen *et al.*, 2011; Heschong, 1979; Sternberg, 2010), human factors (Stanton *et al.*, 2017), occupant research methods (Wagner *et al.*, 2017), building simulation (Beausoleil-Morrison, 2020; Hensen and Lamberts, 2012), and high-performance building design processes (Athienitis and O'Brien, 2015; DeKay and Brown 2013; Grant, 2017), this book is the first to our knowledge to connect occupant needs to the building design process via simulation-based design methods and workflows.

Our chapters largely focus on IEQ and energy-related occupant needs, although there are many more that are beyond the scope of this book. Table 1.1 provides a comprehensive list of building occupant needs that are within designers' control. While some of these needs are highly quantifiable and covered by building codes and standards, others are emerging and may only be included in best practices guidelines and certification programs, such as WELL (Delos Living, 2018).

Table 1.1 A high-level summary of occupant needs that are within the control of designers

IEQ
- Healthy indoor air quality
- Satisfactory thermal, visual, and acoustic/aural comfort
- Absence of low-frequency vibration

Control over environment
- Individual and effective control to improve personal comfort without adversely affecting others
- Effective and usable building and system interfaces

Security and safety
- Secure spaces for people and their possessions without fear of intruders
- Lines of sight to nearby spaces
- Safe passage to evacuate or move to safe spaces in the event of emergencies (e.g., fire) or natural disasters
- Protection and comfort/health during periods of failed energy supply or systems (HVAC, lighting, water supply)

Space
- Adequate space to conduct activities without major constraints or interfering with a sense of well-being
- Ability to relocate to more comfortable locations or orientations

Ergonomics
- Comfortable spaces and furnishings (e.g., workstations, beds, food preparation areas) that allow occupants to maintain their productivity, well-being, and health

Mobility and accessibility
- Safe access to all needed spaces in the building, ideally with opportunities for physical exercise (e.g., stairs instead of elevator)
- Clear signage and wayfinding to assist navigation in unfamiliar spaces
- Mobility and accessibility for people with disabilities

Social well-being
- Ability to obtain privacy (visual, auditory) or companionship, as appropriate

Outdoors
- Access to views (ideally with nature)
- Access to outdoor space with pleasant environmental quality

Nourishment
- Availability of clean and safe drinking water
- Availability of food preparation/storage facilities

This book was primarily written and coordinated by participants of the International Energy Agency's (IEA) Energy in Buildings and Communities (EBC) Annex 79: *Occupant-Centric Building Design and Operations*. The five-year (2018–2023), researcher-led project includes over 100 researchers from 20 countries with the common goal to pursue fundamental and applied research and development to improve the way buildings are designed and operated for occupants. The goals of Annex 79 are outlined in O'Brien *et al.* (2020).

In the ten chapters that follow (and as outlined in Figure 1.1), we provide insights and methods to incorporate occupants into the building design

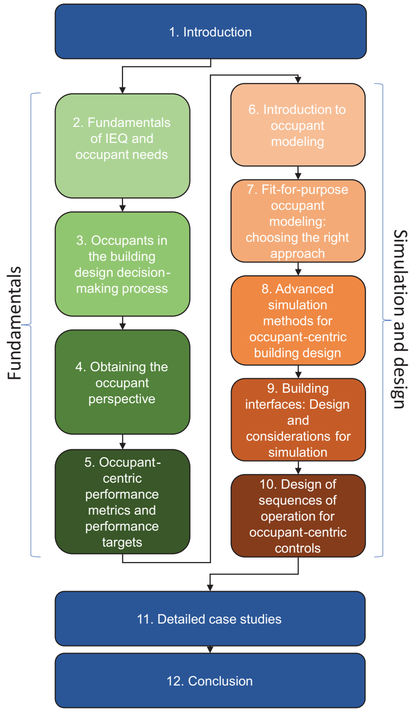

Figure 1.1 Chapter structure of this book.

process. Given the importance of building performance, spanning occupant well-being and environmental aspects, we focus largely on quantitative and evidence-based design. The chapters are not sequential according to design stages, but rather move from building IEQ and design fundamentals to modeling and simulation fundamentals and, finally, to applications. We start with the fundamentals of IEQ, occupant behavior, and behavioral theories. We then progress to design process considerations, including soliciting or otherwise collecting information about occupants. Next, we discuss occupant-centric ways of quantifying building performance. In the second half of the book, we turn our attention to occupant and building modeling. We open with occupant modeling fundamentals and move toward recommendations and best practices for incorporating occupants into building performance simulation. We provide more advanced discussion on the role of building interfaces and controls in the building design process. Finally, we present case studies conducted on seven buildings around the world to demonstrate the methods and techniques described in this book.

The target audience of this book is advanced design practitioners (e.g., architects, engineers, product designers) and researchers (e.g., graduate students, academics, government researchers). The first half of the book (Chapters 2–5) and the case studies (Chapter 11) will be broadly useful to this entire audience, while the second half of the book (Chapters 6–10) is primarily aimed at readers with an interest in occupant modeling and building simulation.

Chapter 1, this chapter, introduces the central principles and arguments of the book and lays out the structure of the chapters.

Chapter 2 provides a foundation for the rest of the book by reviewing theories that define building occupant needs in terms of indoor environment, health, well-being, and so on.

Chapter 3 focuses on the building design process and, most importantly, how to incorporate occupant needs at each phase of the design process.

Chapter 4 describes ways to obtain occupant information (data) for building designers to integrate into the decision-making process. This chapter provides a framework for collecting and structuring such data and outlines a wide variety of methods, with supporting examples from post-occupancy evaluation to virtual reality.

Chapter 5 makes the argument that building performance should be quantified from an occupant perspective. This chapter provides a framework for developing and applying occupant-centric metrics throughout the building life cycle.

Chapter 6 introduces occupant modeling, from current practice to leading research. This chapter is the first to explicitly address occupant modeling and simulation. It provides theory for both simple and advanced occupant modeling methods—a departure from occupant schedules to agent-based occupant models. It also describes methods to implement occupant models in various simulation tools and communicate the results.

Chapter 7 presents theory and a framework for selecting appropriate methods to model occupants according to a fit-for-purpose approach. Building on Chapter 6, this chapter focuses on empowering the users of simulation tools to make decisions about the most appropriate approach for a given application.

Chapter 8 builds on Chapter 7 by providing theory and supporting examples of how occupant modeling in simulation can support design. Methods explored in this chapter range from simple parametric analysis to multi-optimization with the objective of robust design. A single shoebox office model is systematically modeled to illustrate the different design methods.

Chapter 9 addresses the importance of the interface between occupants and buildings and focuses on the design and modeling of building interfaces and how occupants use them. This chapter covers theories of human-building interaction and provides examples and insights about how building interfaces could be a more central part of future simulation-aided design.

Chapter 10 focuses on occupant-centric controls, arguing that the often-opaque domain of building controls is critical to occupant satisfaction and building performance. This chapter focuses on a particular type of building controls—occupant-centric controls—which are defined as controls that learn and adapt to occupancy patterns and occupant preferences, behaviors, and habits.

Chapter 11 includes a set of detailed case study buildings that exemplify occupant-centric design. The case studies are intended to make the theories in the above chapters more concrete and practical. They are diverse in climate, typology, and lifecycle phase.

Chapter 12 concludes the book with a retrospective summary and discussion of concrete actions that can be taken to improve building design practice. This final chapter closes with a discussion of future research needs on the topic of occupant-centric building design.

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2 Fundamentals of IEQ and Occupant Needs

Marcel Schweiker, Christiane Berger, Julia Day and Ardeshir Mahdavi

Summary

In this chapter, we will introduce the link between occupant needs and elements of the indoor built environment, between sensory inputs and perception, and between perception and behavior. We will then review common practices in standards and guidelines. We will close the chapter with a discussion of three topics with open questions that require ongoing work.

2.1 Introduction

The first step toward occupant-centric building design and operation is a fundamental understanding of the relationship between the built environment and occupants' needs for health, well-being, and productivity. We begin this chapter with a brief overview in Section 2.2 of occupant needs and theories related to people's perception of indoor spaces and their behavior. Thereby, we introduce the four main domains of indoor environmental quality (IEQ)—namely, thermal, visual, acoustic, and indoor air quality (IAQ). This description of theoretical foundations is contrasted by Section 2.3, where we reflect on common compliance-checking methods based on codes, standards, and rating systems and the way the large body of scientific knowledge introduced in Section 2.2 is reflected in these forms of guidance. We conclude this chapter with a discussion in Section 2.4 of several critical factors that reflect the complexity of occupants' perception and behavior in indoor environments, bridging factors typically considered in research looking at occupants' needs and variables included in occupant behavioral models.

2.2 The Human Being in a Built Environment: Fundamentals and Theories

The objective of this section is to introduce the relationship between human needs and the indoor built environment, starting with human needs and reflecting on human perception and behavior.

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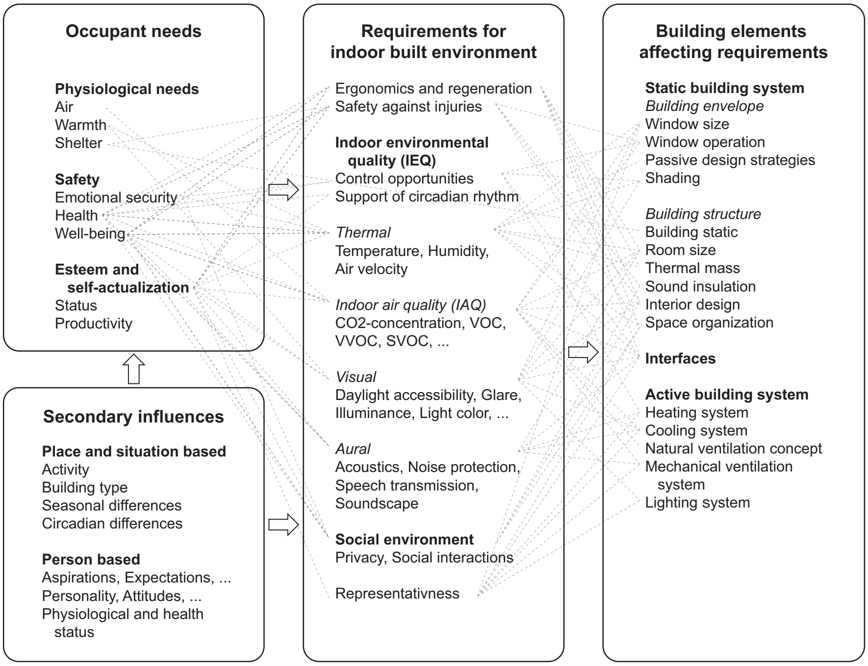

Figure 2.1 Framework reflecting the design flow from human needs in relation to requirements for the indoor built environment to related design elements affecting the performance of buildings as related to the requirements. In reality, this is an iterative process and, once built, a building's elements will affect occupants' needs. Note that elements and connections are only examples for graphical reasons.

2.2.1 Human Needs and the Indoor Built Environment

A basic understanding of human needs is fundamental in occupant-centric building design. While there are various definitions and categorizations of human needs in the literature, their presentation and discussion are beyond the scope of this book. On a very high level, human needs are referred to as the "drivers of people's actions, the motives behind behaviour" (Guillen-Royo, 2014). One of the most prominent categorizations of human needs still widely referred to these days is that by Abraham Maslow (Maslow, 1943, 1954). He distinguishes, in his early work, between deficiency needs (physiological, safety, love and belongings, esteem) and growth needs (self-actualization).[1] His framework offers a suitable structure to discuss human needs and to reflect on their relationship to design elements of the indoor built environment, aiming at occupant-centric building design. Figure 2.1 gives an overview of the mapping between human needs and design elements.

Physiological needs are related to biological requirements for human survival. These include air, warmth, and shelter against environmental hazards. While the vast majority of existing buildings meets these requirements, recent events partly related to climate change emphasize the need to assure that the building design provides conditions for survival. Floods, hurricanes, and other natural disasters have led to the destruction of buildings and corresponding fatalities. The combination of e.g., heat waves, power outages, and building designs relying on active conditioning while ignoring passive design strategies can lead to conditions beyond the limits for human survival.

Under normal circumstances, the building envelope itself—consisting of wall, roof, and floor elements, which may include opaque, transparent, insulating, ventilating, and shading elements—provides shelter and serves as a buffer against natural and man-made outdoor environmental conditions, such as low temperatures, high wind speeds, sunburn, or traffic noise. At the same time, the provision of sufficient fresh air needs to be assured. These examples all relate to the four dimensions of IEQ. The thermal dimension includes temperature, humidity, and air velocity levels.[2] The visual dimension considers illuminance levels, glare effects, color temperature, and color rendering index, among others. IAQ considers the freshness of the air, odors, particles within the air, and the concentration of CO_2 and volatile organic compounds (VOC). The acoustic dimension includes room acoustics, noise insulation, speech transmission, and others.

Depending on weather conditions, the type of envelope, and the activities within the building, the building envelope alone may not be sufficient to meet all the physiological needs required for survival. In these circumstances, the active building system needs to be designed to provide these conditions. If designers consider physiological needs and disregard the need for well-being (as described below), design requirements can remain minimal; for example, when clothing is available, the human body can survive for prolonged periods in a range of temperatures far beyond those occurring in modern buildings.

Safety needs as described by Maslow include financial security, social stability, and law and order, which have not been directly linked to the indoor built environment. Yet, safety needs can also include emotional security, health, and well-being, which have been directly mapped onto design elements of the building. **Emotional security** is linked to both privacy and interactions with others, which are either enabled or complicated by the organization of space and the interior design. The above-mentioned four dimensions of the IEQ and their respective requirements relate to health, well-being, and the concept of indoor environmental comfort (see Rohde *et al.*, 2019) for an extended discussion of the differences between the terms health, well-being, and comfort within the indoor environment). Requirements related to the IAQ domain are often aimed at a reduction of potential **health** implications, such as increased risk of cancer due to asbestos or polychlorinated biphenyls (PCBs), or reduced productivity due to reduced IAQ, such as increased CO_2 concentration levels.[3] The basis for most IEQ-related standards associated with the other three domains is often subjective level of comfort (see Section 2.3 of this chapter). Respective limits are based on a large amount of research following psycho-physical approaches to quantitatively investigating the relationship between physical stimuli and the sensations and perceptions they produce (see also Section 2.2.2 of this chapter). Thereby, the goal is to minimize IEQ conditions that lead to discomfort or dissatisfaction when the building is occupied. These conditions include, among others, temperatures that are too high or too low, glare, darkness, noise, or bad smells. Following the discussion by Rohde *et al.* (2019), **well-being** is distinct from comfort and includes: (1) positive emotional responses, including delight (Heschong, 1979), due to specific stimuli such as pleasant sounds, smells, or views; (2) varied and dynamic environments offering the potential for moments of alliesthesia, a feeling of very high satisfaction; and (3) environments that potentially reduce stress, offer a high level of controllability and contact with nature, and facilitate unrestrained activities. Related requirements for well-being would go beyond the restriction of IEQ conditions in the four domains and promote dynamic environments with conditions outside traditional comfort limits, e.g., set by ASHRAE 55 or ISO 7730.

Additional requirements for the indoor built environment related to health include those related to safety against injuries and harmful conditions. The duration of exposure to different conditions and individual constitution influence the magnitude of these effects. For example, the intent of some IEQ requirements is to limit, minimize, or avoid occupants' exposure to specific IAQ contaminants, which are harmful after short- or long-term exposures and for which effects have been directly assigned to the cause, like asbestos and cancer.

Safety needs related to comfort, well-being, and health also include the need for regeneration, growth, and repair, especially at night. Research on circadian rhythm suggests that a high sleep quality starts with the provision of sufficient daylight required for melatonin suppression during the daytime (Boubekri *et al.*, 2014). A further condition is limited exposure to lighting with reduced blue wavelengths in the evening, which is related to occupants' behavior and the lighting emission design of the lighting system and appliances such as televisions or smartphones (Wahl *et al.*, 2019). Furthermore, access to silent, dark, and well-tempered conditions during the night-time that allows for increased sleep quality (Chepesiuk, 2009) is a further requirement for building design and operation following human needs.

While not immediately apparent, there is a relationship between **esteem and self-actualization needs** and the indoor built environment. Esteem needs include aspects of respect, status, and recognition, while self-actualization is related to the realization of personal potential. All these aspects can, to some extent, and depending on their exact operationalization, be promoted or impeded by the indoor built environment. For example, reaching respect, status, or recognition is associated with success in professional life (Ormel *et al.*, 1997). In addition to health status—influenced partly by IEQ conditions as discussed before—one's ability to perform the tasks required for professional life partly depends on IEQ conditions. Success in viewing and completing tasks may depend on several aspects of the visual environment, such as luminance, illuminance, spectrum, color temperature, direction, color rendering, and contrast. Listening tasks and communication with customers, peers, or superiors, for instance, may be inhibited by excessive and unprotected background noise or poor acoustic properties of an indoor space. At the same time, IEQ conditions can also be designed to manipulate occupants and clients—for example, adjusting light settings to make fruits looking fresher and tastier than they are. The design of a space will likely need to consider the needs of different types of occupants, such as those working in a setting and those visiting, e.g., for shopping or leisure.

In this section, we have outlined a multitude of connections between human needs and the indoor built environment and could describe many more. Before moving forward, however, we should note that there are challenges involved in defining requirements for indoor spaces. For instance, human needs within the indoor built environment vary depending on the intended activities as well as the attitudes and personality of the human itself (Schweiker, Huebner *et al.*, 2018). Likewise, the requirements vary when aiming for an occupant-centric building design. There are seasonal and circadian differences; some needs are more likely at specific times of the day (e.g., sleeping) or year (e.g., the desire for cooling), but in general, most activities may occur anytime. Needs are also related to or can form the basis of occupants' aspirations, which can either be fulfilled or lead to disappointment when they are not met (Schweiker, Rissetto *et al.*, 2020). Some of these needs may be readily evident to human consciousness, such as fresh air to combat bad odors or a certain threshold luminance level, and can therefore be communicated with others. Yet, other needs may remain at the subconscious level—for example, the introduction of fresh air to reduce non-odorous but harmful components of the indoor air, which can be measured but not sensed by the human being. Occupant-centric building design should consider both perspectives to provide satisfying and healthy conditions.

2.2.2 Sensory Input and Perception

This section briefly touches upon the pathway from sensory inputs to perception/sensation and evaluation (satisfaction, comfort) of IEQ-related stimuli. The next section will describe the process from perception to human-building interaction. The whole process is schematized in Figure 2.2. A basic understanding of these pathways and related terminology is fundamental to evaluating key aspects of the literature about the relationship between IEQ

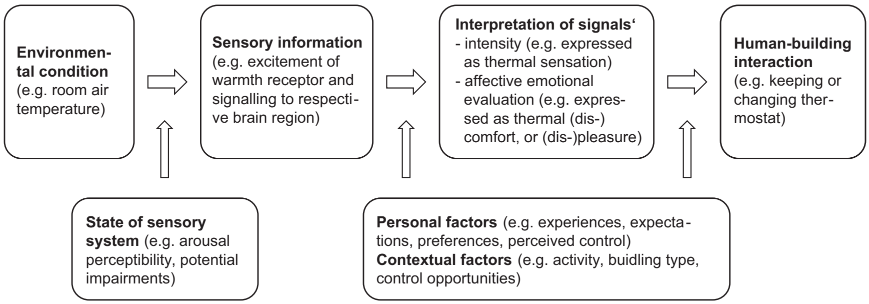

Figure 2.2 Schematic flow from environmental stimuli to human-building interaction.

and human behavior. Readers interested in the details of these processes are referred to corresponding literature (Bluyssen, 2009), as these are beyond the scope of this book.

The human body cannot directly measure parameters of IEQ in absolute terms as, for example, a thermometer might do. The human body can only detect changes to stimuli of our sensory systems. Distinctions are commonly made between the six sensory systems: vision, hearing, touch, taste, smell, and balance. Except for taste, all these factors are related to aspects of the indoor environment, and each of the four domains of the IEQ is related to at least one of them. Balance—often overlooked and taken for granted—is less required for typical plane floors, but can lead to sensory stimuli and training, e.g., as promoted by Hundertwasser in his treatise on the advantages of the uneven floor (Hundertwasser and Schmied, 1985).

Each of the sensory systems consists of sensory receptor cells, neural pathways, and dedicated parts of the brain. Examples of sensory receptor cells are the cold and warm thermoreceptors in our skin (part of the sensory system touch), which react to varying temperatures. The neural pathways carry the corresponding nerve impulses from the receptor to the brainstem and up to specific areas of the brain (Bluyssen, 2009). Except for direct reflexes, such as removing a hand immediately from a hot plate, the information regarding the stimuli is interpreted in various brain regions. Such interpretations can lead to a conscious or subconscious perception. When asking participants in a study or occupants in buildings about their perception of IEQ variables, they are forced to find a conscious representation. Depending on the type of question, they can then report their sensory-discriminative, affective-motivational, or cognitive perception (Schweiker *et al.*, 2017). As Schweiker *et al.* (2017) outlined, sensory-discriminative perceptions include perceived intensity, e.g., a statement between hot and cold in response to the question "How do you feel right now?" or an evaluation in terms of acceptability. Affective-motivational perceptions include aspects such as pleasantness or the motivation to change the conditions. Cognitive perceptions include comparisons of perceptions of previous experiences, perceived controllability of conditions, or the ability to cope (mental or behaviorally) with perceived conditions.

Three points are important to note. Firstly, the type of question influences the type of perception assessed, and a perception of intensity (e.g., the commonly used thermal sensation scale) is, in general, not suitable to assess whether a condition is perceived as comfortable, acceptable, or even stimulating emotions like pleasantness (see also Schweiker, Abdul-Zahra *et al.*, 2020). Secondly, the same physical stimuli can elicit different perceptions of pleasure or dissatisfaction for the same person depending on their internal state (e.g., level of acclimatization, preferences, expectations, experiences), the external conditions (e.g., socio-cultural aspects, relation to source of noise), or the current task or activity. Thirdly, all parts of the sensory system may vary between and within individuals. One example is when a person's visual sensory system changes with age. Age is associated with reduced transmission of light through eye media, a reduction of the width of the pupil, and further processes that, in turn, lead to the average 65-year-old receiving only half the light at the retina as a 25-year-old (Schierz, 2008). Thus, it is important to be explicit in methods that assess occupant needs, not rely on small samples, and strive for variety in the occupants being approached. At the same time, designers and researchers should be careful in following advice based on studies that do not follow these points.

2.2.3 From Perception to Human-Building Interaction

Once the sensory stimuli from the sensory nerve cells are interpreted—again, excluding reflexes—a subconscious or conscious reaction is followed. Reactions related to IEQ have been grouped in various ways. Schweiker *et al.* (2018) distinguished between (1) physiological adjustments done unconsciously, (2) individual adjustments like changing body posture or clothing, (3) environmental adjustments, including interactions with the building interfaces, and (4) spatial adjustments such as leaving a room. Taking no action and leaving everything (internal and external settings) as it is, is also considered a reaction. The type and degree of reaction are influenced by the evaluation of the stimuli together along with additional variables related to preferences, attitudes, experiences, norms, and others.

Subconscious reactions, such as the narrowing of blood vessels (called vasoconstriction) to reduce heat loss through the extremities in cold environments, happen immediately. In contrast, conscious reactions, such as opening a window to improve the IAQ, may begin with a behavioral intention but many factors will impact whether an action is pursued or not (for an overview of related theories see, e.g., Heydarian *et al.*, 2020). It is important to note that human-building interactions do not end the moment an occupant has completed the action, but rather may continue iteratively with further evaluation of subsequent sensory stimulation. The changes detected through the sensory systems impact whether the reaction or interaction will be evaluated as a successful or failed intervention. Repeated failure or the perception of lack of control can lead to dissatisfaction, learned helplessness, and acute or long-term stress reactions that can potentially affect well-being and/or health. Therefore, occupant-centric design demands careful consideration of human needs in addition to the design and selection of the interfaces that are provided to occupants to alter their respective IEQ conditions (see Chapter 4 for methods to collect occupant data, needs, and interface usability).

In any given building, there are many controls or interfaces such as windows, doors, and lights, that occupants can interact with to maintain their comfort, preferences, and so on. These interactions can impact the building's energy use and occupants' IEQ and comfort outcomes, both at the room and individual levels. Hence, due to the above-mentioned individual differences, what is beneficial for one occupant may be annoying for another sharing the same room. Building controls and interfaces lie on a spectrum ranging from fully manual control (human-driven action) to fully automated (machine or technology driven; see Chapter 9 for more details). In between this spectrum, there are also solutions such as human/occupant-in-the-loop control strategies (OCC). For example, with demand-controlled ventilation (DCV) strategies, ventilation rates are adjusted based on indoor air contaminant concentrations (e.g., CO_2) or occupant counts. Chapter 10 of this book covers a wide range of OCC solutions and case studies.

Many factors encourage (or discourage) occupant interactions with a given building, such as comfort, personal habits or preferences, health (e.g., a migraine), or privacy (Schweiker, Carlucci *et al.*, 2018). Different building interfaces offer varying forms of feedback and degrees of control to occupants. Understanding how occupants engage with interfaces—and their respective feedback mechanisms and controls—has important implications for meeting both occupant needs and energy savings design goals (see Chapters 3 and 9). If occupant interface needs are not carefully considered, designers risk not meeting energy goals and occupant comfort and IEQ needs. For instance, while keeping all occupants satisfied and comfortable at the same time is an impossibility, one solution to maximize comfort and satisfaction is to offer occupants local controls to maintain their personal comfort and satisfaction (Day and Heschong, 2016). Based on studies of occupants' heating and cooling behaviors, personal comfort models can predict individuals' thermal preference and lead to improved comfort, satisfaction, and energy use outcomes (Kim, Schiavon *et al.*, 2018; Kim, Zhou *et al.*, 2018). At the same time, we believe that the explanatory capacity of machine learning approaches is still questionable, as observed earlier elsewhere (de Dear *et al.*, 2020). As with other approaches, they may fail when applied to contexts other than those for which they were trained.

The types of controls occupants interact with in their environment vary based on building type, climate, and so on. The nature of occupant interactions with building interfaces will continue to evolve as building technologies and controls as well as occupant preferences continue to advance. Therefore, while there are many interesting hybrid and automated solutions to guide (or prevent) occupant interactions with interfaces, there are also inherent challenges to maintaining occupant comfort, IEQ, satisfaction, productivity, and so on. These challenges and possible solutions will be further outlined in Section 2.4. Additional details of building interface characteristics that influence occupants' interactions are detailed in Chapter 9.

The following section contrasts the above overview related to occupant needs with the content of common compliance checking methods based on codes, standards, and rating systems for the four main domains of IEQ.

2.3 Common Practices Regarding Specification of IEQ

Given the wide variety of human needs in the built environment discussed in the previous section, multiple quality requirements must be considered in the design, construction, and operation of buildings, including building integrity as well as safe and secure building operation. Thereby, requirements regarding IEQ must directly address occupants' needs (see Figure 2.1). A general classification of criteria concerning occupants' requirements could be listed as follows, starting from most evident (basic) to less tangible:

1 Avoid major or irreversible damage to organism due to extreme exposure situations.
2 Avoid long-term health issues due to, for instance, sustained stressful situations.
3 Provide IEQ conditions compliant with requirements pertaining to occupants' comfort and productivity.
4 Provide conditions that are subjectively perceived as pleasant.

It is commonly assumed that scientific disciplines such as biology, physiology, medicine, psychology, and ergonomics provide the evidentiary basis for criteria and mandates tied to IEQ standards. Whereas risks in category 1 above must be avoided at all costs, category 2 risks may be tolerated under certain limited term exposure situations. This means that, in most indoor settings (residential, commercial), the focus is on categories 3 and 4. Note that while the conditions that constitute a comfortable environment ultimately depend on occupants' subjective judgment, the same does not necessarily apply to physical health considerations. Adverse health implications of indoor environmental factors are not always consciously perceived. For example, there are well-known cases of dwellings with dangerously high carbon monoxide and radon concentrations, both of which are imperceptible by humans.

Codes, standards, and guidelines that specify IEQ requirements represent the main reference sources for professionals and stakeholders. Specifically, building designers and engineers are expected to abide by the provisions in these documents. Responsible parties for building construction and operation may need to provide proof of compliance with regard to applicable mandates. More recently, various building quality assessment and rating schemes have been introduced to encourage more holistic building evaluation processes. The intention is to promote better performing and more sustainable building practices. However, actual code compliance processes and adoption of rating systems do not appear to involve, as a matter of course, critical reflection concerning the source, uncertainty, and applicability of the entailed mandates and recommendations. This can lead to a perfunctory attitude of demonstrating compliance with the minimum criteria or pro forma acquisition of some quality label, rather than seeking a genuine understanding of what constitutes a high-quality indoor environment. It would be thus useful to critically examine the content of standards for explicit and implicit references to their underlying theoretical reasoning and the scientific evidence for their prescriptions.

As alluded to previously, the presumed primary purpose of IEQ-related performance mandates in standards is to define conditions that are conducive to building occupants' health, comfort, and well-being (Mahdavi *et al.*, 2020). The assumption might be that the recommendations in such documents have been issued not by edict but based on theoretically sound and empirically derived evidence pertaining to the processes by which indoor environmental conditions influence occupants' health, comfort, and well-being. Unfortunately, the validity of this assumption, as obvious as it may seem, cannot be taken on faith. Past research efforts have significantly contributed to our understanding of IEQ-related human requirements. However, they have also demonstrated that the definition and operationalization of occupants' requirements are rather non-trivial endeavors, given the imprecise and at times overlapping concepts such as health and comfort. It would be thus beneficial to query if typical instances of IEQ-related evaluation schemes and standards bolster their requirements through the explicit inclusion of their theoretical and empirical underpinnings.

To identify such instances, one can begin with frequently deployed building rating and certification systems. A previous review of such systems (Mahdavi *et al.*, 2020) clearly revealed that they do not independently set the IEQ-related criteria but refer to thematically relevant national and international standards. For instance, the certification system LEED (2021) refers to various ISO, EN, and ANSI standards (2021) regarding thermal, IAQ, and acoustic criteria. Likewise, DGNB (2021) includes references to EN, ISO, ANSI, and DIN standards. As the intention of this section is not to conduct an exhaustive review of such documents, the focus is on a number of typical and frequently referenced instances that specifically address the IEQ domains of interest to the present discussion, that is, thermal (e.g., ISO 17772-1), visual (e.g., DIN EN 12464-1), acoustic (e.g., DIN 18041), and indoor air quality (e.g., DIN ISO 16000-1). The study of such resources can reveal if they use content counting as the basis for and reasoning behind the adapted criteria and target values of relevant occupant-centric indoor environmental performance indicators.

2.3.1 Limits, Thresholds, Ranges, and Zones

From a practitioner's point of view, the main elements of interest in standards are likely to be the explicitly mandated values of IEQ-relevant variables and their specifications, usually in terms of minimum or maximum values, recommended ranges, and zones. The numeric nature of the variables' values and the fact that they are, at least in principle, measurable, implies certain practical advantages in terms of rationalizing and streamlining the quality assurance and compliance processes, and contributing to the clarification of liability issues. Mandates may be specified in various formats, including, for example, maximum permissible values (e.g., CO_2 concentration, glare level, noise level), minimum required values (e.g., illuminance level, ventilation rate), recommended or "optimal" values (e.g., comfort temperature, reverberation time), a range of acceptable values (e.g., daylight factors), and multi-variable "comfort" zones (e.g., combination of ambient air temperature and humidity level).

The conceptual graphs of Figure 2.3 illustrate for the thermal comfort domain typical instances of mandated values of recommended operative temperature and maximum permissible air flow speed. When looking for the underlying logic of these types of IEQ-related prescriptions, it helps to think of common code-based regulations in building design and construction domains. Consider, for instance, the prescribed minimum dimensions of basic architectural elements such as doors, corridors, and stairs in common universal design standards. In all these cases, features of various design elements are prescribed, the designs are expected to incorporate those

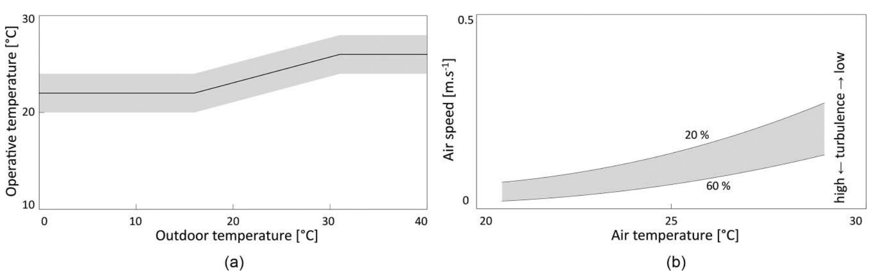

Figure 2.3 Conceptual graphs showing comfort (operative) temperature as a function of the outdoor temperature (left) as well as maximum permissible air flow speed as a function of air temperature and turbulence intensity (ranging from 20% to 60%, right; based on standards EN 16798 and ISO 7730).

features, and they can be checked during post-construction inspections. The assumption is that, as the prescribed minimum width of a door may be inferred from the dimensions of a wheelchair or the dimensions of stairs from basic anatomic features of the human body, it should be possible to infer the mandated values of IEQ-related variables from a relevant, scientifically established knowledge base. However, attempts to directly map from basic facts to specific performance requirements are not at all straightforward. Thereby, two questions are of special interest. First, given the inherent complexity of IEQ-related requirements, can the corresponding standards rely on a comparably objective scientific knowledge base? Second, do IEQ-related standards provide clear and traceable references to whatever scientific foundation they refer to? These questions are further explored in the following section.

2.3.2 Scientific Foundations versus Engineering Guidance

To start with a key observation, IEQ-related standards include much in terms of explicit and specific performance mandates and requirements (see the previous section), but relatively little in terms of direct and explicitly stated underlying science-based reasoning and evidence. The aforementioned rating system instances seldom spell out the details of the IEQ-related mandates, let alone provide explicit reasoning behind them. Rather, they refer to various international and national standards. These, in turn, frequently refer to other standards. Occasionally, references are made to technical papers that are suggested to provide some reasoning. However, such references are not always directly linked to the specific sets of requirements in the standards. Rather, they appear to be included as elements of thematically relevant bibliographies. At least three reasons for the paucity of direct explanations and evidence in common IEQ standards can be identified:

- There is a basic difference between scientific inquiry, which is mainly geared toward understanding phenomena, and engineering, which typically targets practical solutions. Standards and codes are mostly consulted by professionals looking for applicable prescriptions and constraints, not necessarily for the purpose of deep understanding.
- In contrast to "classical" engineering domains such as building construction and structural design, IEQ standards and guidelines regarding human requirements cannot only rely on natural sciences but must also consider insights from life and human sciences (e.g., physiology and psychology). The considerable role of qualitative and subjective factors in such fields can render the definition of standard requirements more challenging.
- The genesis of IEQ standards does not always occur through a completely transparent and thoroughly organized process with human health and comfort requirements as the sole focus. Rather, it can also

involve other factors, including economic considerations (e.g., return on investment) and special group interests. The processes leading to the formulation and publication of standards often require consent and comprise from a diverse set of participants from government, industry, and academic institutions. It is possible that not all content in and all aspects of standards are strictly objective and the direct result of scientific reasoning.

However, even if IEQ standards referred to frequently by professionals do not provide direct and explicit reasoning behind their recommendations, they do include features that point to implicit underlying principles and methods. These features allow for at least a partial backtracking or reverse engineering from standards to theory. A look at the syntax, terms, and formal logic of IEQ standards may thus yield some interesting and useful insights.

2.3.3 Measurements and Constructs

Recommendations in thermal and visual comfort standards are typically based on relationships referred to as comfort equations (Figure 2.4). A comfort equation maps the values of a set of independent variables meant to capture salient indoor environmental conditions to the value of a dependent variable meant to indicate the occupants' level of comfort (Mahdavi, 2020). The former comprises a number of physical parameters that can be measured. The latter is a construct, resulting from methods that make occupants' typically subjective perception (and evaluation) of the indoor environmental conditions measurable (see Table 2.1).

In regulations concerning thermal comfort, measurable independent variables of the indoor environment that are considered relevant include air and radiant temperatures, together with ambient concentration of water vapor and air movement velocity. Occupants' evaluation of thermal conditions is represented via constructs such as estimated voting tendencies, as expressed through qualitative scales common in psychological studies. The inference rules (i.e., the logic of mapping operations in the comfort equation) are often based on two sources. One source relies on physiologically

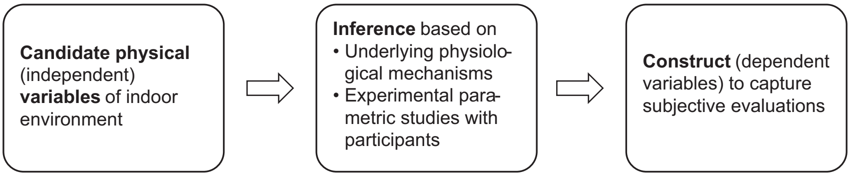

Figure 2.4 Schematic illustration of the elements of indoor environmental comfort equations.

Table 2.1 Illustrative instances of independent variables (thermal and visual indoor-environmental parameters) and dependent variables (constructs assumed to represent subjective evaluations of thermal comfort and visual discomfort) in respective comfort equations

	Thermal comfort	*Visual discomfort*
Independent variables: assumed relevant indoor environmental parameters	Air and mean radiant temperature, air humidity, air speed	Luminance of the glare source, luminance of the background
Dependent variables: comfort constructs representing occupants' subjective assessment of comfort conditions	PMV (predicted mean vote), PPD (predicted percentage of dissatisfied)	UGR (unified glare rating), VCP (visual comfort probability)

based insights. In case of thermal comfort, this is mainly the heat balance of the human body and its significant role in the thermo-regulatory process that maintains, among other things, the human body's core temperature (Mahdavi, 2017). The other source includes experimental studies with human participants who evaluate parametrically varied ambient conditions using the aforementioned subjective scales. The relative contribution of these two sources on the derivation of the comfort equations' mapping rules may be very different. The knowledge of humans' thermoregulatory system plays a significant role in the initial formulations of thermal comfort models. However, experiments with human participants provide key data relating physiologically relevant variables to subjective evaluation processes (see also Section 2.2.2). In the visual performance domain, the physiological basis of the so-called disability glare and the main responsible physiological mechanism (light scatter in the eye) are well understood. Visual discomfort, however, is mainly assessed based on people's subjective complaints.

2.3.4 About the Limits of Limits

Standards and codes typically include very specific requirements (including numeric limits for and ranges of various variables deemed relevant), but they rarely disclose directly and explicitly the corresponding reasoning. Some of the reasons for this circumstance have been alluded to previously, including: (1) the challenges of operationalizing the occupant-centric concepts of health, comfort, and well-being; (2) the identification and measurement of appropriate IEQ proxies; (3) the multi-aspect nature of indoor environmental exposure situations; (4) the diversity and dynamic nature of occupants' dispositions and needs; and (5) the real-life complexities of practical standardization procedures.

The intention of this chapter is not to identify and lay bare IEQ standardization's implicit logic based on unreasonable expectations. Obviously, it is unlikely that the underlying theoretical and evidentiary basis of the multitude of relevant indoor environmental regulatory systems and documents could be reduced to a single scheme or formula. Nonetheless, there is a recurrent pattern, familiar from fields such as physiology, medicine, and psychology. This pattern can be characterized as follows. The values of selected variables thought to represent salient features of the indoor environment are mapped to the values of selected indicators of occupants' health and comfort. The mapping operation is typically based on a mix of two complementary ingredients, namely (a) some physiologically or psychologically grounded theory and (b) available experimental data from research involving human participants. Whereas in cases involving explicit comfort equations (e.g., thermal comfort, visual discomfort), the codes include concrete constructs representing occupant health and comfort (together with their mandated value ranges), in other cases such constructs may not be explicitly present. The de facto assumption in such cases appears to be that by virtue of keeping the relevant indoor environmental variables (e.g., carbon dioxide concentration in the ambient air) within certain ranges, the terms relevant to occupants' health and comfort are met.

There are three notable implications of the preceding discussion about standards and their future development. First, notwithstanding the need for a differentiated stance, the path from standards to their underlying evidentiary basis should be recognized as at times intractable. This bears the risk of reducing standards and their mandates to inscrutable instructions that are followed unreflectively, rather than viewing them as sources of deep guidance for enlightened practitioners. This is not to suggest that standards must reproduce the entire theoretical foundation and scientific data they rely on. As regulatory instruments, they justifiably need to focus on operational matters and concrete instructions. Still, it would not be unreasonable to expect that standards could ideally represent a link between objective, scientifically based sources, and practical instructions. For example, within the German medical field, guidelines clearly acknowledge the procedure to summarize available knowledge, the resulting consequences, and the level of confidence or agreement regarding these points (e.g., Sammito *et al.*, 2014).

Second, in tracing back the standards to their explicitly specified or implicitly indicated sources in theories and data, various limitations stand out. Looking at the state-of-the-art in research on human health, comfort, and well-being issues reveals a continuously evolving field confronted with various challenges and uncertainties. Whereas respectable scientists in this area habitually abstain from doctrinal standpoints and absolute truth claims, regulatory bodies are obliged to boil down what is known to what is mandatory. In other words, to avoid a chaotic situation in the building design, construction, and operation processes, IEQ standards tend to adopt concrete thresholds and specific limits, even if the underlying science is not entirely conclusive. The concern appears to be that the compliance verification processes would become difficult otherwise, if not unfeasible.

Third, the diagnosed challenges of the IEQ-related regulatory frameworks, particularly the paucity of explicit theoretical reasoning, reflect also, at least to a certain degree, the gaps in scientific understanding in this area. There are uncertainties about what physical features of the indoor environment are the "right" variables for health and comfort evaluation processes. There are even more challenges concerning the definition and robustness of the constructs for health and comfort, which insufficiently address the interdependence of physiological, psychological, and even social dimensions of occupants' perception and evaluation of indoor environments. Datasets used for testing and validating perceptual and behavioral theories are limited. The pragmatic dissection of IEQ into distinct domains may fall short of capturing the realistic and inherently multi-domain nature of indoor environmental exposure situations. The current understanding of the extent of occupants' diversity and the dynamics of their requirements has been improving, but perhaps not enough to consider their reflections in the current IEQ standards as sufficient.

The implication of these observations may come across as a truism, but it is a critical one: the study of IEQ-related regulatory frameworks not only reveals their limitations, but also points to gaps in the current state of scientific understanding regarding occupants' needs and preferences in indoor environments. There is a need for a more transparent, traceable, and objective process when translating the current state of scientific knowledge, limited as it may be, into IEQ codes and standards. At the same time, there is also a need to advance and enrich understanding of how human health, comfort, and well-being are influenced by conditions in indoor environments. A number of knowledge gaps in the theoretical understanding of occupants' perceptions of IEQ, as well as related behaviors and interactions with indoor environments are further addressed in the following section.

2.4 Ongoing Work and Open Questions

There is a complex relationship between occupants and the buildings they inhabit, as outlined in Section 2.2. As previously mentioned, IEQ factors such as glare and thermal comfort may impact or drive behaviors, and these building interactions, whether misguided or not fully considered, may impact IEQ factors for other occupants (e.g., comfort) or building outcomes (e.g., energy performance). This section discusses select challenges related to the above topics, as well as viable solutions. Many of the presented concepts are less studied or understood and/or less firmly established or agreed upon when compared to many of the scientific theories presented earlier in the chapter; still, they are all extremely important factors in the design and operation of buildings and are not intended to be downplayed.

2.4.1 Adaptive Thermal Comfort, Perceived Control, and Personalized Control

One challenge in the domain of IEQ and occupant needs relates to occupant control (real or perceived) of building interfaces. A problem may occur when designers perceive building automation as an all-or-nothing situation, or a 0/1 decision where "1" is fully automated (no occupant control) and "0" is no automation (full occupant control). As a solution to this dilemma, there may be a blend of automation and manual control that is most beneficial for IEQ and energy outcomes. These types of solutions are addressed through, for example, hybrid ventilation (Parkinson *et al.*, 2020) and OCC, which are further discussed in Chapter 10. The best solutions may seek a balance of control to best accommodate occupant health, IEQ needs, and energy goals. For example, adaptive thermal comfort, perceived control, and personalized control may all be solutions, in no particular order. Another problem occurs when the level of automation is set in direct relation with the level of energy efficiency (as done in, e.g., EN 15232) in a way that higher automation is unconditionally related to higher energy efficiency.

There have been many models and theories of perceived control, and ultimately, most research has found that occupant satisfaction and perceptions of IEQ are higher when occupants perceive that they have control over their environment (real or perceived). There is agreement that perceived control may lead to positive outcomes (Hellwig, 2015; O'Brien and Gunay, 2014; Yun, 2018) and that designers should be encouraged to consider and implement perceived control strategies. However, perceived control may only be a short-term solution. An even better solution is to encourage designers to give occupants actual control of building interfaces that are not hidden, easily accessible, and intuitive to understand (see Chapter 9). For example, in one study (Brager *et al.*, 2004), occupants were provided with differing degrees of personal control over their windows (with four stages ranging from direct control to no control). Participants showed significant differences in thermal responses, where those with a higher level of control also had higher ratings of personal comfort, even under the same conditions (thermal environment, clothing, and activity levels). Findings from this study illustrate clear support for the adaptive model of thermal comfort (Brager *et al.*, 2004). While most engineers can agree for instance, that personalized controls are beneficial to occupant outcomes, there is still more work to do in terms of how access to controls really impacts people's decisions, perceptions, and behaviors and how all these factors may be impacted by multi-domain aspects and drivers. Some research has begun to address these (e.g., Mahdavi *et al.*, 2020), but more work is needed to identify clear parameters and solutions, especially in real-world scenarios and conditions. In addition, this topic appears to be close to absent in existing standards and guidelines.

2.4.2 Energy, IEQ, and the Human-Building Interactions

While some designers choose to remove control, as addressed above, in most cases, occupants are typically expected to adjust their interior environment to maintain personal thermal and/or visual comfort, environmental satisfaction, and so on. However, issues may emerge when occupants control or manipulate the building in ways that designers did not intend and/or foresee. For example, if controls are not well thought out, or if occupants do not understand how to use their building effectively to achieve or maintain comfort, occupants may disable or override building interfaces-related IEQ factors such as windows and lighting. For instance, an occupant may duct tape over or cover an air vent, block a sensor, and more (see Day and O'Brien, 2017). At the same time, occupants may have needs not anticipated by the designer. Uninformed occupant behaviors can compromise energy-saving goals, building operation costs, worker productivity, and occupant health, especially when occupants do not always understand how to operate building interfaces (Day and Heschong, 2016; Day and O'Brien, 2017). See Chapter 9 for interface characteristics that better facilitate adaptive opportunities.

To maximize occupant comfort and minimize costs associated with productivity and energy use, at times, occupants may need education on building control interfaces and expected behaviors. Many current occupant behavior change programs implement feedback, motivation, and gamification (Jain *et al.*, 2012; Papaioannou *et al.*, 2018; Vassileva and Campillo, 2014), but studies have found that occupants may still not fully understand how their actions may impact others or the conditions within their space. A better scenario is to design the building interfaces in a way that is thoughtful and intuitive and enables occupants to fulfill their needs so that occupants do not require "training."

Although many "human-in-the-loop" approaches do indeed consider humans and behaviors, these methods are often about machines learning from humans and their behavioral patterns as opposed to humans learning the "right" behaviors—an important distinction. Behaviors and preferences may and should vary; however, there are ways in which designers can strive to design to enhance occupant outcomes and minimize unintended occupant interactions (e.g., occupants taping over sensors, tricking thermostats with popsicles [Day and O'Brien, 2017]).

Therefore, there is a critical research need to better understand: (1) how occupant interactions with building controls affect associated building energy use in a real test bed building scenario; and (2) how to best design buildings and interfaces to create and foster informed interactions, while also educating and engaging occupants as needed. The fundamental role of building interfaces and their associated characteristics on occupant interactions have not yet been thoroughly addressed in building or social science research. More importantly, existing occupant behavior models do not consider multiple layers of comfort (e.g., thermal, visual, acoustic, and IAQ) or other drivers/triggers of behavior (e.g., privacy, lack of understanding) that may affect occupant interactions with human-building interfaces. Chapter 9 further discusses specific characteristics, design recommendations, and solutions related to some of these issues related to building interfaces that might further encourage beneficial actions or deter counterproductive interactions.

2.4.3 Interaction among IEQ Domains and Other Factors

Many technical and design solutions rely heavily on solving one primary IEQ solution, and these are often founded on strong scientific foundations. However, some existing technical solutions do not necessarily translate into practice, or perhaps they were founded in a laboratory or experimental settings and are not fully applicable to real-life scenarios where other uncontrolled variables are present. This interaction among other IEQ domains, or lack of testing in field settings, may create unintended consequences or lack of understanding during design. For example, theories in the visual comfort domain often cite glare as a determining factor for blind use patterns (e.g., Day *et al.*, 2019; Reinhart and Voss, 2003). Glare is indeed one key indicator of blind use; however, additional factors may also come into play that are difficult to predict and/or model, such as privacy, job type or needs, inaccessible controls (Day *et al.*, 2012), as well as other IEQ or comfort-related driving factors, such as thermal comfort (Frontini and Kuhn, 2012). In these cases, there are certain factors and relationships among IEQ variables (multi-domain) that have not yet translated into practice—primarily because research is not conclusive regarding how IEQ factors impact one another or the occupant's experience or behaviors.

The challenge is thus the complex relationship between multi-domain aspects of IEQ. For instance, as cited in the example above, opening the blinds to allow for increased illuminance or visual comfort might also lead to a great deal of thermal discomfort. Other features that may improve daylighting, such as low partitions, open spaces, reflective and hard surfaces, and narrow floor plates may also increase instances of acoustic discomfort for occupants. There is much to learn, research, and further understand in terms of how these IEQ factors interact with one another, and how these interactions impact occupant behaviors. More research is needed to address an ever-growing list of questions, such as: How should occupant needs be related to one another? In design (and operation), which form of IEQ should get priority? How is a designer to navigate the various IEQ calculations and standards for a given design decision?

Some of these questions have been swirling around in the minds of researchers for years, and there have been a few efforts to better understand these multi-domain interactions (Bourikas *et al.*, 2021; Mahdavi *et al.*, 2020; Schweiker, Ampatzi *et al.*, 2020), yet there is still more to do.

2.5 Conclusions and Outlook

In this chapter, we first explored the relationship between human needs and the elements of the indoor built environment. Using Maslow's characterization of needs, we explored examples of their interaction with IEQ and other design elements to set the basis for occupant-centric design. We followed the examples with a brief introduction of the pathway from sensory stimuli to human-building interaction via human perception. Next, we explored the status of standardization with respect to available scientific evidence and discussed the role of standardization for occupant-centric design. This discussion was important because standards and guidelines give guidance to designers and engineers, and yet their scientific evidence is often hard to grasp and their formulation a result of interactions between evidence-based recommendations and additional considerations. The challenges and solutions we presented in the third and final part of this chapter included aspects related to perceived and personalized control, levels of automation, energy use, and interactions between the individual sensory domains. These ongoing works and open questions we proposed are certainly not exhaustive, and understanding the right balance of manual vs. automated building interfaces, perceived vs. actual control, occupant expectations, multi-IEQ-domain influences, and other factors that contribute to occupant-building interactions is key to designing for both IEQ and energy outcomes within the context of occupant-centric design.

2.6 Closing Remarks

The first step toward occupant-centric building design and operation is a fundamental understanding of the relationship between the built environment, IEQ, and occupant needs. This chapter started with an overview of occupant needs from physiological needs to self-esteem. Individual needs were linked to the indoor built environment, including the four main domains of IEQ parameters: thermal, visual, acoustic, and indoor air quality. Next was a brief summary of mechanisms, from sensory input to human perception, and from human perception to occupant behavior. The second part of this chapter looked at existing standards and how they incorporate the large body of scientific evidence presented in the first part of this chapter. The third part addressed three topics still being discussed that need further work before conclusions can be drawn. The topics were: perceived control, the relationship between IEQ and energy, and the interaction between individual sensory domains. As such, this chapter laid the foundation for the following Chapter 3, which reflects on how to incorporate the occupant perspective into the building design process, and Chapter 4, which identifies ways to obtain the occupant perspective and needs to inform design. The topic of control and interfaces is further detailed in Chapter 9.

Notes

1 Despite many scholars presenting these needs in the form of a pyramid, the order of needs is not fixed; the order depends on external circumstances and individual preferences. Still, it is reasonable to consider them as different levels, and we will discuss them in order, starting from the most basic level. In addition, it is not required that the needs in one level are completely fulfilled before another one is activated or met (Maslow, 1954).

2 Note that air movement is typically referred to as wind speed outdoors and as air velocity indoors.

3 While CO_2 concentration is often used as an indicator for ventilation performance and overall IAQ, other direct effects of increased CO_2 concentration include decreased performance, e.g., decision-making (Satish *et al.*, 2012).

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3 Occupants in the Building Design Decision-Making Process

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Summary

In this chapter, we will discuss the challenges of integrating considerations of building occupants and occupant behavior into the decision-making process of building designers. We acknowledge the complexities of occupant-centric design within newly deployed information management systems and will propose a framework that integrates occupant considerations into these systems so that these considerations are robustly transferred from design to buildings in use while informing best practice.

3.1 Introduction

Building design practice is a complex scenario full of unknowns and permeated by liabilities. Contractual documents provide clarity on the information required by and for various members of the design team to enable ongoing design discussions and procurement. By framing design processes as the timely exchange of information between team members and different disciplines, in this chapter, we provide clarity on how occupants fit into these processes and how their needs can potentially be accommodated.

We open the chapter with a discussion of how recent changes in design practice that aim to facilitate performance and risk assessment in relation to legislation, regulations, and clients' portfolios can affect building occupants. We then examine the role of information management in coordinating these changes to propose how information and decisions about occupants could flow throughout the design process in a coherent and coordinated way. Next, we consider the impact of design decisions on occupants within built spaces, and then we provide an overview of design considerations affecting and affected by occupants, with a particular focus on the different types of interactions that occupants have within and with buildings as well as with the environment surrounding them. We close the chapter with a proposal for the construction of occupant-centric design patterns (OCDPs) that record and support information transfer regarding occupancy and occupant behavior throughout the design decision-making process and that can

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fit within and support current industry tools such as building information modeling (BIM) and building performance simulation (BPS).

3.2 Recent Changes in Design Practices

The occupants of a building will affect how the building performs; it is also the case that the way in which a building is designed, built, and eventually occupied will influence the behavior of its occupants. More specifically, how a building performs when in use will depend on how the building design responds to what the occupants need, the amount of control the building designers have afforded occupants, and how well the design team anticipated how occupants will want to use the building and its systems in the future. The way and extent to which occupants are considered throughout the decision-making process of any building design project depends on how design decisions are balanced to achieve overarching project targets, negotiated among project team members, propagated into the information flow of the design process, and subsequently revised as the project develops. Several stakeholders play a role and influence each other in this process, which is primarily shaped by the interests of the client (who may or may not be the occupant) and the procurement process put in place to design and deliver the project. In the following section, we examine the role of the client in shaping information about the likely occupants and the way in which this information propagates throughout different delivery design stages. The client's role is examined in the context of the most recent standards[1] and documents issued by professional accreditation bodies[2] (i.e., deployed in practice between 2018 and 2020) that push the construction industry to implement building information management systems as a true record of the design process from design and construction to buildings in use.

3.2.1 Occupant Information for Clients and Design Teams

The client is the "entity, individual or organization commissioning and funding the project, directly or indirectly" (CIOB, 2014:315) and therefore the ultimate decision-maker in the project. Clients might occupy the building, or they might own the building and let or lease the building to occupants (de Wilde, 2018). When the latter is the case, clients are very likely to see "buildings [as] financial assets that figure in forms of market exchange, the operation of which often revolves around shared conventions and agreed forms of standardized description, measurement and provision" (Cass and Shove, 2018:277). This perspective will be particularly true if building occupancy is anticipated to have a large turnover.

A project's ultimate goals always reflect the client's objectives. If the client is the occupant, the client's objectives align with the occupants' objectives; if the client is not the occupant, however, different scenarios are possible. It is always easier to obtain information about occupancy when the client is the occupant, as the client is consulted at different points throughout the design process to ensure the design objectives are aligned with the client's objectives. However, when the client and occupants are distinct, consultation with occupants rarely occurs, as they are either unknown or out of the scope of the client's objectives for various reasons (capital costs, operational costs, etc.).

Different types of information about occupants are used throughout the design process. Table 3.1 illustrates the types of information, their source, examples, their role in practice with regard to their relevance to projects, and their respective impact in contractual arrangements and responsibilities. Mandatory information about occupants (e.g., from building regulations) is always required and considered an important milestone for project approval. Projects also commonly use normative information (i.e., evaluative standards) about occupants, as, for instance, energy performance and comfort standards (e.g., ASHRAE 90.1) are generally used to set project targets, and ergonomics information forms part of the vast majority of project layout proposals. Parts of normative information may be overwritten by business-oriented information (e.g., client's operational targets) and/or lessons learned (e.g., metering, monitoring, post occupancy evaluation (POE)) and/or information from consultations with occupants, especially in cases where the client is the occupant. However, overwriting based on lessons learned and/or consultations with occupants is unlikely to happen if the client is not the occupant, as this process requires special contractual and project management arrangements in which risks and liabilities are shared. Chapter 2 of this book discusses the origins of occupant data in normative information in more detail, while Chapter 4 discusses several methods useful for consulting occupants. Chapters 6 and 7 explore in depth how lessons learned can be generalized and used in new design projects from an engineering perspective through the development and applications of occupant behavior (OB) models.

Performance-based legislation and regulations are starting to more emphatically promote the use of lessons learned in new projects toward developing fit-for-purpose design, as occupants play a key role in influencing operational efficiencies. The phases from design to buildings in use are now being seen as a continuum (BSRIA, 2018), with targets set up during the design process and verified through monitoring during the operational phase, which places joint responsibility on the client and the design team in terms of their needs and aspirations for the occupants.

In an attempt to ensure information transfer from design to buildings in use, plans of work are being modified to include information management standards related to building design and construction (EN ISO 19650-1, 2018; EN ISO 19650-2, 2018; EN ISO 12006-2, 2020) as well as asset management standards (EN ISO 55002, 2018; EN ISO 19650-3, 2020). These changes are further supplemented by documents such as BSRIA Soft Landings (BSRIA, 2018), which was written specifically to support construction

Table 3.1 Types of information about occupants used in practice, with examples and their source, relevance to projects, and impact in practice

Type of information	*Source*	*Examples*	*Relevance to project*	*Impact in practice*
Mandatory	Building regulations, codes, and legislation	Health and safety, universal accessibility, fire evacuation, etc.	Ensure minimums are met, protect occupants' rights	Enforced in every project
Normative	Standards and handbooks	Ergonomics, predicted energy use, carbon emissions, visual and thermal comfort, effect on performance measures of occupant uncertainty, etc.	Set targets (energy, comfort, occupant satisfaction, etc.), replace missing bespoke information about occupants, reduce uncertainties	Cover for practitioners' liabilities
Business-oriented	Client	Energy demand management, client's expectations for occupant behavior, building function and activities, occupant density, etc.	Ensure client's objectives are met, control running costs	Define client's responsibilities
Lesson learned from metering and/or monitoring and/or POE	Client Practitioner	Energy use profile, indoor air quality, occupant satisfaction, preferred adaptive opportunities, etc.	Aid in fit-for-purpose sizing, reduce scope of building operation, reduce running costs	Cover for practitioners' liabilities Require risks and liabilities to be shared in contracts
Consultations with occupants	Building occupants	Bespoke layout, environmental quality, etc.	Provide bespoke information about usage and occupants' needs, requirements, and aspirations	Resolve liabilities (client/occupants) Require risks and liabilities to be shared in contracts ('speculative' client)

clients to incorporate core principles in procurement. However, little is prescribed in terms of how information should be transferred from design to operation, and no methods are yet available to record such information transfer. Currently, it is up to contracts and the client to set roles and responsibilities so that operational phase activities and performance targets can be agreed upon realistically and in consonance with design objectives and desired operational outcomes.

These changes, once fully implemented, will have a significant impact on the construction industry. They will not necessarily ensure better buildings, as their aim is to increase the client's power in decision-making and affect decisions related to project targets from inception to project delivery. Still, these changes will demand robust coordination of information throughout a project's life and form an important record for project quality control for future auditing for liability purposes, thus enabling decisions to be clearly traced back to the project team.

3.2.2 Information Flow on Occupants throughout Project Delivery Stages

Information verification, validation, and quality control methods should be established within project documentation, together with risk management (EN ISO 19650-2, 2018; EN ISO 19650-3, 2020). Project information requirements should include demand management and customer expectation policy, energy efficiency and environmental aspects, plus performance monitoring, safety, health, and environmental management. Table 3.2 illustrates where and how the different types of information identified in Table 3.1 inform the different design stages using documents from two different countries (the UK and USA) as examples. Only the stages related to design are shown and since they vary country by country as a function of when planning application and building regulation approval is needed, they are generically defined according to (EN ISO 12006-2, 2020) as pre-design and design.

As shown in Table 3.2, plans of work are fluid with regard to the granularity of information to be provided at each design stage. This fluidity is because information delivery is closely related to procurement routes and contracts, which are the legal instruments used to set roles and responsibilities and that specify project deliverables (milestones, strategies, data, etc.), information approval and authorizations, and information exchange at different design stages. Information delivery plans contained in contracts describe the breakdown of tasks, roles, and responsibilities throughout project teams in addition to where information about occupants should be provided throughout the design process.

Procurement strategies affect information requirements, high-level objectives for the project and future building operation, information exchange, how the design team will be appointed, and the technical design stage and how it overlaps with the construction stage. In this context, information

Table 3.2 Examples of different types of information about occupants deployed throughout different design stages

Documents by professional accreditation bodies	*Pre-design*		*Design*		
RIBA Plan or Works 2020	**Strategic definition**	**Brief**	**Concept design**	**Spatial coordination**	**Technical design**
	Business-oriented information to be checked against information from **lessons learned**	Incorporate **lessons learned supplied by the client** into brief, targets, and POE requirements	Generate risk assessment report; review concept design and Facility Management (FM) plans **based on lessons learned;** run energy and other simulations	Test performance requirements through **consultations** with design team, FM, occupants, and contractors; coordinate spatial information related to it; set plan of use protocol and develop POE for procurement	Use risk assessment to quality control detailed design and contractor's proposal; use plan of use to prepare tendering information
AIA Sustainability Plan 2020 and AIA BPS Guide 2019[a]	**Preliminary design**		**Schematic design**	**Design development**	**Construction documentation**
	Define code compliance to be achieved (i.e., **mandatory information**) and environmental framework to be used; refer to **normative** information (e.g., LEEDS, LBC); establish vision statements to resonate with all stakeholders involved in the project; promote the use of **business-oriented** information, **lessons learned, and consultations**		Establish fundamental components of the project, including preliminary systems; analyze systems through modeling if possible; design for typical operation (considering benchmarking, i.e., **normative information** from standards) and space flexibility; promote occupants' participation through **community consultations**	Integrate technical knowledge and information to refine a design; refine the proposal involving consultants and specialists using simulations; ensure access to daylight and natural ventilation with openable windows	Refine energy model to represent final design decisions, ensuring occupant-based controls for immediate environment; develop POE plans to check targets to be achieved and **collect lessons learned**

a AIA BPS Guide (AIA, 2019) recommends the type of simulation appropriate for each design stage and AIA Sustainability Plan (AIA, 2020) refers to how sustainability information can be embedded in different types of contracts, without being specific about which design stage this information belongs to. Data from Table 3.2 are therefore inferred by combining these two documents.

management systems are defined by the market and for the market, and performance targets are a function of asset management rather than a response to environmental concerns. However, information management does bring benefits, especially in the context of integrated design process (IDP) guidelines (Sustainability Solutions Group, 2010) and integrated project delivery (IPD) roadmaps (AIA, 2007), which inform management strategies and steps to better integrate project goals related to social, ecological, economical, and sustainability performance. IDP and IPD can be connected to contractual documents to justify the implementation of shared risks and liabilities which would, in theory, facilitate and promote the use of lessons learned and consultation with occupants. There are clear opportunities to promote better design in this new reality, but uptake in practice is still very low (Piroozfar *et al.*, 2019), which potentially calls for stronger governmental intervention.

Lately, practitioners are under pressure to document their decisions, as building information management systems are increasingly framed as reflections of a true record of the design process and gradually being implemented into performance legislation and building codes. However, information management frameworks, procurement routes, project management approaches, and guidelines to practitioners do not provide methods to support the transfer of information about occupants in integration with performance management throughout building projects. Records of these decisions are normally found within project documentation, but they could be better linked with the tools used in design, particularly BPS and BIM. To the best of our knowledge, there is no recognized method for documenting information about occupants and occupant behavior that enables it to be properly inserted into BIM models and coherently transferred to BPS models. This gap increases risks in decision-making for project teams while at the same time hindering the implementation of integrated project delivery toward producing better buildings.

3.3 Methodology: A Place for Occupants in Information-Centric Frameworks

Design decisions related to occupants and occupancy must be considered within the context of information management. Documents issued by professional accreditation bodies have been revised (Table 3.2) and amended to include the deployment of information management systems throughout plans of work to bridge fundamental gaps in information exchange between the design and construction phases of a project. These revisions and amendments establish that information exchange needs to happen in a comprehensive digital model that, in theory, facilitates design for manufacturing assembly and allows for constant refinement until it becomes an asset management model. This digital model, also called a federated model (BIM), is structured to mirror the different disciplines involved in a building project.

This structure enables information exchange and design decision-making to be better controlled and coordinated by the design team. To this end, an efficient way to transfer information about occupants throughout the design team is to connect them with the objects of this federated model. Objects can contain information that is required on almost all projects (e.g., construction assemblages, room usages). Tucker and Bleil de Souza (2016) proposed that objects can also incorporate descriptions of repeatedly used simulation methods (see Chapter 8 for example), occupancy profiles, design requirements, design aims, design decisions, and so on. Often, these objects are used repeatedly on different projects and so could be recorded and held in a library to be retrieved (and possibly modified) by the design team when needed. BIM uses a specific object-oriented structure (EN ISO 12006-2, 2020) consisting of the following objects, all of which can be related to occupant considerations (see Section 3.5):

- *Construction entities* are basic units in the built environment with boundaries clearly defined by a characteristic form and spatial structure and hosting several functions and user activities; in other words, they are the building being designed.
- *Built spaces* are spaces clearly defined by the built environment to host specific user activities and/or equipment and can be classified as spaces for human activity (e.g., living, work, production), storage (e.g., materials, equipment), infrastructure (e.g., routing, transportation), or technical systems (e.g., operational technique, production equipment).
- *Construction elements* are the different components of a construction entity with distinguishable function, form, or position (e.g., wall construction system, furniture system, cooling supply system).
- *Construction properties* are attributes of a construction element, built space, or construction entity and can be classified according to functional (e.g., thermal performance, structural performance), spatial (e.g., shape, size), temporal (e.g., duration), compositional (e.g., assembly, behavior), experiential (e.g., color, comfort), symbolic (e.g., meaning), and administrative (e.g., price, style) properties.

Expanding on these four objects, the following two sections examine, generically and through examples, different types of design aims, requirements, considerations, and decisions—more specifically, how occupants affect and are affected by them when interacting within and with the construction entity as well as with the environment (natural and built) of the wider site. Two levels of information are provided: coarser information for decisions related to construction entities and built spaces, followed by more refined information related to construction elements with their respective construction properties. Section 3.6 presents a template to produce occupant-centric design information that captures decisions and objects in context and in connection with BPS tools. The rationale behind the template is that information about occupants can be deployed into practice in connection with building performance assessment methods using an object-oriented structure.

3.4 The Impact of Design Decisions on Occupants within Built Spaces

The overall impact of design decisions on the occupants of built spaces depends largely on how the client and the design team translate their needs and aspirations for the occupants throughout the design process. Mandatory, normative, and business-oriented information about occupants, potentially combined with lessons learned and consultations with occupants, is interpreted by designers and translated to built spaces, thereby constraining and persuading occupants to use buildings or interact with them in specific ways, but also framing affordances and opportunities for these occupants.

Designers impose ***constraints*** (either consciously or unconsciously) on occupants. Constraints can vary from, for example, the control of environmental systems to the lack of flexibility or adaptability of how occupants can use spaces. Several restrictions in controls come from mandatory and normative requirements together with business-oriented requirements and make use of lessons learned to constrain occupants' use of the building to the way clients intended it to be used. These constraints often result in removing personal control from occupants in favor of automated-only controls supported by energy efficiency standards (EN 15232, 2017).

Persuasive strategies are also starting to become part of design agendas, especially with the wider implementation of automation and smart controls that impose conditions without allowing for occupant override. These strategies, potentially heavily influenced by business-oriented information (e.g., client expectations for occupancy behavior) and supported by normative energy efficient guidelines (e.g., predicted energy use), might give designers the false impression that occupants can be persuaded or directed toward specific behaviors. They neglect the fact that occupants' adaptive needs are driven by behavioral needs (mainly motivated by internal stimuli, see Chapter 2) and change with context and time varying among different people. An iconic example is the known rebound effect in which energy efficiency measures are less effective than predicted because occupants keep energy consumption constant by increasing temperatures and/or the number of appliances in the household (Guerra Santin, 2013).

Affordances are what the building offers its occupants, including the environment the occupants inhabit as well as the way of life or actions possible within this environment (Gibson, 2015). Affordances are directly perceived by the occupants and should therefore require minimal cognitive effort and no explicit instructions, as they are dynamic and open to multiple interpretations (Kannengiesser and Gero, 2012). Affordances include the intended effects a design has on building usage as well as the unintended effects it has

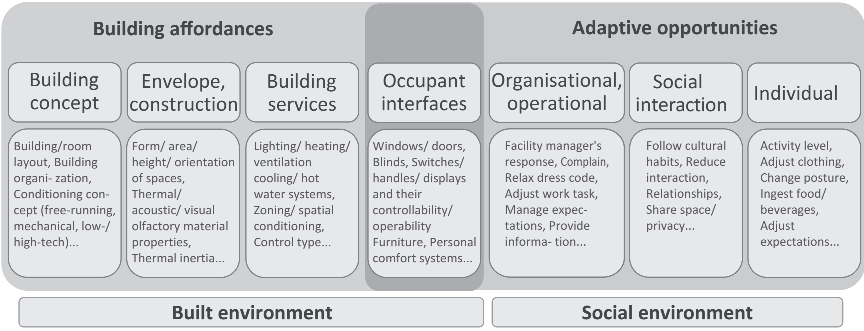

Figure 3.1 Building affordances and adaptive opportunities in the built and social environments.

on how occupants use the building. Sometimes the intended effects do not cover all areas of interpretation by occupants, and sometimes they contain misconceptions of how the occupant will interact with the building, especially when occupants are not consulted in the design process.

Therefore, designing a building that is significantly shaped by the way people live (Alexander, 2002) can only be achieved if designers put themselves in the position of the occupants (Gibson, 2015) and are able to predict expectations and adaptive needs that might occur within the spaces (e.g., feelings, perceived options). These adaptive needs trigger behavioral needs, which will be shaped by what is afforded from the built and the social environments. Consequently, when designing for the occupant, designers need to keep ***adaptive opportunities*** in mind (Figure 3.1).

The term adaptive opportunities, first coined by Baker and Standeven (1997), became a key concept in comprehensive thermal comfort (de Dear and Brager, 1998; Humphreys and Nicol, 1998) and its manifestation in practice is in line with what is defined by Alexander (1979) as the 'quality without a name'. The adaptive opportunities design process (Hellwig *et al.*, 2022) proposes to establish the occupants with their adaptive needs in the building's context (local climate, building type, human context, and local constraints) so that designers can put themselves in the occupants' position. Lessons learned and consultations with occupants can provide valuable information to design adaptive opportunities, especially in speculative buildings; still, far more is needed to increase their uptake in practice, as they require risks and liabilities to be shared in contracts.

3.5 Decisions Affecting or Affected by Occupants

Decisions affecting or affected by occupants are at the core of the design process and mainly depend on overarching strategies set up by the client and design team for the construction entity (i.e., the building). These strategies result in further decisions that define affordances, adaptive opportunities, and constraints and persuade occupants to interact within and with a building and its spaces. Thus, once the climate, site, building type, and overall conditioning strategy for the building are understood and defined, the design team must make a series of decisions related to how occupants will interact within and with the construction entity as well as with the environment (natural and built) of the wider site. These interactions are complex and context-based, but design decisions about the building can be thought of as "typical," as the design team has a finite number of construction elements and construction properties to manipulate toward achieving the project goals (Bleil de Souza and Tucker, 2015).

Table 3.3 presents a list of construction entities and built spaces about which design decisions are made by design teams. Table 3.4 refers to construction elements and their respective construction properties. Both tables are generic with regard to clients' overarching targets, constraints and requirements, procurement routes, and project management approach, and they both illustrate how design decisions related to the building, its spaces, and its elements can affect occupants. The tables are not exhaustive and contain design decisions expanded from Bleil de Souza and Tucker (2015) with the support of activities listed in BIM Forum (2019), RIBA (2020), and Yan and Hong (2018; Tables 8.2.4 and 8.5).

Some of the examples presented in Tables 3.3 and 3.4 are common across all buildings, whereas others are clearly context-based. They presuppose that designers have good information on how the building will be used, regardless of any direct involvement with its occupants, and they are non-specific in terms of what type of construction entity, built space, or construction element is being specified. They highlight the richness of the building design process and how design decisions are thoroughly interwoven with occupant interactions, thus showing that the integration of occupant behavior in design decisions is a non-trivial proposition and can be heavily context-dependent, requiring concerted decisions across different disciplines to address intangible and unquantifiable objectives.

Table 3.4 shows that once construction elements and their respective construction properties are examined in relation to the same types of interactions as explored in Table 3.3, design decisions gradually become more specific and detailed. Therefore, if consideration of occupants is to be integrated into design practice, then design teams need to be prepared to record information about occupants throughout the design process in a structured way so this information can be easily recalled as design progresses.

For example, when designing an art gallery, a designer has passive heating and cooling as the overarching strategy set up by the client, they will need to ensure that the appropriate internal conditions can be met as the design progresses. This strategy needs to be recorded as part of project information in an easily retrievable format so it can be referred to by other

Table 3.3 Examples of decisions related to construction entities and built spaces with examples of design aims/requirements/considerations/decisions that affect or are affected by occupants

Decisions undertaken in relation to construction entities and built spaces	*Examples of design aims/requirements/considerations/decisions*		
	Effects on occupants *within* the building	**Occupants' interaction *with* the building**	**Occupants' interaction *with the environment of the wider site*, through the building**
Building form and volume	Convey a sense of place; Display the status of the building owner	Create exhilarating spaces; Ensure a feeling of 'coziness'; Minimize heating/cooling costs of the building	Help shape the street; Configure outdoor courtyards; Integrate with landscape
Building footprint on site and orientation	Provide places for children to play in the sun; Shape secluded spaces for people to interact outdoors and with each other	Provide clarity of access; Create useful outdoor spaces integrated with the street	Minimize environmental impact on the site; Protect from solar overheating; Lower impact on neighbors' right to light and sun; Take advantage of cooling breezes
Program distribution and orientation	Allow for flexibility in separating or joining rooms; Consider public/private interactions	Determine the relationship of noisy/ quiet, day/night spaces (e.g., isolate the bedrooms from the living area); Orientate spaces with regard to heating and cooling needs	Provide daylight, natural ventilation, and view to the outside for the main living spaces; Enable patients to see the day go by; Enable visual contact with nature
Form and area of building spaces	Provide office workers appropriate visual/aural contact with each other (e.g., open plan cellular/ offices); Consider a mix of functions (e.g., bar, dance space, seating)	Provide an efficient and clear circulation inside the building (e.g., functionality, escape, and evacuation routes); Ensure that spaces support functions	Provide a sense of connection to the outside (e.g., shallow office spaces); Let sunlight into bedrooms in the mornings

(*Continued*)

Table 3.3 Continued

Decisions undertaken in relation to construction entities and built spaces	*Examples of design aims/requirements/considerations/decisions*		
Fire and evacuation routes	Provide for safe evacuation of building occupants	Provide safe routes to the outside; Ensure clarity on emergency access	Provide the required access to external services (e.g., emergency vehicles, hydrants)
Floor to ceiling heights	Convey status; Provide views from the top (mezzanine)	Improve sound dispersion; Manage overheating (stratification)	Improve daylighting and sky views (e.g., large glazing); Facilitate segregated natural ventilation (e.g., above the occupant)
Heating and cooling system choice	Consider running costs for the client; Charge energy bills at room level (e.g., care homes)	Position systems to minimize furniture disruption; Reduce response time on conditioning the building; Consider passive heating and cooling strategies; Shift peak demand in relation to energy tariff	Minimize greenhouse gas emissions; Consider low energy technologies (e.g., heat pumps); Consider heat release and noise affecting pedestrians or outdoor recreation areas
Heating and cooling system demand	Ensure thermal comfort for the expected range of occupants (e.g., doctors and patients in hospital)	Ensure that temperatures and humidity are suitable for building contents; Provide 'thermal delight'	Minimize demands by taking advantage of the climate
Cooking system choice	Ensure that systems are appropriate to occupant's lifestyle (e.g., food type)	Provide appropriate ventilation system and cooking facility	Consider the environmental impact of fuel
Hot water system choice	Ensure that systems are appropriate to occupant's lifestyle (e.g., run a bath and do the dishes at the same time)	Ensure correct system sizing	Consider low energy technologies (e.g., solar hot water)

Table 3.3 Continued

Decisions undertaken in relation to construction entities and built spaces	*Examples of design aims/requirements/considerations/decisions*		
Ventilation system choice and demand	Consider different types of activities; Consider the number of occupants and type of occupancy	Consider occupant preferences (e.g., opening windows, HVAC, ceiling fans)	Consider natural/hybrid ventilation; Avoid outdoor noise; Filter outdoor air pollutants
Heating, cooling, and ventilation control type	Consider provision of shared and/or individual control	Consider provision of 'intelligent' controls; Ensure that controls are appropriate to occupants (e.g., elderly, children) and system type; Ensure that control are customized to activity	Provide climate responsive/ efficient controls (e.g., temperature sensors, Daylight responsive control)

members of the design team when decisions about passive heating and/or cooling are made. Since these decisions would often be made by using BPS to test potential design options (e.g., addition of shading, ventilation, insulation, thermal mass), they might be undertaken by a third party, meaning not only results and design modifications but also changes in occupancy assumptions need to be properly documented when information is handed back to the designer. This documentation is especially important when designing for adaptive opportunities, which are particularly useful in improving the performance of passive design.

Tables 3.3 and 3.4 show that occupancy-related information can potentially be linked to objects, which themselves can carry information back and forth to the design team. The level of detail embedded in each object increases as the project progresses, meaning information about occupants can be added to such objects at a number of appropriate levels and become written or read by different team members at different times. This process can be particularly useful when simultaneous decisions requiring different levels of detail are needed from different design team members; for example, when building designers are defining room internal layout and building service engineers are calculating bulk energy consumption to size equipment rooms. However, more research is needed to establish how these

Table 3.4 Examples of decisions related to construction elements and their respective construction properties with examples of design aims/requirements/considerations/decisions that affect or are affected by occupants

Decisions undertaken in relation to construction elements and construction properties	*Examples of design aims/requirements/considerations/decisions*		
	Effects on occupants *within* the building	**Occupants' interaction *with* the building**	**Occupants' interaction *with the environment of the wider site,* through the building**
Room layout/ furniture layout	Facilitate watching the children while having coffee (café); Create intimate sitting area (bar)	Create a 'sitting wall'; Increase the number of office bays; Guarantee sufficient privacy to undertake an activity	Avoid direct sunlight on sensitive artefacts (e.g., artwork, books)
Appliance layout	Provide a cooking island for people to gather around	Optimize the cooking processes	Ventilate to the outside
Interior finishes and colors	Ensure that the acoustics are appropriate to function (e.g., concert hall, call center, office)	Increase the ease and reduce the costs of cleaning; Consider the interior sound reverberation, absorption and reflection	Increase or decrease the daylight reflection
Transparent element orientation, placement/ dimensions/ properties	Facilitate sitting together in the sun; Provide a quiet space in the sun; Provide an area to watch the world go by; Display merchandise to passers-by; Display the activities of the building	Provide a reading area under a window; Enable occupant to sit close to a window without feeling cold; Ensure that the type of light does not disturb the human circadian rhythm	Frame an outdoor view; Increase the solar intake; Consider incoming light properties (e.g., spectrum, diffusion, direct/ indirect, color); Consider the inside/outside relationship

Table 3.4 Continued

Decisions undertaken in relation to construction elements and construction properties	*Examples of design aims/requirements/ considerations/decisions*		
Transparent element operation	Enable the sitting area to be part of the street; provide an opening window to talk to someone in the street	Consider window operation (fixed/openable); Provide operation appropriate to occupants (e.g., the elderly, children)	Consider the inside/ outside boundary (e.g., sliding glass wall)
Opaque elements construction and properties (floors, walls, roofs)	Segregate circulation using physical barriers to ensure on-way systems	Provide sufficient thermal mass in a room for comfort; Consider radiant temperature of surfaces to improve comfort	Protect cavities against pests; Consider required integrity of building envelope
Shading device type, dimensions, and areas	Enable sitting in shade on a sunny day	Consider possible interaction of shading with indoor climate control (e.g., internal shading devices and operability of window)	Avoid direct sunlight on sensitive artefacts (e.g., art works, books); Consider obstruction of outside views
Control of shading device	Consider individual/ group/no control; Consider combination of automatic control with override	Ensure ease of shading use; Ensure accessible control	Ensure operation is suitable for all sunlight conditions
Glare protection and control	Enable occupants to see each other (e.g., children to see the teacher and board)	Protect sensitive areas (e.g., computer workspaces; museum displays	Obstruct views prone to glare (e.g. outdoor pavement, reflective glazing/surfaces)

(*Continued*)

Table 3.4 Continued

Decisions undertaken in relation to construction elements and construction properties	*Examples of design aims/requirements/ considerations/decisions*		
Artificial lighting type and layout	Enhance jewelry shining; Use best daylight spectrum to display food (e.g., enhance the yellow in the cheese (pizzeria) and the red in the meat (butcher))	Spotlight a work of art; Reinforce the circulation path; Provide task lighting; Ensure visual comfort	Complement daylight illuminance; Replace daylight when needed; Mimic daylight at night
Artificial lighting system control	Enable individual lighting control (task lighting)	Use presence detector sensors	Provide dimming according to daylighting
Ventilation system equipment zoning and layout	Remove food smells; Remove excessive sweat from the gym	Remove chlorine from the swimming area; Remove VOCs; Avoid discomfort (e.g., in sitting areas)	Coordinate perimeter ventilation (natural) with mechanical ventilation
Heating and cooling system equipment zoning and layout	Reconcile gender and cultural requirements (e.g., in offices); Reconcile age requirements (e.g., in nursery, care homes)	Ensure thermal comfort; Consider internal gains	Consider perimeter heating (e.g., if windows can open)

links can happen, especially considering BIM and BPS have different ontologies. In any case, if decisions affecting or affected by occupants are recorded and manipulated in an object-oriented environment, information about occupants and their behavior can be documented through links between these objects. Pathways with these links can therefore be traceable and provide evidence-based information to clients and design teams in future projects.

3.6 Occupant-Centric Decisions in Context

This section presents a template for producing occupant-centric design information that captures decisions and objects in their design contexts. The purpose of the information is to demonstrate to designers how a design problem (and its solution) can affect or be affected by occupants. This information could be attached to or associated with the relevant construction entity or built space, but it could also be linked to relevant construction elements and construction properties. The information is presented to the designer in the form of a design pattern, following the initial concept developed by Alexander, Ishikawa, and Silverstein (1977) and Alexander (1979) and further adapted by Bleil de Souza and Tucker (2016) and Tucker and Bleil de Souza (2016). When the template is instantiated with information relevant to a particular design problem and context, it becomes a design pattern.

Occupant-centric design patterns (OCDPs) describe common situations where design decisions will affect occupants and describe design solutions that will take occupants' needs into account. Alexander and colleagues' original set of patterns (Alexander *et al.*, 1977) described abstract solutions to common abstract problems that designers encounter in the built environment. These problem-solution pairs are a powerful way to transfer and share knowledge as well as provide quality control for design solutions. They enable expert knowledge that is normally deployed in a tacit form to be formalized, stored, and accessed by novice designers or non-experts.

This way of recording information has been highly influential in computer science, where proven solutions have been developed for common coding problems, and there is a need to make these solutions available to novice programmers to reduce coding time and maintain quality. Design patterns have also inspired developments in object-oriented programming by treating programs as a number of self-contained objects that are linked to other objects (Gamma *et al.*, 1994; Buschmann *et al.*, 1996; Fowler, 2002), and they continue to be used in computer science (e.g., Lakshmanan, 2020) to capture best practice. We propose that design patterns are used to better integrate consideration of occupants' needs into design processes.

Each design pattern describes one problem-solution pair with instructions for how to use it, examples of its use, descriptions of the contexts in which it is used, and links to other related patterns. For any particular building project, a number of appropriate patterns are selected. They can be adapted into an object-oriented model, as the pair problem-solution is structured in a consistent and reproducible way and can be linked through the BIM system to a building model.

The structure of patterns was developed by Bleil de Souza and Tucker (2015) to encapsulate expert knowledge for BPS. This structure is further developed to integrate relevant occupant-related information (e.g., models to be used, analytical processes) and make them available to building designers in a user-friendly way. There are already strong connections between simulation and occupant profiling; for instance, Hong *et al.* (2016) recorded occupants' interactions with buildings and considered the types of action undertaken with the potential drivers behind them. They propose an

Table 3.5 Template adapted from Tucker and Bleil de Souza (2016) for the content specification of an OCDP

Index	Index or code to store the proposed pattern in a database for retrieval into a BIM environment. Index could refer to building type, design actions, analytical methods, climate, type of human/building/environment relationship, etc.
OCDP name	Name should clearly reflect the abstract problem-solution pair and can refer to building typology, specific design actions, design goals to be addressed, analytical methods, outputs required, type of human/building/environment relationship, etc.
Introduction	Situates the pattern in its design context and describes how it is related to occupants. The introduction is written in non-technical language and describes how the OCDP is intended to be used. It also describes how it is related to other OCDP's.
Problem	A brief outline of the problem addressed by the pattern, including the aims of the design decision(s) to be undertaken.
Context and examples	Situates the use of the pattern in relation to occupancy, simulation, and design practice and explains the context of the decision(s) to be undertaken by designers and provides examples. Information (e.g., on theory or practice) is provided to justify the advice given by the pattern.
Solution	A description of the occupancy models and simulation methods that will produce the information required by the designers with an indication of what BIM objects can affect or be affected by it.
Pattern elements	Describes the simulation details (e.g., aim of simulation, model settings (simulation and occupancy), processing and analysis methods, simulation outputs, required user interaction with outputs).
Further modeling details	Further notes on modeling.
Interpretation and quality assurance	Instructs the designers on how to interpret results, what to expect from results and why, and which quality assurance patterns to use.
Further patterns	Information on other patterns that may potentially be relevant.
Comments and further development	Further comments and observations for pattern development.

obXML[3] schema connected to simulation software environments to provide highly detailed schedules and data-based models of occupants' interactions with a building's systems, including probabilistic functions—for instance, statistical schedules for window operation in specific building types and climates to be used in thermal comfort and energy simulations (Haldi and Robinson, 2009).

Capturing the correct and meaningful use of successful occupant-related analytic models together with the context in which they work enables the construction of a library of OCDPs that better connect design decisions with different types of performance to be simulated and assessed. Each problem-solution pair contains on its problem side the context in which the decision is made (e.g., the aims of the decision to be made and type of problem at hand). On the solution side, each pair contains a list of relevant and useful information for BPS tools and occupant behavior models to be used in a specific context. The template includes a description of model and simulation settings, types of analysis to be made, recommended output post-processing, and quality assurance procedures. Table 3.5 shows the template for the information contained in an OCDP (adapted from Tucker and Bleil de Souza 2016).

OCDPs focused on performance would help to better provide comfortable conditions and healthy environments, test effects of uncertainty on equipment and system sizing, and achieve economical operation of the building and its systems (see examples in Tables 3.3 and 3.4). The example OCDP given in Section 3.7 below concerns the use of BPS to provide performance information, therefore linking occupant information to building performance assessment.

3.7 Example of an OCDP

Table 3.6 shows an example OCDP that depicts information from the Eco-Housing case study in Chapter 11 in which consultations with occupants were undertaken to build occupancy schedules and test their impact on energy use. This OCDP contains a combination of technical details, notes, hyperlinks to other patterns, and engineering details. It focuses on the energy performance aspects of building occupancy, as these relate clearly to the use of simulation. That is not to say that an OCDP cannot be more broadly related to non-simulation design aspects of occupants; Tables 3.3 and 3.4—particularly the interactions within the construction entity column—suggest many examples that could be developed into patterns.

Further examples of how patterns can be presented to the designer and linked to design stages are discussed in Tucker and Bleil de Souza (2015), including hierarchies or classification of patterns (e.g., based on RIBA work stage, climate, building type), automatic linking between patterns based on their outputs to create a network, and the possibility of simply selecting patterns from a list. The development of an OCDP involves a process of consensus among experts and can also be done through using combinations of different information types described in Table 3.1, which vary from recording mandatory information about occupants to information coming from consultation with occupants. The activity of generating patterns leads to ideas for new ones, improvements to existing ones, or indeed the deletion of those not found to be useful, so that information on how design can affect

Table 3.6 Example OCDP for testing building energy use following consultation with occupants to develop custom-build schedules as described in Chapter 11

Index	#	
OCDP name	***Effect on building energy use of occupants in low energy co-housing apartment building***	
Introduction	Low energy co-housing can provide a sustainable solution for affordable housing for low-income occupants. The requirements of this building type are low running costs and some shared rooms and facilities. A participatory design process is used to inform details of occupancy schedules for the project at hand as well as obtaining feedback on the design from its future occupants. This OCDP is used to reduce energy demand and energy costs to occupants. It is used to test the effects on the thermal performance of a range of building occupation schedules that can result from the variety of employment conditions that typical inhabitants may expect to encounter. It provides simulation output information that should more accurately reflect actual heating, cooling, and ancillary energy use and therefore help address the performance gap between simulation results and buildings in use, which in turn can support decision-making on heating, cooling, and renewable energy system sizing. This OCDP also affords custom inputs to schedules based on the availability of survey data. Such data can also be used to inform design decisions on shared building facilities. This OCDP is intended to be used at a detailed design stage when the construction and form of the building are known.	
Problem	The problem is to provide a range of occupancy schedules that describe the effect on thermal loads of differing occupancy patterns, represent levels of uncertainty in the results, and to allow data input of survey results where available.	
Context and examples	Example 1: Apartment building in Budapest, Hungary. This research examined the effect of different occupancy profiles on heating and cooling loads (details in Chapter 11).	
Solution	ASHRAE, UK NMC, and French Th-BCE 2012 schedules plus co-design informed (active, passive, and weighted average) schedules are used in the simulations to provide information on magnitude and variance of heating, cooling, and plug loads in each apartment or zone. Model variants are simulated using the appropriate full hourly weather file.	
Pattern elements	Aims	– To inform the designer of the effect on performance metrics of uncertainty in occupancy schedules. This information contributes to a robust design. – To be able to compare performance metrics for heating and cooling energy use for different occupancy schedules that are automatically run and/or defined by the designer.

Table 3.6 Continued

Index	#	
	Model settings	– Construction entity = Whole building. – Construction elements and Construction properties (discrete) = combination of designer defined and defaults for built spaces and their respective services (e.g., plant ideal load in early stages with detailed plant in later stages). – Climate file: full year (hourly). – Operation parameters = designer defined + defaults. – Occupancy schedules: ASHRAE, UK NMC, French Th-BCE 2012, and custom co-design.
	Processing and analysis	– Full-year simulation. – Comparative assessment of each metric across models. – Metric 1: heating loads (kW). – Metric 2: cooling loads (kW). – Metric 3: heating energy (kWh). – Metric 4: cooling energy (kWh).
	Outputs	*Overview:* – Time series: occupant heat loads all profiles (W/person). – Bar chart: annual heat energy all profiles (kWh). – Bar chart: annual cooling energy all profiles (kWh). – Time series: typical summer day occupant heat loads (all profiles), cooling loads (all profiles).
	Interaction with model and outputs	*Interaction afforded:* Zoom in location and time. *Designer can select*: Individual space, occupant profile. *Outputs afforded:* As for Overview (see above).
Further modeling details	– Surrounding buildings should be modeled.	
Interpretation and quality assurance	– Advice on heating and cooling load interpretation. – Record of operational model settings (ventilation rates, internal gains, occupancy profiles).	
Further patterns	Follow-up patterns include detailed design patterns for HVAC design and/or specific obXML model of occupant interaction with the building or its systems.	
Comments and further development	An early design stage version of this pattern could use a massing model and small range of default building constructions and parameters to give indicative figures on heating and cooling load variance.	

building occupants can be constantly revised, updated, and integrated into the various stages of a building project.

In sum, the proposed template and OCDPs are an attempt to develop a way to record and trace design decisions related to occupants in a single environment that is compatible with BIM federated models and BPS tools so that multiple assessment points can be scheduled throughout the design process and design decision-making can be evidence-based and better integrated with performance in use. The advantage of supporting design decisions using an object-oriented information system is that the discussion is not tied to project stages, but rather to a network of generic objects detached from country-specific systems or contracts. Different levels of detail can be set to a single object and recalled as design progresses, which would make it possible to develop and record context-specific entities in a centralized environment, which would open the door for future work to implement this structure within common BIM tools to facilitate agility and distributivity in decision-making. In addition, this framework can be used to record best practice and therefore clearly connect information management with performance targets needed to design better buildings that benefit occupants and the environment, thus filling a current gap in practice.

3.8 Closing Remarks

In this chapter, we argued that information about occupants should be properly documented throughout the design process such that it is linked not only with BPS but also with BIM in order to fit within the information exchange between team members of different disciplinary backgrounds and thus support collaborative initiatives from a technical perspective.

The framework we proposed in Sections 3.6 and illustrated in 3.7 would enable practitioners to record and store sequences of problem-solutions for future retrieval and develop blueprints for how occupant information flows through design projects. The framework would also enable practitioners to identify how similar problems and issues concerning occupants reappear across projects, which would promote the creation of corporate object libraries that link BIM, BPS, and occupant behavior modeling tools to inform performance assessment. In this library, decisions could be recorded in context by the agreement of all involved stakeholders to avoid misalignment between design goals and intentions and occupant expectations throughout all stages of the design process. The process would be transparent and traceable, thus making information on potential solutions and best practice easily accessible to design teams, promoting a shared understanding by combining pattern recognition with context knowledge developed through consensus among practitioners. The following chapters of this book discuss different components of this framework.

Notes

1 EN ISO 12006-3 (2016), EN ISO 19650-1 (2018), EN ISO 19650-2 (2018), EN ISO 55002 (2018), EN ISO 19650-3 (2020).
2 AIA (2019, 2020), RIBA (2020).
3 obXML is an occupant behavior XML data exchange format developed by Lawrence Berkeley National Laboratory. https://behavior.lbl.gov/?q=obXML download.

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4 Methods to Obtain the Occupant Perspective

Clinton Andrews, Julia Day, Philip Agee, Rich Wener, Quan Jin and Jennifer Senick

Summary

In this chapter, we will critically examine methods for learning about the occupant's perspective regarding the design of buildings. We will discuss the nature of occupant data; the strengths and weaknesses of self-report, observational, and simulation methods; and the need to represent occupants prudently during the design process. These methods help make an occupant-centric approach to building design feasible.

4.1 Introduction

Building designers necessarily make significant assumptions about occupant needs and comfort because during the design process, the occupants are usually not yet present. Thus, the project developer's or the client's priorities, governmental regulations, industry norms and standards, and the designer's prior experience serve as proxies for the occupants' interests. This is a satisfactory situation when the developer or client will occupy the building, regulations and standards are well-crafted and current, and the designer has substantial and relevant prior experience. Unfortunately, this is not always the case. For example, clients that develop buildings on a speculative basis may prioritize short-term financial returns, or large institutional owners may mandate regulatory minimums due to capital constraints. Such circumstances can lead occupants to experience uncomfortable and even unusable buildings.

The previous chapter, Chapter 3, provided a valuable perspective on occupant needs from the designer's point of view. It highlighted the designer's information needs at different points in the design process and the importance of client and design team interactions, while also identifying formal and informal constraints on design possibilities. Chapter 3 closed with a proposal for occupant-centric design patterns that link typical problems and solutions to guide design practice. In this chapter, we offer a counterpoint to Chapter 3 by highlighting the potential direct roles of occupants

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in the design process. There is a visionary aspect to this proposal because today, non-client occupants rarely play a direct role in the design process. Enhancing their role would require overcoming practical barriers. For example, occupants are diverse and have varied needs, and some occupants may have difficulty articulating their needs if they have limited literacy in building systems and construction. In this chapter, we consider practical ways to bring in the occupant to inform the design of new buildings.

Our proposal is significant. Buildings are meant to provide shelter to people and the things they care about, and so designers should inherently be concerned about occupants. Traditionally, design practitioners have done their work *on behalf of* occupants, applying their expertise to achieve outcomes that satisfy what designers assume to be the occupants' needs and wants. To guide these decisions, designers have developed standard models of occupants' functional requirements and behaviors (as discussed in Chapters 2 and 3). Unfortunately, some models ignore the variability of occupants' needs, capabilities, and perceptions, or fail to consider the occupant as an active participant in building performance outcomes. This traditional design approach can result in buildings that perform poorly and do not satisfy their occupants. Adverse examples include divergence between intended and actual building operational schedules, air temperature and illuminance levels, or usability of control interfaces by different types of occupants (Stazi *et al.*, 2017).

The emerging paradigm of occupant-centric design reframes the design process by stipulating that practitioners do more of their work *with* occupants. At every stage in the building life cycle, design practitioners should seek to interact directly with occupants to hear what they like and dislike, what creative ideas they may have, and what is working or not. This democratization of the design process is philosophically satisfying, but how is it done?

In this chapter, we argue that there are multiple opportunities to integrate occupant-centric elements into traditional design processes. Traditional building design processes are conceptually relatively linear, progressing from the owner's abstract program to a final refined design that gets built and occupied. In contrast, occupant-centered design processes involve much iteration, invoking what Lindblom (1959) called *mutual incremental adjustment*. For example, if the user is known, a pre-intervention study to identify their needs can augment the linear design process. Likewise, a circular design process considers building design, construction, operation, and adaptive renovation to be ongoing and iterative activities (Cobaleda Cordero *et al.*, 2017). As we move through this chapter, we consider designers' and operators' need for information about occupants, the nature of occupant data, methods for acquiring occupant data, how to manage the occupant–practitioner relationship, and how to engage occupants throughout the building life cycle.

4.2 Designers' and Operators' Informational Needs throughout the Building Life Cycle

Practitioners need to know and understand different things about occupants as a project advances through the building life cycle. Professional specialties and the associated toolkits lead programmers, architects, engineers, constructors, and operators to seek distinct types of data.

In the pre-design stage, architectural and engineering programs need basic information, such as the number of people who will use the building and for what general purposes. Residential building programs necessarily focus on households or other social units, and they allow occupants to perform a relatively standard set of activities, including sleeping, hygiene, nourishment, and recreation. Commercial building programs allow groups of many sizes to enact myriad production or consumption activities. Chapters 2 and 3 provide relevant details on occupant needs and the relevant design decisions.

An integrated design process proceeds through stages of increasing detail, from schematics to shop drawings, where at each stage there is a need for information about—and ideally from—occupants. The process begins with identifying occupants' functional needs and translating those to design requirements. For example, questions of how many people doing what and where dictate the sizes and adjacencies of spaces. Questions of occupant capability, responsibility, and motivation translate to levels of building automation. Questions of occupancy levels and schedules guide equipment specification and estimates of building performance. Occupants' desired levels of thermal comfort, indoor air quality, lighting, and noise guide design targets. The range of expected occupant behaviors anticipates risk management and usability strategies. Designers and their clients may start with assumed answers to all these questions, but the outcome likely will be better if occupants or their proxies weigh in because occupants exhibit much variability (Belazi *et al.*, 2018).

Except in cases where the design project is a renovation, or the client is also the occupant, methods for acquiring occupant data draw on evidence from existing buildings to inform a new building's design. This practice raises important questions about the transferability of insights from one building to another and the limits of extrapolation from collected evidence to hypothetical future circumstances. The reproducibility, validity, and representativeness of data collected using the methods discussed below become important dimensions for assessing the data's value. These dimensions extend beyond the data to include the models that use the data. To illustrate, is the transferable item a "typical" value, such as the average floor area per person needed in an office environment; an inferential statistical relationship, such as a multivariate regression model linking observed indoor air temperature to subjective thermal comfort sensations; or a rule-based dynamic relationship, such as a parameterized agent-based model of occupants' adaptive responses to changing lighting conditions? Each type of transfer bundles different assumptions with the transferred data (Andrews *et al.*, 2016).

Once a building is constructed, occupant behavior moves from hypothetical to observable. Post-occupancy evaluation of the building and its operations allows assessment of its as-built performance, identifies issues that need resolution, and extracts lessons for future building designs. Seeking ongoing feedback from occupants allows operators to respond in real time to changing building conditions and allows occupants to participate in improving the building's performance. The nature of these interactions differs between commercial buildings, which may have building automation systems that operate without occupant involvement, and residential buildings, which may have a consumer-grade digital assistant that interacts frequently with occupants.

4.3 The Nature of Occupant Data

Occupants can be counted, tracked, timed, observed, and queried to yield useful data for designing and operating buildings. These many types of occupant data have properties that vary widely and may limit what can be done with the data.

Some occupant data is objective, meaning that it is directly observable by reliable instruments or people. Two observers should be able to agree on the number of people occupying a room, for example, and on the occupancy schedule, these people follow. Instruments such as infrared-beam-breaker people counters placed in doorways, or more advanced overhead counters that rely on computer vision algorithms to interpret video feeds, will vary in their level of accuracy and reliability, but they all seek to measure something objectively quantifiable.

Other occupant data is subjective, meaning that it is not directly observable in the same way by all instruments and people. For instance, two reasonable observers may perceive things differently because of personal beliefs or feelings that color their observation. An occupant's thoughts are inherently subjective because outside observers cannot see them; hence, the observers must ask the subject what they are thinking. Although professional observers use standardized surveys and interview instruments that have been previously tested and shown to perform reliably, the subjective element remains.

Psychological models of behavior attempt to explain and predict behavioral outcomes based on models that include both objective and subjective input data. This spectrum spans values, beliefs, attitudes, preferences, perceptions, norms, intentions, habitual behaviors, reactive behaviors, reasoned behaviors, social behaviors, and more. For example, Ajzen's (1985) Theory of Planned Behavior attempts to predict behavior based in part on expressed intentions, which are in turn based on subjectively measured attitudes and driven by subjectively measured beliefs. Wide-ranging empirical tests of this model have found that subjective data on beliefs and attitudes can be reasonably good predictors of subjectively measured intentions, but intentions accurately predict objectively measured behavior only about one-third of the time (Armitage and Conner, 2001).

Underlying the occupant behavior modeling challenge is a serious epistemological problem in the social and behavioral sciences. Recall that *epistemology* refers to theories of knowledge, or the study of how we know what we claim to know. When studying phenomena in physics and chemistry, for example, scientists develop theories and evidence to understand better how the natural world works. The roles of the subject (actor) and object (recipient of action) are clear: scientists are studying nature, although sometimes (such as in quantum mechanics) there is an observer effect that affects measurements. When studying human behavior, action goes in both directions: while social scientists study the behavior of other humans, those humans are reacting to being studied. Worse, both sets of humans share social circumstances that add subjectivity to their interpretations of the data collected. Hence, the social and behavioral sciences are afflicted by what Giddens (1987) calls the *double hermeneutic*, which acknowledges the interactions between subject and object, the inherent subjectivity of research in this domain, and the possibility that everything we claim to know depends on who is doing the interpretation.

There are two ways out of this intellectual dilemma: first, practice intellectual humility regarding what experts assume they know about people (Andrews, 2002); and second, acknowledge some objective agreement on the material facts of the physical world (Sayer, 1992/1984). Thus, a key practice of good occupant behavior research is to let people speak for themselves, i.e., ask people directly what they perceive. A second key practice of good occupant behavior research is to study people in their physical context, i.e., study occupants as part of a coupled building-occupant system.

4.4 Methods for Acquiring Occupant Data

Traditionally, the information used to make spatial design decisions has been based on standards, building codes, the personal experience and training of designers, and input from clients—all documented with an eye on considerations of legal liability, as discussed in Chapter 3. Often left out of this process are the end users, i.e., those who live, work, shop, or otherwise regularly use a space, even though they are the most affected and often the most knowledgeable about space needs. This oversight is especially relevant in buildings meant to be energy efficient, since user behaviors can play a significant role in energy use (Sonderegger, 1977; Guerra-Santin and Itard, 2010; Majcen *et al.*, 2016). Design-behavior research has begun to address this gap by providing empirical, user-based information about user behavior, perception, and needs for spatial design (Zeisel, 2006; Wener, 2008; Horayangkura, 2012).

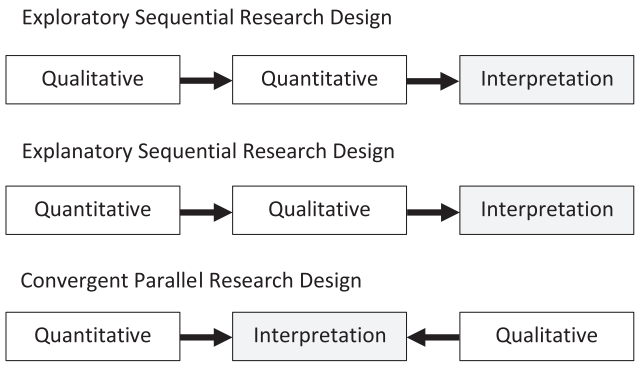

Figure 4.1 Mixed methods data collection designs.

There are various social science methods for collecting data on user spatial behavior, needs, and perceptions. Since each method has strengths and sources of bias, whenever possible it helps to use multiple data sources to enable triangulation of findings. Multiple data sources pointing to similar results increases confidence in the validity of the outcomes. A mixed methods approach that uses both quantitative and qualitative measures—for instance, a combination of questionnaires, interviews, diaries, and virtual reality-based exercises—may provide more data and deeper insights (Jin *et al*., 2019). Mixed methods designs differ depending on whether the data collection is exploratory (early stage), explanatory (later-stage), or convergent (for robust design guidance). As shown in Figure 4.1, an exploratory design uses quantitative methods to confirm qualitative insights, an explanatory design uses qualitative methods to clarify quantitative results, and a convergent design compares qualitative and quantitative results to triangulate across methods (Bergman, 2008).

In the following sections, we expand on two types of qualitative and quantitative data collection methods for building design researchers to better understand occupant needs: (1) participatory, self-reported or self-engaged measures collected through methods such as questionnaires, interviews, focus groups, and diaries; and (2) less participatory and often unobtrusive observational methods such as behavior tracking, mapping, instrument-based data collection, photography, and videography (Wener, 2008). A third type of method, simulation, creates synthetic data based on patterns detected in primary data.

Self-report measures allow researchers and designers to understand how users perceive a space and their own needs. Information can include, for instance, what users consider the key characteristics of a space that helps them engage in better and more productive work, or how they feel about adjusting thermostats or lighting (as per the example shown in Figure 4.2).

Figure 4.2 Example of collecting self-reported information from occupants via wireless voting devices (Berquist *et al.*, 2019).

As stated previously, the simplest way to get information on how people behave in a space and what they want and need is to ask them. At the same time, informants may not always be fully aware of what they do, where they do it, or how these behaviors fit into broader patterns of spatial behavior. They may forget, misremember, or give biased answers reflecting, for example, socially desirable responses (Fowler Jr, 2013; Hine *et al.*, 2016; Moy and Murphy, 2016). Triangulation using mixed methods can help overcome self-reporting bias.

Self-report techniques can include open-ended questions (questions that allow free-form responses from the subject) and closed-ended questions (those with a discrete number of fixed-choice response items). Careful sampling and survey design can reduce potential biases. In the best cases, researchers will make use of survey scales that have been developed and tested in previous studies, providing obvious advantages in terms of reliability, validity, and comparability of data.

Participatory techniques are especially important for occupant-centric design practice. There are many such techniques, ranging from design charrettes to crowd-sourced data collection. As part of design, these techniques can be simple and direct, as illustrated by the temporary display inviting occupant participation shown in Figure 4.3. They can also be quite elaborate and involve a substantial information infrastructure, as shown in Figure 4.4.

Behavior observation offers another approach to gathering occupant data and has the potential to show broader patterns of group behavior that go beyond individual activity. This approach provides an objective view of placement, patterns, and flow of behavior in a space, often directly linking these to physical features. The choice of which observational methods to use and how to use them depends on the kinds of data needed and the time and resources that are available. Formal observations, such as behavioral maps

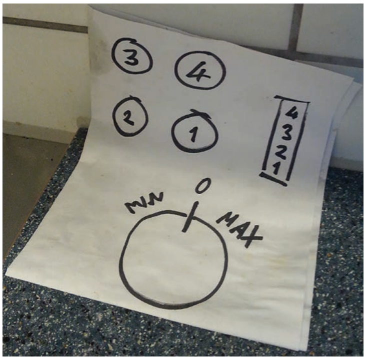

Figure 4.3 Example of folk labeling, which can be used as an indicator for opportunities to improve design.

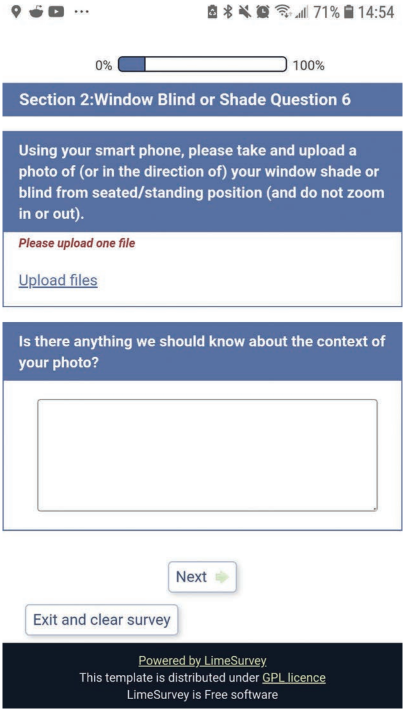

Figure 4.4 Example of smartphone-based survey that asks participants to upload photos of building features from a seated position at their workplace.

(i.e., time-sampled snapshots of who is where and doing what) or behavior tracking (i.e., following the movement of one person at a time through a space; Ittelson *et al.*, 1967), can be used to obtain a more complete and less biased picture of how and where users spend their time than self-reports provide. Mapping and tracking can be time consuming, but their use has been much aided by the development of portable telecommunication devices (Dalton *et al.*, 2012, 2013). Sensor-equipped buildings can greatly facilitate such data collection, as shown in the example in Figure 4.5.

Still and time-lapse photography and videography are other useful sources of observational data on space use, though these methods must consider the ethical bounds of consideration of the privacy of the occupant. White (1980) used a time-lapse film of people using public plazas in New York City and elsewhere to demonstrate the impact of design on activity, which led to critical changes in the city's zoning laws governing the design of such spaces. More than a half-century after White's pioneering work, photography and videography are mainstream techniques, now supplemented with computer vision tools for extracting occupant behavior patterns (Tomé *et al.*, 2015).

Crowd-sourced photographic evidence using tools such as smartphone apps (see example in Figure 4.4) is gaining popularity in occupant behavior research (Day *et al.*, 2020). Crowd-sourced observational evidence combines the strengths and weaknesses of self-reported and observational data and illustrates how methods continue to evolve.

An emerging method synthesizes new data from simulation models based on primary occupant behavior data. It allows model-based interpolation and extrapolation from a limited number of direct observations or self-reports. The validity of this approach is enhanced by its ability to adjust for behavioral context but is constrained by the model's limitations.

Interface design for building systems, such as light switches and thermostats, is an important special category in the study of occupant behavior. It is iterative by nature, and its success depends on the input of reliable data about occupants' perceptions of the interface's user-friendliness in a specific application context. There are numerous methods that provide relevant data, such as qualitative affinity diagramming and cognitive walk-throughs, and quantitative ergonomic analysis and eye-tracking studies (Agee *et al.*, 2021). These specialized methods will not be discussed further in this chapter. For reasons explained in Chapter 9, it is sensible to view each method as providing only part of the information desired, and the contingency of the social and behavioral sciences suggests that triangulation and mixed methods approaches can help build confidence in the insights such evidence can provide to the design process.

The methods discussed in this chapter can generate vast quantities of qualitative and quantitative time-series data. Examples include individual occupant beliefs, attitudes, intentions, and perceptions; observed occupant presence and actions, local indoor environmental conditions, building system status, and other variables; and system measures such as building-wide

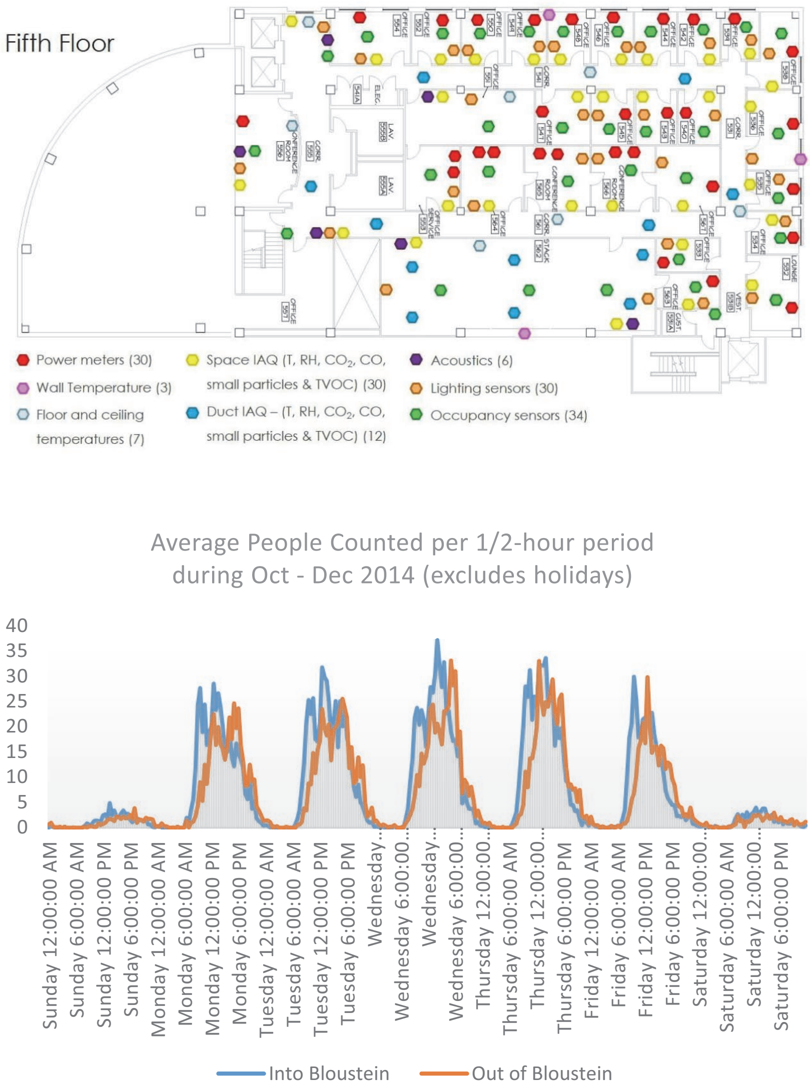

Figure 4.5 Example of a building suite equipped with sensors for monitoring indoor conditions and resulting data on occupant presence.

energy consumption. Some methods track change by the millisecond and others by the year. Wrangling these heterogeneous data is a significant challenge.

Table 4.1 summarizes the characteristics, strengths, and weaknesses of methods for occupant behavior data collection methods and provides pointers to published examples of their use. Regardless of method, most

Table 4.1 Methods, applications, strengths, weaknesses, and examples

Method	*Applications*	*Strengths*	*Weaknesses*	*Example(s)*
Self-reported and self-engaged (participatory)				
Interviews	Concept, schematic, and design development, post occupancy	Inexpensive, not overly-taxing for designer/researcher or participants, typically targeted by respondent position (e.g., facility manager, tenant administrator)	Not representative of "rank-and-file," might miss important data	Agee *et al.* (2021) and Day *et al.* (2020)
Focus groups	Design phases and possibly contract administration	Inexpensive and not overly taxing, allows for deeper dive into specific topics	Some participants may try to dominate the discussion, scope is necessarily limited	Jin *et al.* (2019)
Charrettes	Concept and schematic design	Hands-on co-creative approach, newer tech such as VR for added interest and range suits some participants	May not be representative (self-selection participant bias), relatively larger effort required	Andrews (2008)
Virtual reality (visualization, auralization, etc.)	Through the design process	Allow occupants to understand/experience space/design/layout without needing to interpret drawings and other technical documents	Requires effort to build 3D model	Jin *et al.* (2019)
Questionnaires	Concept design, post-occupancy	Sample size not limited (typically a population sample), careful sampling strategies can help to reduce bias, open-ended questions can motivate new considerations	Development and deployment are time-consuming and therefore more expensive, requires building owner/tenant approvals), potential participant bias, may be difficult to encourage participation	Day *et al.* (2020), Zhao *et al.* (2017), Zagreus *et al.* (2004), and Tsoulou *et al.* (2020)

Diaries (traditional)	Post-occupancy	Opportunity to obtain quasi-systematic chronological activity data. Smart-phone voice-enabled and other technologies may help to automate and relieve burden on participant	Recall bias is a known limitation. Not well-suited to address behavioral change and lacks context, can be taxing for the participant, may be difficult to sustain interest (even with incentives)	Jin *et al.* (2019)
Ecological Momentary Assessments	Post-occupancy	Samples/records participants real-time behaviors with preservation of context, minimizes recall bias, encompasses a wide range of technological (low-high) options, and may include individual sensing. Particularly good for interventional study	More complex administration—e.g., random time sampling is common as is a multi-method approach (telephone + electronic diary + physiological sensor)	Roa *et al.* (2020)
Social Media Posts, Individual Sensing (posts)	Post-occupancy	Opportunity to gain "uncensored" data and to learn about building occupant triggers to report, capture of "citizen scientist" data	Data needs to be carefully quality controlled, participant bias and bias toward the more sensational	Lu *et al.* (2021)

(*Continued*)

Table 4.1 Continued

Method	*Applications*	*Strengths*	*Weaknesses*	*Example(s)*
Observational				
Direct	Post-occupancy	Creates a record of contextual markers for understanding activity use data, works well in combination with archival data (e.g., charting direct observations on interior floor plan)	Researcher and participant subjectivity	Zimring and Rosenheck (2001)
Photography: still and time lapse, video	Post-occupancy	Creates a record of contextual markers for understanding activity use data, may be dynamic in nature	Researcher and participant subjectivity, ethical boundaries not always clear	Day *et al.* (2020)
Occupancy and flow counters	Post-occupancy	Objective measure with spatial coordinates, some contextual data preserved. Increasingly important given the prevalence of flexible work hours (partial load conditions) and management of airborne disease	Counter errors occur, occupants may “trick” the counters, limited activity use data, high variability in how different devices store and send data, format incompatibilities	Trivedi and Badarla (2020)
CO2 and IAQ (building) sensors	Post-occupancy	Objective measure with spatial coordinates, heightened importance/focus per COVID-19 pandemic	Limited context or activity use data	Tsoulou *et al.* (2020)

Building Management System logs	Post-occupancy	Archival measure potentially with a large and varied sample, likely to include both objective (e.g., temperature, humidity, CO_2) and subjective (e.g., occupant reports) data	Quality and quantity of BMS logs vary widely. Underlying bias of occupant reports based on willingness to report	Schweiker *et al.* (2019)
Simulated Occupant Behavior Models	Design phases through post-occupancy	Allows "what-if" simulations to inform design; clarifies the role of occupant behavior in building performance	Requires much data, time, and expertise	Senick *et al.* (2018) Andrews *et al.* (2016) Chandra Putra *et al.* (2017) Andrews *et al.* (2011)
Digital Twins	Design phases through post-occupancy	Facilitates greater (pre-design/build) experimentation and specific assessments (e.g., on organizational compatibility, detailed use cases)	Requires significant investment in data, time, and expertise; masks uncertainties	Onile *et al.* (2021)
Affinity Diagram	Concept, schematic, and design development, post occupancy	Extracts insights from qualitative data, supports group discussions	Subjective results can be influenced by user's skills, biases, and chosen interaction process	Ortiz *et al.* (2020)

researchers who seek to publish work based on these methods will be required by their employer or sponsor to submit their research protocols for approval by an institutional review board (IRB) that works to protect human subjects from harm during the research process (Chen *et al.*, 2018). Practitioners using these methods may face fewer such requirements but should still acknowledge their responsibility to respect occupant privacy.

4.5 Managing the Occupant-Practitioner Relationship

Many different relationships between occupants and building practitioners are possible, and understanding how they differ is important for successful design and operational outcomes. Arnstein (1969) proposes a power-based ladder of lay engagement with practitioners that ascends from expert-dominated non-participation by lay people, to tokenism and mere consultation, all the way to delegation of decision-making power to lay people. Renn, Webler, and Wiedemann (1995) suggest that it is beneficial to acknowledge tensions between the competing objectives of fairness (to lay participants) and competence (of lay participants) when choosing how to structure this relationship. In other words, practitioners should only relinquish decision-making authority in areas where occupants are likely to be equipped to make good decisions. This stance provides an aspirational, occupant-centric contrast with the assumed power asymmetry that is baked into many owner–tenant and client–contractor relationships.

Whereas occupants are likely to have some knowledge of their own needs and desires in terms of building design, building practitioners generally have substantial knowledge about both typical occupant needs and how building systems work (as discussed in Chapter 2). Ensuring fairness might mean that all voices—that is, both occupants' and building practitioners'—are heard, and ensuring competence might mean appropriately matching tasks to roles. However, the challenges of successfully managing the occupant- practitioner relationship are many, including (at least) the following:

- *Philosophy of control*: Do designers and their building owner clients trust occupants enough to give them local control of key features? If occupants know their own comfort preferences best, it makes sense to build in local controllability of systems that provide occupant comfort, such as incorporating many small thermal zones and associated thermostats into the HVAC system design. Designers who do not trust occupants, or clients who prioritize other considerations, may create large zones and no means of local control.
- *Usability*: Are the interfaces occupants use to control building systems comprehensible, efficient, and effective? However well designed the rest of the system is, if the interface is flawed then occupants will struggle to perform with competence. See the interface discussion in Chapter 9.

- *Transferability:* Designers do their work before the building is constructed, and so the actual occupants are not yet in place to be asked about their preferences and perceptions. Instead, designers seeking occupant input will need to ask occupants about existing buildings that are similar to the new building in terms of occupant characteristics, activity types, climate, and physical details. Alternatively, the designer will need to rely on the client developer or building owner, or a behavioral consultant to speak for the future occupants, or they can turn to established design guides and standards.
- *Data ownership:* Building operations have been traditionally guided by data collected by building management systems or consultants hired by the client owner. However, it is increasingly common for occupants to install devices to monitor indoor environmental quality independently. These consumer-grade devices provide evidence that occupants can use to challenge factual claims made by owners about the building's performance (He *et al.*, 2020). Some regulations and leases specify performance requirements for tenanted spaces, making this a financially relevant development. Like the citizen science movement, data streams provided by occupants can disrupt traditional authority relationships and provide new insights about problems (Kim *et al.*, 2019). A constructive role for practitioners is to help citizen-scientist occupants ensure quality control and to incentivize continued occupant engagement (Andrews, 2016).

The above challenges highlight that the occupant–practitioner relationship is multi-faceted and varies by building and occupant type. An occupant-centric design philosophy emphasizes local control, usability, direct communication with occupants, and openness to consideration of occupant-provided data.

4.6 Engaging Occupants along the Building Life Cycle

The relationship between occupants and practitioners will necessarily vary throughout the building life cycle. Broadly, in the earlier stages, from conceptual design through completion of construction, occupants can be engaged in *formative* evaluation activities designed to specify directional targets, monitor progress, and provide ongoing feedback to the design and construction processes. After the building is occupied, it becomes possible to conduct *summative* evaluations by occupants to determine how well the building works.

At the outset, the client developer or owner needs to decide where and when they are comfortable placing occupants within the design process, from no participation to putting occupants in charge of specific decisions. An occupant-centric design process seeks to be closer to the empowerment end of the spectrum. A common example is allowing tenants to choose the

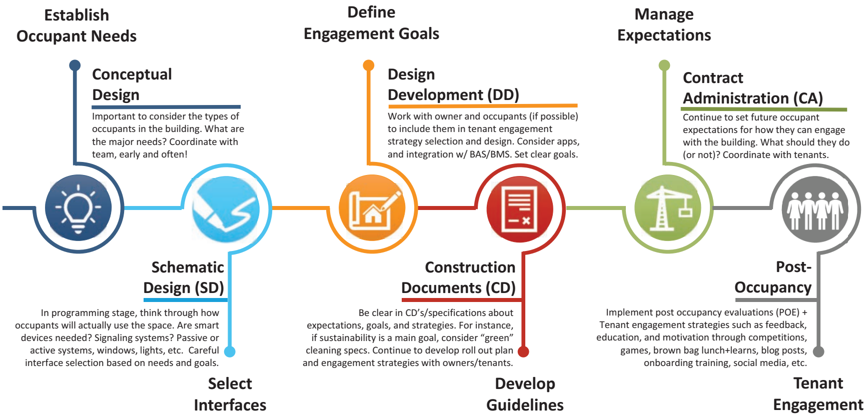

Figure 4.6 Diagram demonstrates ways in which to engage occupants throughout the design process.

color of interior paint. A more inspiring example is the redevelopment of public housing by the Charlottesville Redevelopment and Housing Authority (CRHA), where residents were directly involved in the initial needs assessment and conceptual design as well as throughout the remainder of the design and acceptance process (CRHA, 2021). The Budapest housing co-design case study in Chapter 11 is another encouraging example.

Traditionally, each stage of the building life cycle requires different data from occupants. In Figure 4.6, we illustrate the life cycle using stages defined by U.S. practitioners (AIA, 2019), recognizing that these may differ in other countries. As shown in Figure 4.6, occupant engagement at the conceptual design stage is focused on establishing occupant needs; at the schematic design stage, the focus shifts to selecting interfaces; during design development, it is on defining engagement goals; during preparation of construction documents, it is on developing guidelines; during contract administration, it moves to managing expectations; and, finally, in post-occupancy, the focus is on occupant engagement.

Agha-Hussein (2018) offers prescriptive guidance for engaging occupants in the design process, including core principles such as sharing risk and responsibility, involving the end users and operators, using feedback to improve design, and communicating and informing.

4.7 Using *Personas* to Integrate Occupants into the Design Process

Occupant data can become overwhelming in its detail, with ubiquitous sensors collecting observations every few seconds, over many months, about perhaps hundreds of occupants in dozens of rooms in a medium-sized building. Such data can only provide insights if it is aggregated. Standard aggregation approaches focus primarily on characterizing the central tendency of the probability distribution—i.e., the "average" occupant—or the dispersion around the mean, such as the predicted mean vote/predicted percent dissatisfied construct used in thermal comfort surveys (Andrews *et al*., 2016). A different approach that fits well with the occupant-centric design perspective is to work with clusters of relatively homogeneous occupants that can be represented as archetypes or personas, as discussed below. Personas belong to a spectrum of approaches that use increasingly sophisticated models to process occupant data, as discussed in Chapter 6.

Figure 4.7 summarizes the process of creating personas from a set of occupant data collected through a mixed methods approach. Data are applied toward the development of user personas in four discrete steps. First, the researcher collects energy use data and develops descriptive statistics. Second, they deploy a behavioral survey. The survey might ask participants demographic questions as well as questions about preferred thermostat set points, adaptive comfort behaviors, dishwasher use, shower length, and other indoor environmental quality factors. Survey responses are initially categorized by demographics (e.g., age). The researcher then generates descriptive statistics of the survey responses. Third, the researcher interviews a small subset of users (e.g., 5–10) to add richness and additional context to the persona. The interview script probes user attitudes, beliefs, and preferences for human-building interaction (e.g., acceptance of automation). Fourth, the researcher codes the interview transcripts and develops affinity diagrams for

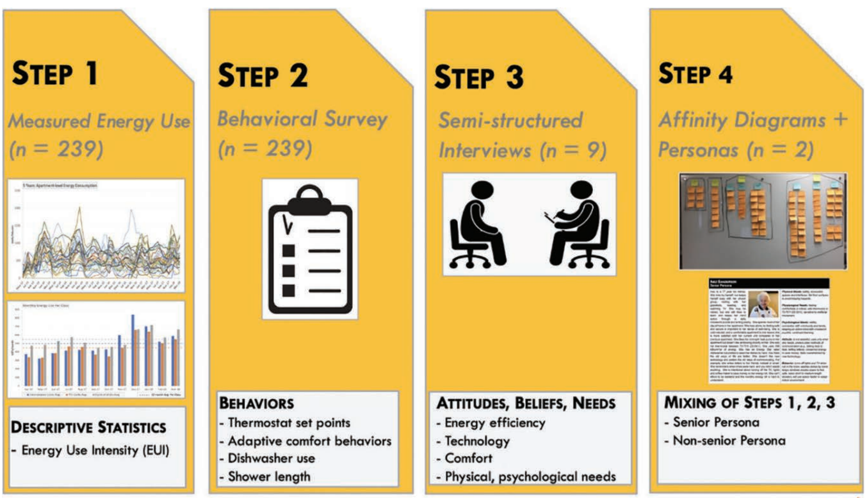

Figure 4.7 Multi-step, mixed methods approach to develop a persona for an energy use study.

categorizing themes in the data. Employing the persona(s) during the design process provides a basis for occupant-centric problem-solving. For example, when faced with a decision regarding building systems or interfaces, the designer would ask what would [Persona name] want or need in this system.

Personas also have particular value for constructing occupant indoor environmental quality (IEQ) comfort profiles. Such profiles can help designers and building developers to better appreciate individual differences and needs in the early design phase. Some recent examples in which personas provided analytical and design insights include the following:

- Hong *et al.* (2020) defined six human-building interactions behavior profiles: average, reserved, environmentally friendly, role model, self-centered, and mechanist.
- Kim and Bluyssen (2020) clustered office workers into the following categories: healthy and satisfied, moderately healthy, and noise-bothered, and unhealthy and air and temperature bothered.
- Despenic *et al.* (2017) identified four lighting preference profiles: activeness, tolerance, dominance, preference.
- Eijkelenboom and Bluyssen (2020) established IEQ clusters for outpatient staff: uncomfortable with air and preference for control of ventilation, moderately comfortable and preference for fresh air, moderately thermally uncomfortable and preference for control of temperature, comfortable and preference for good acoustics, and uncomfortable and preference for not too cold or hot temperature.

There are several advantages of personas, including that teams often perform their work with no or limited knowledge of building occupants. Personas can help project teams have a more complete understanding of the system they are designing through the integration of human factors. Generalizing user needs, particularly behavior and attitudes, is helpful for resisting technology-centered solutions (Hannington and Martin, 2012). For example, with the proliferation of building management systems (BMS), personas can assist simulators in making decisions regarding the likelihood of a user accepting the BMS. Further, personas can be used as a communication tool to communicate user needs across stakeholders as well as inform simulation inputs, as shown in Chapter 8. Personas can serve as a guideline at various stages of design and construction; for instance, they can be applied for spatial design, building simulation, and automation. A significant advantage of personas is that designers can use them to evaluate what-if scenarios with diverse occupant behaviors.

At the same time, it is important to acknowledge the limitations of personas. First, some building uses may limit the efficacy of trying to develop a generalized user. Building uses also change, particularly commercial buildings. Some building simulators lack the skills needed to collect and analyze the mixed quantitative and qualitative data required to develop a rich persona. Further, building simulation is often developed to understand compliance with energy standards, and so, while the integration of personas in the design and simulation workflow of a project may add value from an occupant-centric design perspective, it may not be valued by compliance-focused clients. Personas may be most realistic for retrofitting, as data can be collected from current occupants, but it may pose a challenge for new buildings when the users are unknown. Conducting surveys to create personas for different projects is also time-consuming and expensive for industry practitioners. A final—and significant—limitation is the lack of systematic processes and/or set rules for integrating personas into simulation.

4.8 Closing Remarks

In this chapter, we presented three key arguments. First, building designers and operators can learn much from occupants, and the occupant-practitioner relationship will vary according to the stages of the building's life cycle. Second, the methods needed to engage occupants successfully draw upon traditional social and behavioral sciences methods, and new methods are emerging as sensing and computing technologies advance. Finally, occupant-centric design approaches that employ these methods can improve both the depth of insights generated during the design process and the likelihood of successful building and occupant outcomes. Metrics, discussed next in Chapter 5, provide an occupant-centric perspective on how to link occupant data to building performance.

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5 Occupant-Centric Performance Metrics and Performance Targets

Tianzhen Hong, William O'Brien, Han Li, Jakob Hahn, Clarice Bleil de Souza and Zoltan Nagy

Summary

In this chapter, we will describe occupant-centric performance metrics and their main use cases in the building life cycle. We will start with the background of occupant metrics in relation to occupant needs, and then describe a suite of occupant metrics within a classification framework. Next, we will present methods to quantify the occupant metrics. Finally, we will discuss the basis to set the energy and environmental performance targets.

5.1 Introduction

Building performance is mainly determined by six factors, as studied in the International Energy Agency's (IEA) Energy in Buildings and Communities Programme (EBC) Annex 53 (Yoshino *et al*., 2017): climate, building envelope, building services and energy systems, building operation and maintenance, occupants' activities and behavior, and indoor environmental quality (IEQ). To quantify building performance, metrics have been developed and widely used to guide building design, code compliance, and performance benchmarking and rating. However, most building performance metrics adopted by current building standards (e.g., ASHRAE 90.1, ASHRAE 189.1, ISO 17772, ISO 52000) and certifications (e.g., LEED, BREEAM, and DGNB) focus on either whole-building (Coleman *et al*., 2015), system-level (Li *et al*., 2020), or equipment-level energy use, peak demand, or energy efficiency. They are usually normalized by the floor area of a building; for example, the energy use intensity (EUI) in kilowatt-hours per square meter (kWh/m^2) or thousand Btu per square foot ($kBtu/ft^2$) represents the annual whole-building energy use per building floor area. The peak demand intensity, in watts per square meter or square foot (W/m^2 or W/ft^2) represents the annual peak electricity demand per building floor area. Most existing metrics do not explicitly consider occupants, which can lead to significant bias in evaluating building performance (O'Brien *et al*., 2017).

With increasing concerns over each building's environmental performance by building owners and occupants, it is critical to consider building

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performance with regard to occupants rather than merely normalizing by floor area. Unlike normalizing by floor area, normalizing performance by occupants simultaneously credits buildings for both space utilization efficiency and energy performance. New space utilization models for occupancy (e.g., co-working, Airbnb, hoteling, post-COVID-19 pandemic hybrid working schedules) are challenging conventional assumptions upon which traditional metrics were developed.

More frequent extreme weather events and the increasing penetration of distributed energy resources (DER)—including renewable energy, storage, and electric vehicles—impose a need to quantify building energy flexibility and resilience to support research and development of grid-interactive efficient buildings (GEBs) (Neukomm *et al.*, 2019). Occupant-centric performance metrics are essential for evaluating how passive building designs and demand-flexible operations affect occupants in the GEB context.

Meanwhile, occupant needs (described in Chapter 2) in current building energy codes and standards (e.g., ISO 7730, ASHRAE 62.1, ASHRAE 55) and design guidelines are usually represented as static and homogeneous criteria for IEQ. These include indoor air temperature and humidity within a narrow comfort zone, illuminance levels based on space type, maximal allowable carbon dioxide (CO_2) concentration based on activity type, and occupancy duration (O'Brien *et al.*, 2020). These metrics often miss usability, individual comfort, exposure (e.g., to viruses and light), and space utilization. They are not designed specifically from an occupant perspective and do not consider occupants' diverse and dynamic needs and interactions with building systems or the latest research (e.g., see Chapter 1 for a list of misconceptions about building occupants).

With major energy end uses such as lighting and heating, ventilation, and air conditioning (HVAC) being continuously improved via efficiency measures, occupant-related performance is considered increasingly important (Coleman *et al.*, 2015; D'Oca *et al.*, 2018) to improve occupant wellness, comfort, and health (e.g., via the WELL international standard, concerns for COVID-19). Not including occupant perspectives in most metrics downplays occupants' importance during the design process and discussion, and it precludes opportunities to benchmark and diagnose building performance from those perspectives.

Occupant-centric perspectives include: (1) use of resources, such as energy, water, and space; (2) environmental impacts, such as greenhouse gas (GHG) emissions and solid waste management; (3) indoor environmental quality, including thermal, visual, acoustic, and indoor air quality (IAQ); and (4) human-building interactions. The critical human-building interactions are represented as the degree and flexibility of adjustments that occupants can make to building systems (e.g., operable windows, movable shades, thermostats, dimmable lights, ceiling/portable fans) for maintaining comfort and health—as well as means for providing feedback to building operators or managers on IEQ or other needs.

The widely deployed sensors, meters, and Internet of Things (IoT) devices in buildings have been collecting a growing volume of data, including occupancy (e.g., people count, presence), IEQ, energy end uses, building system operational parameters, and outdoor weather conditions. Those data enable quantification and tracking of occupant-centric metrics, which can enable performance goals to be achieved or maintained throughout the building life cycle. With the advancements in occupant modeling and simulation (see, for example, Chapters 6–8 of this book and Hong *et al*., 2016), it is feasible to calculate the occupant-centric performance metrics in building performance simulation to enable their use for informing building design options and technology evaluation. The new approach is in contrast to previous modeling approaches, which allowed fractional occupants and rarely considered individual behaviors, exposure to the environment, or presence.

In this chapter, we define occupant-centric performance metrics as those that capture the quality of services occupants receive and the degree of a building's flexibility to accommodate occupants' interactions with the building systems that influence building operations and, consequently, resource usage and environmental performance. It should be noted that the examples of occupant-centric performance metrics we present in this chapter are not intended to be exclusive. These metrics are intended to be used by building designers, architects, engineers, building owners, and occupants, and can be adopted in post-occupancy evaluation as well as in design charrettes.

This chapter builds on the occupant needs discussed in Chapters 2–4. In Section 5.2, we describe a framework to define and exemplify a suite of occupant-centric performance metrics. These metrics aim to cover the main use cases in the building life cycle representing performance of (1) resource uses to provide services for occupants and their environmental impacts; (2) IEQ, ensuring a comfortable and healthy indoor environment for occupants; and (3) human-building interactions, which entails the degree of freedom for occupants to interact with buildings and systems and to provide feedback. In Section 5.3, we describe calculations or measurements to quantify these metrics and corresponding visualization techniques used to facilitate communications with architects, building designers and engineers, occupants, building operators, and policymakers. In Section 5.4, we further discuss the basis of setting occupant-centric performance targets.

5.2 Occupant-Centric Building Performance Metrics

In this section, we first introduce the key attributes of occupant-centric metrics, and then present a framework that covers their important aspects. We review building performance considerations in existing literature, building codes, and standards from the occupant perspective. The review includes current limitations and future improvement opportunities of occupant-centric building performance evaluations. Finally, we provide example use cases of occupant-centric metrics in the building design phase.

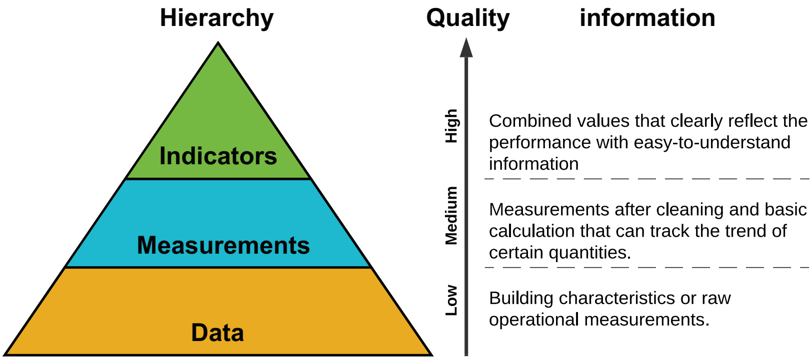

Figure 5.1 Hierarchy, quality, and information for building performance quantification.

5.2.1 Key Attributes of Building Performance Metrics

de Wilde (2018) describes a hierarchical structure of quality and information for use in the analysis and quantification of building performance (Figure 5.1). The term *occupant-centric metric* in this section is used to describe indicators.

Performance metrics translate raw data into actionable information that is easy to understand and can be incorporated into a clear performance evaluation target, such as energy use, IEQ, or space utilization. The following are the key attributes of performance metrics:

- **Accessibility/reproducibility:** Metrics should be easy to obtain repeatedly with existing infrastructure and technologies and reasonable effort and cost. Specifically, the sources of data and how they can be measured should be straightforward.
- **Quantifiability:** Metrics should have a clear definition of either direct measurements or robust and straightforward formulas for calculating the values. For example, the metric definition should be clear about which sensor, meter, and building characteristics are needed for the calculation. Quantifiability is the foundation of performance tracking, verification, and benchmarking.
- **Actionability:** Metrics should be target-oriented. They should provide actionable information to inform solutions to specific problems; for example, reducing lighting energy consumption per person by improving the lighting control.
- **Comparability:** Ideally, metrics should be easy to compare across different scales, countries, building types, and other settings, to maximize utility. A good metric should be generic and not building-specific.
- **Unbiased:** Metrics should be fair and objective. For example, performance metrics normalized for real-time vs. designed occupant count may be misleading.

5.2.2 A Framework of Occupant-Centric Metrics

Occupants are the main recipients of building services. They interact with the building and its systems to ensure their needs are met. At the same time, buildings and their systems consume resources to provide the required services, while byproducts such as waste and GHG emissions influence the environment. Therefore, occupant-centric building performance can be represented by three aspects (Li *et al*., 2021): (1) resource use and environmental impact, (2) IEQ and other services provided by the building and their influence on occupant comfort and health, and (3) human-building interactions. Figure 5.2 depicts these three interlinked aspects. For resource use and environmental impact, examples are building- or zone-level energy consumption, peak power demand, water usage, and GHG emissions during partial and full occupancy. For building services, we consider five categories, which include four key components of IEQ—thermal quality, visual quality, acoustic quality, and indoor air quality—as well as other services, such as the use of miscellaneous electric devices, service water, internet connection, and space. For human-building interactions, we consider the building's capability to accept occupant inputs and provide feedback and control system operations with respect to occupant-centric needs.

There are diverse factors to consider when defining or selecting occupant-centric metrics. For instance, there are different levels of granularity in

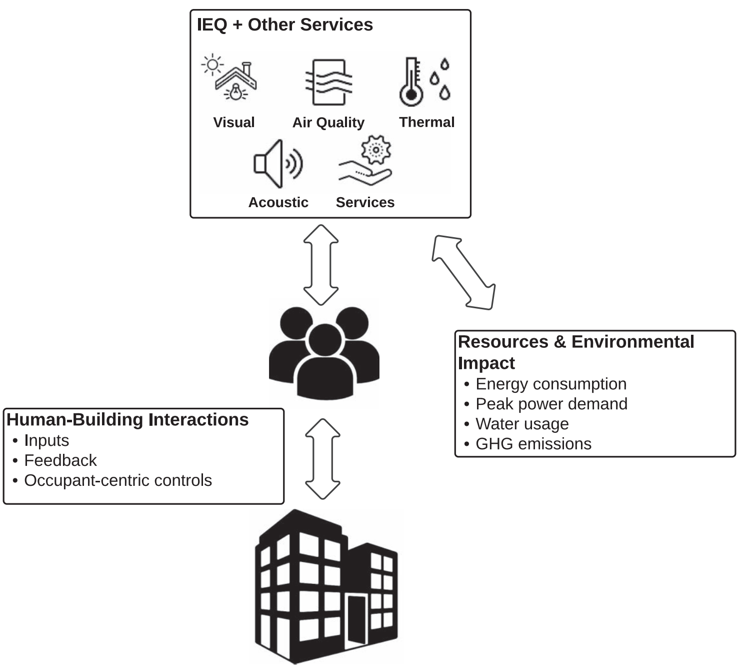

Figure 5.2 A framework of occupant-centric building performance metrics.

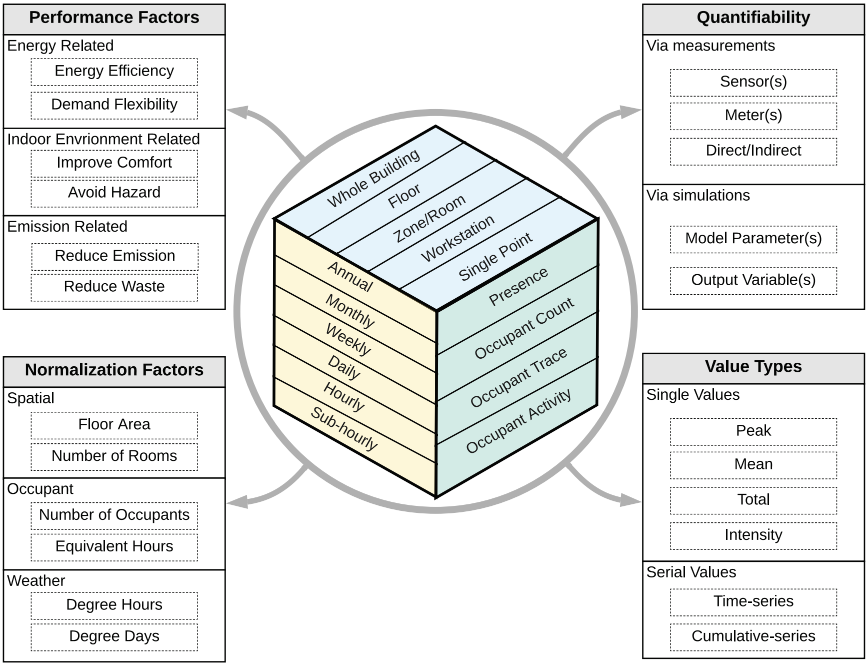

Figure 5.3 Examples of dimensions and important factors of occupant-centric metrics.

terms of occupant and other related data. In the temporal dimension, the resolution ranges from the annual to the hourly or sub-hourly level. In the spatial dimension, the resolution ranges from the whole building to a specific point. In the occupant dimension, the resolution ranges from occupant count at the building or zone level to individual occupants and their activities. In addition to the three dimensions, other factors such as the performance goal, quantifiability, normalization factors, and value types should be considered. Figure 5.3 shows the dimensions and important factors to consider when choosing occupant-centric metrics.

5.2.3 Examples of Occupant-Centric Metrics

Table 5.1 shows examples of metrics covering the three categories. A comprehensive list of occupant-centric metrics and factors is available in Li *et al.* (2021). The example metrics are for demonstration purposes and may not be applicable to all scenarios.

In addition to the normal operating conditions, occupant-centric metrics can also cover extreme scenarios, such as when occupants are in extreme

Table 5.1 Examples of occupant-centric metrics

Category	*Sub-category*	*Metric name*	*Metric definition*
Resource and environmental impact	Energy Use	kWh/ OccupantHour	Annual total site energy use (kWh)/annual total occupant-weighted hours for the whole building
	Water Use	kg water/person	Annual water use (kg)/ number of maximum occupants
	GHG Emissions	kg CO_2e/person	Annual CO_2 equivalent emission (kg)/number of maximum occupants
Building Services	Lighting	Underlit Occupancy Hours	The hours when the indoor light level is below the adaptive setpoints for a particular occupant when the room is occupied
	Thermal	Degree-Occupant-Hour Criterion (DOHC)	Sum of occupied hours multiplied by the number of occupants and operative temperature exceeding the corresponding comfort range
	Air Quality	Weighted CO_2 Exceedance × Occupant Hour	The sum of CO_2 concentration exceeding a reference level, multiplied by the number of occupants during each occupied hour, weighted by the range in which the CO_2 concentration is in (e.g., higher weights when CO_2 concentration is unhealthy)
	Acoustic Quality	Global Index of the Acoustic Quality	A global index that is the weighted function of five partial indices, namely: reverberation index, intelligibility of speech index, uniformity of loudness index, external disturbance index, and music sound quality index
	Other services	Hoteling Potential	Minimum ratio of the required number of workstations to the number of employees if they relocate on a weekly or daily basis for 95% and 99% of the time

(*continued*)

Table 5.1 Continued

Category	*Sub-category*	*Metric name*	*Metric definition*
Human-Building Interaction	Controllability	Controllability of HVAC	Percent of occupants who can adjust thermostat settings for their local environment
	Controllability	Accessibility of operable windows	Percent of occupants who can open/close the operable windows
	Occupant and Response	Accessibility to Building Information	Percent of occupants who have access to building information (e.g., a dashboard to see energy use, demand, space use, and IAQ of their floor or space)
	Occupant Feedback	Mechanism to provide feedback	Can occupants provide feedback about their IEQ needs? Is there a periodic survey of occupant satisfaction?

environments, e.g., very high or very low indoor air temperature during extreme weather events such as heat waves or cold snaps due to power outages. In such cases, traditional thermal comfort metrics, such as predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) are not sufficient; other metrics may be more appropriate to represent the thermal hazard (Sun *et al*., 2020). For example, heat index (HI) considers both indoor air temperature and relative humidity to measure the human-perceived equivalent temperature. It is widely used for assessing outdoor thermal comfort and thermal resilience in the United States. There are five levels of risk based on the heat index: (1) Safe (HI ≤ 26.7°C); (2) Caution (26.7°C < HI ≤ 32.2°C, fatigue possible); (3) Extreme Caution (32.2°C < HI ≤ 39.4°C, muscle cramps and/or heat exhaustion possible); (4) Danger (39.4°C < HI ≤ 51.7°C, muscle cramps and/or heat exhaustion likely); and (5) Extreme Danger (HI > 51.7°C, heat stroke highly likely).

5.3 Methods to Quantify Occupant Metrics

This section describes methods to quantify the occupant metrics using measurements or simulations, taking into account fundamental differences between users (e.g., age, gender) to properly reflect their conditions and preferences, as well as to address potential inequities. Several examples are provided to demonstrate how occupant metrics can be calculated using building automation system (BAS) and IoT data, and from simulations.

Table 5.2 Types of data needed for occupant-centric metrics calculations

Data type	*Example*
Occupancy information	Occupant presence/absence and/or people count at the space or whole-building level
IEQ parameters	Air temperature, humidity, CO_2 concentration, volatile organic compounds, illuminance level, and acoustic level
Resource usage	Energy use of the whole building or major end uses including lighting, HVAC, plug-in equipment, and service water heating. Water use for the whole building or broken down into HVAC (cooling tower), drinking, and other uses (washing, flushing toilet, etc.)
Environmental impacts	GHG emissions and solid waste associated with building services
Human-building interaction measurements	Percent of occupants able to interact with building systems and components, e.g., open/close windows, adjust thermostat settings, open/close shades, turn on/off or dim lights, turn on/off plug-in equipment, occupant feedback system

5.3.1 Methods based on Measured Data

Occupant-centric metrics can be either directly measured or calculated using measured data for existing buildings. As per the framework in Figure 5.2, the data needed for calculating occupant-centric metrics have multidimensional traits (i.e., temporal, spatial, and occupant) and can have a range of resolutions. Depending on the selected metrics, the types of data and examples at various temporal resolutions (from minutes to hourly to monthly to annual) shown in Table 5.2 may be needed for measurements.

Occupancy information is essential for occupant-centric metric calculations. Numerous methods can be used to measure occupant presence or absence in a space. They are differentiated by whether occupants are counted implicitly or explicitly (Dong *et al*., 2018). Implicit methods determine occupancy indirectly, via a secondary signal. The most common example is measurement of CO_2 as an indication and variation of occupancy over time. Other measurements have also been suggested and used with varying degrees of success. For example, in office-work types of environments, plug loads can indicate operation of computers and thus, occupancy. Indirect methods need to be calibrated and often recalibrated to avoid drift and maintain accuracy.

Explicit methods link a measurement count directly to a person without the need for complex calibration. A common example is motion detectors, typically based on passive infrared (PIR) sensing. PIR sensor data, however, are not usually logged in building management systems, but rather directly linked to, for example, lighting control. Recently, methods that use available IT infrastructure have emerged. Most notably, the use of Wi-Fi signals. Analyzing connected mobile phones (or other Wi-Fi-capable devices) gives an indirect count of the number of people in the vicinity of the wireless access point, which is linked to a certain space/zone in the building (Hobson *et al*., 2019).

The study by Hahn *et al.* (2020) demonstrates the value and implementation of occupant-centric performance indicators and targets in energy analysis through a post-occupancy evaluation (POE). The study examined high-efficiency residential buildings in the south of Germany within the context of the POE process, and included monitoring, occupant information and training, and surveying. The objective was to draw a comparison between the calculated energy demand according to standards, such as in energy certificates, and the actual monitored consumption (thermal energy for domestic hot water and space heating, electricity for appliances/plug loads) over several years (2013–2016). The study was conducted annually from 2013 to 2016.

With the dimensions and factors (Figure 5.4) in mind, traditional building energy performance metrics (e.g., from current standards) usually only consider intensity normalized by floor area, which overlooks heterogeneous occupant density and variety of behavior. However, occupant factors are known to be among the most influential ones affecting building energy consumption, and so they must be included. To keep the basis of comparison, the measured floor heating energy was normalized by heating degree days (HDD) and adapted to the test-reference year (TRY). The individual units were considered. In addition, the number of permanent residents from POE in each unit was used to obtain an occupant-centric indicator. The inclusion of occupant-centric indicators enables energy consumption and subsequent emissions to be compared considering the occupant factors, which informs decision-making of building designers and energy modelers. It demonstrated that, for example, "wasters" or "savers" were not necessarily wasteful or saving when the number of inhabitants was taken into account. In addition, the observation over several years discovered "personal fingerprints," as the normalized energy consumption remains relatively constant

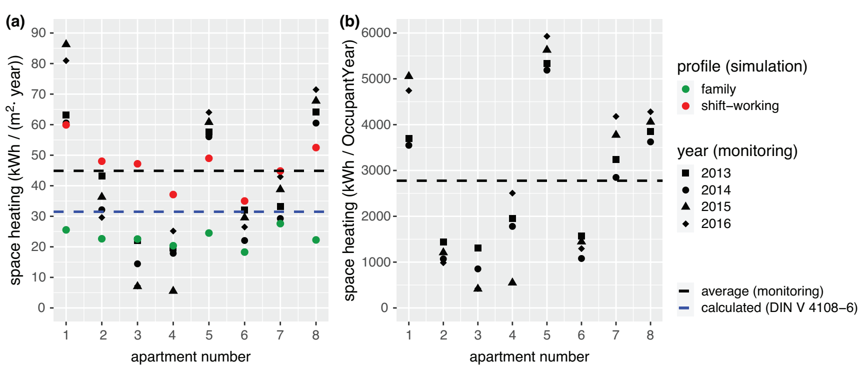

Figure 5.4 Thermal energy for space heating in the example building with eight units: kWh/(m^2 × year) (left) and kWh/OccupantYear (right). Both metrics are weather-normalized (Hahn *et al.*, 2020).

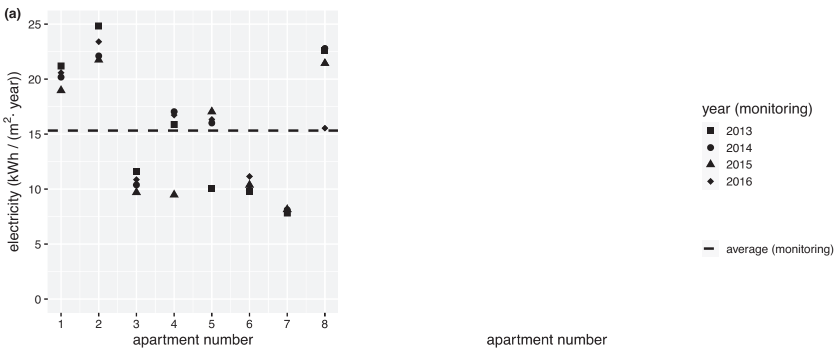

Figure 5.5 Annual electricity use of the example building with eight units: kWh/(m^2 × year) (left) and kWh/OccupantYear (right) (Hahn *et al.*, 2020).

with low variations (Figure 5.5). Figure 5.4 shows the annual space heating energy for the building with eight units and energy consumption scenarios with simulated profiles for "'families" and "shift-working."

Further improvements regarding the indicators can be achieved by counting the real occupancy hours. This can lead to a higher temporal resolution (kWh/OccupantHour). Considering the topology of residents, these metrics can be grouped by life and work style to provide a more reasonable peer-to-peer comparison. For example, working families' and seniors' houses should be considered in different groups.

5.3.2 Methods based on Building Performance and Occupant Modeling

Building performance simulation (BPS) provides an approach to quantifying different performance aspects such as energy demand and IEQ, which are important bases of comparing different design alternatives for new buildings and operation strategies for existing buildings (Hong *et al.*, 2018). Recent advancements in BPS (Yan *et al.*, 2017) have made it more feasible to calculate occupant-centric performance metrics.

Getting realistic occupant-related assumptions is essential for occupant-centric metrics. There are many ongoing efforts to improve occupant-related assumptions. Table 5.3 summarizes recent advancements based on the occupants' presence and actions (OPA) framework (Schweiker *et al.*, 2018) in building occupant modeling, and how they benefit occupant-centric metrics calculations.

In addition to the occupant modeling assumptions, another necessary step to quantify occupant-centric metric is post-processing. This step involves looking up the metric formulas, processing the simulation outputs,

Table 5.3 Advancements in occupancy estimation and occupant behavior modeling improvements

Occupant behavior modeling	*Recent advancements*	*Benefit*
Presence/Movement	1. Occupancy estimation and prediction with easy-to-measure environmental parameters, Wi-Fi connections 2. Stochastic occupant movement modeling	Provides high temporal and spatial resolution of occupancy information and helps users convert them into occupancy schedules for simulations.
Actions	Modeling of the adaptive behaviors 1. Window operation 2. Solar shading operation 3. Lighting operation 4. Thermostat adjustment 5. Appliance use 6. Clothing adjustment	Provides insight into occupants' individual IEQ preferences and helps users calculate occupant-centric metrics with respect to realistic occupant demand

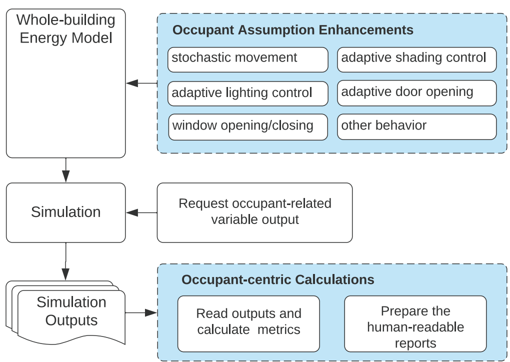

Figure 5.6 Calculation of occupant-centric metrics from simulations.

and calculating the metrics, which can be tedious and error-prone for energy modelers. Therefore, easily accessible tools that provide automatic, standardized occupant-centric performance metric calculations could be very helpful. Figure 5.6 shows how the occupant modeling assumption enhancement module and automatic occupant-centric metric calculation module could be integrated into the five-step process introduced previously (Li *et al.*, 2021). The occupant assumption enhancement module reads a whole-building energy model, generates more realistic occupant-related assumptions that can consider climate and cultural differences, and injects the improved assumptions into the simulation. The occupant-centric metric calculation module adds required variables to the simulation, extracts the outputs after the simulation, calculates the metrics, and reports them in a user-friendly manner. This way, the occupant assumption enhancements and metric calculating and reporting are encapsulated, which helps to streamline and standardize the process.

Some tools have been developed recently following the paradigm described above. For example, researchers at Lawrence Berkeley National Laboratory have developed an occupancy simulator (Chen *et al.*, 2018) that models stochastic occupant movements in office buildings and converts it into occupancy schedules. This tool is integrated into an OpenStudio measure (Li and Hong, 2020) that could be easily adopted in the EnergyPlus and OpenStudio simulation processes. Following the same idea, an occupant-centric metric OpenStudio reporting measure was developed. This measure also can be adopted in EnergyPlus and OpenStudio simulations and automatically calculate and report the occupant-centric metrics in a standardized way. The improved occupant modeling and standardized occupant-centric performance metrics calculation measures allow building designers and modelers to evaluate how building and system designs influence occupants, and vice versa.

5.4 Setting Targets of Occupant-Centric Performance Metrics

Traditionally, throughout the building life cycle, building performance targets have mostly avoided consideration of occupants out of convenience, technological limitations, and uncertainty about occupancy. For example, energy is primarily normalized by floor area through detailed design (e.g., using simulation) and operations (e.g., using meter data), given the ease of accessing floor area data. Meanwhile, comfort may be defined using some abstract metric (e.g., PMV or hours within a certain air temperature range) that focuses on the space rather than the occupants and their exposure to conditions. Previously, without the tools to accurately predict occupancy through the design process (e.g., via simulation tools) and the ability to measure occupancy in an operating building (e.g., via sensors), occupant-centric metrics have been difficult to quantify. Performance risks and user requirements should be assessed at every stage, together with suggestions on how this should happen with regard to sustainability (RIBA, 2019). For instance, the Plan of Works (RIBA, 2020) refers to the RIBA (2019) for numerical targets and implementation strategies and suggests the appointment of a sustainability champion to integrate sustainable strategies to client requirements and the business case, as well as to further develop the strategy as the project progresses.

In the context of the design process, traditional performance metrics such as EUI have several important limitations. For instance, focusing on energy performance per unit of floor area sidesteps the design strategy of improving space utilization to reduce energy use. Normalizing resource use by person, in contrast, can provide a better indication of occupant needs together with what the building affords. For example, how does the subject building compare in floor area per person to other buildings of that type? Are appropriate levels of outdoor air, water, and lighting provided to occupants once the real occupant utilization in a space has been considered? Moreover, occupant-centric metrics have the implicit benefit of reframing design discussions to be about occupants, who are the ultimate users of the building (see Chapter 4 for further discussion). Such metrics are also more relatable and informative for occupants during a building's operational stage since they are expressed at the occupant scale.

In the upcoming section, we argue and demonstrate how occupant-centric building performance metrics or other indicators can be set early in the design process and evaluated from design development through operations. These metrics can be used to benchmark a particular building (or part of a building, such as a tenant or apartment) with respect to others or to detect and possibly address undesirable anomalies. Moreover, they may help to explain outliers that cannot be explained via traditional metrics. For example, an open-plan office space that is converted to hoteling/hot desking may experience a significant increase in plug loads, but this would be completely justifiable if the average occupancy is increased. Of course, IEQ-related occupant-centric metrics such as noise exposure also could be tracked to quantify the potential consequences of increased occupancy density. The following section is divided into two interrelated parts: the first part focuses on setting targets, while the second part discusses the application of targets through the building life cycle.

5.4.1 Approaches to Setting Targets for Occupant-Centric Performance Metrics

We consider two complementary approaches to quantifying occupant-centric performance methods: top-down and bottom-up. These terms are used in the engineering sense, where top-down means a disaggregation of the sum and bottom-up means aggregation of the parts. Top-down methods start with high-level metrics to derive occupant-centric performance metrics. For example, the annual energy use of a building can be divided by the number of nominal occupants or occupant-hours per year to obtain occupant-centric metrics. For a more specific example, Canada's residential building sector consumes about 1,600 petajoules (PJ) ($1{,}600\times10^{15}$ J) total, or about 42 gigajoules (GJ) per person (Government of Canada, 2020). This value could be used as a starting point for a target, e.g., 21 GJ per person (or a 50% reduction from the current housing stock).

Bottom-up methods start with individual occupants and their needs and may aggregate these up to the building level. For instance, we might consider the daily water needs for occupants and then use this information to estimate building-level water use (e.g., 100 occupants times 50 liters (L)/day of water leads to expected water use of 5,000 L/day).

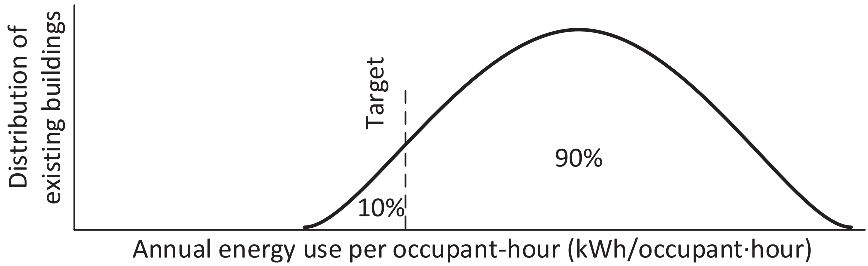

Figure 5.7 Example of a top-down approach, where an occupant-centric metric target is based on the distribution of energy use per person for existing buildings.

Top-down methods are generally easier to apply, as they stem from conventional metrics that may be available using national statistics on building energy or existing targets, such as net-zero energy. For nearly all occupant-centric performance metrics of interest, occupancy is a needed input. Thus, estimates must still be made for real or designed occupancy (e.g., by collecting these data from real buildings or via occupancy schedules in simulation). To set targets, we may aim for a building to be in the 10th percentile of existing buildings of that type (e.g., Figure 5.7) or use population-level targets for guidance.

While bottom-up methods may be more challenging to generate, they more closely follow the intent of occupant-centric performance metrics. The bottom-up approach can be built up and aggregated from individual occupant needs. The targets may be obtained based on standards, such as normalizing lighting or ventilation by occupancy instead of floor area, and other available data, such as the best available office equipment. For example, Coleman *et al.* (2015) benchmarked their office equipment (computer, monitor, task lamp, and phone) per occupant (nominal power of 56 W) against more typical equipment (367 W). This target can be used through simulation-aided design, procurement, and eventually be measured once the building is occupied.

The low-level bottom-up metrics may or may not be directly additive, as has been previously done for energy and costs (Hitchcock *et al.*, 1998). Consider the example of Figure 5.8. A variety of occupant resource requirements are separated and quantified using a bottom-up approach. The values are obtained using measurements, statistics, or engineering judgment, and then summed to estimate a higher (e.g., floor or building) level at different temporal scales (e.g., annual).

In some cases, the resources are fixed (e.g., the refrigerator is likely to run regardless of occupancy), whereas others vary with time of day and year (e.g., lighting or ventilation, if occupancy-controlled). Notably, in some cases, resources are required for building operations even if the building

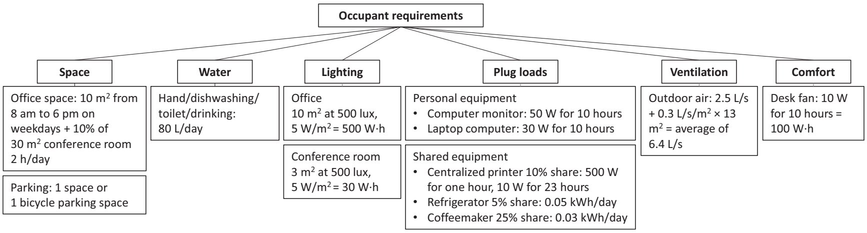

Figure 5.8 Example of a bottom-up approach to establish occupant metrics and targets.

Figure 5.9 Example of measuring occupant-level exposure using a wearable dosimeter (see red device worn by the occupant on their belt).

is vacant—for example, overnight. These include systems such as HVAC to prevent freezing and to ensure conditions are comfortable when occupants return, as well as emergency/security lighting. Moreover, some resources, such as heating, are difficult to allocate to individual occupants (e.g., space heating supplied by a centralized HVAC system).

Another class of bottom-up occupant-centric metrics involves individual occupant exposure of environmental conditions. Rather than the classic approach of imposing targets or limits on spaces (e.g., ventilation rate, noise dose limits), advanced occupant simulation and sensing allow us to quantify the exposure dose for individual occupants. For example, if we use an occupant model that involves the occupant traveling between multiple rooms in a building, we can quantify their exposure to noise over the course of a day and compare it to standards. For buildings with hazardous exposures, occupants may wear dosimeters to measure the severity and duration of exposure to conditions (e.g., noise, radiation) that individuals encounter (Figure 5.9)

In the future, we recommend that a database be developed to improve the ease of benchmarking and setting targets for occupant-centric building performance metrics, as has been done for energy performance and comfort (Chung, 2011). Ideal design situations should be made of several iterations between top-down and bottom-up approaches in which aggregations and disaggregation are negotiated among the design team until all design objectives referring to occupancy and building performance are properly satisfied. This promotes transparency in setting up occupancy data for spaces, which are normally provided by architects to mechanical engineers, so that more realistic ranges of use can be agreed upon. Agreeing on ranges and tolerances within design teams is important when abiding by tight environmental targets. Architects will set up provisional building layouts based on a series of discussions with clients following principles of functionality and ergonomics (Neufert and Neufert, 2012), whereas engineers will need to attribute ranges and tolerances to these principles to account for heating and cooling risks.

5.4.2 Use of Occupant-Centric Performance Metric Targets through the Building Life Cycle

Using any of the approaches above, occupant-centric performance metric targets can be set early in design or in planning and then maintained and monitored throughout the building life cycle. At the start of the building design process, normally occupancy can only be estimated, and IEQ and usability can only be predicted based on the proposed building systems and design. Aspirational targets can be set, but they likely need to be refined as more information becomes available from BPS (or other tools) and the design matures. Designers—and even operators—should be prepared to update assumptions about occupancy.

BPS tools are now at the stage where individual occupants can be modeled and significant detail on IEQ can be obtained. BPS tool outputs are of sufficient resolution during design that they can be compared to measured data during the use stage. A sample of occupant-centric metrics through the building life cycle is summarized in Table 5.4.

Subsequent design stages that follow the definition of the design brief (i.e., the report with building design details) integrate these performance metric targets into design solutions, thus increasing the level of detail as the project progresses. The stage in which spatial coordination is supposed to happen—and planning, certification, and building regulations applications are being prepared together with more detailed costs—is normally a point for assessment and feedback for sustainability outcomes, as well as for more detailed coordination of them with health and well-being of occupants. This stage normally happens at the end of the schematic/conceptual design stage and the beginning of the detailed design/specification stage. In the pre-construction design stage, targets are updated in accordance with final specifications, and risk assessments are undertaken with potential Plan Bs for contractors, so sustainable outputs and well-being targets can fit within updated specifications.

Table 5.4 Example available data and a comparison of conventional versus occupant-centric metrics

	Life-cycle stage			
	Programming/ design brief	*Schematic/ conceptual design*	*Detailed design/ specification*	*Use*
Typical available data/ information	Planned occupancy, space uses, estimated floor area	Early BPS results with simple HVAC and lighting systems	Detailed BPS outputs, including occupancy and IEQ predictions	Measured data for energy, IEQ, etc.; subjective post-occupancy evaluation
Conventional metrics	Floor area per activity; target EUI	Total energy use	Total energy use or energy use intensity; energy end-use breakdown; unmet hours; overheating hours; nominal lighting and plug load power density	Energy use intensity; end-use breakdown at the building level or submeter
Sample occupant-centric metrics	Energy use/ person (based on similar buildings or national statistics)	Total energy use normalized by nominal occupancy	Energy/occupant-hour (including end uses); ventilation per person; lighting energy per person; IEQ exposure per person—all based on estimated occupancy; plug-in equipment power per occupant	Energy/-occupant-hour (including end uses); ventilation per person; lighting energy per person; IEQ exposure at occupant resolution

When delivery guidance such as the BG 38/2018 Soft Landings core principles are followed and design and occupied buildings are seen as a continuum, a tangible procedure should be followed with regard to monitoring. For example, BSRIA's Soft Landings (BG 38/2018) guidance recommends that a Year 1 assessment should be designed for settling down adjustments until stable operation is achieved. Year 2 should be used for a post-occupancy evaluation (POE). Year 3 should be used for responding to the POE and maintaining monitoring, using the POE to gauge energy performance, IEQ,

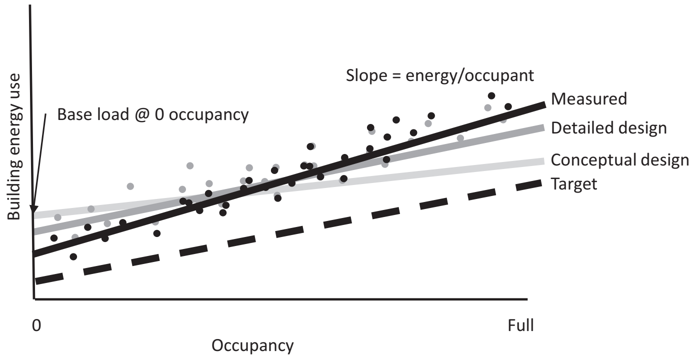

Figure 5.10 Building energy use vs. occupancy plotted as a means to track building performance throughout the building life cycle. Note the lines are not necessarily linear.

and occupant satisfaction against what was initially specified by the client, with the flexibility that "…performance targets should be revisited, checked and altered where necessary" (BG 38/2018). Feedback loops should be in place so designers can be informed about the performance of earlier projects when designing subsequent ones, thus providing a reality check to design decision-making. Involvement by end-users is strongly recommended to inform the design team of their needs and expectations, especially if they are heavily involved in controlling indoor environmental conditions.

Metrics and their targets may include single values (e.g., energy per occupant-hour) but may also include curves (Hitchcock *et al.*, 1998). For example, Figure 5.10 shows the relationship between occupancy and building energy use for a hypothetical building. By fitting hourly data to a line, the building can be characterized according to its ability to adapt to varying levels of occupancy. The y-intercept represents the average building energy use when the building is vacant, and the slope indicates the additional energy per occupant (e.g., in kWh per occupied hour). Kim and Srebric (2017) used measured data to show that the slope and intercept values can differ by an order of magnitude due to building function and operations. In an ideal case, the y-intercept is 0 and the slope is minimized. However, as noted above, many buildings have base functionality during vacancy for the safety and security of the building. Nevertheless, the y-intercept should be minimized via passive measures (e.g., well-insulated envelope) and active measures (e.g., occupancy-controlled lighting and ventilation).

5.5 Closing Remarks

In this chapter, we described the motivation and a framework to define occupant-centric performance metrics in three major categories: resource use and environmental impact, indoor environmental quality, and human-building interaction. These metrics are intended to complement current practices of representing and evaluating building performance and can be adopted by stakeholders to quantify building performance from the occupants' perspectives, which can inform decision-making in the building life cycle. We described two methods—using measurement and using building performance simulation—to quantify these metrics. We also provided a suite of occupant-centric performance metrics as examples to illustrate their potential use. We closed the chapter with a discussion of the basis for setting reasonable targets for these metrics and provided recommendations for stakeholder communication on building performance using these metrics. The next two chapters provide an overview of occupant modeling methods and discuss various aspects to consider in selecting the most appropriate occupant models for a specific application in the building life cycle.

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6 Introduction to Occupant Modeling

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Summary

In this chapter, we will provide an overview of occupant modeling, beginning with key definitions and a background on common occupant modeling approaches. Next, we will present more advanced modeling approaches, including data-driven stochastic models, agent-based models, and personas. Finally, we will discuss methods to implement occupant models into building performance simulation tools and methods to communicate occupant model characteristics.

6.1 Introduction

Computational modeling and simulation are powerful techniques to create a representation of buildings. In general, building performance modeling and simulation provide a deeper understanding of a given system to inform decision-making at any or all phases of the building life cycle, from early-stage design to operations and management. In the past two decades, occupant modeling has gained significant traction by researchers and practitioners due to the increasingly significant impact of occupants, interest in occupant well-being, and increased computational and simulation capabilities. Occupant modeling is a mathematical approach to characterize how people occupy and act in buildings. When integrated into building performance simulation (BPS), occupant modeling can be used to estimate how occupants might behave in buildings for a year or longer, and how building design and operation might affect occupants.

Ultimately, occupants can profoundly affect building performance relative to predictions. This impact has been evidenced in studies of architecturally similar spaces or buildings whose performance varies greatly as a result of their occupants (Dong *et al.*, 2015; Iwashita and Akasaka, 1997). The so-called energy performance gap—the difference between predicted and measured energy use—tends to be even larger for high-performance buildings. For instance, as insulation levels and airtightness increase as a consequence of stricter regulations, occupants' control over building systems

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and equipment will have higher relative effects on heat transfer and energy use (Carpino *et al*., 2017; Guerra Santin *et al*., 2009). Occupant control of windows and blinds can also significantly impact energy flows across the envelope (Hoes *et al*., 2009).

Failure to accurately characterize occupants in the building design process caries two risks: first, it may lead to a performance gap; second, and perhaps more critically, it may lead to poor design decisions (Gilani *et al*., 2016). For example, optimistic assumptions about how occupants will behave (e.g., in an energy-optimal way) or pessimistic assumptions about occupant density (e.g., very high values for HVAC equipment sizing) may lead to design decisions that impact a building's performance for life.

In the past decade, occupant modeling has been used extensively to support building design (discussed further in Chapter 8) and to close the gap between the predicted and actual energy performance (e.g., Goubran *et al*., 2021; Mahdavi *et al*., 2021). For example, occupant modeling can be used to assess the impact of occupant interactions with architectural features and technologies (e.g., adaptive facades) (Hong *et al*., 2017; O'Brien and Gunay, 2015; Luna-Navarro *et al*., 2020; Stopps and Touchie, 2021; Yan *et al*., 2015). Occupant modeling can also be used to design more comfortable and energy-efficient spaces and to avoid oversizing or undersizing equipment and spaces (e.g., O'Brien *et al*., 2019).

Aside from energy performance, occupant modeling can be used to better understand comfort and adaptive opportunities, such as adaptive facades, clothing, and thermostats (Deng and Chen, 2021). It can also be used to help develop strategies toward healthy indoor spaces, e.g., to control the transmission of COVID-19 and other pathogens (Li *et al*., 2021). Building models, for example, can be used in combination with various occupant scenarios to create profiles of individual heat exposure (Sailor *et al*., 2021) and analyses of occupant presence and behavior (Yan *et al*., 2021).

This first section introduces basic occupant modeling concepts and definitions, and subsequent sections delve into more details and more complex methods.

6.1.1 Occupancy and Occupant Behaviors

In this chapter and throughout the book, we distinguish between two major occupant characteristics: occupancy and behavior. Occupancy is used synonymously with presence and quantitatively defines the number of occupants or density of occupants in spaces. It can be defined as a binary state: occupied (at least one person present) or vacant (no occupants in space or building). It can also be distinguished by occupant types and groups (e.g., children, students, guests, staff). Accurate modeling of occupancy is important for estimating latent and sensible heat gains and air contaminant loads and to understand schedules and logic for controls and operations. Yet, one of the primary reasons to try to predict occupancy is to predict occupant behaviors and actions; except for cases of remote actions (e.g., smartphone-based thermostats), occupant presence is a necessary condition for actions to occur.

In contrast to occupancy, behaviors are actions that occupants take that affect building performance directly or indirectly (e.g., energy, indoor environmental conditions). In many instances, occupants are triggered to act by indoor environmental conditions (e.g., open a window in response to stale air). These are known as adaptive triggers. In turn, these behaviors affect indoor environmental quality (IEQ) and potentially building energy use. However, other behaviors (e.g., use of office and entertainment equipment) affect building performance but are not related to IEQ. These are known as non-adaptive triggers and may be a result of habits or tasks (e.g., occupant turns on computer when they arrive at work).

Occupant actions may be triggered by physical, physiological, psychological, or social phenomena. The relationship between triggers and actions is often moderated by contextual factors (e.g., office dress codes constrain opportunities to modify clothing levels) (O'Brien and Gunay, 2014). Figure 6.1 represents the relationships between actions, behaviors, and triggers (Schweiker *et al*., 2018).

6.1.2 *Occupant Modeling Approaches*

Following the terminology of Figure 6.1, occupants' presence and behavior can be modeled as actions (e.g., the action of turning on/off the heating/cooling system) and states (e.g., the state of light switch, state of windows opening, thermostat setpoint). An action changes the state, which then normally remains constant until a new action is taken, though interventions from mechanical and electrical systems may occur (e.g., overriding controls).

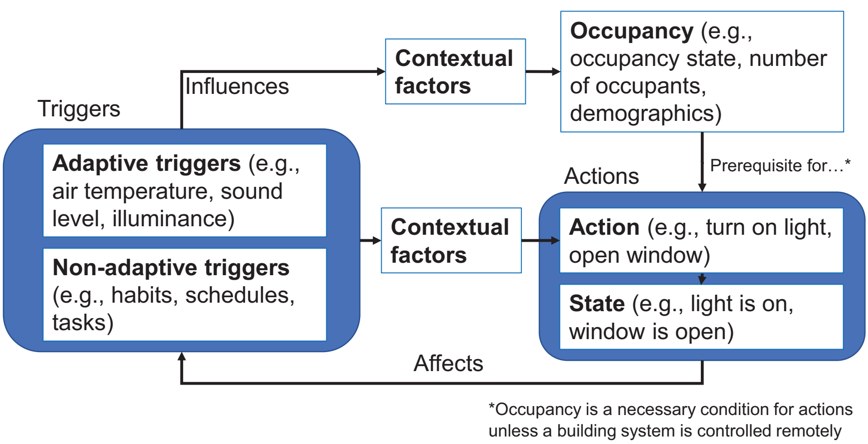


Figure 6.1 Relationships between actions, behaviors, and triggers in buildings.

A state can be defined by more than two levels and options, depending on the accuracy and targets of the modeling approach. For example, a window can have several states, including fully open/closed or half-open, percent open/closed, or lighting can be switched on/off or can include dimming (Schweiker *et al.*, 2018).

Ultimately, the objective of occupant behavior modeling is to predict either occupant actions/interactions with building systems or the resulting state of the building systems. It is generally accepted that accurately predicting individual actions is difficult, but predicting long-term trends is feasible if enough data is available to make generalized models. Defining generalizable predictors and model coefficients is challenging due to the diversity of available studies and the fact that many actions are contextually sensitive (e.g., climates, cultures, building types, systems) or differ for personal characteristics (Carlucci *et al.*, 2020; Schweiker and Shukuya, 2009). In addition, influencing variables for some domains, such as spatial movements or changes in body posture, can be important yet difficult to define and measure (Jakubiec and Reinhart, 2012; Schweiker *et al.*, 2018). Therefore, there is a strong need for researchers to collaborate on standard frameworks; this was one of the main motivations of initiating IEA EBC Annex 79 (O'Brien *et al.*, 2020).

While this book is broadly focused on buildings and building performance simulation, it should be noted that there are many other applications and domains for occupant modeling in the built environment. For example, human mobility and behavior modeling is of primary interest in scientific disciplines that explore topics such as evacuation in emergencies, pedestrian flow in public transportation, and motion in vehicles. Such models have the advantage of capturing occupants at the individual level while attaining realistic collective activities. For instance, people's velocities and buildings' structure (Lizhong *et al.*, 2003), occupants' health status and social influence (Liu *et al.*, 2020), and herd behaviors (Yang *et al.*, 2014) are some of the key factors affecting evacuation efficiency. Modeling frameworks to capture pedestrians' walking behaviors use a combination of concepts from the social force model, behavioral heuristics, and materials science (Porter *et al.*, 2018). Aircraft boarding models are implemented considering individual properties to explore the dynamics of passengers' motions (Tang *et al.*, 2012). With this background on occupant behavior and presence, the following section provides greater depth on traditional occupant modeling methods.

6.2 Traditional Occupant Modeling

To date, the dominant method to model occupants in building simulation is through relatively simple schedules, values, and simple rules. A survey of building simulation users indicated that the majority of them use occupant modeling approaches that are specified by building codes, in part to avoid the liability of making other assumptions that may prove to be incorrect

(O'Brien *et al*., 2016). In another study, practitioners were found to rely on default tool values, which also likely originated from codes and standards (Duarte *et al*., 2013). However, applying the same schedules and other values to all buildings neglects the impact of building design and people. This approach is akin to the way that weather files are imposed in building simulation, i.e., as a boundary condition; however, it fails to recognize that building design influences occupant behavior (O'Brien and Gunay, 2015).

It is relevant to precede our discussion of the state-of-the-art and future of occupant modeling by acknowledging *why* using schedules to represent occupants became a long-standing norm. The practice of assigning a single occupancy value to a modeled interior space for any simulated point in time dates back to at least the early 1980s and the first generations of building energy performance simulation tools, including but not limited to DOE-2 (Clarke, 2001; Diamond and Hunn, 1981; Norford, 1984; Vine *et al*., 1982). This was a time where 3D computer-aided design had yet to be introduced to the buildings industry. Interior building volumes simulated in the BPS tools of the day were prescribed numerically, using simplified metrics for building geometry such as wall area, window area, and interior volume. With respect to building heat transfer modeling, these volumes were represented as perfectly mixed indoor air spaces, with only a single value representing the air temperature within an interior volume at any given time. Similarly, internal heat gains, including occupancy, were represented as single point source loads, nominally determined by a user-assigned schedule as per the engineering manuals of the time (York and Cappiello, 1981). The location of an occupant in any simulated volume would be either fully non-spatial or located in an assumed fixed position of the floor space.

While the processing capabilities of computers today are worlds apart from the computers used in the early days of BPS, the legacy of this simplified approach to representing occupants and building geometry lives on. The same numerical methods DOE-2 used to represent occupants in its original source code remains engrained in the engineering of established, present-day BPS tools, such as EnergyPlus (the direct successor to DOE-2) (Crawley *et al*., 2001). Hence, it is common that users of BPS tools today specify similar time-based schedules and densities to represent building occupancy as would have been done by their predecessors 40 years ago. The term *diversit*y is often used to describe these schedules, in recognition that peaks are unlikely to occur simultaneously (e.g., an office might only have 80% of occupants at a given time, compared to maximum or nominal capacity). To reinforce the simplicity of common occupant modeling practice, Table 6.1 provides a summary of common methods to model different aspects of occupants based on the results of O'Brien *et al*. (2016) and O'Brien *et al*. (2020).

An example of a common modeling approach for occupancy is shown in Figure 6.2, where the occupancy density and schedule for numerous countries' energy code specifications are compared. These graphs show that

Table 6.1 Summary of commonly considered occupant-related domains and the corresponding modeling methods

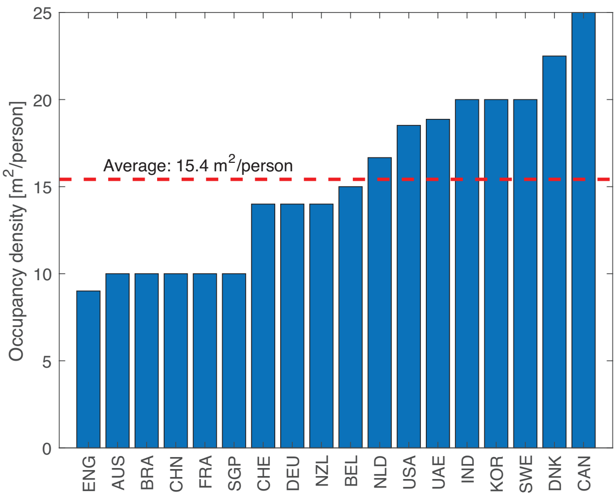
Domain	*Common modeling approaches/assumptions*
Occupancy (presence)	Daily diversity schedules (hourly resolution) with a corresponding density (e.g., m^2 per occupant), usually specified for different building or space types
Plug-in equipment and appliances	Daily diversity schedules with a corresponding power density (e.g., watts per m^2)
Operable windows	Windows are closed
Lighting	Daily diversity schedules or daylight-controlled (otherwise turned on with occupancy) with a corresponding lighting power density (e.g., watts per m^2)
Window blinds/shades	Always open/non-existent (considered furnishing) or closed during glare events (e.g., above 1,000 lux, as per IES LM 83 [IESNA, 2012])
Water appliances (e.g., showers, toilets, sinks)	Hot water volume or energy per day per person or per floor area (e.g., L/person/day)
Thermostats	Daily setpoint schedules with the possibility to turn off systems or use a temperature setback for unoccupied and/or overnight periods
Clothing level	Seasonal schedule (e.g., 0.5 clo in summer and 1.0 clo in winter [ASHRAE, 2020])

typical occupancy modeling approaches are remarkable similar across different regions. They also show the inconsistency among different countries, suggesting a need for a global effort to standardize the way occupants are considered in building simulation.

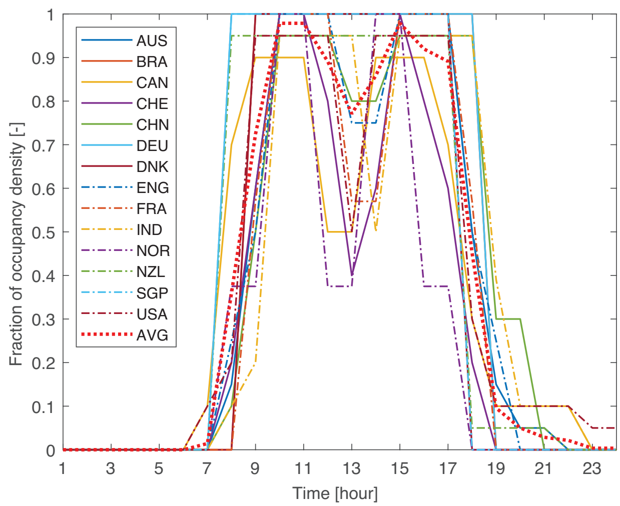
A common question about occupant modeling approaches is where values and rules originated. Unfortunately, to date, data to support the development of occupant-related schedules has been obtained in a relatively dated and ad hoc way (e.g., "engineering judgment") (Abushakra *et al.*, 2004; Deru *et al.*, 2011; Duarte *et al.*, 2013). O'Brien *et al.* (2020) reported that several building codes' occupancy density values have roots in non-energy applications, such as fire codes, which may be intentionally conservative. In the case of fire codes, for example, the relative risk of human safety is considered over the accuracy of energy estimates.

Aside from the challenge and importance of selecting appropriate schedule values to represent occupants, the schedule-based approach has fundamental problems. While these traditional occupant modeling methods are straightforward (e.g., mathematically simple), consistent (i.e., same results each run), and transparent (to the BPS tool user and stakeholders alike), they also have some drawbacks:

- **They lack recognition of two-way interactions between people and buildings**. The models assume occupants behave the same regardless of building



(a)



(b)

Figure 6.2 Example comparison of occupancy levels and schedules for office buildings in 15 different countries.

design. For example, they assume occupants control lights the same regardless of window geometry.

- **They are deterministic, which means that possible ranges of building performance and occupant behavior are not modeled**. They assume that every occupant behaves the exact same way for a given set of circumstances (e.g., all occupants turn on their light at a specific time of day).

- **They separate each occupant-related domain separately, without considering interdependencies**. For example, schedule-based models tend not to consider the linkages between occupant presence and adaptive actions (e.g., opening windows, turning on fans).
- **They are rather coarse and abstract, thus allowing practitioners to avoid deeply considering occupants**. Superficial occupant modeling does not require design practitioners to think about how building design can affect behavior (e.g., accessibility to and ease of opening windows).

These limitations have major implications for building design practice (see Chapters 8 and 11), and significantly limit the power of simulation-aided building design. Traditional methods are rooted in confirming or estimating building energy performance, rather than exploiting a better understanding of the two-way relationship between buildings and their occupants.

6.3 Advanced Occupant Modeling

In contrast to traditional methods of modeling occupants (see Section 6.2), more advanced occupant models tend to have one or more of the following possible and desirable traits (see Chapters 7 and 8 for additional discussion):

- **Stochastic:** A randomness to consider the reality that occupants' individual decisions are often diverse, unpredictable, and inconsistent. Stochastic modeling is used given that we cannot fully characterize, through any measurement, all the boundary conditions that might lead to a specific action. Moreover, there is unknown diversity among people and how they respond to current conditions, which means there is uncertainty about the specific individual occupants who will occupy a building.
- **Dynamic**: The recognition that conditions (e.g., air temperature) alter the way occupants behave and locate themselves within a space. In this way, the two-way relationship between occupants and buildings is characterized such that building design and operations can affect occupants' decision-making.
- **Data-driven:** The trait that occupant models are generated based on measurements. While most existing occupant modeling approaches are based on some measurements or observations, more advanced occupant models tend to use some form of model fitting (e.g., regression to relate behavior to one or more other variables).
- **Agent-based:** The acknowledgement that occupants interact with buildings and/or each other through a series of decisions that are likely a result of one or more conditions (e.g., IEQ, presence or behavior of others). While any of the methods described in Section 6.3 could be considered agent-based, the term is normally reserved for particularly sophisticated models (as discussed in Section 6.3.3).

In the following section, we provide an overview and mathematical details of some of the most common advanced occupant modeling approaches that include some or all of the above traits. We aim to provide an overview, coupled with key technical and mathematical details, and references where readers can seek greater detail. At the end of the section, we highlight two more advanced occupant modeling methods: agent-based modeling and personas.

6.3.1 Deterministic Models

Deterministic or non-probabilistic models are based on fixed values (e.g., an average and constant value for the internal gains in residential buildings) or schedules that are derived from assumptions or empirical observations, such as those described in Section 6.2. As argued in that section, such models offer ease of application, transparency, and reproducibility. However, they are independent of design and operations, and they typically do not capture uncertainty.

We should note that schedules and other non-probabilistic models could be made stochastic, though this is rare in practice. For example, schedules or densities could be stochastic (e.g., shape parameters randomly chosen from distribution) and data-driven (O'Brien *et al.*, 2019). They could also be customized based on a particular building design (Ouf *et al.*, 2019), or several clusters of occupant types with stochastic weightings could be used.

6.3.2 Stochastic Models

Probabilistic, or stochastic, models make use of stochastic processes to reproduce occupancy and a variety of behaviors, resulting in a probabilistic distribution of predicted results, from the timestep up to annual results. Several stochastic models have been used to reproduce human actions within buildings; in this chapter, we focus on four such models (described in each of the next four sections): binomial models, Markov chains models, hidden Markov chain models, and mixed effect models. Table 6.2 provides a general summary of the purpose and potential application of each model type. We describe each of the models in more depth in the sections that follow, with a focus on the models' application to the field of occupant modeling. For a more extensive explanation of the mathematics behind the different models, we recommend referring to more detailed sources (D'Oca *et al.*, 2019; Mahdavi *et al.*, 2017).

6.3.2.1 Binomial Model

A well-established statistical model used to both analyze and model binary dependent variables is the binomial model, often referred to as logistic regression[1] (Hastie and Tibshirani, 2017) when using the logit function as a link function. It can be used to model, for example, the state of a window

Table 6.2 Summary of four common occupant modeling approaches

Model type	*Typical purpose*	*Application*
Binomial model	Data analysis (e.g., to understand which factors influence occupants to execute an action) and stochastic modeling (e.g., to simulate human operations in building performance simulation software)	A model for predicting binary outcomes (e.g., yes/no, awake/asleep, open/closed, opening action/closing action)
Markov chains	Stochastic modeling with time dependencies (e.g., to model an event that is more likely to happen at a particular time of day, or a particular day of week)	A model for predicting outcomes with *n* states, where *n* can be an integer and represent—for example, specific locations in a building, occupant presence (e.g., present and awake, present and asleep, absent), or position of a window (open, half opened, closed), e.g., at different times of the day
Hidden Markov chain	Data analysis and stochastic modeling	A model for predicting outcomes with *n* unmeasured states, where the states are not measured but are deduced by related information (e.g., the presence of an occupant in a specific room, while only their activity is known)
Mixed effect	Data analysis and stochastic modeling	A model for predicting binary outcomes (see *binomial model regression*, above)

(e.g., closed or open) or the change of state of a window (e.g., from closed to open and vice versa) (Andersen *et al*., 2013; Calì *et al*., 2016).

Binomial models can be used for both analysis and predictive modeling purposes. For the former, it can be used, for instance, to understand the drivers (i.e., leading causes for change, e.g., Fabi *et al*., 2012) leading occupants to take an action. The results can provide researchers with background about how occupants make decisions depending on the indoor environment, weather, time of the day or day of the week, and/or any other measured entity. An illustrative example of binomial models is in Calì (2016), who applied binomial modeling with multiple explanatory variables to 300 monitored windows to generate 300 different models. For each window, the author determined which of the measured explanatory variables had a major influence on the probability of a change of window state and which did not. The variables were then classified depending on the number of times they appeared in the 300 models, where the more frequent the variable, the more important it was considered.

For modeling purposes, the binomial model can be used to dynamically model occupants (e.g., presence in a room, opening/closing a window) within a building simulation model. The model can be called at each timestep or at some selection of timesteps (e.g., only if an occupant is present in a room) and it reacts to the actual room conditions.

The binomial model using the logit function as a link function is based on the logistic function as expressed in Equation (6.1). $p(x)$ expresses the probability function for a certain event to happen (e.g., a window state changes) depending on an explanatory variable x, and, by definition, $p(x) \in [0,1],\ \forall\ x$. Equation (6.1) can be rewritten as in Equation (6.2).

$$p = \frac{1}{1 + e^{-(\alpha + \beta x)}} \tag{6.1}$$

$$ln\left(\frac{p}{1-p}\right) = \alpha + \beta x \tag{6.2}$$

where α is the intercept, β is a coefficient, and x is the explanatory variable. Equation (6.1) describes the probability of a certain event (e.g., opening a window, switching off the heating system) depending on one explanatory variable (e.g., the outdoor temperature) and is therefore used for simple linear regression analysis. For regression analysis with n explanatory variables, the probability function p can be expressed as in Equation (6.3).

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_0 x_0 + \beta_1 x_1 + \ldots + \beta_n x_n \tag{6.3}$$

Andersen *et al.* (2013) suggested the inclusion of interaction terms in the probability function for some circumstances. That is, the probability of an action might depend on x_i at one level of x_j as compared to another level of x_j. For example, the probability of opening (or closing) a window, the coefficient β_i of the x_i explanatory variable at a certain period, e.g., in the morning, might differ from the coefficient β_i at a different period, e.g., at night. Also, there might be cases where an increase in the room air temperature might result in an increase in the probability of opening a window in the morning, and in a decrease in the probability of opening a window in the evening. Equation (6.4) can be used to include interaction terms (γ). It is good practice to use only interaction terms between continuous and categorical variables—time of day can be represented, for instance, in categorical variables such as morning, afternoon, evening, and night.

$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta_0 x_0 + \beta_1 x_1 + \ldots + \gamma_{1,2} x_1 x_2 + \ldots + \gamma_{1,n} x_1 x_n + \ldots + \gamma_{n-1,n} x_{n-1} x_n \tag{6.4}$$

As mentioned above, binomial models can be used to understand and model a state or a change of state. For occupants' use of building systems, binomial models can be used to model the action rather than the state (e.g., light switching action rather than on/off state). As noted by Fabi *et al.* (2012), the status of the window itself influences the indoor environment (hence the explanatory variables used for the modeling) and therefore affects the model.

Calì (2016) provides an example of the application of a binomial model for modeling occupant interactions with operable windows in a residential building. Figure 6.3 shows sample plots of the analysis, with the probability of the opening action of a specific window from a specific living room of a specific apartment, which was found to vary by time of the day, the indoor CO_2 concentration, and the indoor air temperature. The results suggest that window opening probability increases with indoor temperature and CO_2 concentration. Also, occupants are much more likely to open the window during the day than at night.

6.3.2.2 Markov Chain Models

This section describes discrete-time Markov chain models of the first order—henceforth, simply Markov chain models. Markov chain models are useful to model processes with two or more states, such as the position of a window (e.g., closed, open, half open) or the state of a fan (e.g., on or off, low flow, medium flow, high flow). When the state that has to be modeled is measured, a discrete-time Markov chain of the first order can be used (e.g., Calì *et al.*, 2018; Haldi and Robinson, 2009; McKenna *et al.*, 2015; Page *et al.*, 2008). Alternatively, when the state that has to be modeled is measured indirectly (e.g., the position of a window is inferred by the CO_2 concentration in the room, or the presence of occupants with one specific room is inferred based on a time use survey indicating only the activity of the occupants), hidden Markov models (see next section) can be used.

The paragraphs that follow include a brief description of the principles of Markov chain, inverse function sampling, and the Markov chain Monte Carlo technique. A deeper illustration of the Markov chain technique can be found in Feller (1968). The Markov chain Monte Carlo method is well described in (Gilks *et al.*, 1995).

To begin, a Markov chain is a random process that, within a state space, undergoes a transition from one state to another. The Markov property, which characterizes the Markov chain (illustrated in Equation (6.5)) states that the probability distribution of the next state (X_{n2}) depends on the current state (X_{n1}) and not on the events that preceded it. This property is also known as the memory-less property since the Markov process does not keep previous states in memory.

$$P\{X_{n1}|X_{n2}, X_{n3}, X_{n4}, X_{n5}, \ldots\} = P\{X_{n1}|X_{n2}\} \tag{6.5}$$

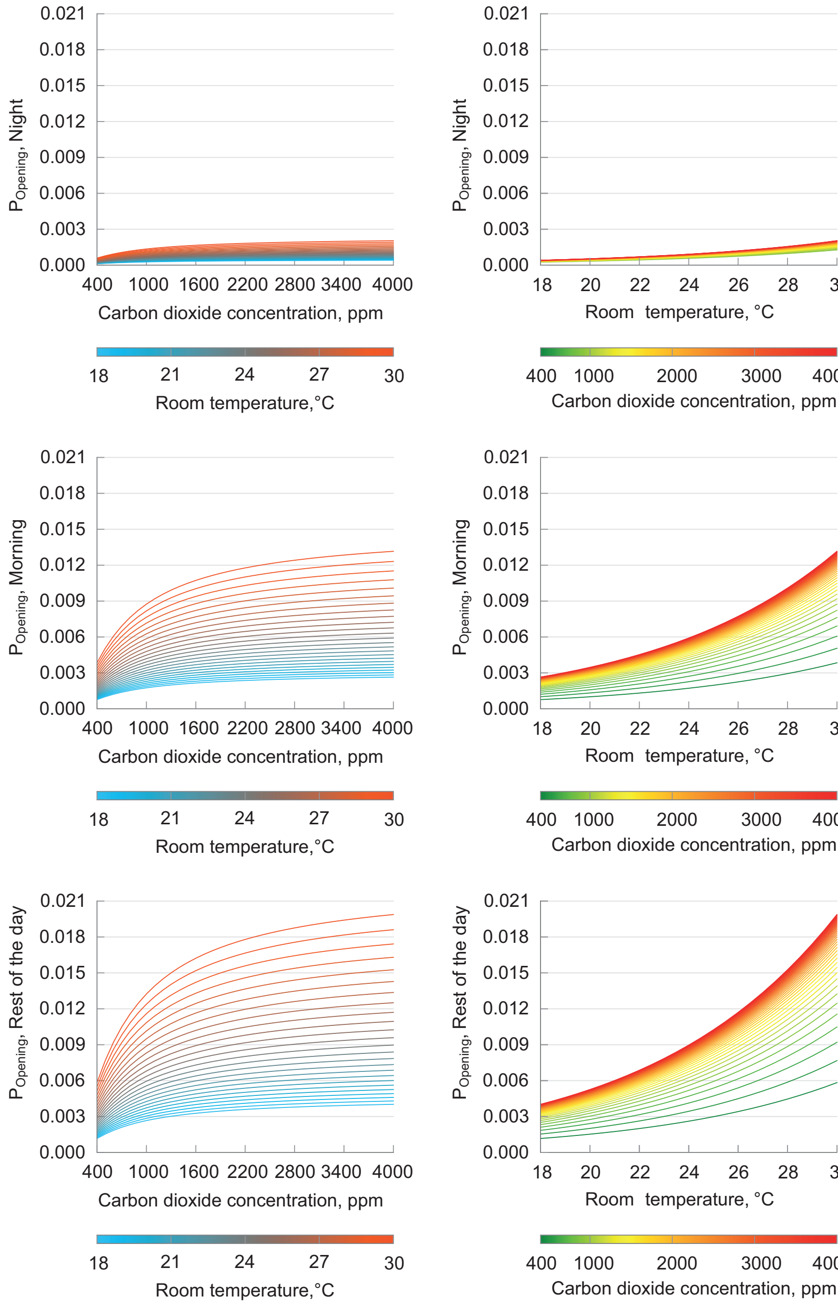


Figure 6.3 Probability of opening action of a window in a living room of a specific apartment (Calì, 2016) at three different times of day, within the next minute.

State changes in the process are called transitions; the probability of such transitions is stored in transition probability matrices (TPMs). When the transition probability does not depend on the time—and hence, the transition probability does not vary with the time—the Markov chain is called time-stationary or time-homogeneous, and this property is expressed in Equation (6.6).

$$P\{X_{n1}|X_{n2}\} = P\{X_{n2}|X_{n3}\} \tag{6.6}$$

Examples of time-homogeneous Markov chains include the "random walk" or the number of successes on bets by flipping a coin. As mentioned above, the presence or absence of occupant(s) as well as the state of a window can be modeled through Markov chains. However, in those cases, the probability of a change of the state (e.g., window opened/closed, occupant present/absent) varies over the time: in such cases, the Markov chain is time-inhomogeneous or simply inhomogeneous.

Equation (6.7) and Figure 6.4 show a two-state TPM for the status of a window at a given point in time: the state "0" indicates a closed window, while the state "1" indicates an open window; $S_{n,00}$ indicates the probability that a closed window (first 0) stays closed (second 0); $S_{n,01}$ indicates the probability that a closed window (0) will be opened (1); $S_{n,10}$ indicates the probability that an open window (1) will be closed (0); $S_{n,11}$ indicates the probability that an open window (first 1) stays open (second 1). For this particular example, at the given time *n*, there is a probability of $S_{n,00} = 0.95$ that the window remains closed if it was already closed at the preceding time n-*1*; in the case of the window being open at time *n - 1*, the probability that the window remains open is $S_{n,11} = 0.75$. The numbers in red in the figure represent the probability of a state change: $S_{n,01} = 0.05$ for a change from closed to open and $S_{n,10} = 0.25$ for a change from open to closed. The two dimensions illustrated in the example are related to the change of status for the time interval [*n* - 1, *n*].

Occupant behavior depends on time; for instance, occupants are more likely to sleep at night, windows are more likely to get opened in the morning,

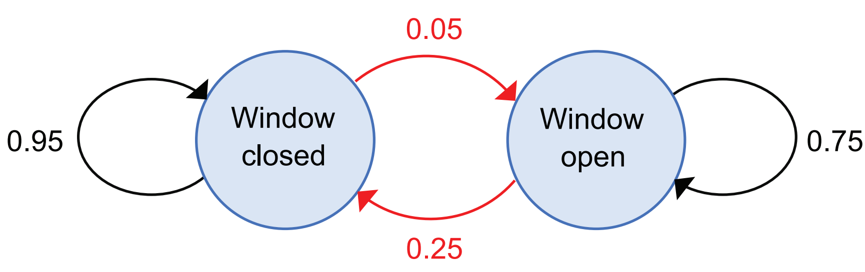


Figure 6.4 Two-state transition graphic for the TPM, at a given time instance, as shown in Equation (6.3) (Calì, 2016).

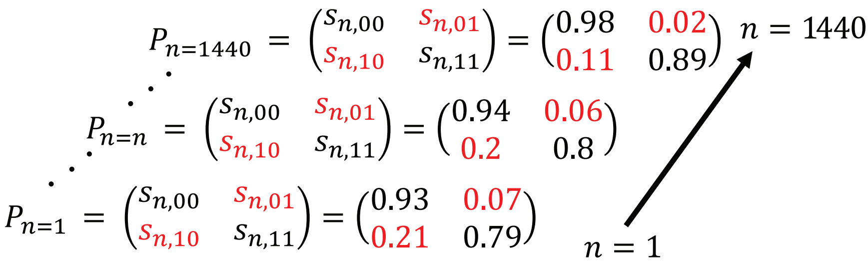


Figure 6.5 TPM over n states (Calì, 2016).

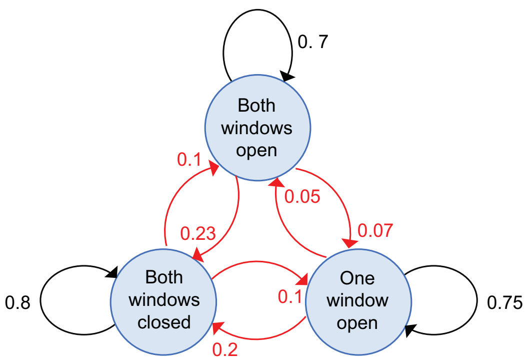


Figure 6.6 Three-state transition graphic for the TPM, at a given time instance, as given in Equation (6.4) (Calì, 2016).

and so on. Thus, the TPM needs a third dimension that allows probabilities of state change that vary over time. For a two-state process with transitions changing each minute during an entire day, the TPM shape will be 2 × 2 × 1,440 (Figure 6.5).

$$P_n = \begin{pmatrix} s_{n,\,00} & s_{n,\,01} \\ s_{n,\,10} & s_{n,\,11} \end{pmatrix} \tag{6.7}$$

There are cases where two states are not enough to model occupant behavior, such as when the goal is to model the presence of a number N of occupants or the opening and closing of a window with two movable panes. In the latter case, for instance, if a distinction between the panels is not necessary—for example because the two panels are the same size—a three-state Markov chain can be used. In the case of the panels being different sizes, a four-state Markov chain is necessary. Equation (6.8) and Figure 6.6 demonstrate an example of a three-state TPM for the status of a double-paneled window (with panels of equal size) at time n. In this example, "0" indicates a completely closed window, “1” indicates that one panel of the window is open, and “2” indicates that both panels are open.

As for the two-state TPM, for the three-state TPM, the sum of the values of each row at each time is equal to 1. In this way, the Markov chain does not stop within the simulation process.

$$P_n = \begin{pmatrix} s_{n,00} & s_{n,01} & s_{n,02} \\ s_{n,10} & s_{n,11} & s_{n,12} \\ s_{n,20} & s_{n,21} & s_{n,22} \end{pmatrix} \tag{6.8}$$

The generation of the TPMs can be done separately for each window or together for all windows based on the observed status changes of those windows at each measured time interval.

6.3.2.3 Hidden Markov Chain Models

Unlike the Markov chain model, the hidden Markov chain model (HMM) consists of two components: an unobserved Markov chain $\{X_t\}$ and an observed sequence $\{Y_t\}$. Y_t only depends on the current state X_t, and not on its own history $\boldsymbol{Y}^{(t-1)}$, as expressed in Equation (6.9).

$$P\left(Y_t|X_t, \boldsymbol{Y}^{(t-1)}, \boldsymbol{X}^{(t-1)}\right) = P\left(Y_t|X_t\right) \tag{6.9}$$

The distribution of $Y_t|X_t$ is called response distribution. In an HMM, the parameters are given by the set $\{\{A, B, \pi\}\}$, where A corresponds to the TPM, B corresponds to the response distribution, and π corresponds to the distribution of the unobserved state of X_0 in the initial timestep. For the estimations of the parameters, the Baum-Welch algorithm can be used (Rabiner, 1989; Zucchini and MacDonald, 2009). The Baum-Welch algorithm is based on the maximum likelihood estimation principle. When dealing within the context of HMM, the most likely sequence of unobserved states for a given sequence of observations can be of interest. This sequence, called global decoding, can be efficiently calculated through the Viterbi algorithm. An example of an application of a hidden Markov chain for the generation of occupants’ presence profiles within buildings based on a time-use survey is provided by Wolf *et al.* (2019).

6.3.2.4 Mixed Effect Models

We previously described a generalized linear model (GLM; see Footnote 1), specifically a binomial model with the logit function as a link function, that describes the probability of an action for a specific window, in a specific living room, and in a specific apartment. Thus, if the goal is to use the GLM for simulating the performance of a building with a number X of apartments, each with a number Y of rooms, we will need to have $X{\cdot}Y$ models for the opening action and $X{\cdot}Y$ models for the closing action: one model for each window. Hence, within the simulation of the performance of a building, it will be difficult to choose among one of the many models, for each room and each apartment. Ideally, there would be a unique model able to address behavioral diversity.

A solution can be represented by the addition of a further predictor of random nature, x_k (McCulloch *et al.*, 2003; Pinheiro and Bates, 2006), following the approach proposed by Haldi (2013) and resulting in a generalized linear mixed model (GLMM), as demonstrated in Haldi *et al.* (2016) and O'Brien *et al.* (2017). An example of a mixed model is the mixed-effects logistic model defined as in Equation (6.10), where there is a fixed effect (like in Equation (6.3)) and a mixed effect. An application of this model to the case of window action, applied to residential and non-residential buildings from Germany, Denmark, and the United Kingdom is illustrated in Haldi *et al.* (2016).

$$\operatorname{logit}(p) = \beta_0 + b_0 + \sum_{k=1,\ldots,\,n} \left(\beta_k x_k + b_k x_k\right) \tag{6.10}$$

In conclusion, binomial models are GLMs that can be used to analyze and predict the probability of specific binary events, such as opening or closing a window or switching on or off a device. Markov models are particularly useful to model the probability of an action that is observable, the state of a window, if this state has been observed, and that varies with time. Hidden Markov models are useful to analyze and model the probability of an action that has not been observed (e.g., the state of the window) based on an observable variable (e.g., the carbon dioxide concentration in the room). Finally, generalized linear mixed models can be used to model the probability of a particular event, adding a mixed effect to represent the differences among the population (e.g., different apartments, different occupants).

6.3.2.5 Selection of Explanatory Variables

When addressing a modeling case with different potential explanatory variables, it is important to decide which explanatory variables (e.g., outdoor and indoor temperature and humidity, indoor carbon dioxide concentration) are relevant to evaluate and select the most appropriate model. Schweiker and Shukuya (2009) suggest using "forward" and "backward" selection of the variables for the regression models and scoring the models using the Akaike information criterion (AIC). This process allows the selection of a "best model" containing only the most important explanatory variables (i.e., variables that have a consistent impact on the probability function). Besides the

AIC, other criteria can be used, such as the Bayesian information criteria (BIC) (Schwarz, 1978).

The process for the selection of the best model can be executed by using the step function within the glm function in the statistical language R, with *n* explanatory variables. This process is described as follows:

1. Each coefficient of each variable is fitted by the regression model in a single variable model, and the related AIC is computed for each fit;
2. The variable with the lowest AIC is selected, and the model is fitted *n*-1 times with the selected variable and each of the *n*-1 remaining variables;
3. The model based on two variables with the lowest AIC is selected. Then, the AIC of this model is compared to the AIC of the best single-variable model (the single-variable model with the lowest AIC). Then:
   a. If the new model (two-variables model) had a consistently lower AIC, the process can go to step 4;
   b. Otherwise, the single-variable model is selected;
4. The previously excluded *n*—2 variables are then used to fit the model together with the two variables of the "two variables model" with the lowest AIC from step 3, in a "three variables model" (this is the so-called "forward selection"). Hence, from the three variables model, three two-variables models, obtained by dropping each of the variables recursively, are fitted (this is the so-called "backward selection"). Then:
   a. In the case that none of the three-variable or "new generated" two-variable models has a consistently lower AIC than the two-variables model with the lowest AIC from step 3, the model with the lowest AIC from step 3 is the final model,
   b. Otherwise, the process goes as in step 4, adding one more variable recursively.

6.3.2.6 Inverse Transform Sampling

The generated TPMs can be used to generate occupants' profiles within a simulation process. Within this scope, the so-called inverse transform sampling (ITS) or "inverse function method" is utilized to sample random numbers in Page *et al.* (2008). Through this method, sample numbers can be randomly generated from any probability distribution given its cumulative distribution function (cdf). For the case of windows or occupancy, a uniform distribution can be used. The first step of the ITS is related to the generation of a random number from a uniform distribution, between zero and one. Thus, the generated random number p is compared to the cdf in order to define the next state of the Markov chain. Using the window case as an example, if the generated value p is smaller than the probability of a state change of the window $P_{n+1,\ XX}$, at the given time, the window remains in the same state; otherwise, the window changes its state. Figure 6.7 is a flowchart

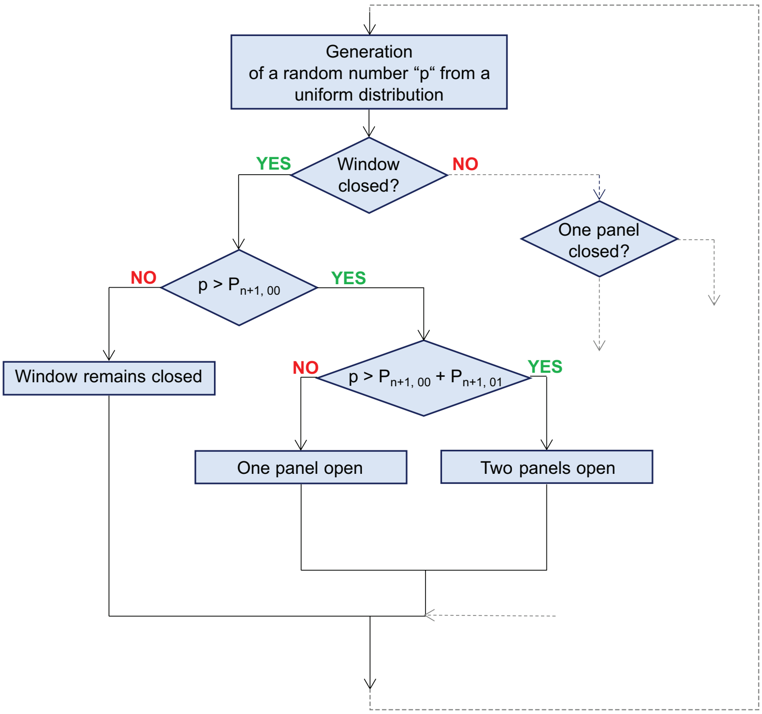


Figure 6.7 Inverse transform sampling Markov chain flow chart example (Calì, 2016).

of the simulation process (for the time instance "*n* + 1") of a double-paneled window, where both panels are closed at time *n* (Calì, 2016).

6.3.2.7 Evaluation and Validation of Occupant Models

Previously, we described a procedure to develop a model with an optimal selection of explanatory variables. Yet, the generated model needs to be evaluated and validated. It is generally understood that an exact prediction of building performance or each occupant-related event is impractical and unrealistic (e.g., timing of window opening actions). However, modelers can still strive for models that yield reasonable estimates and direct designers to near-optimal designs. This section briefly discusses occupant model evaluation and validation. Interested readers are encouraged to consult additional resources (Langevin *et al*., 2015; Mahdavi and Tahmasebi, 2017; Tahmasebi and Mahdavi; 2016).

The first quality of interest is that the model can reproduce the occupant actions or states for the building from which the data was first collected. In other words, the validation process relates to the model at hand and how well it predicts the behavior of a particular process (e.g., the act of opening a window) in a particular space or building. This validation should not be confused with a generalization of the model to other situations. For instance, this validation does not indicate the applicability of this model to other contexts (e.g., buildings, climates, occupant types). The second quality of interest is that the occupant model can predict occupant actions or states in other contexts. This has been proven to be more difficult to achieve since behavior can be sensitive to building technologies, local customs, and climates (Schweiker *et al*., 2012).

One technique for validating of a model for a single space or building is the k-fold cross-validation. To apply it, each data sample (i.e., the set of data of the observed phenomenon that is being modeled and the potential explanatory variables) is partitioned into k-ordered subsamples. If k=10, for example, nine subsamples are used for training a model following the method described above and one subsample is used to test the model. The test of the model is done by using the measured input variables of the 10th subsample (i.e., the subsample that was not used for the training) as input to the model, thus comparing the model output with the actual, monitored change of window position. This operation is executed ten times in total; the ten combinations of nine out of ten subsamples are used to train the model, while the last subsamples is used each time as a validation subsample. The process is summarized in Figure 6.8 and described further in Calì (2016).

When creating a model, a validation process of the model should be undertaken to select the best possible model and ensure that the selected model is correctly representing the behaviors it is intended to portray. In the case of a model with a binary outcome (e.g., the change of state of a window from closed to open or from open to closed) to infer the "state change probability" (i.e., probability of opening or closing actions), the data sample should be partitioned into two subsamples:

1 Subsample A "window closed": This subsample is used to infer the probability that a window will change its status to open.
2 Subsample B "window open": This subsample is used to infer the probability that a window will change its status to closed.

The complete modeling process to achieve, as an example, a model describing the opening and closing operation of windows, is described in Figure 6.8.

To evaluate the applicability of an occupant model to another building, the model can be simulated in another context (e.g., climate, building design) to assess whether it accurately predicts occupant behavior in that building. The results may be compared on numerous metrics, such as a fraction of time when the state is correct and the number of actions per year (Mahdavi and Tahmasebi, 2017).

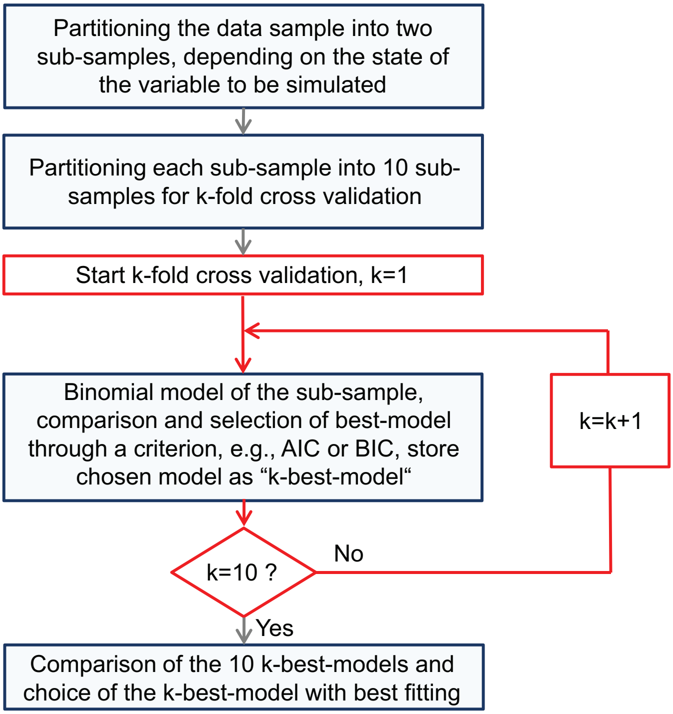


Figure 6.8 Flowchart of the process to generate and obtain the best fitting binomial model (Calì, 2016).

6.3.3 Agent-based Models

Building upon the previous sections and modeling techniques, agent-based modeling (ABM) is a technique capable of representing autonomous agents, their interactions with each other and their environment, and the resulting impact on the system as a whole (Gilbert, 2019). Agents (e.g., building occupants, households, cars) are assigned attributes that govern their interaction with each other and their environment (e.g., building space or geographical area). Each agent can evaluate the environment and the state of other agents and decide whether to take action (or not) based on a set of rules. The global behavior of the system then emerges from the micro-actions and interactions of these agents. The unique ability to simulate decision-making at the individual agent level enables ABM to simulate real-world systems with complex, nonlinear, and dynamic properties (Bonabeau, 2002).

Figure 6.9 shows the main steps to build an agent-based model, based on the work of Salgado and Gilbert (2013) and Sayama (2015). The core of the figure describes the ABM implementation stage following the specification

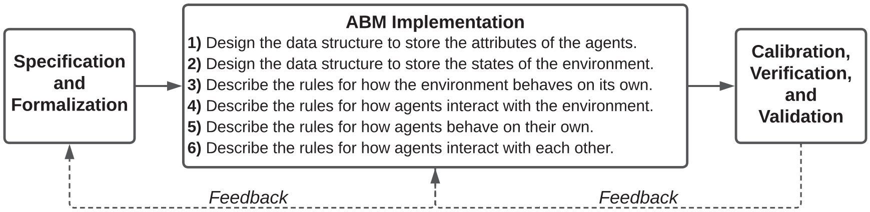


Figure 6.9 Main steps to building an agent-based model, adapted from Salgado and Gilbert (2013) and Sayama (2015).

and formalization of the problem to solve. The main implementation steps include the design of data structures for agents and the environment followed by steps to describe the behavioral rules and interactions (between agents and with the environment). Once the model is executed, calibration, verification, and validation efforts are performed with the model being revised as needed.

In terms of the programming environment, agent-based models can be implemented using general programming languages (e.g., Python, Java, C++) or software packages and toolkits created to help in the development and visualization of simulations (e.g., RePast, NetLogo, Anylogic).

ABM shares attributes with other modeling techniques, such as the probabilistic methods described in Section 6.3. For instance, it is common to define probabilistic rules that guide agents' actions based on information collected from their environment or other agents. As an example, when entering a shared office with uncomfortable thermal conditions, a "person" agent might interact with other nearby persons in the area (based on probabilistic rules) and adjust thermostat settings based on the group's preferences. Similarly, probabilistic rules could be used to model agents adapting their preferences (and behavioral rules) following interactions with other agents. In general, Bonabeau (2002) recommends the use of ABM when the real-world system to model has one or more of the following characteristics:

1 When interactions between agents exist and are of a complex, nonlinear, or discontinuous nature (e.g., the behavior of an agent potentially being influenced by that of another agent)
2 When the topology of interactions is heterogeneous (e.g., in social networks)
3 When space is an essential element of the problem with dynamic positions of agents (e.g., agents moving and interacting within an environment)
4 When the population of agents is heterogeneous (e.g., agents with different characteristics and adaptive behaviors)
5 When agents show complex behaviors (e.g., with learning and adaptation features)

ABM has been applied in numerous fields, including epidemiology (Tracy *et al.*, 2018), population dynamics (Pablo-Martí *et al.*, 2015), economics (Tesfatsion, 2002), transportation (Bernhardt, 2007), electricity grids (Ringler *et al.*, 2016), among others. In the past decade, ABM applications have been extended to cover the building science domain, particularly occupant behavior applications. Berger and Mahdavi (2020) reviewed scholarly articles that applied ABM to simulate building occupants for energy and indoor-environmental performance analysis. Papadopoulos and Azar (2016) presented an ABM framework that captured different and changing energy use characteristics of agents while accounting for their level of control over building systems. Their ABM framework also featured surrogate models of building systems to translate the agents' characteristics to building energy performance estimates. Lee and Malkawi (2014) proposed an ABM approach to mimic the behavior of real-world occupants of commercial buildings in response to environmental stimuli. After evaluating their indoor conditions, agents could increase their comfort levels by adjusting their clothing and activity levels or controlling building systems, such as windows, blinds, fans, and space heaters. Other applications of ABM include occupants' water consumption patterns (Linkola *et al.*, 2013), occupants' movements and shared activities (Schaumann *et al.*, 2017), and HVAC control optimization (Gopika, 2015; Sangi *et al.*, 2017).

Despite the many advancements in applying ABM to understanding and improving building performance, several limitations exist that motivate future work on the topic. First, most ABM applications in building studies are focused on understanding and improving building operation. Little research extends the scope of analysis to include occupant-centric design practice and applications. This gap is not limited to ABM studies but extends to occupant-centric building design research in general (Azar *et al.*, 2020). Second, current ABM studies often fail to provide information on the implementation of their models, particularly on the level of detail and resolution at which they modeled occupants' behaviors. More clarity and consistency are needed to determine the level of complexity needed to achieve the models' specific objectives. Finally, as highlighted by Berger and Mahdavi (2020), ABM applications are rarely based on robust and validated human behavior theories, which are needed to increase the levels of confidence in the developed models and their solutions. Future ABM studies should consider stronger theoretical underpinnings for agent rules and behaviors, in parallel to extensive observation studies for validation purposes.

6.3.4 Personas

The final method for modeling occupants that is considered in this chapter is personas. Personas are archetypal characters that are representative of the expected occupants. While the above mathematical formalisms in Section 6.3 are relatively abstract, the use of personas offers a promising approach to modeling occupant behavior and beliefs and group behavior in a more tangible and understandable by a wide range of stakeholders. Personas are fictional, but representative, characters capturing occupant characteristics, behavior, and goals (Cooper, 1999) for user-centered design. Personas can help designers and simulation users anchor their work in a user's needs (Takai and Ishii, 2010). Like the other modeling approaches described earlier in this chapter, personas can be either data-driven or developed by the designers' judgment. Personas are somewhat analogous to clusters in machine learning, in that representative agents are extracted from a population.

Personas can be fictional (Blythe and Wright, 2006), goal-oriented (Cooper *et al*., 2014), role-based (Pruitt and Adlin, 2010), or engaging (Nielsen, 2013). Fictional personas may be imaginative or empirical. Goal-oriented personas focus on specific workflows, needs, motivations, and attitudes of the persona to accomplish their goals (e.g., save energy or improve thermal comfort) (Cooper *et al*., 2014). Role-based personas assume the role the users play in their context and environment (Pruitt and Adlin, 2010). For example, in a large building context, personas may be developed for occupants and building energy managers. Engaging personas consider characters and stories to "produce involvement and insight" (Nielsen, 2013).

6.3.4.1 Past Use of Personas in Building Design and Simulation

While personas are widely employed in fields like human–computer interaction (HCI) and human-centered product design to anchor design in human needs from the beginning to the end of product development, their use in building design to represent different types of occupants is a relatively unexploited opportunity. Only recently, have examples of the application of personas in building design and operation emerged. For example, personas have been used to design spaces for people with dementia (McCracken *et al*., 2019) and as a lens through which to evaluate the retrofit of buildings according to different behaviors, motivations, and attitudes (Haines and Mitchell, 2014). Bennetts *et al*. (2020) used a persona-based approach to create thermal guidelines for older people in Australia using hierarchical cluster analysis (HCA) on data collected from the participants (ideas, beliefs, knowledge, etc.). Unlike traditional comfort standards, the comfort guidelines were developed for six different thermal personalities (Bennetts *et al*., 2020).

To date, personas have not been implemented as standard features in mainstream building simulation tools. Goldstein *et al*. (2010) used the schedule-calibrated and weighting coefficients method to generate personas for office buildings. The model considered office parameters such as arrival, departure, desk meetings, team meetings, and onsite and offsite breaks. This method helped create diverse occupant profiles for office buildings, but they did not consider other parameters like comfort and energy-related parameters.

6.3.4.2 Developing Personas for Building Simulation

Personas can be designed for particular building contexts (e.g., police stations, schools), comfort issues, and user types (e.g., older people, children). The data for these personas can be derived from literature, surveys, participatory workshops, among others. For new buildings, information can be estimated by looking to a similar project type, obtaining details from the client, or considering extreme conditions. Here, we focus on data-driven personas. We note that care must be taken to avoid unconscious bias/discrimination when creating personas, as the associated implications may influence design and neglect certain populations of occupants (e.g., persons with disabilities).

For data-driven personas, the richer the data collection and analysis (e.g., mixed methods, methods that capture user-system context), the more useful the persona will be for designers and simulation users. An example of a data-driven persona is provided by Agee *et al.* (2021). Agee *et al.* (2021) collected both quantitative and qualitative data from 20 multifamily housing developments (representing 239 units) in Virginia, USA. Data were collected and analyzed in four steps, as summarized in Chapter 4, to create the persona in Figure 6.10.

Sadie
Senior Persona

Physical Needs: *safety, easy-to-access and understand spaces and interfaces, level floor surfaces and transitions to avoid tripping hazards*

Physiological Needs: *her comfort is critical, she keeps thermostat between* 72 and 75°F (22 and 24°C), she is keenly aware of drafts/air movement

Psychological Needs: *safety, connection with community and family, continuing to stay active and involved in her family and community*

Attitude: *uses only what she needs, prefers traditional communication (e.g., talking face to face, writing letters), conserves energy to avoid wasting money, feels agnostic toward technology*

Figure 6.10 Data-driven persona representing a senior occupant.

Source: Agee *et al.* (2021).

Sadie
Senior Persona

Sadie is a 78-year-old retiree and widow. She lives by alone, but keeps a full schedule of commitments (e.g., with her church group, visiting with her grandkids, reading, and watching TV). She enjoys learning and keeping an active mind with a daily crossword puzzle and reading her Bible. She spends most of her day at home in her apartment. She lives alone, so feeling safe is important to her sense of well-being. She is cold-natured, and a cozy housing unit is one reason she is more satisfied with her current unit compared to her previous unit. She likes the heat pump in her apartment but is sensitive to direct air blowing on her. She sets her thermostat between 72 and 75°F (22 and 24°C). She uses 88 kWh/m^2/yr of energy. She has an Energy Star-rated dishwasher but cleans her daily dishes by hand. Sadie feels the old ways of life are better. She doesn't like new technology and prefers the old ways of communicating. For example, she writes letters to her friends instead of email. She remembers when times were hard and you didn't waste anything. She is intentional about conserving energy and money (e.g., turning off the TV, lights, and coffee). She lives on a fixed income and cannot afford to be wasteful.	***Behavior:*** *turns off lights and plug loads when not in the room, cleans dishes by hand, takes short to medium length showers, uses space heater to adapt indoor environment*

In closing, personas are a powerful tool to map observed or imagined occupant characteristics onto one or more representations of occupants. While they have not been extensively used in building design, we recommend their future research and implementation because of their desirable traits (e.g., relatability and tangibility to all stakeholders, complexity, and richness in characteristics). Ultimately, for personas to be incorporated into BPS tools, their characteristics must be mapped to simulation inputs and models. There is strong potential for personas to be developed in conjunction with agent-based models and the advanced occupant models described in Section 6.3. For example, a persona could be developed based on a large number of single-behavior models; the model parameter could be varied depending on the persona characteristics (e.g., very reactive to low illuminance levels).

6.4 Implementation of Occupant Models in Simulation Tools

Thus far, in this chapter, we have described a variety of occupant modeling approaches. In this next section, we provide an overview and analysis of common methods of implementing occupant models in simulation tools. Since the remainder of this book focuses on building simulation, this preliminary overview of implementation is an essential step before occupant modeling can be discussed in terms of supporting the design process (Chapters 7 and 8). This section describes current available methods to implement occupant models in BPS tools as well as offering discussion on limitations and future research and development needs.

6.4.1 Occupant-Centric Simulation Tools and Approaches

While modeling occupants using schedules in BPS tools is commonplace (see Section 6.2), more advanced models require more sophisticated means for implementation. In general, BPS tools with a graphical front-end interface are more restrictive, while research-grade tools with open-source capabilities have greater flexibility to implement advanced occupant models. Most BPS tools provide at least one of the following approaches to model occupants (Hong *et al.*, 2018). We hereby divide implementation methods into two categories: those which are integrated into BPS tools and those which generate inputs in advance of integrating them into BPS (i.e., offline and stand-alone). BPS-integrated methods include:

- **Schedules** (deterministic)—These built-in or user-customized schedules generally represent occupant-related states as repeating time-varying parameters (e.g., occupancy profiles, lighting/equipment loads, temperature setpoint). The level of schedule resolution varies among BPS tools, with some allowing sub-hourly resolution and others being restricted to hourly. Ideally, tools represent these schedules graphically to identify errors quickly.
- **Rules** (deterministic/stochastic)—This method enables simulation users to use built-in rules or specify a set of rules for different building systems such as lighting, windows, and shading devices. For example, rules can be set to turn off lights when daylight illuminance reaches a certain threshold to simulation typical occupant behavior. The threshold can be probabilistic to simulate the variability of occupants' manual interactions with lights. While some BPS tools do not use such rules at all, others allow custom rules to be defined, such as User Function in DOE-2 and EMS in EnergyPlus (Gunay *et al.*, 2016). Moreover, models from external standardized languages can be integrated into the simulation tool, such as TRNSYS or IDA-ICE. Although user-customized controls allow more flexibility for the users to incorporate bespoke models, their implementation and debugging require a strong knowledge of the occupant models and programming.
- **User-defined source code** (deterministic/stochastic)—Some occupant models involve more than simple rules and may necessitate that the

source code modifications. However, advanced user knowledge is required for this approach.

- **Co-simulation** (deterministic/stochastic)—Occupant models can also be implemented in BPS via co-simulation that allows the dynamic exchange of information between BPS tools. For example, the occupant behavior Functional Mockup Unit (obFMU) is an example of a co-simulation method that supports reading the data in a standardized XML format through a new schema, titled 'occupant behavior XML' (obXML). The initial repository of obXML contains 52 models (Belafi *et al.*, 2019). A more advanced and flexible interface is Building Control Virtual Test Bed (BCVTB) which is based on a stand-alone interface (*Ptolemy II*) to host certain programs (Wetter, 2011). Similar to user-customized source code, advanced knowledge is required. Moreover, co-simulation can significantly increase computation time.

6.4.1.1 Stand-Alone (Offline) Methods Include:

- **Occupancy simulator** (stochastic)—This method is a web-based platform to provide hourly or sub-hourly occupant presence and movements based on stochastic models for an individual occupant in the form of CSV files (Chen *et al.*, 2017), which can then be used as an input for BPS tools such as EnergyPlus. Although this approach considers the diversity and stochasticity of occupancy, it is limited to occupancy schedules without considering two-way interactions between occupants and the environment. Moreover, this approach typically neglects interdependencies between different aspects of occupant behavior.
- **Offline techniques** (deterministic/stochastic)—An alternative method is to conduct sequential simulations to integrate occupant interactions in a building. Programming languages such as Python or R have the capability of high-level programming functions using a wide range of libraries and packages. The two main approaches are: (1) a pre-processing stage where occupant-centric control metrics are derived as inputs for further evaluation using BPS tools (Hobson *et al.*, 2021); or (2) a post-processing stage when a set of design alternatives are initially simulated as datasets to program occupant-centric control functions (Ouf *et al.*, 2019). Both techniques can deliver deterministic (e.g., rule-based) or probabilistic (e.g., supervised learning) controls to model occupant behavior. Further discussion on ways to simulate occupants to inform design is provided in Chapter 8.

While stand-alone offline methods potentially offer greater transparency and versatility, they do not offer dynamic interaction with the simulation. As such, interactions between triggers (e.g., IEQ) and occupant actions are not captured; thus, offline methods are more suitable for non-adaptive occupant features such as occupancy and office equipment use.

6.4.2 Current Limitations and Recommendations

Each of the major stages of building performance simulation—inputs, simulation, and outputs—have limitations with respect to occupant modeling that should be addressed in the future.

- **Inputs—**Generally speaking, increasing the number and complexity of occupant-related inputs will increase the level of occupant modeling detail in building simulation. These inputs can include occupant demographics and diversity, details on energy-related occupant behavior, and relationships between occupants (and the impact of these relationships on behavior). Current methods to specify occupant behavior are often abstract and implicit (e.g., refer to traditional occupant modeling approaches as in Section 6.2). Moreover, most tools treat occupants in much the way building systems are specified rather than as active participants in building performance. For example, in EnergyPlus, occupants' actions regarding blinds control are categorized as *window properties* rather than *people* objects and there are missing quantitative metrics to control certain functions such as shading systems through vertical eye illuminance (Tabadkani *et al*., 2020). We recommend that occupant-related inputs are reframed and increased in detail to parallel recent research developments (e.g., more advanced models). Additionally, given the significant uncertainty during the design stage about the occupants that will occupy a space, features to allow ranges of occupant traits is a beneficial feature (Ouf *et al*., 2019).
- **Simulation—**Most common BPS tools have very limited capabilities regarding occupant modeling (i.e., similar to those described in Section 6.2, rather than Section 6.3). Thus, for the reasons argued in Section 6.3, we strongly recommend an increase in the number and capability of occupant models in research-grade and mainstream BPS tools. Common BPS tools can process only a single simulation at a time without defining a correlation between occupants' behavioral aspects (e.g., occupancy profile and light switching) (Ouf *et al*., 2018). However, more complex occupant models often necessitate multiple simulation runs, e.g., to quantify uncertainty and stochastic model distributions. Thus, we recommend new BPS tool features to automate batch simulations. While co-simulation has shown significant flexibility for implementing and simulating occupant models, it is not compatible with many BPS tools and requires advanced modeling knowledge, which hinders industry adoption. To overcome existing limitations of common BPS tools in terms of linking different occupant-related variables together (e.g., occupant density and lighting/equipment loads), parametric design tools such as open-source Ladybug Tools can be used to allow the definition of correlations among inputs algorithmically. Parametric-based interfaces enable simulating a large number of iterations automatically to efficiently quantify the impact of different occupants or occupant models.

- **Outputs—**Because BPS is rooted in annual energy use predictions, BPS tool outputs tend to focus on building performance rather than occupants (e.g., discomfort hours of the building rather than discomfort hours of occupants). BPS tools should be more informative and use an occupant-centric approach such that results are output and presented them from an occupant experience perspective. Moreover, many occupant-related simulation outputs are not available for reporting (e.g., number of light switching actions, view to outdoors). Future BPS tool should have features that support the output and visualization of occupant uncertainty (and other sources of uncertainty), such as probability distributions resulting from stochastic occupant models. Further discussion on simulation outputs and communicating results is presented in Section 6.5.

This section briefly summarized existing methods through which occupant models can be incorporated and implemented into BPS tools. It also provided recommendations on BPS tool inputs, simulation, and outputs to support occupant modeling. The next section explores the improvement of transparency of occupant modeling for practitioners and other users.

6.5 Communication and Practical Application

As the complexity of modeling approaches and their underlying statistical methods has increased, so has the number of variables taken into account when creating occupant behavioral models. Several researchers have attempted to classify the growing number of data sources and modeling approaches. For example, Mahdavi and Taheri (2017) presented an ontology for the classification of building performance data (e.g., air temperature, energy use), and others have discussed ways to select the most appropriate model for a specific simulation task (Gaetani *et al.*, 2016; Mahdavi and Tahmasebi, 2017; Tahmasebi and Mahdavi, 2016) (see also Chapter 7). As discussed in Section 6.2, most current approaches focus on schedules, which are relatable and simple to interpret for practitioners. In contrast, more advanced modeling approaches presented in scientific literature (and Section 6.3) are not suitable to communicate model results such as schedules or, for stochastic models, the variance in behavioral patterns.

Accordingly, there is a need to communicate occupant model properties and results in a comprehensible way, especially for those who apply these models, such as building engineers, without expertise in statistics. This argument is emphasized by O'Brien *et al.* (2016) who conclude, based on data from a survey among practitioners, that time and understanding are major obstacles of using more advanced occupant modeling. Thus, increasing the comprehensibility of occupant models may be a prerequisite for their widespread application in building performance simulation for design and operation of buildings. To date, there are only a few attempts to communicate to simulation users the impact of occupant modeling choices (e.g., Chen *et al.*, 2017; Gunay *et al.*, 2016; Ouf *et al.*, 2019; Schweiker *et al.*, 2019).

Discussing all potential methods to communicate occupant models is beyond the scope of this chapter and still debated among researchers. The most important aspects of a model's behavior to be communicated depend on the characteristics of interest and whether the practitioner is, for example, an engineer applying a model in communication with the researcher who developed the model, or an architect or investor communicating with the simulation engineer. Basic characteristics need to be communicated to enable (1) the comparison between different models and (2) judgment of the suitability of a model, including the number and type of input and output variables, potential hidden values, the basis of model (e.g., type of data collection, type of building and occupants monitored, region, climate), and the validation status of the model together if available with validation results.

To ease the understanding of a models' behavior, a breakdown of potentially complex model behaviors into transferable and communicable parameters is desirable. Such parameters could be descriptive values, such as the predicted mean duration of the behavior, the number of actions, the sensitivity of model to variance in input parameters, or the effect of the predicted behavioral patterns on other outcome parameters (Gunay *et al.*, 2016; Schweiker *et al.*, 2019). For example, Gunay *et al.* (2016) presented a method to compare a variety of occupant behavior models in terms of behavioral characteristics as well as energy use variations. Other ways to present the behavior of complex models is the generation of exemplary schedules resulting from their application. Such an approach is presented by Ouf *et al.* (2019) for stochastic models of lighting usage and by (Schweiker *et al.*, 2019) for window opening models' behaviors. The latter presented a method to compare model behaviors parametrically for combinations of different climates and building properties (see also Figure 6.11).

6.6 The Future of Occupant Modeling and Simulation

Major challenges and opportunities exist regarding occupant modeling, in the context of the methods proposed in Section 6.3. Care must be taken to balance accuracy gained by the relatively advanced statistical modeling of that section (relative to the knowledge of most BPS practitioners) with the opaqueness and obscurity that results (e.g., see Section 6.5). Ultimately, a simple model that is fit-for-purpose (see Chapter 7) is better than an inappropriately advanced model. With the Internet of Things (IoT), Internet-connected building automation systems, and other smart building technologies, the availability of occupant-related data is improving and becoming less costly to collect. We expect this to greatly enhance the ability to develop robust, data-driven occupant profiles for a variety of domains, building types, climates, etc. However, centrally managed and coordinated efforts, such as ASHRAE's Global Occupant Behavior Database (Dong *et al.*, 2021) are still

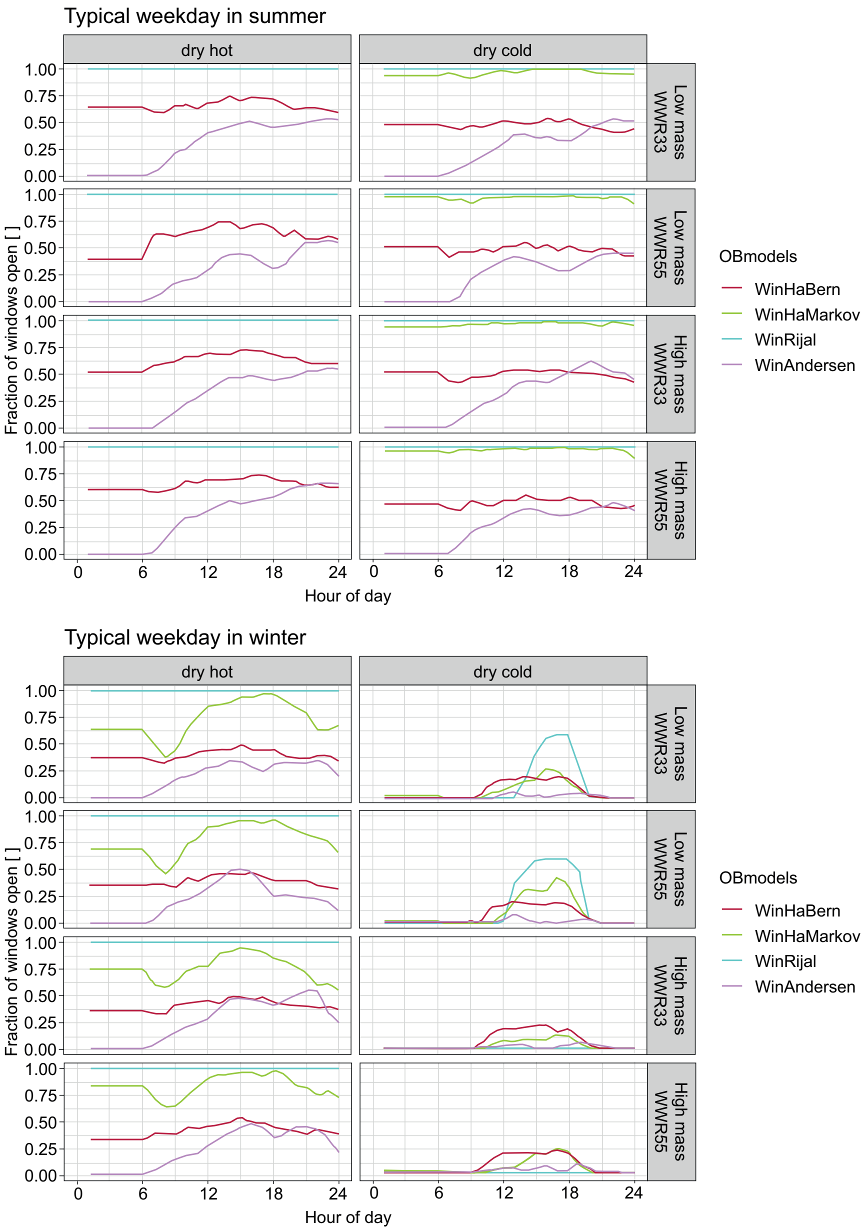


Figure 6.11 Example visualization of the behavior of four different window opening behavior models for simulated summer and winter day depending on weather data file and building characteristics.

required to maintain model quality, reliability, and consistency. Commensurate with any centrally-managed occupant data and model repository should also be rigorous verification of the generalizability of occupant models, much like the early work of (Schweiker *et al.*, 2012).

We must also recognize that while the buildings industry will witness the emergence and widespread use of new occupant modeling techniques in the future, as summarized above and throughout this chapter, it is likely that the industry will simultaneously experience a widening or shifting of the disciplines that undertake the activity in practice.

Despite the many advances that have been made with respect to methods for generating occupancy schedules, the inherent simplification of occupancy presence in existing BPS tools remains a research gap facing the future of occupancy modeling as a whole. Rooms within buildings, like an open-office space, are subject to thermal and occupant asymmetries. An occupant sitting near a window will face unique thermal conditions, and may respond uniquely to environmental control decisions compared to an occupant located in a different position of the same modeled room (Brager *et al.*, 2004). Different HVAC concepts can also produce unique asymmetrical thermal environments, where the specific position and location of an occupant in an HVAC-conditioned space, including the extent to which one's own limbs are exposed in that space, produces a unique regime of thermal sensation across the occupant's body (De Dear, 2011). These asymmetries are known to increase uncertainty in predicting occupant control decisions and predicting building energy demand using existing BPS tools (Halawa *et al.*, 2014).

Accurately simulating spatial asymmetries between occupants and the built environment involves overcoming at least two challenges: (1) predicting the specific location and orientation of an occupant with respect to 3D space and time; and (2) directly modeling the asymmetrical relationship between the occupant and the indoor environment. Established advances in coupling BPS with computational fluid dynamics (CFD) have long-since illustrated how the latter challenge can be overcome (Zhai *et al.*, 2002). The first challenge persists, however, albeit with a number of emerging solutions in the research pipeline. Most interesting is that these solutions are originating from fields that have historically lagged behind BPS, namely, architecture and computer-aided design.

Whereas decades ago, only a few architects were using computers for design, let alone simulation, the division of computer and simulation literacy between engineers and architects has narrowed considerably. Simulation and software programming has not only been introduced to architects, it is also fast becoming a standard skillset in the field (Riekstins, 2018). Credit for this goes particularly to Grasshopper 3D, a visual programming language that was created in 2007 by Rutten and McNeel (2007) to enable parametric, programmable computer-aided design. Grasshopper is effectively a functional mock-up environment which connects a programmable computer-aided design process with a growing suite of third-party simulation tools and other plug-ins written natively for the Grasshopper environment. Like the coupling of BPS with CFD modeling, Grasshopper provides the opportunity to couple BPS with highly spatial, parametric design algorithms that can include the modeling of occupant movement, behavior, and thermal sensation in fully-resolved 3D spaces.

Several recent examples of Grasshopper-based occupancy modeling are relevant to acknowledge. Aviv *et al.* (2022) used Grasshopper to develop a raytracing-based radiant heat transfer model to resolve the radiant asymmetries between occupants and the built environment. PedSim Pro, a pedestrian movement simulation tool developed for Grasshopper, was used by Pan *et al.* (2021) to generate time- and space-varying building occupancy profiles. Yi (2020) achieved a similar outcome by using Grasshopper to couple a BPS model with a hybrid agent-based model of occupant movement and behavior. As more Grasshopper-based BPS tools emerge and become popular, such as ClimateStudio (Solemma Inc., 2022), we can expect the field of highly-spatial occupancy modeling to grow more capable, and commonplace, in the years to come. We can also expect to see more and more architects leading this charge in future practice.

6.7 Closing Remarks

In this chapter, we provided an overview of occupant modeling from traditional and current practices to advanced occupant modeling. We explained why we should model occupants and that representing occupants using fixed schedules has some major limitations in simulation-aided building design.

We also covered the major traits of occupant models (stochastic, dynamic, data-driven, and agent-based) and their implications for simulation and building design. It explained how the different model types can be developed from various sources of occupant data. Next, we provided an overview of methods to implement occupant models into building performance simulation tools, ranging from schedules to co-simulation. We concluded the chapter with a discussion on how occupant models and their characteristics can be better communicated to users as well as in future work.

While in this chapter we discussed model selection in the context of accuracy and strengths and weaknesses, the next two chapters delve into details on selecting the most appropriate occupant models for a given purpose and then methods to use occupant models to support building design.

Note

1 Both logistic and probit regression are generalized linear models (GLM). In such models, instead of using the outcome Y, a link function is used, which is a function of the mean of Y. The difference between logit and probit models is in the link function: logit models make use of an inverse normal function, and the probit model makes use of a logit link function.

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7 Fit-for-Purpose Occupant Modeling

Choosing the Right Approach

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Summary

The most appropriate approach to modeling occupants depends on the purpose and the object of the simulation. In this chapter, we will offer conceptual and practical guidance for choosing the most appropriate occupant behavior modeling approach, following a fit-for-purpose rationale. The aim of the fit-for-purpose approach is to achieve the most relevant possible representation of occupant behavior for a specified simulation aim in an efficient manner.

7.1 Introduction

Many different approaches exist to model occupants and their behavior (see Chapter 6). It is important to take a step back and reflect on how *people* are considered in today's design practice. People are first and foremost the recipients of a design in terms of experience. Attention is directed toward the social and cultural context of a project from the very initial stages of the design process. Designers typically gather qualitative information about the future occupants of their buildings through user journeys and stakeholder workshops. However, often the future occupants are not yet known, and even if they were, building owners are naturally eager to keep the building functions as flexible as possible in order to cater to a wide range of potential tenants throughout the lifespan of a building.

When it comes to modeling, occupants are considered during building design and operation in terms of three main attributes: movement, presence, and behavior (Figure 7.1).

The following applications of occupant modeling to the building design process have been identified (Dong *et al.*, 2018) (Figure 7.2):

- *Building performance analysis*: Examples of building performance analysis include energy performance analysis (from component to whole building), comfort performance analysis (people presence and behavior), and daylight performance simulation (heavily influenced, among others, by behaviors such as blind/shade operation);

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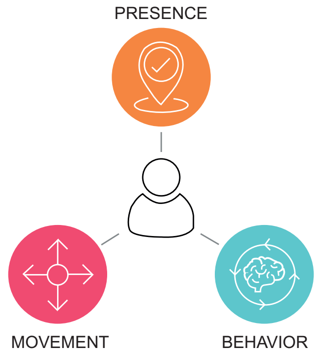

Figure 7.1 The three categories of people modeling.

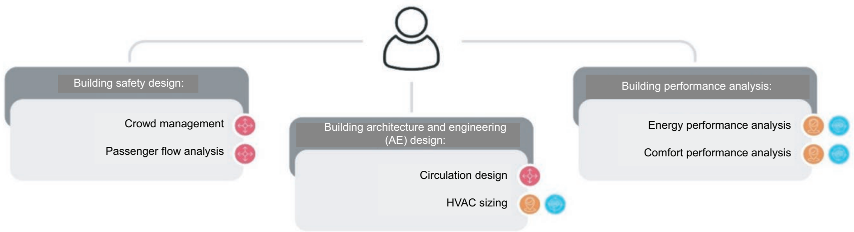

Figure 7.2 Applications of people modeling during the building design phase.

- *Building architecture and engineering design*: Circulation design (people movement) and heating, ventilation, and air-conditioning (HVAC) sizing (people presence and behavior);
- *Building safety design*: Crowd management and passenger flow analysis (especially relevant in public buildings), people movement, and structure vibration subjected to crowd loads (Jones *et al.*, 2011).

The modeling of people movement for circulation design, safety design, crowd management, and passenger flow analysis is well-established in architecture and engineering practice (Yan *et al.*, 2017). In contrast, presence and behavior modeling falls short of implementation in the design workflow. This gap is the focus of this chapter.

Current occupant behavior (OB) modeling practices are aligned with the tasks from building codes and standards, which tend to treat occupant behavior superficially, considering it in terms of either basic schedules or minimum requirements for personal control. This practice is likely to change as standards become increasingly focused on operational performance. For example, NABERS (Residovic, 2017) is a building rating standard valid for

12 months only that places value on representing a building or workplace's actual operational performance. Other standards also request a comparison of in-use measurements and model assumptions, e.g., WELL (International WELL Building Institute, 2020). This shift in building standards toward operational performance is likely to drive the need for more realistic OB modeling practices.

Current OB modeling practices are illustrated by O'Brien *et al.* (2017). When the authors asked practitioners to describe their overall assumptions about occupants in building performance simulation, most interviewees responded they used values derived from standards (e.g., ASHRAE 90.1 [ASHRAE, 2013]) or they modified the default settings based on personal experience and judgment. Assumptions notably varied according to the purpose of the simulation, yet there was no convergence or transparency regarding individual modeling practices. For example, when asked to describe their assumptions regarding plug loads use during detailed design and equipment sizing, a similar number of people responded with 'All equipment is always on', 'Based directly on occupancy schedules', and 'Standard profiles from modeling standards'. These findings show that the current consideration of occupants in design workflows is sub-optimal and lacks clarity, transparency, and awareness regarding the impact of assumptions on the design. Gaetani *et al.* (2020) also showed that the high number of models for occupant presence and behavior available in academic contexts seldom find application in practice.

It is important to mention that different OB models have different requirements for their implementation in building performance simulation. Choosing the 'right' approach also means using models within their applicability range. Lindner *et al.* (2017) as well as Mahdavi and Tahmasebi (2016b) investigated the requirements of occupant behavior models for use in building performance simulation. These studies highlighted a number of challenges connected with more advanced models, such as: the fact that some models do not provide an output in a binary form (i.e., a window is open or closed at a given simulation timestep, as required by the simulation software), which makes it necessary for the modeler to formulate further assumptions; the lack of reproducibility of simulation results employing stochastic models (see Chapter 6); improper model behaviors leading to an exaggerated frequency of occupant actions occurring in short timespans; and an absence of reversal functions. Regardless, if these challenges were to be addressed, there would still be a lack of guidance on actual model selection for practical purposes.

The above indicates a strong potential to improve current design workflows with regard to occupant behavior modeling. Generally, authors agree that the chosen modeling approach should depend on the purpose of the simulation (Gaetani *et al.*, 2020; Gilani *et al.*, 2016; Mahdavi and Tahmasebi, 2016b; Roetzel, 2015), which is the topic of this chapter. We begin with a conceptual overview of a fit-for-purpose modeling rationale in Section 7.2.

7.2 Fit-for-Purpose Modeling: A Conceptual Overview

Models are used to explain and predict diverse phenomena in various domains. Once a reliable computational model of a phenomenon is constructed, the model can be seen as its virtual version. Models' computational core (including the implemented routines and algorithms) map inputs to outputs. As the statistician George Box put it, 'All models are wrong, but some are useful' (Box, 1979). Fit-for-purpose models are, in short, models that are suitable and useful for the purpose for which they have been developed.

In the field of building simulation, model input variables and parameters are typically descriptors of building-related entities. Such entities can encompass building components and systems, whole buildings, or ensembles of buildings. Input variables also include external (e.g., weather) and internal (e.g., use patterns) boundary conditions as well as information on human–building interaction. Frequently, the overall computational model includes sub-models for the generation of data related to boundary conditions and interaction. Instances of such sub-models include weather data generators and occupant data generators. Model output typically entails variable values relevant to entities' behavior or performance. There are many facets to buildings' performance, including, for instance, building integrity, energy efficiency, and indoor environmental quality. Certain aspects of performance such as thermal and visual conditions, air quality, and acoustics are directly relevant to occupants' requirements and needs; others, for example, energy and environmental performance, can be influenced by occupants' behavior. Consequently, in these and similar instances of building performance simulation utilization, information and models regarding occupants' presence and behavior in buildings need to be included to achieve a complete representation of the building and its use patterns.

Building performance simulation typically generates data that either entails values of building performance indicators or is processed to arrive at such values. Simulation-based building performance assessment commonly involves the comparison of computed values of the performance indicator with desired or mandated benchmarks. Simulation models can be used to find answers to what-if types of questions. As such, models are used to find answers to two broad types of questions: direct and indirect. Direct questions ask, 'What output (performance indicator value) do I get for a given input?' Indirect questions ask, 'In order to have a certain output, what input do I need?' To answer the second type of question, simulation is typically run iteratively. Iteration can be conducted manually or facilitated by computational tools that either support parametric simulation or are coupled with optimization routines.

Given this background, building performance simulation can be viewed as an activity to derive the values of relevant performance indicators given specific model input assumptions (building description, boundary conditions, use patterns). Whereas in this chapter we focus on the present contribution to occupant-related matters, the simulation activity can serve a host of purposes (Chwif, Barretto, and Paul 2000; Dong *et al.* 2018; Mahdavi and Tahmasebi 2016b). Several such purposes are listed in broad categories below:

- a Building component design/optimization (e.g., heat transfer in building details)
- b Building design support (i.e., decision-making regarding buildings' modeling shape and geometry, construction, envelope)
- c Building systems design support (configuration and sizing of systems for heating, cooling, ventilation, and lighting)
- d Building operation support (e.g., model-predictive control)
- e Urban-scale performance assessment (e.g., prediction of airflow and pollution migration patterns)
- f Evidence of compliance (with requirements formulated in codes, standards, certification, and ratings systems)
- g Competition, promotion, education.

It seems reasonable to suggest that a simulation model must fit the purpose if it is to reliably answer the questions that are directed at it. As the answer provided by the model comes in the shape of a performance indicator value, the following is suggested to simplify the matter: in order to formulate a guiding principle for the selection of a proper simulation model (and the choice of the occupant model included therein), the specifics of the building performance indicator under consideration must be considered. This statement can be reiterated in terms of two assertions: First, the nature and resolution of the selected simulation model must correspond to specifics of targeted performance indicator. Second, the occupant model embedded in the simulation model must be compatible with the selected simulation model. In other words, the nature of the building performance inquiry implies a fitting building performance indicator, the target indicator implies a fitting general simulation model, and the general simulation model implies a fitting occupant model.

To tease out the practical ramifications of these observations, as a first step, a kind of classification or typology of performance indicators is needed. Detailed ontological treatments of performance-related data in general and building performance indicators in particular can be found in (Mahdavi and Taheri, 2017, 2018; Mahdavi and Wolosiuk, 2019). For the sake of the present discussion, it may suffice to consider three main dimensions of building performance indicators, namely topical domain, spatial attribute, and temporal attribute, where:

- i The topical domain specifies the field of performance inquiry. Queries may concern, for example, energy use, thermal comfort, noise exposure, or daylight availability.

ii The spatial attribute concerns the physical extent of the entity whose performance is being queried. For instance, radiant asymmetry can be computed for an office workstation, parameters of the acoustic field for a lecture room, energy use for a whole building, and temperature stratification for an urban canyon.
iii The temporal attribute specifies the point in time or the duration of the interval for which the performance indicator value is obtained. For example, task illuminance level may be simulated for a specific time of the day, and a building's heating load may be specified on an hourly, daily, monthly, or annual basis.

Given sufficient computational means and resources, the values of performance indicators can be obtained at very high levels of resolution. Moreover, in most cases, it would be a simple matter of aggregation to derive, from high-resolution arrays of data to lower-resolution values. This would suggest that through basic statistical operations of summation and averaging, the annual heating load of a building or the mean annual illuminance of a room, for example, could be derived from respective hourly or even subhourly simulation results. The fact that this process inevitably involves a loss of information explains why the reverse process is problematic. In other words, the process of disaggregation, that is the derivation of high-resolution values from aggregate ones is non-trivial in principle, if not infeasible.

This observation may lead to the naïve assumption that there is a simple solution to the fit-for-purpose problem: ideally, simulations should always be conducted at the highest possible spatial and temporal resolution and apply aggregation and averaging procedures to fit the resolution of the results to the level commensurate to the purpose, i.e., as represented by building performance indicator values with the right resolution. There are multiple reasons of practical and conceptual nature why this assumption is naïve. From a practical perspective, high-resolution simulation models come with a cost in terms of time, resources, expertise, difficulty in identifying model faults, and higher risk of errors due to the number of inputs. Moreover, it has been argued that, particularly in design support scenarios, there is often not sufficient information to generate high-resolution simulation models. Consequently, an early design stage simulation model would have to be fed a considerable amount of detailed but uncertain data. The corollary of this circumstance would be that simulation would generate results with higher levels of resolution, but also with higher levels of uncertainty.

These reflections seem to suggest that, conceptually speaking, higher resolution does not always mean higher accuracy or better suitability of a model to the task at hand. Model selection should target the right resolution, not necessarily the highest possible resolution. A common criterion with regard to the temporal adequacy of the simulation algorithms is related to the nature of the modeled processes. Specifically, in the thermal domain, proper consideration of thermal inertia, latency, and storage require transient simulation and, depending on the nature of deployed numeric solutions, certain minimum levels of temporal resolution. This thermally relevant interval-to-interval carryover of computational results is of lesser concern in the visual and acoustic simulation domains.

These observations seem to justify why conducting and interpreting computer-generated examinations via simulation models has occasionally been referred to as both an art and a science. In more prosaic terms, when it comes to competent use of simulation tools, experience is of crucial importance. Nonetheless, the preceding discussion does imply certain general directions regarding the proper selection of simulation models and associated occupant models. Before engaging in a more detailed discussion of these directions, we need to address the representational options concerning occupants' patterns of presence and behavior in buildings. Detailed treatment and classification of occupant models have been presented in previous publications (Gaetani *et al.*, 2016a, 2020; Lee and Malkawi, 2014; Page *et al.*, 2008); hence, we focus here on the broad classes of such models as relevant to the present discussion.

Taking thermal performance simulation as a case in point, we begin by considering what types of information need to be captured in an occupant model. Such a model must capture the basic state attributes of the occupants (e.g., presence, metabolic rate, clothing level) as well as their effects on the indoor environment. The latter effects can be classified in terms of passive and active effects. Passive effects pertain to, for instance, occupants' release of sensible heat, latent heat, CO_2, and water vapor in the indoor environment. Active effects mainly pertain to occupants' interactions with building control devices and systems (e.g., windows, shades, fans, thermostats). The categorization of models of occupants' presence and behavior in buildings can be approached in a similar manner as the dimensions of performance indicators. Occupants' passive and active effects could be assigned to specific domains. For instance, whereas occupants' metabolic rate is relevant to the thermal domain, the sound absorption effect of their clothing is relevant to the room acoustics domain. The spatial attribute is relevant as well; occupants may be represented as a collective (e.g., all people in a building, on a floor, in a room) or they may be assigned to individual locations (e.g., a workstation, a single-occupancy office). Concerning the temporal attribute, changes in occupants' presence state at a location can be expressed in intervals of various lengths. Likewise, their actions can be assumed to occur within such intervals, or, in the case of event-driven simulation runs, at specific points in time.

An additional dimension of occupant models relates to the question of whether occupants' position and actions are expressed as fixed recurrent patterns or in probabilistic terms. As will be discussed later in this chapter, a probabilistic occupant model may be more appropriate than simple schedules and rules in certain cases. We suggest that the variety of the occupant models can be categorized in terms of their respective loci within this multi-dimensional space. Taking the thermal domain as a case in point, simplified spatially single-zone and temporally annual or monthly calculation models tend to reduce the occupant down to their share in internal gains (typically lumped with other contributors, such as lights and equipment) and their fresh air requirements (frequently expressed in terms of ventilation rates), both specified in terms of fixed daily schedules. At the other end of the spectrum, a simulation platform with integrated agent-based modeling routines can consider each occupant individually and model their impact on the spaces and their interactions with the systems in a dynamic, high-resolution, and probabilistic manner.

To provide a clearer understanding of these issues, we exemplify them using three related thematic foci: the code compliance use case, the temporal dimension of the performance indicators, and the potential of probabilistic modeling. Each is described in turn in the paragraphs that follow.

First, in the case of code compliance, the scope and dimensions of performance indicators are typically predefined. In many instances, even the requirements regarding the deployed computational tools may already be predetermined. Moreover, in code compliance scenarios, the submitted performance indicator values are typically expected to be reproducible, at least in theory. The implications for the selection of the occupant model may be summarized as follows. The resolution of the occupant model should be, in principle, in line with that of the computational model. If a code or certification procedure requires an aggregate performance indicator (such as monthly heating and cooling energy demands), it is not necessary per se to have a high-resolution simulation model or occupant model, unless the use of such models is mandated. In this context, it is perhaps useful to note that a number of rather simplified code-based performance assessment methods were actually introduced as replacements for earlier prescriptive codes and procedures. For example, in the domain of buildings' thermal quality, the prescriptive codes focused on certain requirements concerning building fabric and envelope, with no relationship whatsoever to occupants and use patterns. As such, the shift to a performance-based approach, in terms of energy demand calculations was meant to replace—or at least supplement—the prescription of maximum thermal transmittance values of walls, windows, and roofs. The point is that the inclusion of occupant-related assumptions was not originally geared toward measuring buildings' performance sensitivity to occupant behavior. Rather, such assumptions were indeed meant to provide a normalized basis for measuring the impact of other factors on buildings' energy performance. Of course, the specifics and meaningfulness of specific occupant-related assumptions in simplified calculation methods could be questioned, but the reasoning behind their standardized format must be understood before they are criticized.

Second, decisions regarding model selection need to consider the temporal dimension of the building performance indicator. As alluded to earlier, in contrast to visual and acoustic simulation, the modeling of buildings' thermal behavior requires mapping of comparatively slow processes attributable to buildings' and systems' inertia. Consequently, systematic thermal analysis of the dynamics of buildings' behavior requires numeric simulation tools capable of modeling transient phenomena. The community has converged toward hourly simulations in basic simulations of energy performance and thermal conditions. However, both sub-hourly intervals and even event-driven simulation procedures might be necessary and appropriate, particularly when dealing with human interactions with and automated control of systems for shading and ventilation.

Third, it has been argued that both the patterns of occupants' presence in buildings and their behavior (specifically, their interactions of buildings' control systems and devices) display probabilistic features. It may be thus more appropriate, at least for certain simulation use scenarios, to make use of probabilistic occupant models (Mahdavi 2011; Mahdavi and Tahmasebi 2016a). The application of probabilistic methods obviously does not result in single values of performance indicators, but distributions of values. This can indeed be useful, as probabilistic modeling can address, in theory, the uncertainty arising from occupant-related events and processes. However, it is important in this context to avoid a common fallacy: probabilistic occupant models that are insufficiently or not at all validated may generate the look of realistic occupant-related processes but may not provide meaningful and reliable results. If a probabilistic model's underlying empirical basis is limited or unreliable, so will be the data it generated. In such cases, it would be more meaningful to express the inherent uncertainty of simulation results via sensitivity analysis. Thereby, distributions of building performance indicator values simply express the implications of model input uncertainty, rather than pretending to generate more accurate predictions.

To summarize the above, consider the simple matrix of Table 7.1. Therein, the basic requirements concerning occupant models (i.e., their spatial and temporal resolution as well as presence of probabilistic features) are given for the general categories of simulation purpose (i.e., code compliance, building design support, building systems design support, and building operation support). Spatial resolution is differentiated in terms of low

Table 7.1 Desirable features of occupant models (concerning spatial and temporal resolution and in view of support for probabilistic modeling) for different purposes

	Code compliance	*Building design and retrofit support*	*Building systems design support*	*Building operation support*
Spatial resolution	Low/medium	Medium/high	Medium/high	High
Temporal resolution	Low/medium	Medium/high	High	High
Probabilistic modeling	NA	Low	Medium	High

(e.g., whole buildings, floors), medium (e.g., rooms), and high (e.g., individual workstations). Likewise, temporal resolution is denoted as low (e.g., annual or monthly), medium (hourly), and high (sub-hourly, event-driven). Assuming the model is sufficiently tested and based on reliable and fitting empirical data, the relevance or appropriateness of probabilistic occupant models is again characterized as low, medium, or high. Note that this latter qualitative classification of probabilistic methods is motivated by the fact that not all applications of probabilistic modeling are at the same (presumably high) level of resolution. For instance, the application of occupancy patterns with more or less random fluctuation characteristics may occur at the aggregate level of a whole building or floor/space in a building or at the level of individual occupants. At the other end of the spectrum, agent-based modeling applications routinely involve high-resolution and dynamic representations of individual occupants. In the case of building operation support, a key employment area of probabilistic methods pertains to model-predictive control applications. Whereas the predictive utility of such applications typically targets short future time horizons, the required resolution of the underlying data is high, whereby predictions could be required at the micro-interval level or even in event-based modus.

Needless to say, this table is not intended to provide a recipe for occupant model selection. Given the complexity and variability of building design and operation processes and their dependence on technical, typological, local, climatic, economic, and cultural factors, such a recipe would be neither realistic nor useful. Rather, the intention is to communicate a general overview of the relevant factors and considerations. Ultimately, the expectation is that higher levels of awareness concerning such factors and considerations could translate into more robust technical decisions concerning the choice of appropriate simulation tools and methods in general and occupant models in particular.

The next section provides an overview of how to translate these concepts into practice.

7.3 The fit-for-Purpose Approach in Practice

In Section 7.2, the purposes of simulation and building performance indicators and their relation to the appropriate model complexity were introduced. These topics are further developed in this section, which aims at providing practical steps to apply the fit-for-purpose approach to modeling problems.

It is worth noting again that this approach is strictly dependent on the purpose of the simulation and, hence, on the performance indicator. As a result, it is also important that demonstrative studies select sensible performance indicators—for example, the heating peak load of a building could appear to be heavily influenced by occupant behavior if such load is calculated as maximum yearly value, but it could turn out to be independent of occupant behavior if the load itself is calculated as 95% load duration curve instead.

7.3.1 Why Should I Use a Fit-for-Purpose Approach?

The first important point of consideration is why a fit-for-purpose approach should be used.

The state-of-the-art of occupant behavior modeling in practice is to adopt fixed *a priori* schedules and other simple rule-based models to describe occupant presence and behaviors. The use of such models assumes a completely foreseeable and repetitive environment, where changes occur based on shifts in one or more variables (such as time or environmental triggers). However, it has been argued that this oversimplified approach to occupant behavior modeling could lead to underperforming building designs and building controls that are not optimized for real occupants and their behaviors (with negative consequences on both energy and comfort/well-being performance of the building), as well as potential for over- or under-sizing of building systems (O'Brien *et al.*, 2019). Especially during the design phase, a careful consideration of OB acknowledges that the building might be used in a variety of ways. The ability of a building to maintain the desired performance under uncertainties in building operation—also known as 'building robustness' (Kotireddy *et al.*, 2018)—is an important criterion to consider when evaluating design alternatives.

For example, Gaetani *et al.* (2017a) showed how a fit-for-purpose approach can aid in designing buildings that are optimized for 'real' occupants. In the study, a simplified south-facing cubicle with varying thermal properties was chosen as a case study to determine whether manual blinds were preferable to a fixed 0.5 m overhang as a shading strategy to limit cooling loads. Without applying the fit-for-purpose approach, the manual blind design outperformed the design with overhang in both fictitious buildings with low thermal insulation. In contrast, when using a fit-for-purpose approach, the cubicle with overhang (and 40% window-to-wall ratio) outperformed the design with blinds. The design with overhang showed a similar median value of cooling energy demand to the design with manual blinds; however, it also showed to be more robust (less sensitive) to occupant behavior.

As briefly explained in Section 7.2, a fit-for-purpose approach does not advocate for the use of complex models at all costs. Simpler models might be preferable for two reasons: (1) the use of more complex models, which typically need a higher number of input parameters, might introduce errors if such input parameters are uncertain; and (2) the use of more complex models for occupant behavior aspects that do not affect the investigated building performance indicator is a waste of time and resources.

The first point is best explained by means of Figure 7.3, which clearly shows the trade-off between abstraction error and input uncertainty at growing model complexity.

If the input parameters to a given model are uncertain and the degree of uncertainty cannot be reduced, then this uncertainty could have a larger effect on the prediction error for the higher model complexities compared

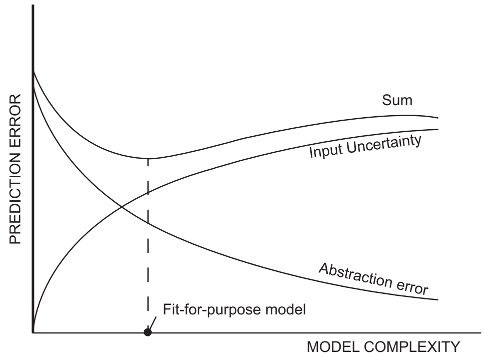

Figure 7.3 Model complexity versus prediction error.
Adapted from Alonso (1968).

to the lower model complexities. The user is advised to perform a sensitivity analysis to ensure that the input uncertainty does not cause an unexpected propagation of errors in the prediction.

The second point implies the knowledge of those aspects of occupant behavior that affect the investigated performance indicators and the relationship and co-dependencies among various aspects of OB. The latter is by no means self-evident, as explained in greater detail in the following section.

7.3.2 Which Aspects of Occupant Behavior Matter for My Case?

The building performance indicator that is investigated for a simulation might or might not show sensitivity to occupant behavior, or it might show sensitivity to only specific aspects of occupant behavior. Because buildings and their surroundings are complex systems, understanding whether the investigated case is sensitive to one or more aspects of OB without simulating it is not trivial.

A fit-for-purpose approach implies gaining an understanding of the sensitivity of the investigated performance indicators to various aspects of OB. This sensitivity depends on multiple factors, such as occupant behavior aspects themselves and degree of uncertainty, performance indicator, time- and spatial scale of the performance indicator, scale of the object of the simulation (e.g., single building vs. urban environment [Happle *et al.*, 2018]), and so on.

A very first step is to assess which aspects of OB should be included (i.e., are present) for a specific case. Take an educational building as an example. Any simulation attempting to optimize the energy performance of such a building would reasonably include the heat gains of students. Conversely, when considering the energy performance of a data center, it might be unnecessary to add the heat gains of the few technicians that operate the data center to correctly predict the cooling load. Indeed, people's presence and their degree of freedom are related to the building typology. For example, nobody would expect to be able to open windows in a movie theatre, but everyone hopes to do so at home. The degree of influence that occupants and their behaviors have on building performance and occupant comfort are also related to the building concept. For example, occupants' window opening and closing behavior very much affects the performance of naturally ventilated buildings. Likewise, the behaviors of turning on/off personal devices and comfort needs are significant factors to consider in the design and performance evaluation of buildings with personalized controlled workstations.

To apply a fit-for-purpose approach, the following questions need to be addressed before assessing how to model the various aspects of OB:

1 Are one or more aspects of OB present? (e.g., are people present in the building? Are blinds manually operated? Are blinds operated automatically but people can still override?)
2 Are one or more aspects of OB uncertain? (e.g., can occupants set the thermostat according to their preference or is it set by the facility management according to a known schedule?)

If an OB aspect is not present, then it is also not necessary to model it. Similarly, if an OB aspect is not uncertain, then existing knowledge can be used to model it. Pupils entering a classroom every day at 8 am and leaving at 1 pm is an example of an OB aspect that is present (people are present), but not uncertain (the bulk of the occupants follow a known, predetermined presence pattern).

If an OB aspect is present and uncertain, then it is worth investigating the most appropriate model for that particular OB aspect. However, assessing which OB aspects are relevant to the investigated building performance indicator(s) is not trivial. Relevance can be interpreted as the sensitivity of a performance indicator for a certain OB aspect.

To assess which OB aspects are relevant to the investigated performance indicator(s), various types of sensitivity analysis can be used (Hopfe, 2009; Hopfe and Hensen, 2011; Rezaee *et al*., 2015). A few methods that are used in the context of fit-for-purpose OB modeling are discussed below.

The Impact Indices method (Gaetani *et al*., 2018) is a sensitivity analysis based on the results of a single simulation run. By looking at the breakdown of heat gains and losses that make up the heat balance of a building, it is possible to derive simple indices that quantify the relative importance of the various heat flows. The indices' definition is based on the building heat balance and borrows from the concept of skin load-dominated buildings versus internal load-dominated buildings. Simply put, the heat balance of skin load-dominated buildings is more likely to be highly affected by, e.g., blind use, which directly affects the solar gains and ultimately the role of the façade as an interface between indoor and outdoor environment, while a variation in internal loads is expected to only have a marginal effect. Instead, the amount and distribution of internal loads are especially critical in internal load-dominated buildings. The concept can be better understood by considering the following analogy: shading devices are likely to be highly influential in a greenhouse, while the heat released by a person in the greenhouse is probably negligible because the indoor environment is primarily affected by the outdoor conditions. While this is intuitively evident at a qualitative level, the Impact Indices Method attempts to offer a quantitative base for this intuition.

Another method to test whether a building performance indicator is sensitive to variations in one or more OB aspects is a scenario analysis. Contrary to typical sensitivity analyses, scenario analysis evaluates the effect of changing a number of variables at the same time. When using scenario analysis to evaluate the sensitivity of a building performance indicator to one or more OB aspects, the following remarks are relevant:

- The use of high/low variations of OB aspects through scenarios is a useful method to test their impact on the building performance indicators.
- As with every type of scenario analysis, the outcome is strictly dependent on the formulated scenarios, which should be inclusive, extreme, yet plausible scenarios of OB and should possibly be agreed upon with the simulation client.
- While terms related to occupant attitudes such as 'energy-conscious', 'austere', 'wasteful', or 'green' are often seen in literature in relation to formulated scenarios that have an impact on the energy and comfort performance, such terms are better avoided. Depending on the building performance indicator and the OB aspect, a given variation in a behavior can lead to saving or wasting energy. For example, a more intense use of the plug loads will increase the building's electricity use but also decrease the need for heating through higher heat gains.
- Caution should be used when formulating scenarios 'one-at-a-time', i.e., that change only one aspect of OB while the others remain unchanged. While this method can be preferred due to its ease of implementation and low computational costs, the correlations and co-dependencies between various aspects of OB are such that any scenario that does not consider the combinations of behaviors is potentially erroneous.

  As an example of scenario analysis, Gaetani, Hoes, and Hensen (2017b) applied identical high/low perturbations to presence, HVAC use, equipment use, light use, heating setpoint, cooling setpoint, blind use, and window operation (for a total of 256 scenarios) to 16 fictious building variants located in Amsterdam (Building ID 1–8) and Rome (Building ID 9–16). The investigated performance indicators were cooling energy, heating energy, and weighted overheating hours. Figure 7.4

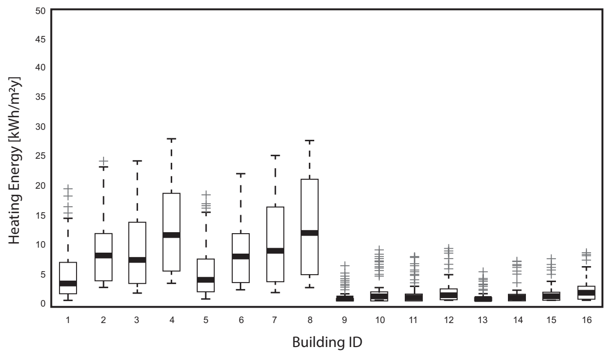

Figure 7.4 Variation in heating energy use due to high/low patterns for uncertain aspects of occupant behavior; see text for explanation of legend and results.

shows the simulated impact of occupant behavior on heating energy use. Depending on the building design, the impact of the OB scenarios was quite different (consider the range between Building 1 and Building 4). For all building variants located in Rome (Buildings 9–16), the heating energy demand was lower than 10 kWh m^{-2} a^{-1} regardless of OB.

Whether such relative variation is important or not is a decision that should be made according to the purpose of the simulation. In this example, the simulation user might decide that it is not important to take the OB aspects into account for heating energy demand calculations in Rome, but it is for Amsterdam.

Scenario analysis also allows for a preliminary understanding of the impact of one or more OB aspects on the building performance indicator. In some cases, the performance indicator distribution resulting from the scenario analysis might be enough to make a conclusive decision (e.g., prefer one design over another). In this sense, the scenarios might be themselves considered as a first increase in the OB model complexity compared with the single schedule or IF-THEN models.

At times, however, the distribution of the performance indicator resulting from the scenario analysis does not clearly point to a conclusive decision. A method for discerning influential and non-influential OB aspects given a performance indicator distribution might be needed. Gaetani *et al.* (2020) advise using the Mann-Whitney U test to this end.

7.3.3 Which Model Should I Choose?

In the previous sections, we explored the need to first assess whether an OB aspect is present and uncertain for the case at hand, and second whether the performance indicator(s) is (are) sensitive to such an aspect. If a preliminary analysis shows that one or more OB aspects (presence and/or behavior) are present, uncertain, and influential, the simulation user could attempt to account for such impact and uncertainty within the model, arriving at the question 'Which model should I choose?' The core of the fit-for-purpose approach is the hypothesis that model complexity should only be increased for those OB aspects that are present, uncertain, and influential.

The choice of model is not trivial and several factors must be considered:

- *Models need to be used within their application range.* The application of a given model for a case other than the one it was validated for is questionable. In practice, this means that the simulation user should first assess whether a model is available for the needed application—e.g., is there a model that quantifies the probability of occupant interaction with blinds in a south-facing, fully glazed office located in Melbourne, Australia, or a similar climate? If not, the simulation user could either create their own model or accept the scenario analysis as the next best option.
- *Models need to be used appropriately.* Using poorly documented models that overpromise should not be attempted. It is the research community's duty to improve the level of documentation of published models and clarity about their applications. The user (as well as the developer) should be clear about model pitfalls and possible workarounds that can be adopted to reduce such pitfalls. For example, the nature of probabilistic models (hence, to be based on a probability curve) clashes with the very nature of building performance simulation software, where the exact same model outputs result from a given set of initial conditions. Often, this discrepancy is solved by comparing a generated random number to the probability of presence or of an action to be undertaken as described in the model; this means that the presence status or occurrence of behavior is questioned every simulation timestep (as often as every five minutes). A typical workaround is to 'freeze' a behavior for a reasonable amount of time to avoid action being triggered too often. The simulation user should only use models that they feel confident are being used as intended. If this is not the case, the simulation user should either go back to the model developer and seek further assistance or accept the scenario analysis as next best option.
- *Less complex models should be preferred, and more complex models should be adopted only if needed.* If several models that can be used appropriately and in their application range are available for the case at hand, the simulation user should opt for models with fewer input parameters and lower resolution in order to avoid prediction errors due to input uncertainty.
- *All input data to a model must be known; otherwise, a sensitivity analysis must be performed.* If one or more of the input parameters to a model are not known, the simulation user should input a range of parameters and verify their effect on the results.

As an example, let us consider the cooling energy use of a building for which the scenario analysis resulted in a high potential variation due to OB (from roughly 10 up to 70 kWh m^{-2} a^{-1}) (Gaetani, Hoes, and Hensen 2016b). This particular building and performance indicator were shown by the authors via sensitivity analysis to be sensitive to light switch behavior but not sensitive to blind and window operation. The authors show the distribution in cooling energy deriving from the scenario analysis ('Patterns') with the performance indicator's distribution obtained by applying higher complexity models for various OB aspects (light switch behavior, shading devices operation, and window operation) (here reported in Figure 7.5).

As expected, changing the model complexity for light switch behavior—in this case, by means of Reinhart's Lightswitch-2002 model (Reinhart, 2004)—causes the distribution in the results to change radically (Figure 7.5). The predicted cooling energy use, which was simulated between 10 and 70 kWh m^{-2} a^{-1} by means of the scenario analysis ('Patterns') is now estimated to be in the range of 10–45 kWh m^{-2} a^{-1}. The model approach selected to mimic the light switch behavior had a very strong impact on the results.

Conversely, adding model complexity to the other considered aspects of OB, to which the performance indicator was previously identified as non-sensitive, led to negligible differences in the results.

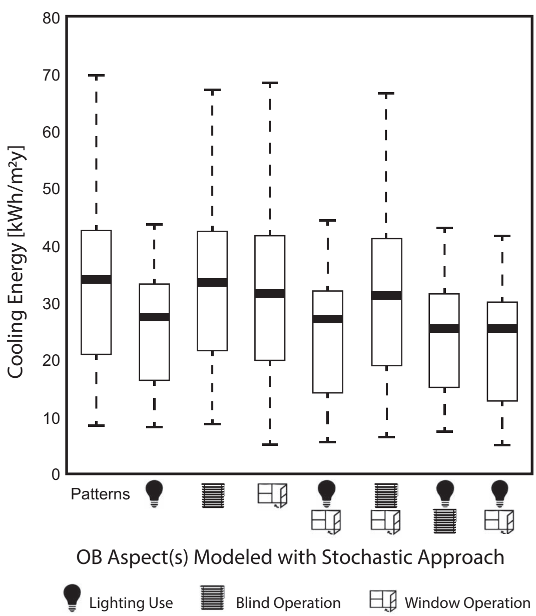

Figure 7.5 Effect in cooling energy use distribution by changing the modeling approach for influential aspects of OB (light switch behavior) and non-influential aspects of OB (shading devices and window operation), as well as all possible combinations; see text for explanation of legend and results.

As this example shows, it is important to consider combinations of aspects to investigate the interactions among behavior; while some effect is noticeable, for the case investigated in the study, modeling the lights' operation alone causes the greatest variation.

To conclude, it is important to carefully consider the effect of assumptions regarding occupant presence and behavior on the decision-making process based on simulation outputs. Most building simulation models require the simulation user to input a high number of occupant-related parameters simply to run correctly. But does the simulation user know where these assumptions come from? Are they realistic and appropriate to the purpose of the simulation (e.g., a maximum heat gain scenario may be appropriate for assessing overheating risks, but not necessarily to size the building system)? Does the simulation user understand the impact of such assumptions on the simulation outputs?

If the answer to any of these questions is no, a sensitivity analysis (Section 7.3.2) may be needed. Moreover, more refined models may have to be sought after (Section 7.3.3) for those aspects of OB that are present, uncertain, and influential.

7.4 The Future of Building Performance Simulation and OB: Our Vision and How to Get There

As often the case, the advances in academia need to mature before they find their application in practice. In the field of OB modeling, we are now at a stage where 'we know we should do better' but we still have several barriers to overcome.

Our vision for the next few years can be summarized as follows:

- Building performance simulation including OB modeling is fully embedded in the design workflow, building performance prediction is part of the decision-making process that leads to a design proposal, and the performance variations due to different potential behaviors are easily visualized.
- OB modeling is fully integrated into the building performance simulation tools, with a database of models of varying complexity available to the simulation user (such as Deme *et al.*, 2019; Ouf *et al.*, 2018) depending on the investigated building, the design stage, and input uncertainty.
- OB models are progressively replaced by actual data in the operational phase of the building when the building performance simulation model is used as a digital twin.

In order to fulfill this vision, efforts should be directed toward improving workflows, models and tools, information, education, and communication. Regarding workflow improvements, research work should be devoted to developing clear, user-friendly, and robust workflows and methodologies, so that OB modeling can become more intelligible for the design team and become part of an actual design tool, as opposed to being relegated to the domain of specialists. Such workflows would ideally contain visualizations and be backed by building performance simulation engines. A change of culture in the way occupant (and especially OB) modeling is perceived by architects and designers is essential to embark the clients onto people-centric visions and feedback practices.

In terms of improving models and tools, for fit-for-purpose occupant behavior modeling to become state-of-the-art, the available models and tools must support the design process in a seamless manner and without requiring OB-modeling expertise. In particular, efforts (Hong *et al*., 2015) must be directed toward making tools more architect-friendly. Attia *et al*. (2009, 2012) explored whether building performance simulation tools are viewed as architect-friendly or not. While the authors did not specifically consider OB modeling, some of the findings may help map barriers to the wider implementation of OB modeling during the design stage. For example, Attia *et al*. found that for architects, the most important criterion concerning usability and graphical visualization of building performance simulation interfaces was the graphical representation of output results (Attia *et al*., 2012). In terms of information management, the creation of comparative and multiple alternatives is of paramount importance.

In another interview-based study, Gaetani *et al*. (2021) show that architects want to have confidence in creating real sustainable designs and obtain a quick performance analysis that supports decision-making. The interoperability of the performance model with 3D computer-aided design tools (Revit, Rhino, Maya, SketchUp, 3DS Max, etc.) was seen as essential. These findings are in agreement with (Attia *et al*., 2012). When the authors asked architects to identify the most important features of a simulation tool, 77 architects (31%) responded, 'integration of intelligent design knowledge base to assist decision-making', followed by 'friendliness of the interface concerning usability and information management and interoperability' (70 architects, or 28%).

Ultimately, behaviors are complex, and so tackling occupant modeling is necessarily an interdisciplinary, collaborative effort. Current modeling practices still include high levels of uncertainty, and it is questionable whether comprehensive models (i.e., models that attempt to cover presence and all OB aspects at once) make sense. Validation and verification require a high-resolution dataset, whose collection has traditionally been very time-consuming. The widespread adoption of smart sensors in buildings is a significant opportunity to create and share OB datasets and databases in an open-source manner. Collaboration between researchers and industrial parties who have access to the data would ensure a fruitful use of such fundamental sources of knowledge. Guidelines for model implementation are emerging to guide the simulation user through the multitude of available models, such as the ASHRAE Global Occupant Database (Dong, 2021), which aims to provide a diverse set of data on occupant presence, movement, and behavioral activities for various building types in multiple countries.

An additional area of improvement is regarding information, education, and communication. The benefits of appropriate OB modeling and their design implications are still considered unclear by design teams. Clear examples and real-life case studies can help onboard designers, consultants, and their clients. O'Brien *et al.* (2017) illustrated that the second most important reason not to include OB modeling as a standard practice in the design workflow was lack of understanding/education. Researchers and scientist should work collaboratively with architecture and design firms to clarify the potential influence of OB on building performance and the implications of appropriate people modeling for building design. Finally, the language of OB modeling may still be too dry and technical for some clients and practitioners; better communication may direct clients toward people-centric designs that include post-occupancy evaluations as a standard practice. A business case is required for agile POEs that are fed back to the design team to help improve their models and designs.

7.5 Closing Remarks

The modeling approach that is chosen to represent occupants and their behaviors can have an impact on the simulation results and, consequently, on the design choices that are based on those results. For this reason, it is worth for simulation users to investigate which modeling approach to adopt for the case at hand. In this chapter, we have advocated for the use of a fit-for-purpose rationale, where the type of model and its complexity for each aspect of occupant behavior depends on the purpose and object of the simulation. Occupant behavior is still not fully integrated into the design workflow. Our hope is that the renewed interest in buildings' actual operational performance will push the community toward a more appropriate consideration of occupant behavior modeling and its importance in achieving informed design decision-making and accurate building energy use predictions. Researchers are already showing a commitment to improving workflows, models and tools, and, in particular, enhanced information, education, and communication concerning the role of human-building interaction for building performance. To further address this challenge, Chapter 8 will specifically focus on the integration of occupant models in simulation-aided design methods.

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8 Advanced Simulation Methods for Occupant-Centric Building Design

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Summary

In this chapter, we will introduce a series of simulation-based design methods that incorporate models of occupant behavior to achieve occupant-centric design objectives. To this end, we will first summarize the scenarios in which occupant behavior models can be integrated into simulation-aided design (Section 8.1). We will then explore a number of key simulation-aided design methods and objectives with a focus on the role of occupants (Sections 8.2 and 8.3). Finally, we will demonstrate and test the occupant-centric simulation-aided design procedures on a carefully described prototypical building model (Section 8.4).

8.1 Occupants in Simulation-Aided Design

Before we delve into the description and demonstration of occupant-centric simulation-aided design methods, this section provides a general framework to better understand different ways in which occupants can be incorporated into simulation-aided design methods. The framework is based on two key questions about modeling occupants in the design process:

1. Do the occupant models respond to iterative changes in the building design, i.e., are the occupant models *static* or *dynamic* in relation to the changes in building design?
2. Are the occupant models themselves subjected to iterative changes in the design process, i.e., are occupant-related assumptions among the design's *fixed* or *variable* parameters?

We refer to the four possibilities resulting from the questions above (static-fixed, static-variable, dynamic-fixed, dynamic-variable) as occupant behavior modeling approaches in simulation-aided design process and discuss them in the following.

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It is important to note that this chapter does not intend to provide a definitive answer as to which approach to model occupants is suitable for which type of building performance query thorough the design process. Rather, the aim is to review the key relevant considerations to help modelers/designers make an informed decision with regard to incorporating occupant behavior models in a given design problem. Chapter 3 (see in particular Sections 3.4 and 3.5), Chapter 5 (which introduces occupant-centric metrics), and Chapter 7 provide further insight into this challenge from different perspectives.

8.1.1 Static Occupant Behavior Models as Fixed Design Parameters

In the simplest approach, occupants can be incorporated into a simulation-based design process as static models that remain fixed throughout the iterative design evolution. Arguably, due to the relative ease of access to the required data for this modeling approach and its straightforward implementation in building simulation tools, it has been widely adopted in simulation-based design efforts. As highlighted in Chapter 6, many building energy standards recommend static assumptions for different types of buildings and spaces, such as maximum values and schedules of occupancy, lighting, and equipment use. As well, dynamic building thermal performance simulation tools generally have native components for definition of this type of occupant model. However, adopting a static occupant modeling approach means turning a blind eye to human–human interaction within a building as well as human–building and human–environment interactions (see Chapter 3). In particular, because of the disconnect between the design's indoor environmental conditions and occupant operation of the environmental control systems, design performance is not fully captured. Moreover, this type of simulation-aided design investigation does not reveal whether the building performs as expected when occupied differently than intended. With these limitations in mind, the building performance modelers should consider whether this simplified occupant modeling approach is suitable for their specific design problem.

The following example clarifies the above approach and its key limitations. In a performance-based design of a window, the designer/modeler aims to find the optimum size of the window that minimizes the energy demand of an office space in a typical year. The building thermal model used for energy demand estimation represents the room occupancy with specific assumptions, including the maximum number of occupants, lighting and equipment power density, and the corresponding schedules for weekdays and weekends. Thus, the building model captures the internal heat generated by the occupants, lights and equipment, and the optimization process finds a solution for window size that, for example, minimizes the sum of heating, cooling, and electrical energy use. However, in this optimization process, design iterations with larger windows are not favored by the optimization algorithm, as the building energy model does not consider the relation between the provided daylight levels and the use of electrical lighting by occupants. Moreover, since the occupant-related assumptions are not subjected to iterative changes through the optimization process, the modeler is not able to investigate if different patterns of occupancy or occupant behavior yield different window sizes as the optimum design solution.

8.1.2 Static Occupant Behavior Models as Design Variables

To some extent, the implications of different occupancy patterns for design performance can be studied while benefiting from the simplicity of static occupant models. Building on the example in Section 8.1.1, if the designer/modeler has control over the number of occupants in the room, the maximum occupant density can be set as a continuous or discrete design variable to represent a reasonable range of occupancy density or different predefined occupancy scenarios. Similarly, different sets of occupancy-related schedules can be defined and assessed during the design process. In both cases, the simulation-aided design exploration may either find the fittest occupancy patterns to minimize the objective function or determine if different patterns of occupancy yield different design solutions to be judged by the client. It is important to note that when using static occupant behavior schedules as design variables, the modeler should ensure that occupancy-related assumptions (such as lighting and equipment use schedules) are tied to the changes in occupancy, so that the studied behavior not only includes the number of users but also reflects their interaction with appliances.

8.1.3 Dynamic Occupant Behavior Models as Fixed Design Parameters

Given the limitations of static occupant models in simulation-based design processes, it is worth considering a dynamic modeling approach to capture relevant interactions of occupants with building environmental control systems, such that the design process is informed by the two-way relationship between design performance and occupant behavior. While dynamic occupant behavior models can be deterministic or stochastic, arguably both types have the potential to enhance the representation of occupants in the design process. Stochastic models capture the probabilistic nature of occupant environmental control actions. However, they come with a challenging computational cost, especially if the design process relies on numerous iterative simulations. Deterministic dynamic occupant models are not computationally expensive, but the modeler should be aware that they mirror ideal theoretical or automated scenarios of adaptive actions (see Chapter 6).

To revisit the example from Section 8.1.1, the designer/modeler could, for instance, incorporate a deterministic dynamic model of a light switch into the building model such that a number of the lights are switched off when the indoor daylight illuminance at a certain point exceeds a given threshold.

Although this model expresses a building-environment interaction not directly related to occupancy, it can be used to mimic a human–environment interaction using the building control system as a surrogate for an ideal scenario of occupant-adaptive action. Of course, there are a number of data-driven stochastic light switch models available that the modeler could opt for. However, either way, the light switch model enables the optimization process to reward larger windows due to their potential for reducing electrical lighting use.

It should be also noted that, once the libraries of occupant behavior are rich enough, dynamic occupant behavior models will also allow for investigating the impact of environmental control interfaces on occupant behavior and building performance within the simulation-aided design process (see Chapter 9).

8.1.4 Dynamic Occupant Behavior Models as Design Variables

Inclusion of the new generation of occupant models (as dynamic, data-driven, stochastic, and agent-based models) in the simulation-aided design process makes it possible to capture the occupant interactions with building environmental control systems, and provides further opportunities to test the design for different occupants and operation scenarios. As discussed in Chapter 6, many studies of occupant adaptive behavior have observed large samples of occupants and documented a wide range of interactions with different environmental control systems in different types of buildings. A number of these studies have also established personas based on distinct types of environmental control behavior (see Chapter 4). Thus, with these occupant behavior models, the simulation-aided design process can, among other things, test the robustness of building design schemes in relation to different types of occupants and/or finetune the design process for specific types of occupants – for instance, the elderly.

Returning to the example in Section 8.1.1, data-driven dynamic occupant models allow to study how different types of occupants (for example, in terms of their readiness to switch lights on and off depending on daylight availability) yield different optimum window designs. This is, for example, particularly relevant when designing for people with limited mobility. Thus, applying occupant behavior models as design variables could inform the design process to develop environmental controls that better fit to specific types of users. Thereby, the design team can either target the most representative type of occupants for a given project, accommodate specific "edge cases", or propose multiple design solutions based on different assumptions on future occupants to be discussed with the client.

8.2 Simulation-Aided Design Methods

Having considered the approaches to integrate occupant models in design process, this section describes four common simulation-aided design methods used by different members of design teams to make design decisions factoring in occupancy behavior: uncertainty and risk assessment, sensitivity analysis, parametric design, and optimization.

Building designers need information to understand what is significant to the design challenge at hand and, at the same time, information that is useful to make design decisions (Bleil de Souza and Tucker, 2015). In this context, designers are assumed to undertake building performance queries (i.e., investigate the performance of their design proposal) as well as seek design advice (i.e., look for guidance to proceed from the performance of the building proposal to an improved design; Mahdavi, 2004). This type of interaction between designers and their work happens in most stages of the design process. Occupancy data is part of this wider exploration of design and building performance, where occupancy (as discussed in Section 8.1) is either seen as a fixed design parameter or as a design variable, depending on the design stage and the type of performance query or design advice needed.

The methods discussed in this section are mainly normative, i.e., they are procedures that describe decisions to be made so that best choices are ensured (de Wilde, 2018). Their use in practice is limited by the time available to undertake a project, knowledge of the design team, and resources available to make decisions. Thus, they may not always be followed "as prescribed" (e.g., toward achieving optima). The design team may settle for whatever is satisfactory to fulfill a set of stakeholders' needs, mainly specified by the client and the main contractor. However, despite still being bounded by practice-based constraints, the importance of these methods in design decision-making is growing as the industry is pushed toward performance-based design (e.g., Directive (EU) 2018/844, EPBD, 2018) and occupant-centric design (e.g., EN ISO 55000, 2014), which means that methods are needed to not only substantiate decisions but also enable tracing accountability and liabilities toward achieving tighter targets for carbon emissions and occupant health. This is primarily where uncertainty and risk assessment come into play.

Briefly, uncertainty is defined as a "deficiency of information, related to understanding or knowledge of an event, its consequences, or likelihood" (EN ISO 55000, 2014). Risks are "often expressed in terms of a combination of the consequences of an event (including changes in circumstances) and the associated 'likelihood'... of occurrence" (EN ISO 55000, 2014). Both uncertainty and risks are dealt with by project teams at the very early design stages before design briefs are developed, and they cascade down to all project stages, including commissioning. They are formulated initially by project managers with regard to meeting the client's objectives and expectations, and then translated by the design team into design objectives to be implemented throughout the design process. Uncertainty and risk assessment are further explored in Section 8.2.1.

A key normative method to gauge uncertainty in relation to occupancy and to make more informed design decisions is sensitivity analysis (de Wit and Augenbroe, 2002), which is described briefly here and in more detail in Section 8.2.2. Defined as a way "to establish which of the input parameters have the most impact on experimental outcomes" (de Wilde, 2018), sensitivity analysis is mainly used by engineers and consultants to make decisions related to building services and systems at spatial coordination and technical design stages. It can also be used by consultants to generate design alternatives that help building designers "decide on the alternative that gives the highest chance of a desired outcome" (de Wilde, 2018) related to building form, spatial distribution, materials choices, etc. in conceptual and technical design stages.

However, when building designers are exploring a universe of design solutions, they often rely on parametric design to create and express ideas and make decisions related to building form and its relationships with different aspects of performance (structural, shading, daylight, etc.). More than a method, parametric design is a set of scripting tools that aid architects in manipulating relationships between different design elements by means of parameters, which provides fast feedback on performance to keep pace with the rapid design evolution that happens in conceptual design stages (de Wilde, 2018). Parametric design is examined in more depth in Section 8.2.3.

Finally, Section 8.1.1 focuses on optimization, which is "the process of finding the best [design] alternative" (de Wilde, 2018) out of a range of alternatives to satisfy specific objective functions. Optimization has questionable use for building designers who normally deal with multiple objective functions and simultaneously manipulate several design parameters that are not always quantifiable (de Wilde, 2018). However, the method can be used by engineers and consultants in technical design stages when main design parameters are already defined and fine-tuning of best combinations of alternatives is being investigated.

8.2.1 Uncertainty and Risk Assessment

In simulation-aided building design, uncertainty is the inability to accurately predict the impact of assumptions, decisions, or, generally, the inputs on building performance. As a simple example, a lack of knowledge about building occupancy patterns when designing an office building increases uncertainty about the lighting or plug-in equipment energy use.

Uncertainty during simulation-aided building design can be attributed to several sources, including human error, weather data, accuracy of simulation tools, accuracy of materials' physical and thermal properties, and accuracy of assumptions about occupants and their behaviors (de Wit and Augenbroe, 2002). Additionally, client-driven design changes (McGraw Hill Construction, 2014) and discrepancies between assumptions used during design (Abuimara *et al.*, 2020) are also recognized as possible sources of uncertainty.

8.2.1.1 Risks Associated with Uncertainty

Uncertainty in the outputs of simulation-aided building design is associated with several risks that undermine the credibility of design predictions. The widely recognized performance gap is typically attributed to uncertainty in design assumptions and predictions that mismatches post-occupancy conditions. Uncertainty during design can also lead to the risk of making suboptimal design decisions that would compromise the energy and comfort performance of buildings. Examples of suboptimal design decisions include over-/under-sizing of HVAC equipment and flow rates, selecting inappropriate window shading devices, overlooking adaptive technologies (e.g., lighting controls, DCV), and over-/under-sizing windows (O'Brien *et al.*, 2019). These suboptimal or conservative design decisions lead to high operational costs throughout the building lifecycle.

8.2.1.2 Assessing and Managing Uncertainty during Design

A typical approach for mitigating risks that stem from uncertainty in the design process is to make conservative assumptions and follow conservative approaches. In other words, designers base their decisions on the worst-case scenario (Djunaedy *et al.*, 2011). This approach might work in some but not many situations, as it often leads to increased capital and running costs of the buildings (Wang *et al.*, 2018). It could also compromise the energy and comfort performance of the building. Therefore, assessing and handling uncertainty during simulation-aided building design is of great importance for building cost, performance, and stakeholders' expectations.

In order to manage uncertainty in a simulation-aided design process, first and foremost, the modelers need to acknowledge and communicate it in the performance predictions. Reporting a performance range instead of deterministic values is an effective way of implying uncertainty (Sun and Hong, 2017). Aiming at robust design strategies is also considered a promising approach for mitigating uncertainty (see Section 8.2.2).

There are various quantitative and qualitative techniques that can assist in determining uncertainty (Burhenne *et al.*, 2010; Smith, 2013). Examples of quantitative methods are sensitivity analysis, Monte Carlo simulation, and Bayesian statistical modeling (de Wit and Augenbroe, 2002; Tian *et al.*, 2018). An example of a qualitative method is the confidence level test.

8.2.1.3 Occupants as a Source of Uncertainty

The nature of building occupants and their behavior makes them one of the major sources of uncertainty in building design. With regard to occupants' presence in building, the inability to predict the actual number of occupants and the changes that might occur throughout the building life cycle is considered a key source of uncertainty in assessing building performance (see, for example, Doiron *et al.*, 2011). Inevitably, the difficulty of predicting adaptive behavior of occupants means it might be assumed to act either in favor of or against the designer's objectives, which ultimately informs decisions that affect building performance. For example, assuming that occupants will behave in favor of designer's objectives might involve relying on them to turn off lights when not in use or opening window blinds when there is adequate daylight. A contrary example is assuming that occupants will misuse operable windows (e.g., leave windows open during a cold winter's day) and so fixed windows are designed.

The mismatch between what is assumed during design and what occurs post-occupancy has several implications for building performance and is linked to the so-called "performance gap" in this field. Arguably, energy-intensive occupant behaviors can turn a building that is intended to be energy-efficient into a building that performs worse than a conventional building (Norford *et al.*, 1994).

Ongoing efforts have been undertaken to quantify and mitigate the occupant-related uncertainty in the design process. Most notably, as discussed in Chapter 6, the development of data-driven occupant models has aimed to achieve a more reliable representation of occupants during building modeling process. Additional efforts have been made to account for occupant-related uncertainty by testing variable occupant and occupant behavior scenarios to quantify their impact on energy and comfort performance (see, for example, Abuimara *et al.*, 2019; Sun and Hong, 2017).

8.2.2 Sensitivity Analysis

Sensitivity analysis (SA) refers to analyses that explore the impact of inputs' uncertainty on the outputs (Saltelli, 2002). SA is a necessary step in model creation under any setting. SA in building design refers to the process of identifying the most important design parameters by quantifying their impact on design performance (Heiselberg *et al.*, 2009). SA assists designers in shortlisting design parameters in the search for optimal design solutions.

8.2.2.1 Methods and Types of Sensitivity Analysis

SA can be categorized into screening, local, and global studies. Screening SA, also known as the one-parameter-at-a-time (OAT) method, is done by varying the value of each design parameter individually using the standard value of the parameter as a control. Typically, two extreme values of the design parameter on both sides of the standard value are tested. Then, the difference between the results obtained from standard and extreme values are compared to identify the design parameters that are highly influential on design outcomes (Hayter *et al.*, 2000).

Local SA is also conducted in an OAT manner, whereby the values of one design parameter are varied based on its probability density function while keeping other design parameters unchanged (Heiselberg *et al.*, 2009). While OAT SA is a useful technique for eliminating low-impact design parameters, in many cases it is considered inadequate, as it neglects the interactions between design parameters.

In global SA, a wide range of values for multiple design parameters are tested and the outcomes are evaluated. A global SA considers the probability density function of design parameters and accounts for the interactions between different design parameters and their impact on performance. The output of global SA is typically a distribution which is mapped to space of inputs using a random sampling technique (Heiselberg *et al.*, 2009). Global sensitivity analysis can be conducted using various techniques such as Sobol's sensitivity estimates, the Monte-Carlo-based regression-correlation indices, and the Fourier amplitude sensitivity test (FAST) (Zhou *et al.*, 2008). Global SA, however, can be computationally demanding for assessing large numbers of variations.

8.2.2.2 Application in Occupant-Centric Design

As a widely used technique in simulation-aided building design, SA has been used frequently to study occupant-related parameters during the design process. For example, studies by Blight and Coley (2013), Sun and Hong (2017), and Abuimara *et al.* (2019) employed different SA methods to quantify the impact of occupants and occupant behaviors on building performance and design decision-making. Sun and Hong (2017) implemented occupant-related measures such as lighting control, plug-in equipment control, HVAC control, and window use control, which yielded up to 23% reduction in energy consumption when implemented one-at-a-time and a potential 41% reduction in energy consumption in combination. Abuimara *et al.* (2019) conducted a sensitivity analysis to determine the extent to which the energy-saving potential and associated ranking of a number of design options (e.g., improving envelope thermal insulation, window assemblies, and systems efficiency) were sensitive to the assumptions about occupants.

8.2.3 Parametric Design

Parametric design is a method that allows the designer to systematically explore the design alternatives by iteratively testing different combinations of design parameters. In a performance-based parametric design, the designer can assess the range of design performance resulting from the variations of geometric and non-geometric design parameters. To this end, building performance simulation tools offer two workflows:

1. Manual workflows, where conventional simulation tools are deployed to initiate a design concept, and changing the modeling input involves

manual editing of the design parameters or repeating the model creation process until the resulting design performance is satisfactory. The manual method is typically applicable where a limited range of possibilities, such as two ends of a spectrum (best- and worst-case scenarios), are explored (Azar *et al*., 2020). Relying on this workflow might hinder the applicability of parametric analysis when a large number of design alternatives need to be tested (Gilani *et al*., 2016).

2 Algorithmic workflows, where the model is defined by explicit definition of the design parameters and their dependencies to enable generation and examination of potentially a vast number of design alternatives in an automated or semi-automated manner. These workflows can elevate the iterative solution search to a more in-depth investigation of trade-offs, facilitate customization of specific design scenarios, and explore the impact of design uncertainties on performance.

8.2.3.1 Parametric Design Tools

The discourse of parametric design and its integration with building performance simulation has resulted in developing tool sets that have been of great interest to researchers in recent years. In particular, typical building simulation tools such as EnergyPlus, OpenStudio, and TRNSYS, which were not originally developed for the purpose of parametric design or modeling complex geometries, can now be deployed via plug-ins and interfaces such as ArchSim (for EnergyPlus), DIVA (for Radiance and EnergyPlus), Ladybug-tools (for Radiance, EnergyPlus, and OpenStudio), and jEPlus (for EnergyPlus and TRNSYS), which largely enhance their capabilities for parametric design. These tools are equipped with algorithmic workflows to enable generation and simulation of a large number of design alternatives in a single environment to facilitate the exploration of cause-and-effect relationships. A commonly used interface for parametric modeling is Grasshopper (the visual scripting platform for Rhinoceros 3D modeling software), which allows users to program via different languages such as C#, Visual Basic, or Python. This scripting capability has facilitated the creation of applications such as DIVA and Ladybug Tools, which offer extensive parametric simulation possibilities to non-programming users to explore both geometric and non-geometric aspects of their designs (Roudsari and Pak, 2013).

8.2.3.2 Applications in Building Design

Deploying parametric design tools allows for evaluating individual, multiple and interrelated design variables, assessing trade-offs, and arriving at optimum design solutions. Parametric simulation platforms can also facilitate multi-disciplinary dialogue through visualization of the mapping

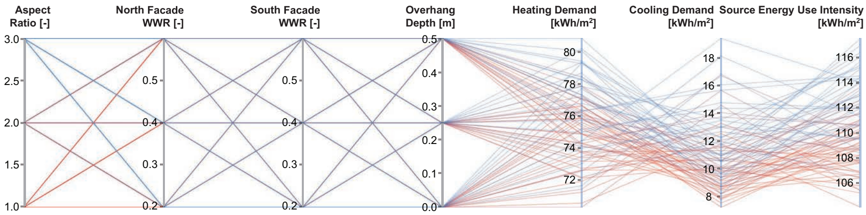

Figure 8.1 An example parallel coordinates plot depicting the mapping between design parameters (here, building aspect ratio, north and south façades window-to-wall ratio, overhang depth) and performance indicators (here, heating demand, cooling demand, source energy use intensity).

between the design variables and corresponding values of performance indicators. To this end, commonly a brute-force (or exhaustive search) approach is adopted, where the designer generates and simulates the entire full-factorial space of relevant design configurations using an automated algorithm. These can be then visualized and explored using, for example, parallel coordinates plots with tools such as Design Explorer (Figure 8.1). Understandably, for complex parametric design simulations, generation and simulation of all design scenarios is computationally intensive, which may make optimization-based design methods more favorable (see Section 8.3.4). However, the evolution of cloud-based simulation platforms (such as Pollination Cloud) allows building performance simulations to run much faster, thus expanding the applicability of parametric design to complex performance-based design explorations.

8.2.3.3 Occupants in the Process

Parametric design can integrate occupants in the process as design variables to generate a mapping between occupant-related design scenarios and building performance indicators. This method can inform the design process about the implications of different occupant-related scenarios for building design and operation and increase the design robustness against occupant-related uncertainties. As suggested in Section 8.1, this is best achieved if the design models consider occupants' interactions with the environmental control systems. For example, if the window size changes substantially through iterative model generations without capturing the potential adaptive actions of occupants, the process may not lead to a reliable performance assessment or an acceptable design solution for occupants. Additionally, while parametric design environments generally allow modelers to easily tie inter-dependent design parameters together, this consideration of interdependencies should be also applied to occupancy-related design parameters. For instance, if variations in the number of occupants do not change the use of equipment and lighting, then the parametric design exploration does not properly capture the implications of occupancy density for design performance.

8.2.4 Optimization

The use of optimization algorithms in simulation-aided design has grown in recent years thanks to advancements in computational and design tools (Attia *et al.*, 2015; Ouf *et al.*, 2020). Building performance optimization (BPO) allows designers to investigate millions of design alternatives without running substantial parametric analyses that would otherwise require significant computational time (Attia *et al.*, 2013). This process relies on different types of algorithms to significantly reduce the solution space (i.e., all possible design alternatives) and identify optimal design parameters that achieve specific performance objective(s), while considering the conflicting system-level design trade-offs (Bucking, 2016).

Generally, mathematical optimization problems can be represented by $x \in X \min\ f(X)$ where $x \in X$ is the vector of design variables, $f : X \rightarrow R$ is the objective function (i.e., optimization goal, such as reducing energy use), and $X \in\ R^n$ is the constraint set (i.e., parameter constraints, such as allowable values for design parameters). If more than one objective function exists, then a multi-objective optimization problem arises. However, the design process is always multi-objective. Therefore, transferring actual building design problems into the mathematical domain has some limitations, including that commonly used optimization algorithms applied to building design problems are not comprehensive enough to account for all design objectives.

Meta-heuristic optimization algorithms provide a higher-level procedure that performs iterations on populations of representative building designs; thus, they are also known as population-based algorithms (Evins, 2013). Due to their nature as partial search algorithms, near-optimal solutions can be obtained with comparatively less computational time, and issues such as discontinuity and non-linearity can be handled efficiently to avoid converging to local minima. However, running meta-heuristic search algorithms may not always result in finding the same optimal solutions due to their stochastic nature. Despite this issue, Evolutionary Algorithms (EA), which are meta-heuristic search algorithms, are the most commonly used optimization technique in the reviewed literature (Hamdy *et al.*, 2016). The most popular evolutionary algorithm used in building-related research is the Genetic Algorithm (GA) (Attia *et al.*, 2015), which uses the principle of natural selection to evolve a set of solutions toward identifying an optimum design solution.

8.2.4.1 Simulation-Aided Design with Building Performance Optimization

BPO algorithms can be used to achieve various design objectives once they are formulated as an optimization objective function. Notably, energy use reduction is one of the most common design objectives that can be achieved using BPO, as it requires systematic evaluations of various design parameters that interact with each other, often resulting in very large solution spaces (Bucking, 2016; Carlucci *et al*., 2015). In this case, using brute-force parametric simulations to evaluate all possible design alternatives may not be a viable solution, which highlights the need for BPO. Furthermore, BPO can be used to evaluate design robustness (Hoes *et al*., 2011), which can be defined as the ability of a building to maintain the preferred performance objective despite different uncertainties (Taguchi and Clausing, 1990).

When more than one design objective is being evaluated, BPO can be performed using two main approaches. In the first approach, different design objectives can be combined into one objective function with variable weights, such that the optimization objective is to minimize this objective function (e.g., Gunay *et al*., 2019). In this case, an optimal design alternative that represents a compromise between competing design objectives is identified. In the second approach, a multi-objective optimization problem can be formulated and then used to identify optimal design alternatives that lie on the trade-off curve, known as the Pareto Frontier. Improvements in any of these design alternatives to achieve one objective would typically negatively affect the other objective(s) (Attia *et al*., 2013; Evins, 2013; Machairas *et al*., 2014).

8.2.4.2 Occupants in Building Performance Optimization

Capturing the bi-directional relationship between building design and occupant behavior is one of the least studied aspects in BPO literature (Bucking, 2016). Previous studies have attempted to represent this relationship in BPO using three main approaches. The first approach relies on statistical methods such as Monte-Carlo simulations to randomly select building loads distributions that represent occupant-building interactions from pre-identified distributions (see, for example, Bucking *et al*., 2011; Sun *et al*., 2015). The second approach focuses on defining several scenarios in which combinations of pre-determined occupant-related variables are used (e.g., occupancy profiles, heating setpoints, light use profiles), and then each scenario is optimized independently. This approach was used by Kim (2013), Hoes *et al*. (2011), and Bucking *et al*. (2011) to investigate BPO results under predefined occupant scenarios. However, the main limitation of both approaches is that they do not consider the effect of design choices on occupant behavior within the simulation process. To address this issue, Ouf *et al*. (2020) introduced a third approach in which dynamic and stochastic occupant behavior models were incorporated into the BPO process. This approach

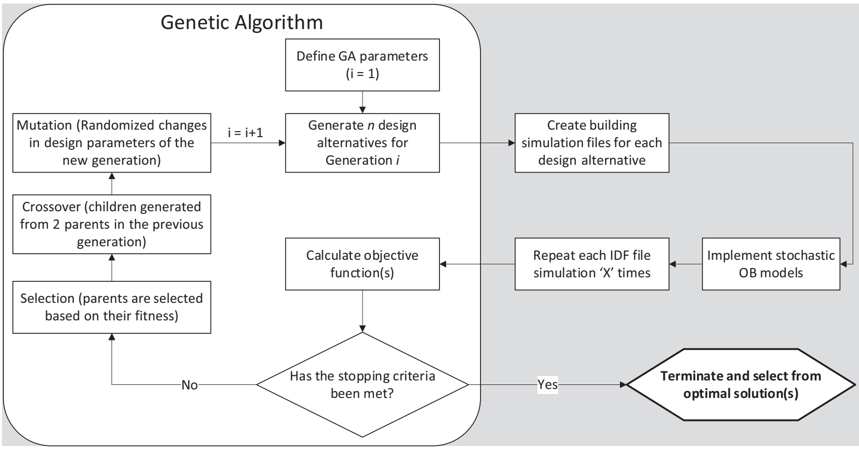

Figure 8.2 Overview of integrating stochastic occupant behavior in optimization using the genetic algorithm.

Adapted from Ouf *et al.* (2020).

accounted for the effect of design parameters on occupant behavior during every timestep of building simulation, which identified optimal design solutions subject to dynamic and stochastic occupant behavior.

Figure 8.2 provides an overview of the process used by Ouf *et al.* (2020) to integrate stochastic occupant behavior modeling within an optimization process using the GA algorithm. For each design alternative generated by the GA algorithm, stochastic models were implemented in building simulation to predict occupants' presence and arrival and departure times. Other models were also implemented to predict occupants' interactions with lights and blinds based on indoor and outdoor illuminance at every timestep. These implementations can be extended to other occupant-building interactions such as thermostat key presses depending on design and optimization objectives. Given the stochastic nature of these occupant behavior models, it is typically necessary to repeat the simulation multiple times to obtain results that represent an average and a range of performance under occupant behavior. The exact number of repetitions (X) should be case-specific depending on the models used in the simulation. The main outcomes of this workflow proved that the approach used to represent occupants can significantly influence the choice of optimal design parameters (Ouf *et al.*, 2020).

8.3 Simulation-Aided Design Objectives

Regardless of whether they are undertaking design queries or seeking design advice during the design process, designers/modelers normally have clear objectives or goals in mind when structuring their simulations, i.e., they have clear ideas about using simulation to generate the necessary evidence for them to make decisions. In the following sections, four such design objectives and their associated treatment of occupants are discussed, namely performance compliance checks, robustness to different occupancy and occupant behavior patterns, adaptiveness to different occupant behavior patterns, and resilience to extreme weather conditions.

8.3.1 Performance-Compliant Design

Performance-based building standards incorporate simulation tools to enable objective assessment of building performance while authorizing design flexibility and technological innovation to achieve energy and environmental targets (CIBSE, 2015). The standards may target different stages in the project life cycle for compliance evaluation; this section, however, focuses on as-designed compliance methods.

In the context of building energy codes, the simulation-assisted compliance checking process commonly involves modeling the proposed design in an authorized building simulation tool to compare its energy performance with that of the so-called notional (or baseline) building. The notional building commonly has the same shape, size, orientation, zoning arrangements, usage scenario, and HVAC types as the proposed design, but the properties of building fabric and HVAC systems are defined based on the values given in the standard.

To provide practical, consistent, and replicable procedures, building performance modeling for the purpose of compliance demonstration needs to rely on standard assumptions and simplified methods (CIBSE, 2015; Tregenza and Wilson, 2011). As such, the standards provide reliable assumptions for designers in the absence of information. They are therefore important industry quality assurance mechanisms for “assumed usage” that can be referred to in litigation cases and insurance claims.

However, the abovementioned characteristics of standards have made them particularly stringent in terms of innovations in occupant-centric design (O’Brien *et al*., 2020). This inflexibility is in contrast to the freedom with which the designers can, for instance, explore building physical properties and HVAC setup and components in the process. Specifically, the standards not only require the same usage scenario in the proposed and notional buildings, but they also enforce specific types of occupancy models or assumptions. For instance, ASHRAE 90.1 demands the use of schedules to model hourly variations in occupancy, lighting power, miscellaneous equipment power, thermostat setpoints, and HVAC system operation, and recommends specific schedules if actual schedules are not known. The National Calculation Methodology in the United Kingdom even mandates specific occupant behavior and system operation schedules from its database. As documented in an international review (O’Brien *et al*., 2020), the current building energy codes mostly rely on overly simplistic assumptions about occupant adaptive actions (such as modeling operable shades as constantly open).

Given the impact of regulations and building standards on the building design process and current limitations in terms of the representation of occupants in the process, compliance modeling is best seen as an initial stage in the occupant-centric design process. This stage needs to be followed by more explorative design modeling efforts that allow for more flexible and impactful consideration of occupants in the process. Examples of such simulation-aided design efforts are discussed in the next sections.

8.3.2 Robust Design

Building performance can be highly uncertain during the design process. This uncertainty is related to weather, construction quality, material properties, operational strategies, occupant behavior, and so on. This section focuses on occupants and how the uncertainty associated with their behavior can be addressed by a robust design.

In general, uncertainty is mostly addressed by making conservative assumptions. Designing for weather, for example, considers 99% of conditions. In the case of HVAC, equipment is sized large enough to maintain comfortable conditions in a building 99% of the time, and the temperature is too warm or too cold for the HVAC to meet all building needs just 1% of the time. The assumption is that the conditions during that 1% of time will not be too extreme compared to the 99% conditions; and even if they are, the duration will not be very long. Analogous approaches are commonly taken for occupancy, whereby cooling equipment is designed to be large enough to remove heat if the building is fully occupied.

Designing conservatively for (near) worst-case scenarios is costly, however. It means sizing equipment and other systems to be large enough to address circumstances that will rarely be encountered – for example, sizing a chiller to cope with nearly all conditions (O'Brien *et al*., 2019) or a PV array to be nearly certain that a net-zero energy building will produce as much on-site energy as it consumes over a year (Abdelalim *et al*., 2019). Design conditions tend to be most extreme when there is great uncertainty about operating conditions. The operating conditions cannot necessarily be controlled; however, they can be – or at least attempted to be – quantified and buildings designed accordingly.

Robust design is an established design method developed by Genichi Taguchi (Phadke, 1995), whereby a system is optimized to reduce variation of performance under a range of operating conditions. In the context of this chapter, the goal is to reduce the uncertainty of building performance as a result of occupancy and occupant behavior. Graphically, this can be represented by probability distributions, where the objective of robust design is to reduce the variance of the distribution and ideally reduce/increase the mean

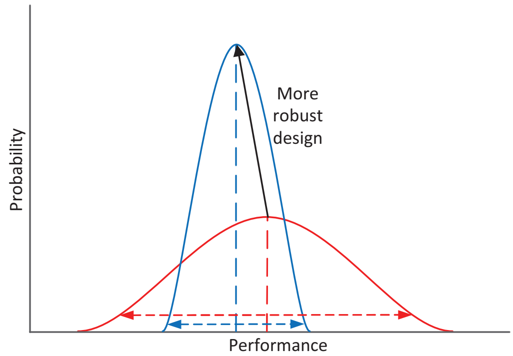

Figure 8.3 Probability distribution for two different design options. Robustness is indicated by the spread (variance) of the distributions. In this case, the design depicted by the narrower distribution is preferable because it is not only less uncertain but also has a lower mean predicted performance.

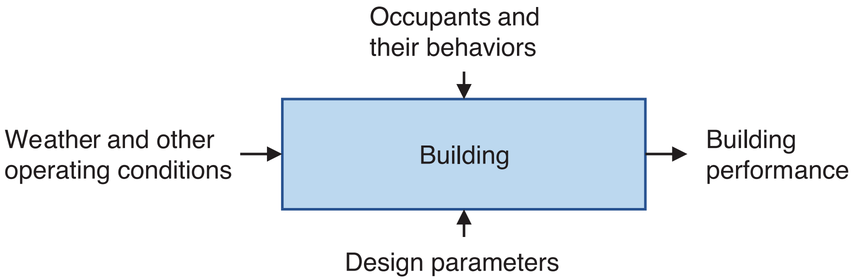

Figure 8.4 P-diagram for robust design applied to buildings and uncertainty from occupants.

(depending on the objective function). This is depicted in Figure 8.3, which shows the probability distribution for two different building design options.

The relationship between the system, uncertainty, and performance is normally depicted with a P-diagram, as shown in Figure 8.4. The description of the figure is premised on the assumption that simulation is used to perform robust design. Starting on the left side of the figure, the weather and other operating conditions are imposed on the model (as normal). Two additional sets of variables are imposed on the model: occupant parameters and design parameters. The occupant parameters are described below and likely consist of one or more occupant traits with a distribution of values for each. The design parameters are the building features that are varied to understand the relationship between building design and the distribution of predicted building performance levels. Finally, the output of the simulation is a probability distribution of performance levels (e.g., like those predicted in Figure 8.3).

In practice, to perform robust design using simulation, a range of occupancy or occupant behaviors is required in the form of a distribution. They may be, for example, a Gaussian distribution of occupancy densities. It could also be as simple as a uniform distribution with a range from the lowest to highest foreseeable occupant densities. If a stochastic occupant model is used, then it has the inherent property of yielding different results each time it is run.

One or more occupant features can be evaluated simultaneously. For instance, occupant density and schedules could be simultaneously considered with behaviors related to computer equipment, manual lighting, and operable window use.

While a factorial approach could be used to assess an exhaustive set of occupant parameter combinations, a Monte Carlo approach is likely to be the most efficient. For instance, a building model may be run *X* times, each with randomized occupant parameters. With the simulations runs, a probability distribution of performance levels can be established for a given building design (including the design parameter settings). While this distribution may be interpreted in absolute terms, it is typically more valuable to assess multiple designs against each other for their robustness.

8.3.3 Occupant-Adaptive Design

Aiming for occupant-centric design, adaptability to changing occupant behavior is another key design objective. Building adaptability is defined as the ability of a building to adapt to varying conditions while satisfying its primary function in an efficient way. In the context of occupant-centric design and operation, it is the ability of a building and its components to adapt to varying occupancy (Ouf *et al.*, 2019). Figure 8.5 illustrates a conceptual comparison between the optimal adaptability of a building and a building with traditional non-adaptive features.

Because buildings experience temporal and spatial variation of occupancy (Gilani *et al.*, 2019; Newsham, 1992), including adaptive features in buildings and building systems is necessary to achieve energy efficiency and comfort (O'Brien and Gunay, 2019). For example, demand-controlled ventilation (DCV) is an adaptive ventilation technology that is proven to improve energy efficiency, especially in buildings with varying occupancy (Lawrence, 2004). DCV manages and adjusts the supply of outdoor air to building spaces according to actual occupancy (occupancy-based DCV) or CO_2 concentration (CO_2-based DCV) (Fisk and De Almeida, 1998). Other examples of adaptive building technologies include: lighting controls that offer the ability to provide lighting when and where needed, which suits variable occupancy in buildings (Pandharipande and Caicedo, 2015); automated

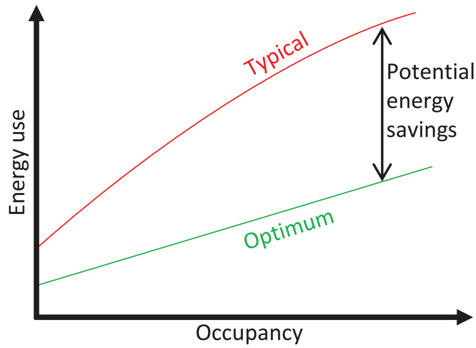

Figure 8.5 Conceptual representation of a building with adaptable features versus a building with traditional non-adaptive features.

window shading devices that can respond to weather variations and satisfy occupants' comfort; and manual or occupant-controlled features, such as operable windows and manual window blinds. These technologies, however, can also have negative impacts on energy use and comfort if misused (e.g., leaving a window open during a cold night).

Designing buildings that adapt to common occupant behaviors can mitigate occupant-related uncertainty and have a positive impact on building energy and comfort performance. For instance, a common energy-intensive and wasteful practice in commercial buildings is supplying ventilation to building spaces based on a fixed schedule of fully occupied or vacant spaces. An alternative adaptive approach is to introduce outdoor air into the spaces as needed depending on the number of occupants. Another example is an occupant who closes the window shades to avoid glare but leaves them closed for days, relying instead on electrical lighting at that time. Technologies such as automated shading devices, which are controlled based on occupancy and solar irradiance, can mitigate this unnecessary lighting energy use.

8.3.4 Resilient Design

The concept of resilience has attracted increased attention in recent years. Extreme weather events, such as heatwaves, hurricanes, and wildfires, inflicted a record \$210 billion in damages worldwide in 2020 (Dure, 2021), and their frequency and intensity are projected to increase (Mora *et al.*, 2018). In particular, extreme temperature is one of the leading causes of weather-related deaths globally. During 2004–2018, an average of 702 heat-related deaths (415 with heat as the underlying cause and 287 as a contributing cause) occurred in the United States annually (Vaidyanathan *et al.*, 2020). Extreme cold events, especially coupled with power outages, such as what happened in Texas in the winter of 2021, can be life-threatening, too (Weber and Stengle, 2021). Therefore, as a commitment to occupant health and comfort, it is critical to take thermal resilience into account during the building design process.

Resilient design aims to improve the building's capability to prepare for and adapt to extreme weather events, resist their impacts, and recover rapidly from disruptions. This aim is different from robust design, which targets to reduce the uncertainty of building performance brought by occupancy and occupant behavior. The ultimate goal of resilient design is to keep occupants safe and comfortable throughout the extreme weather events. However, thermal resilience requirements have not been formally incorporated in current building energy codes and standards, such as ASHRAE 90.1, ASHRAE 189.1, or California Title 24. The LEED rating systems give credits for passive survivability (Wilson, 2015), which improves heat resilience, but is not mandatory. RELi is a rating system that provides a comprehensive certification for socially and environmentally resilient design and construction (U.S. Green Building Council, 2018), but, similar to LEED, it is not mandatory either.

As advanced building control technologies continue to develop, buildings are increasingly designed to be more and more automatic, which leaves occupants with relatively fewer control possibilities. While this trend may benefit energy efficiency in general, it may also constrain occupants' abilities to improve the indoor environment during extreme weather conditions (e.g., open a window for free cooling), especially during a power outage when automatic controls cannot function. Therefore, resilient design should also include strategies to empower occupants to self-rescue during extreme conditions.

To evaluate resilient design strategies, extreme weather conditions should be defined and used in building performance simulation. For example, a heat wave can be characterized by three metrics: duration, intensity, and severity (Laouadi *et al.*, 2020). The duration is measured in terms of the number of days of sustained heat events. The intensity is measured by the average elevation of outside air temperature above a reference temperature. The severity is the time integral of the elevation of outside air temperature above a reference temperature over the whole heat wave period. Historic weather data over the past few decades can be mined to find the most significant extreme event. As extreme events are expected to happen more frequently, designers may also use predicted extreme weather data for future scenarios to enhance safety. The weather data provided by CIBSE could be a good resource for future weather data (CIBSE, 2016).

Various metrics are used to evaluate the thermal resilience of buildings to reflect the impacts of extreme events on human health. Broadly, there are two types of metrics: simplified biometeorological indices, such as the Heat Index, and heat-budget models, such as the Standard Effective Temperature (SET; World Meteorological Organization and World Health Organization, 2015).

Temperature (°C)

Relative Humidity (%)	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43
40	27	28	29	30	31	32	34	35	37	39	41	43	46	48	51	54	57
45	27	28	29	30	32	33	35	37	39	41	43	46	49	51	54	57	
50	27	28	30	31	33	34	36	38	41	43	46	49	52	55	58		
55	28	29	30	32	34	36	38	40	43	46	48	52	55	59			
60	28	29	31	33	35	37	40	42	45	48	51	55	59				
65	28	30	32	34	36	39	41	44	48	51	55	59					
70	29	31	33	35	38	40	43	47	50	54	58						
75	29	31	34	36	39	42	46	49	53	58							
80	30	32	35	38	41	44	48	52	57								
85	30	33	36	39	43	47	51	55									
90	31	34	37	41	45	49	54										
95	31	35	38	42	47	51	57										
100	32	36	40	44	49	54											

Caution — Extreme Caution — Danger — Extreme Danger

Figure 8.6 Heat Index chart (National Oceanic and Atmospheric Administration, 2018).

The Heat Index and SET are considered suitable metrics for quantitative analysis of extreme events and have been adopted by existing research on thermal resilience (Opitz-Stapleton *et al.*, 2016; Sun *et al.*, 2020; Wilson, 2015). Figure 8.6 defines four levels of heat hazards and their associated Heat Index ranges.

Two power availability scenarios are suggested for evaluating resilient design strategies: grid-on and grid-off. A grid-on scenario assumes that electric grid power is available and that the building is under normal operation status during extreme events. As HVAC systems are sized based on design day weather conditions, they may not meet the cooling or heating needs during an extremely hot summer or cold winter. Therefore, in a grid-on scenario, the major concerns are whether the air-conditioning system has adequate capacity to meet the cooling/heating loads during extreme weather, and if not, how many hours the occupants will experience thermal discomfort.

In contrast, a grid-off scenario assumes that electric grid power is not available due to a power outage. The overlapping of extreme weather conditions and power outage could be life-threatening, particularly for vulnerable populations such as the elderly (Weber and Stengle, 2021). In this case, the major concerns are indoor temperature rise (how long occupants will be overheated during a heatwave) and indoor temperature drop (how long occupants will be uncomfortably cold during a cold snap). Regarding vulnerable populations specifically, the concept of resilience is also embedded in universal design (Buildings.com, 2021), a framework that emphasizes accessibility, inclusion, and equity in the design of environments (Progressive AE, 2021).

Different metrics and thresholds apply in both of the power scenarios. For the purpose of resilience evaluation, each metric is defined with thresholds, where exceeding the thresholds indicates that the indoor thermal conditions are out of the comfort or safety zone. For the grid-on scenario, the indoor environment is less extreme because HVAC systems can still provide cooling/heating, and so the metric thresholds are selected mainly to evaluate the impact of the indoor environment on occupants' thermal comfort. For the grid-off scenario, however, the indoor environment can become life-threatening, and so the metric thresholds are selected mainly to evaluate the impact of indoor environment on occupants' health.

8.4 A Prototypical Testbed for Simulation-Aided Design

This section presents a series of exercises to demonstrate applications of the simulation-aided design methods and objectives described in Sections 8.2 and 8.3. A prototype shoebox model representing a private office is used in these exercises (with some modifications) to demonstrate the simulation objectives as described below.

8.4.1 Description of the Prototype Model

The shoebox office was modeled with dimensions $W \times L \times H = 4.0 \times 4.0 \times 3.0$ m. A 3 by 2 m window was added on the south side, the dimensions of which could be modified depending on the simulation and design objectives of each exercise. A version of this model is shown in Figure 8.8. The shoebox office was located in Ottawa, Canada (ASHRAE climate zone 6), and simulated in EnergyPlus V8.8 using the Canadian Weather for Energy Calculations (CWEC) annual weather data file, which is based on average weather data measured between 1998 and 2014.

The south-facing wall was exposed to the outdoor environment, while all other surfaces of the room were assumed to be adjacent to spaces with the same thermal conditions. The south-facing window (U-factor = 1.2 $W/m^2 \cdot K$, solar heat gain coefficient = 0.55 and visible transmittance =0.6) was assumed to be fixed with thermally-broken aluminum framing with a U-factor of 5.79 $W/m^2 \cdot K$ and profile width of 6 cm. The outside wall insulation's U-value was specified as 0.325 $W/m^2 \cdot K$ which exceeds the performance path requirements of ASHRAE Standard 90.1–2016. The internal heat gains from occupants, lighting, and electric equipment were assumed to be 130 W, 8.5 W/m^2, and 8.1 W/m^2, respectively, as specified in ASHRAE Standard 90.1 2016. Fresh air was supplied into the office room at a rate of 7.3 L/s based on ASHRAE Standard 62.1 during the occupied period. The infiltration rate into the office was assumed to be 0.3 air changes per hour (ACH), which is a typical infiltration rate for office buildings (Kim and Leibundgut, 2015). The HVAC system was modeled as an air-based ideal load system with heating and cooling capacity of 1,500 W since this study focused on the use of occupant models to inform early-stage design decisions rather than modeling HVAC systems. This heating and cooling capacity was chosen based on a preliminary sizing run. Heating and cooling setpoints were assumed to be 21°C and 24°C during occupied hours and 15.6°C and 26.7°C during unoccupied hours.

8.4.2 Occupant Modeling Approach

Two versions of the modeled shoebox office were created: the first version relied on ASHRAE Standard 90.1 fixed occupancy assumptions, and the second version used advanced occupant behavior models to represent occupants' presence, use of blinds, and manual switching of lights. For example, while the first version of the model uses a fixed occupancy schedule for office building occupants from ASHRAE 90.1, the second version deploys an occupancy model developed by Wang *et al*. (2005), which relies on random sampling of arrival and departure times from a normal distribution. The arrival and departure events were as follows: (1) arrival time at 9h00 ± 15 min; (2) a coffee break at 10h30 ± 15 min; (3) a lunch break at 12h00 ± 15 min; (4) a second coffee break at 15h00 ± 15 min; and (5) departure time at 17h00 ± 15 min. Figure 8.7 shows the ASHRAE Standard 90.1 occupancy schedule compared to the average weekday occupancy profile that resulted from applying Wang *et al*.'s (2005) occupancy model.

For lighting use, the first version used the ASHRAE Standard 90.1-2016 schedule. The second model used predicted light switch behavior using the Lightswitch-2002 model (Reinhart, 2004), which is based on occupancy status and work plane illuminance at each timestep. The lighting model

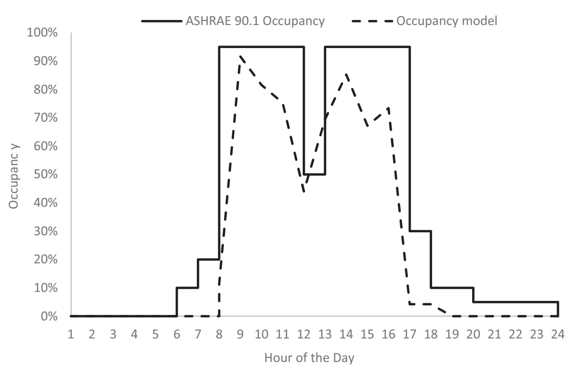

Figure 8.7 Average weekday occupancy profile based on ASHRAE Standard 90.1 schedule and Wang *et al*.'s occupancy model.

assumes a higher probability of switching lights on upon arrival than during intermediate occupancy. Upon departure, the likelihood of switching lights off is predicted based on the expected duration of absence, which increases as the expected duration of absence increases.

ASHRAE Standard 90.1-2016 stipulates that manual fenestration shading devices, such as blinds, shall not be modeled (which is effectively equivalent to modeling them as always open); thus, they were not included in the first version. In contrast, the second version included blinds, which were simulated based on the Haldi and Robinson (2011) model. This model of blinds use predicts the probability of blinds being fully open, partially open, or closed, based on indoor and outdoor illuminance, occupancy state, and previous blind position at each timestep.

The occupant behavior models used in the second version represent the ability to account for occupants as dynamic, not as merely passive recipients of environmental conditions. These models consider how changes in daylight availability can trigger occupants to turn the lights on or open or close blinds, actions that also affect work plane illuminance and solar heat gains. Table 8.1 shows the main differences between the occupant modeling approaches used in the two versions.

8.4.3 Test 1: Robust Design Optimization

In this robust design exercise, the premise is that fixed shading can be optimized to reduce the frequency of glare occurrence and corresponding shade-closing events. As we know from the literature (e.g., O'Brien, 2013; O'Brien and Gunay, 2015), occupants often close shades as a result of glare, but then are likely to leave them closed for an extended period. It follows that occupants are more likely to turn on lights if indoor illuminance is reduced because of closed shades. Therefore, a brief instance of daylight glare can result in significant increases in lighting energy as well as affect solar gains. Aside from the desire to minimize lighting energy use, there is also value in minimizing the uncertainty of lighting energy use, as this uncertainty translates to uncertainty for other components (e.g., cooling loads) as well as reaching certain targets (e.g., energy use intensity).

8.4.3.1 Methodology

For this exercise, the stochastic occupancy, lighting, and shade models are used (see Table 8.1). It is assumed that both lighting and shades are operated manually only (i.e., no automation). Due to the stochastic nature of the occupant model, plus the interest in the variability of the lighting energy as a function of design, we ran the model 50 times for each design iteration to obtain the mean and standard deviation of performance. The number of simulations was determined by repeatedly running the model until the standard deviation did not significantly change.

Table 8.1 Comparison between occupant modeling approaches used for each occupant-related domain in the two versions of the model

Domain	*First version: ASHRAE Standard 90.1 schedules*	*Second version: occupant behavior models*
Occupancy	Standard schedule for occupancy (Appendix G-I)	Randomly sample five arrival and departure times each day from pre-defined normal distributions (Wang *et al*., 2005)
Lighting	• Standard schedule for lighting (Appendix G-I) • Daylighting controls using continuous dimming	Predict light switch behavior based on occupancy state and work plane illuminance (Reinhart, 2004)
Blinds	No blinds modeled	Predict blinds use behavior based on occupancy state, work plane illuminance, and outdoor illuminance (Haldi and Robinson, 2011)
Output	One simulation	50 simulations

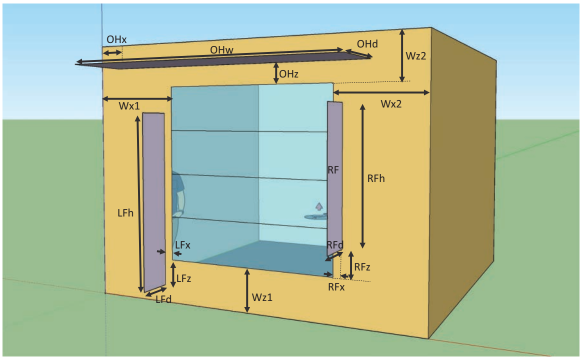

Figure 8.8 Parametric office geometry with variables for robust design test. Note that the window is modeled as four windows for the purpose of simulating partially closed shades.

In this study, we optimized the fixed solar shading and window geometry (see Figure 8.8) to minimize the mean and standard deviation of annual light use. While other energy end uses are important, we focused on lighting for the purpose of illustrating robust design.

A single and a multi-objective optimization process was then used to identify shading and window geometry. For the single-objective optimization process, an objective function was set up to minimize the value of C as given by:

$$C = \mu_{Elight} + 1.28\sigma_{Elight}$$

where μ_{Elight} and σ_{Elight} are the mean and standard deviation of lighting energy use obtained from 50 simulation runs for a given building design. The set of predicted lighting energy use results is assumed to be normally distributed. As such, the value 1.28 corresponds to the *z*-score for a normal distribution so that we are 90% confident that the lighting energy use for a particular building design will not exceed the value *C*.

For the multi-objective optimization process, the first objective aimed to minimize the mean of 50 simulation runs for a given building design, while the second objective aimed to minimize the standard deviation of these simulation runs. Consequently, multiple design alternatives were identified on the trade-off curve, in which improvements to achieve the first objective would negatively affect the other. For both the single and multi-objective optimization, the ranges of allowed values for parameters were wide to maximize flexibility; however, constraints were imposed to prevent issues such as the window exceeding the façade boundaries.

The genetic algorithm (GA) was implemented in MATLAB to call EnergyPlus for both optimization processes. The optimization was allowed to run for 30 generations. Each generation had a population size of 15. As noted above, 50 repeated simulations were used to capture the distribution of predictions for a given design; as such, 22,500 simulations were required. The crossover fraction used was 0.5, elite count was set to 1, and mutation probability for each parent vector was randomly assigned from a Gaussian distribution with 0 as its mean. Refer to Ouf *et al.* (2020) for more details on a similar example for optimizing building design with stochastic occupant models.

8.4.3.2 Results

The results of the single-objective optimization are shown in Figure 8.9, where an improvement of 18% of lighting energy is achieved between the first generation (randomized) and the 20th. The optimal shading geometry is summarized in Table 8.2, and the corresponding appearance of the façade

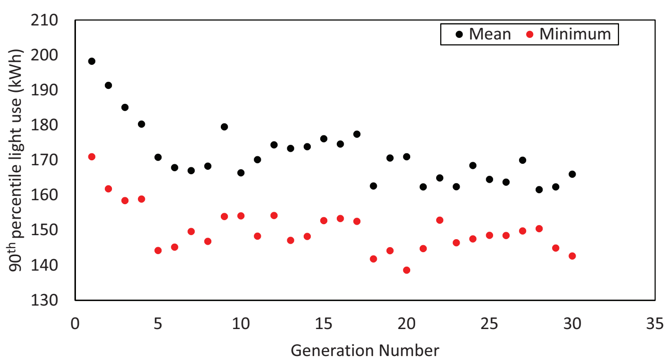

Figure 8.9 Optimization results through 30 generations.

Table 8.2 Optimal shading geometry parameters, compared to the minimum and maximum allowed parameter range for the optimization

	Wx1	*Wx2*	*Wz1*	*Wz2*	*LFx*	*LFz*	*LFd*	*LFh*	*RFx*	*RFz*	*RFd*	*RFh*	*OHx*	*OHz*	*OHd*	*OHw*
Opt.	0.73	0.10	0.72	0.97	0.30	1.33	0.50	4.00	0.10	–1.00	0.52	2.27	–0.33	1.11	1.58	4.46
Min.	0.1	0.1	0.1	0.1	0.1	–1.0	0.1	0.1	0.1	–1.0	0.1	0.1	–1.0	0.0	0.1	1.1
Max.	2.0	1.9	1.5	1.4	1.0	2.0	1.0	4.0	1.5	1.0	2.0	4.0	1.0	2.0	2.0	5.0

All values in meters. Refer to Figure 8.8 for parameter definitions.

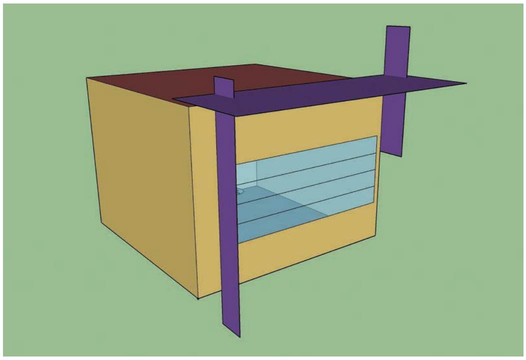

Figure 8.10 Optimal fixed shading design corresponding to the lowest predicted lighting energy use.

with the optimal shading geometry is shown in Figure 8.10. Note that the side fin surfaces above the overhang have no practical impact on indoor illuminance. Also note that while the resulting optimal design appears to be reasonable from a practical standpoint, many designs were near-optimal. Thus, we recommend that the near-optimal set of designs be manually explored to consider practical design implications.

While each simulation yielded different results, Figure 8.11 illustrates the shade and light states over the course of a year for the optimal design and baseline (no fixed solar shading). For the optimal design, the window shades are rarely closed except in the winter. This appears to result in a few days with lights on at all. In contrast, the shades are closed for significantly more time in the baseline, which results in the lights being on often throughout the year. Based on the simulations, the lights were on nearly twice as long (about 1,000 hours) for the baseline (without any fixed shading) compared to the optimized shading (about 500 hours).

The multi-objective optimization, on the other hand, resulted in three design alternatives that lie on the Pareto frontier (i.e., in which decreasing the average light use would result in increasing the standard deviation), as shown in Figure 8.12.

By analyzing these three design alternatives, we found that an overhang is necessary to decrease the average light use and standard deviation. A larger right fin was found to further decrease the average light use, but may slightly increase standard deviation (i.e., the level of uncertainty). However, a smaller right fin and wider overhang were found to decrease such uncertainty (standard deviation) while slightly increasing average light use, as shown in Figure 8.12. These results further highlight the need for manually exploring automatically generated design alternatives to consider practical implications and other contextual factors. Although this optimization

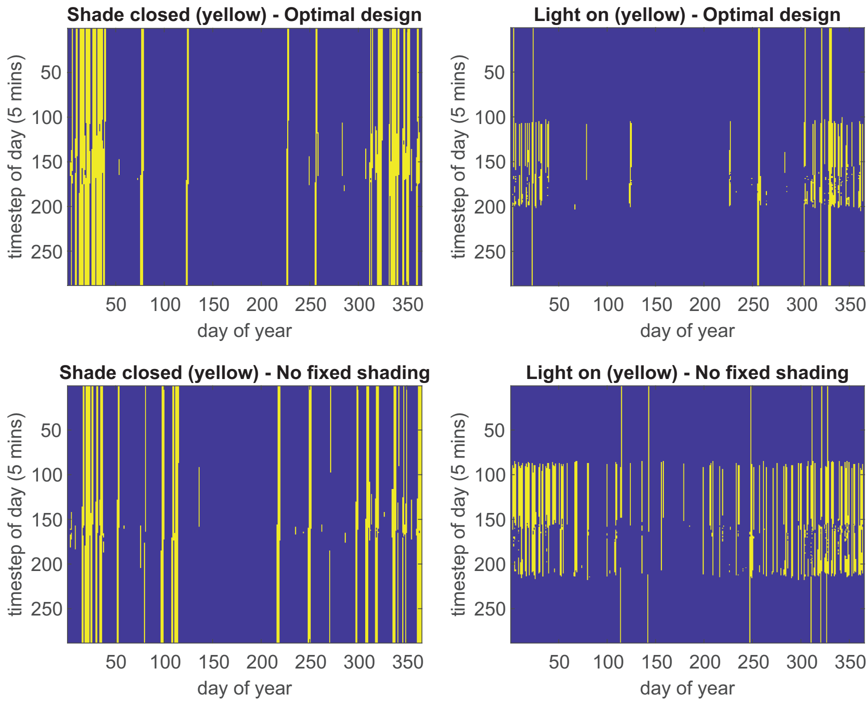

Figure 8.11 Comparison of light and shade states for a single simulation for both the optimal and no fixed shading cases.

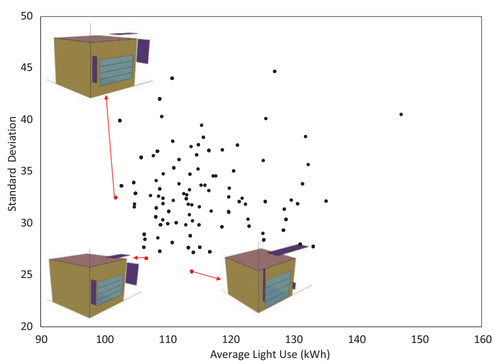

Figure 8.12 Pareto-optimal design alternatives for minimizing average annual light use and standard deviation.

process considers the effect of design choices on occupant behavior, other contextual factors as well as aesthetics would still necessitate designer judgment.

8.4.4 Test 2: Adaptive Design

An adaptive design exercise was performed to test DCV on the building model with both fixed and stochastic occupant models. The first set of simulations involved using the model with deterministic occupant models (i.e., fixed schedules and occupant densities) with and without enabled DCV. Figure 8.13 demonstrates a comparison of energy use by category between the model with and without DCV. It is evident from Figure 8.13 that DCV was not very beneficial in terms of energy use savings when deterministic models are used. This is not a surprising outcome, as deterministic occupant models assume constant and near-full occupancy throughout days and weeks, which leads to little difference when DCV is deployed. The modest savings in heating energy can be attributed to switching ventilation to per person when DCV is deployed instead of per floor area in the default settings.

However, much more significant energy-saving benefits were observed with the model with stochastic occupant models. Figure 8.14 presents the results of simulating the model with and without DCV. The end-use comparison shown in Figure 8.14 demonstrates the significant changes in heating and cooling energy uses when DCV was deployed. DCV is known for being more beneficial in terms of energy savings with changing occupancy (Lawrence, 2004) and the fluctuating nature of occupancy levels is only captured by the stochastic occupancy model.

These findings indicate that the use of building adaptive technologies/solutions offers an opportunity for handling occupant-related uncertainty.

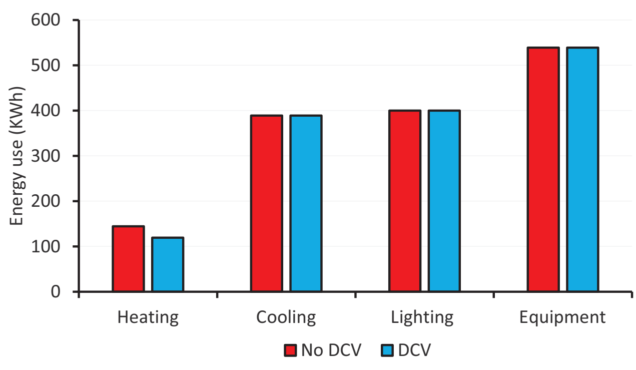

Figure 8.13 Energy use by category obtained from the building model with deterministic occupancy models with and without DCV.

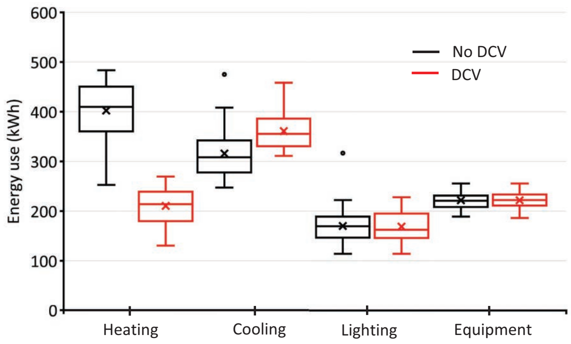

Figure 8.14 Energy use by category obtained from the building model with stochastic occupant models. The results demonstrate the energy use benefits of deploying adaptive technologies such as DCV.

This study also provides a case for the discussion in Section 8.1, that the use of oversimplified static occupant models can conceal the potential benefits of specific design alternatives.

8.4.5 Test 3: Resilient Design

This study uses the prototypical testbed introduced in Section 8.4.1 to demonstrate how to evaluate the thermal resilience of a building design and its influence on occupants. To this end, we model the indoor environmental conditions during extreme weather conditions and evaluate the effectiveness of a number of measures to enhance the resilience of the design.

8.4.5.1 Methodology

For the purposes of the current test, we treated the prototypical building introduced in Section 8.4.1 as a residential unit, as during extreme weather conditions (especially coupled with power outages) it is likely that people will not go to work but rather shelter at their home. We assumed the residential unit is occupied 24/7 throughout the extreme event. A heat wave was used as an example extreme weather event in this case study.

Figure 8.15 illustrates an overall workflow of the resilient design modeling approach. First, a baseline model was developed, and its performance under extreme weather conditions was evaluated under two power availability scenarios (see Section 8.3.4 for details). Second, selected design options or measures were applied to the baseline model and their effectiveness in improving thermal resilience was evaluated under the two power scenarios. Third, the models with resilient design features were simulated and analyzed

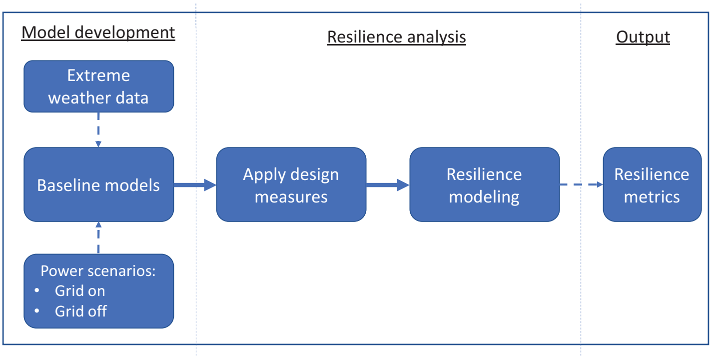

Figure 8.15 Workflow of resilient design simulation.

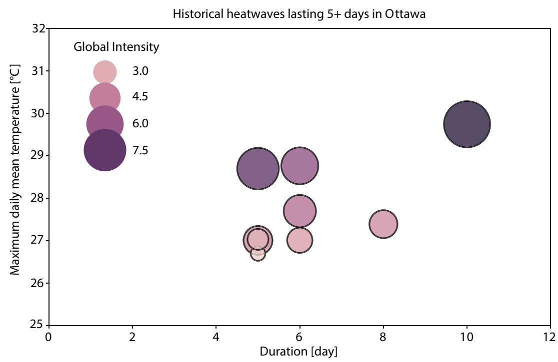

Figure 8.16 Historical heat waves that lasted longer than five days in Ottawa. Note: The size of each bubble represents the global intensity of a heat wave. Global intensity is defined by the cumulative difference between the temperature and the S_{deb} threshold during the event, divided by the difference between S_{pic} and S_{deb}. S_{pic} is the daily mean temperature threshold beyond which an event is detected, and S_{deb} is the daily mean temperature threshold that defines the beginning and the end of the heat wave (Ouzeau *et al.*, 2016).

with appropriate resilience metrics. As per Section 8.3.4, the Heat Index was used as the example resilience metric in this case study.

The key input assumptions of the baseline model were extreme weather conditions and power scenarios. We collected 30 years of historical weather data from Ottawa, Canada, identified all heat waves that lasted longer than five days (Figure 8.16), and selected the most severe heat wave period (in 2001) as the extreme weather condition for the simulation (upper right circle in Figure 8.16). Predicted future weather data can be used in resilient design, too, but the associated uncertainty should be specified.

Two power scenarios were considered for resilience analysis: grid-on (electric grid power available) and grid-off (electric grid power unavailable). For the grid-on scenario, we adopted the standard schedules for lighting and plug load from ASHRAE 90.1-2016 and assumed the air conditioners were available 24/7. For the grid-off scenario, the lighting, plug load, and air conditioners were off. We assumed the blinds were not used for the baseline model. To test an extreme case, we assumed windows were closed throughout the heat wave in the baseline model, which is not common but may still happen in some situations, e.g., the windows are blocked for security or other reasons.

Four passive measures were selected as examples to demonstrate the workflow of resilient design evaluation. A measure was categorized as a passive measure if it still works when the power is off. The measures were as follows:

1 Add solar control window film. These window films help reduce solar heat gain and protect against glare and ultraviolet exposure. They are best used in climates with long cooling seasons because they also block the sun's heat in the winter. The properties of the window film were as follows: thermal transmittance 4.94 $W/m^2{\cdot}K$, solar transmittance 0.34, solar heat gain coefficient (SHGC) 0.45, and visible transmittance 0.66.
2 Add an exterior overhang shade. This measure added an exterior overhang to the upper edge of the window. An exterior overhang can help block the solar irradiance when it is not desired.
3 Seal windows and doors to reduce infiltration. For conditioned buildings, reinforcing air sealing can reduce the amount of undesirable outdoor air flow into the building, thus generally reducing the HVAC system's cooling and heating load.
4 Enable natural ventilation. Natural ventilation can provide free cooling when the outdoor environment is cooler than the indoors. This measure assumed that the windows in the building were operable, and that the occupants could and would open and close windows as needed. The windows were assumed to be opened only when the outdoor air temperature was lower than indoor air temperature and the temperature difference was large enough to be noticeable by occupants, which was assumed to be 2°C in this case study. When grid power is available, windows and air conditioners are operated in concurrent mixed-mode. In this mode, natural ventilation has higher priority to provide cooling, and air conditioners provide supplementary cooling when natural ventilation alone is not enough to meet cooling load. In other words, if natural ventilation can meet cooling loads, the air conditioners will be turned off.

8.4.5.2 Baseline Model Performance

The most severe heat wave identified in Ottawa in the past 30 years lasted ten days from August 1 to August 10, 2001. We began the simulation one

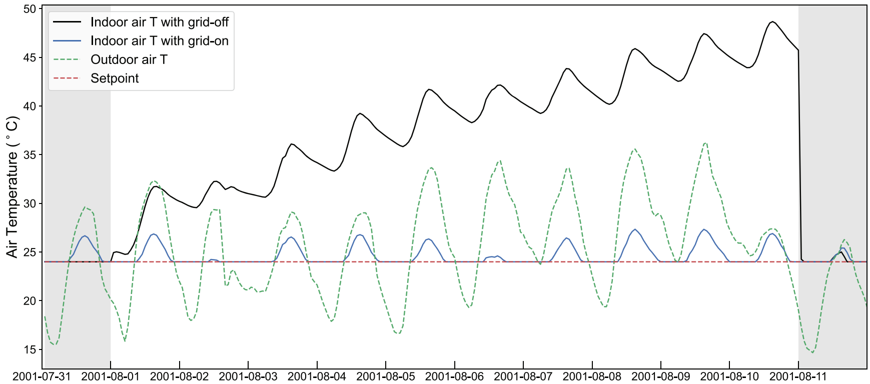

Figure 8.17 Comparison of outdoor and indoor air temperature under power-on and power-off scenarios. The greyed-out periods are one day before and one day after the heat wave under normal operation to illustrate the impact of the heat wave.

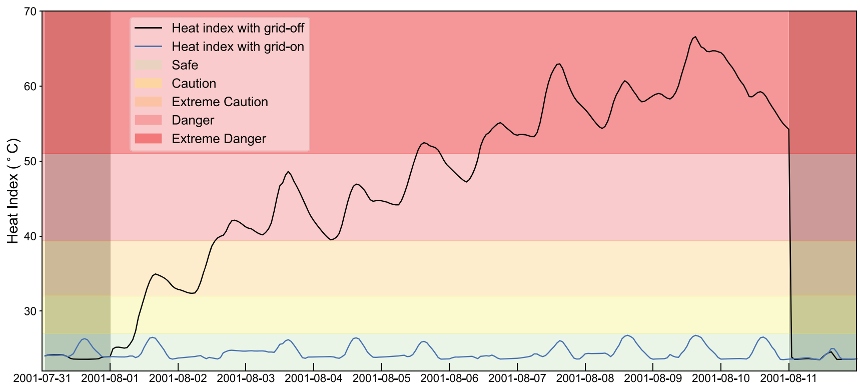

Figure 8.18 Hourly indoor Heat Index, with and without grid power. The greyed-out periods are one day before and one day after the heat wave under normal operation to illustrate the impact of the heat wave.

day before the extreme event and ended it one day after the event, to reflect not only the building's response during extreme conditions, but also the variations from normal to extreme conditions and vice versa. Figure 8.17 shows the outdoor air temperature and baseline indoor air temperature, and Figure 8.18 shows the baseline Heat Index variation, both under two power scenarios. With no air conditioning and no mitigation solutions, the indoor temperature could rise to as high as 49°C on the last day, with Heat Index entering an extreme danger level from the fifth day and rising as high as 67°C on the last day. Such conditions could be extremely dangerous to the occupants, especially vulnerable populations such as the elderly and young children.

However, with grid power available to run the cooling system, the indoor temperature could be maintained at lower than 28°C and the Heat Index kept at a safe level. This is because the cooling capacity was sized based on design day conditions that were developed using 1% dry-bulb and 1% wet-bulb cooling design temperatures, which had a maximum dry-bulb temperature of 28.9°C. Also, the outdoor temperature during the heat wave period was no higher than 35°C and had at least 10°C–15°C variation between day and night. In this case study, the grid-off scenario was analyzed further and applied with passive measures to explore design strategies for improving thermal resilience.

It should be noted that, in cold climates like Ottawa, many residential buildings are not equipped with air conditioners and could still experience life-threatening conditions during heat waves even when grid power is available. If these passively operated buildings are designed properly, they can better cope with heat waves.

8.4.5.3 Impact of Design Measures on Thermal Resilience

After the baseline performance is established, the four selected passive measures listed in Section 8.4.5.1 were applied to the baseline model without grid power, and the indoor environment was simulated to evaluate their effectiveness in improving thermal resilience. Figure 8.19 illustrates the heat hazard occurrence distribution of the baseline and the passive measures without grid power. An occurrence was defined as a heat hazard level happening at one timestep. The total occurrence percentage of heat hazard levels "Danger" and "Extreme Danger" during the selected heat wave period (in this case, August 1st to 10th) was adopted as the indicator to quantify the resilience improvement (Sun *et al.*, 2020).

Among the four example measures, natural ventilation performed the best, reducing "Extreme Danger" from 70.5% to 8.3%. This result suggested that natural ventilation was able to leverage a large amount of free cooling because the indoor temperature exceeded the outdoor temperature for majority of the time, as shown in Figure 8.17. Adding window film and exterior overhang shades was also considerably effective, reducing "Extreme Danger" from 70.5% to 40.6% and 56.2%, respectively. The only passive measure that countered resilience was air sealing. In conditioned buildings, reinforcing air sealing can help cut down heat gain through infiltration, which effectively saves energy use of the HVAC systems. However, during extremely hot conditions with no grid power available, the outdoor environment can be cooler than the indoor environment, in which case reducing infiltration ends up being harmful for thermal resilience. On the other hand, if a building allows for natural ventilation, occupants do not need to rely on infiltration to counter the building overheating.

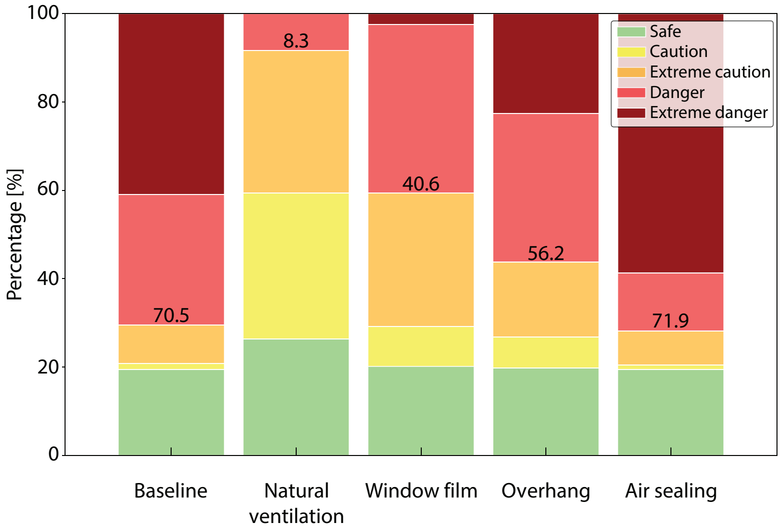

Figure 8.19 Heat hazard occurrence distribution of the baseline and design measures (labeled numbers refer to the total percentage of "Danger" and "Extreme danger" occurrences).

It is worth noting that some measures are occupant-dependent, i.e., they need occupants' active interactions to function well in reality. For example, natural ventilation can be very effective if occupants are alert and monitor the indoor and outdoor air temperature closely, and they open the windows only when the outdoor air temperature is lower than the indoor air temperature and close the windows on the contrary condition. Although the results of this case study show that some passive measures can significantly reduce "Extreme Danger", they still cannot guarantee sufficient safety of occupants. When the buildings are occupied by vulnerable populations who are sensitive to heat, the designers should take active measures, such as on-site power generation via solar PV, electric battery, and/or thermal storage into consideration to guarantee safety.

8.5 Closing Remarks

In this chapter, we focused on the role of occupants and occupant models in the building design process. We introduced a number of simulation-based design methods – namely, uncertainty and risk assessment, sensitivity analysis, parametric design, and optimization. We also presented examples of simulation-aided design objectives – namely, performance compliance, robustness, adaptiveness, and resilience. Finally, to promote a better understanding of occupant-centric design efforts, we tested three specific simulation-aided design procedures on a prototypical building model and documented and discussed the findings. These occupant-centric design methods will be further discussed in real-world case studies provided in Chapter 11.

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9 Building Interfaces

Design and Considerations for Simulation

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Summary

In this chapter, we will first present key human-building interaction (HBI) research to provide a framework for understanding how humans process information and interact with buildings. Following this foundational discussion, we will define user needs and HBIs for simulation by presenting some of the current challenges of incorporating interfaces into simulation and then provide an illustrative case study of lighting in private offices. We will conclude the chapter with recommendations for future research.

9.1 An Introduction to Human-Building Interactions and Interfaces

Significant progress has been made in simulating occupant behavior in buildings, but more work is needed to expand the understanding of occupants and their role as dynamic users of buildings as well as their interactions with building controls and interfaces (e.g., thermostats, lighting, windows). In general, buildings are unique, as are their occupants. Currently, simulation does not accurately reflect how people actually use buildings; in particular, simulation generally does not yet capture the wide range of behaviors in buildings, nor the dynamic nature of building interactions. If human interactions in buildings can be better understood and represented, then they can be simulated and thus inform the design of better buildings that support real people and their needs.

To explore these issues, in this chapter, we first define building interfaces and present examples of interface characteristics. Then, we discuss HBIs, especially as they relate to the need for building simulation tools that accurately predict HBIs. Next, we present a theoretical framework that better understands HBIs in the context of simulation and then a process that can be leveraged to translate user needs to better predict and define HBIs. We also discuss some of the challenges surrounding the incorporation of interfaces and HBIs into simulation as well as current occupant modeling and simulation tool capabilities. To offer a glimpse into how simulation methods

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are emerging to address these challenges and gaps, we then present a case study example of lighting interface design and controls logic in private offices. In the final section, we offer summary recommendations for further exploring and integrating HBIs into building performance simulation and future research needs. Throughout the chapter, "occupant", "user", and "human" are used interchangeably to describe the people who inhabit and interact with buildings.

9.1.1 Defining Building Interfaces

Supporting both building energy goals and occupants (e.g., well-being, comfort, satisfaction, performance) is a challenging task. To effectively achieve the balance between building performance and positive occupant outcomes, intentional consideration of predicted occupants' interactions with their built environment and the touch points for those interactions is required. Yet, a critical but often overlooked aspect of building design is the *building interface* (Day and Heschong, 2016). For the purposes of this chapter, a building interface is defined as a system component(s) where intentional or unintentional interaction occurs between a human, a building, and its subsystems (e.g., plumbing, electrical devices/controls, mechanical systems or thermostats, windows, blinds). Building occupants interact daily with building interfaces, such as when they turn on a light in a room or enter and exit a building (see Figure 9.1).

Some interfaces are simple (e.g., on/off) and others are more complex (e.g., learning thermostats); this range of variability and the sheer number of touchpoints and opportunities for interactions make it difficult to understand and predict how occupants will behave in buildings with respect to specific building interfaces. On the one hand, a well-designed interface may not be used as predicted because of poor placement or unanticipated behavioral drivers. On the other hand, a poorly designed interface may be used ineffectively (e.g., leading to decreased comfort or increased energy use) due to an occupant's lack of understanding of the control. In the former example, a designer may alleviate some of these issues by carefully thinking

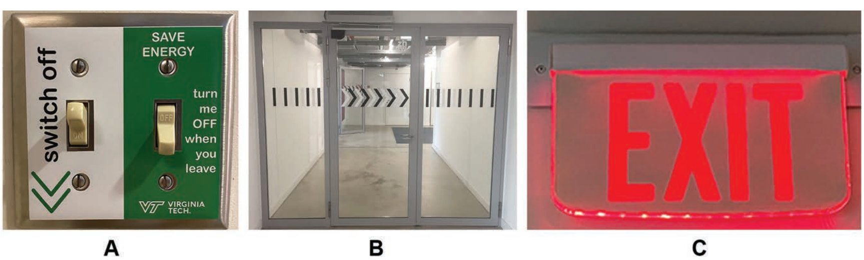


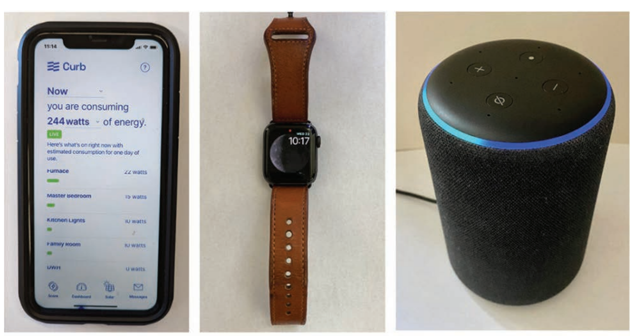
Figure 9.1 Examples of common building interfaces. (a) Lighting controls, (b) room entry, (c) wayfinding for egress.

through the use and placement while also collaborating closely with the occupants to better understand their needs. In the latter example, a better understanding of what makes a good interface and how to design and implement them for intended human interactions is needed.

Building system control interfaces have traditionally taken the form of fixed visual displays such as lighting controls and thermostats. Visual displays are the visual information link between humans and systems; thus, their system requirements are bound by the capabilities of the human visual system (Hainich and Bimber, 2016). In other words, it is important to consider display features such as shape, size, icons, target and background color(s), and clutter, as well as the anticipated distance and position of the user from the visual display.

Emergent interfaces move beyond fixed, visual displays toward mobile visual displays (e.g., smartphone applications with push notifications), wearable visible displays with haptic response (e.g., smart watches), and integrated auditory interfaces (e.g., Alexa) (see Figure 9.2). These emergent interfaces support new and distinct types of HBIs, while challenging building designers and simulation users to consider the impact of interfaces on building performance and occupants' well-being and more.

As new interfaces and modalities of interaction are developed, moving beyond technology-centered approaches toward usable, human-centered approaches will be critical for optimizing both human experiences in buildings and building performance (Agee *et al*., 2021). It is clear that there are many ways for occupants to interact with their buildings through many types of interfaces. There are also many reasons people choose to interact with their buildings. Many of these behavioral and comfort-based concepts and theories, such as thermal or visual or physiological/psychological reasons for interactions, are discussed in Chapter 2. There are also established methods for collecting information about how occupants will interact with



A B C

Figure 9.2 Emergent interfaces: (a) mobile applications, (b) wearables, (c) integrated auditory.

the space and the associated building interfaces (see Chapter 4 for further discussion).

This chapter focuses less on behavioral or physiological reasons for HBIs (e.g., the drivers) and more on how humans process the information relayed to them by the interface, as well as the characteristics of the interfaces that facilitate those interactions. The following section presents a more in-depth discussion of HBIs.

9.1.2 Human-Building Interactions

The study of HBIs with interfaces encompasses a broad, emerging research area and area of practice that draws upon human factors engineering, interior design, and traditional architecture and engineering. To focus our efforts within this chapter, we provide examples of HBIs that impact comfort, environmental quality, and building energy use (e.g., windows, blinds, thermostats, lighting).

To effectively understand human experiences in the built environment, it is critical to understand how HBIs impact building performance and the human experience within the built environment. There are common building interfaces that most users in industrialized societies interact with daily (e.g., system controls for lighting, thermal controls, plumbing) (see Figure 9.3), but not all interfaces and/or interface interactions are created equally. In particular, researchers have observed salient differences between commercial and residential interface use in terms of automation, perceived control, accessibility, and more (e.g., Day and O'Brien, 2017; Day *et al.*, 2020).

While it is increasingly understood that occupants, interfaces, and the resulting interactions in a building vastly impact comfort and energy outcomes, simulation tools used do not yet account for these factors. Building performance simulation (BPS) tools, originally developed for the purpose

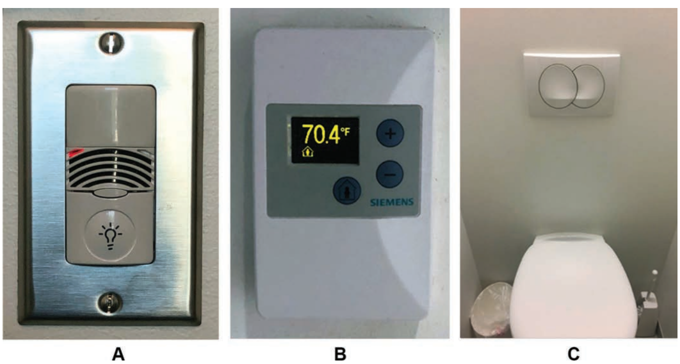


Figure 9.3 Examples of common building interfaces for: (a) lighting, (b) HVAC, (c) toilet.

of modeling static concepts, including occupants' presence, have yet to integrate HBIs as variables during simulation.

To illustrate, thermostats, a frequently studied building interface, account for nearly 9% of total energy use in the United States (Peffer *et al*., 2011). Recognizing the role of user behavior in energy use, EnergyStar developed and implemented specifications for programmable thermostats, including several scheduling and energy-saving features (Meier *et al*., 2011). However, in the years that followed the release of these specifications and subsequent installations, studies began to emerge that showed users were interacting with programmable thermostats in unanticipated ways. Some households were using more energy than those with simpler thermostats, seemingly because of complex features, poor design, and/or lack of understanding. However, relatively low thermostat replacement rates (Tamas *et al*., 2021) suggest many programmable thermostats remain in place—and will likely remain for many decades. If users' interactions with thermostats were better understood (e.g., using modeling and simulation) and the characteristics of those thermostats better considered, the unintended consequences resulting from this large-scale roll-out of programmable thermostats might have been avoided.

Consider Figure 9.4, which shows a typical BPS input (left image) and output (center image) that represents the thermostat interface daily use, as well as a typical thermostat interface (right image). On the thermostat on the far right, the user is confronted with over a dozen buttons with the ability to customize the setpoint schedule (i.e., for the occupant to interact with the device physically), yet this ability to alter and change the thermostat and the reasons for those HBIs are not considered in the image on the left.

To expand on this example, in any given thermostat, the interface has numerous qualities that impact use and level of interactions such as interface characteristics (e.g., size, text type, color, contrast, labeling), important contextual details about placement and accessibility (i.e., ease of access in this example), level of automation and control, and so on. Moreover, if a particular thermostat is internet-enabled, occupants can adjust it from afar, which presents even more opportunities for interaction. However, in the

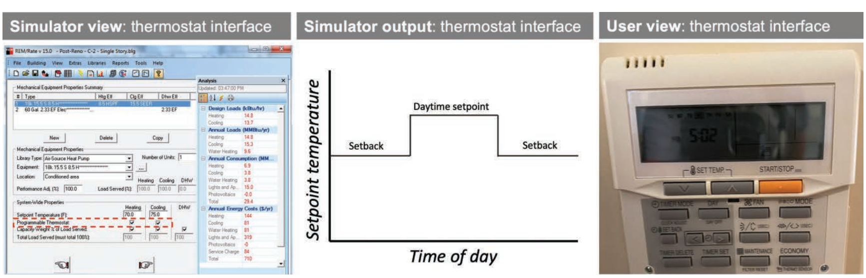


Figure 9.4 Comparison of interfaces.

simulation world, these complex variables, interface characteristics, and the frequency of interactions are not currently considered. Instead, typical BPS inputs are simple static schedules, such as the one depicted in the center of Figure 9.4 and fixed temperature setpoints. Put simply, there is a disconnect between the model and reality.

To date, little work on BPS tool development has incorporated the impact of interface design and use. Several tools (e.g., BEopt, Home Energy Saver) have taken a top-down approach whereby certain assumptions are made about the impact of interface selection. For example, BEopt allows energy modelers to choose a programmable thermostat that is automatically associated with a default setpoint schedule (e.g., 22°C for cooling and 18°C for heating), but it uses constant setpoints otherwise. However, it has been documented that occupants frequently override schedules (Huchuk *et al.*, 2021), which may not have been configured correctly in the first place. Thermostats are an example of a building interface that typically has infrequent occupant interactions; yet, other interfaces with more frequent and complex interface interactions (e.g., light switches, ceiling fan interfaces, water taps) are also treated simply and implicitly in simulation tools.

As stated above, there is a clear disconnect between how occupants use building interfaces and how their uses are simulated. This disconnect is emphasized if different players in a building perceive interfaces differently. For example, an energy modeler might view window blinds as a numerical factor or as on/off, 0/1, time, automation yes/no, etc. without considering the motivators or drivers behind their use. A building occupant might consider window blinds as a tool to block glare, control heat gain, increase privacy, or as decoration. In contrast, a building operator might consider manual blinds as something to fix or maintain and automated blinds as another thing to program, control, and commission.

Further adding to the complexity, there are also specific qualities of building interfaces themselves that might further facilitate or hinder occupant interactions. These qualities are described in the next section.

9.1.3 HBIs with Interfaces: A Missing Link in Building Performance Simulation

HBIs and the resulting user experience (UX) of direct or indirect outcomes from those interactions are illustrated by the simplified framework depicted in Figure 9.5 (Day *et al.*, 2020).

Feedback to the user may be immediate, such as when a light is turned on/off, or it may be delayed or lagged, such as when someone changes the settings of a thermostat. Often, elements on the right side of the figure are considered in simulation, whereas those on the left are not. The integration of building automation systems (BAS) into this loop adds further complexity to HBIs and necessitates consideration for interface design and integration into BPS.

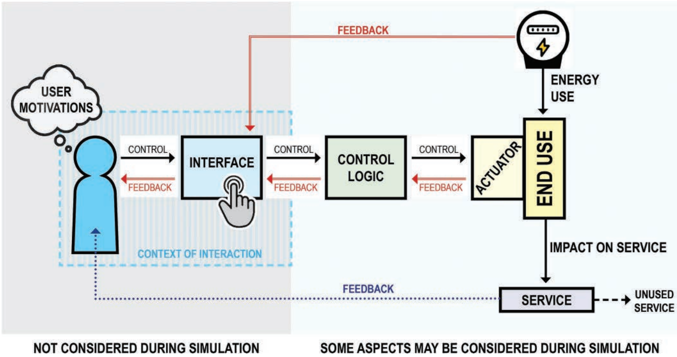


Figure 9.5 Conceptual model for understanding HBIs with interfaces.
Adapted from Day *et al.* (2020).

For example, when a BAS operational scheme is used to manage lights, space conditioning systems, and/or ventilation systems, the user(s) in the building lose control of their environment to a remote machine (i.e., the BAS system). The integration of autonomous systems in the built environment should not only prioritize operational savings but also aim to achieve the joint optimization of humans and technology. Figure 9.6 summarizes the relative strengths of humans and machines in the context of interactions with building interfaces. Design teams should consider human versus machine strengths throughout the design, construction, and operation phases of a project, as HBIs and outcomes may also vary based on the level of automation.

Current BPS oversimplifies BAS as a binary (on/off) input or schedule-based parameter. However, to more accurately reflect HBIs in buildings, it is necessary to characterize and allocate system functions across the human–system interface. It is often the case that an interaction across an interface is in fact somewhere along a spectrum from human-dominant (H) to technology-dominant (T), or a combination of the two (H-t, H-T, h-T) (see Figure 9.7).

For example, in commercial buildings, a technology-dominant (T) approach shifts building control to remote operators and/or facility managers that may not even occupy the building. In this case, interfaces may be completely autonomous. In contrast, perhaps in a residential context, a human-dominant (H) approach views automation as a tool to support human performance and needs (Norman, 2013), and some or all interfaces might be manual and intended for use by the occupants. Interfaces may also take the form of a blend of technology-human control rather than fully manual or fully automated. In this case, designers and simulators could use the function allocation approach demonstrated in Figure 9.8 to characterize and

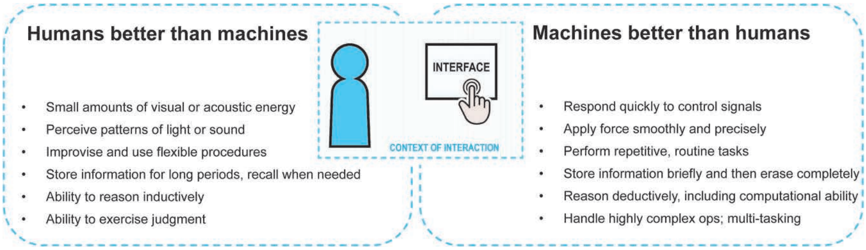


Figure 9.6 Human and machine strengths.
Adapted from Fitts *et al.* (1951).

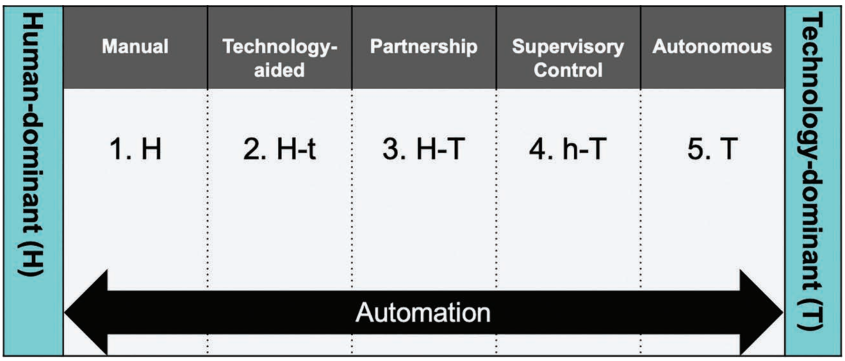


Figure 9.7 Taxonomy for classifying human-technology interactions. Technology-dominated (T) and human-dominated (H) and combinations of the former as Ht, ht, hT.
Adapted from Agee (2019).

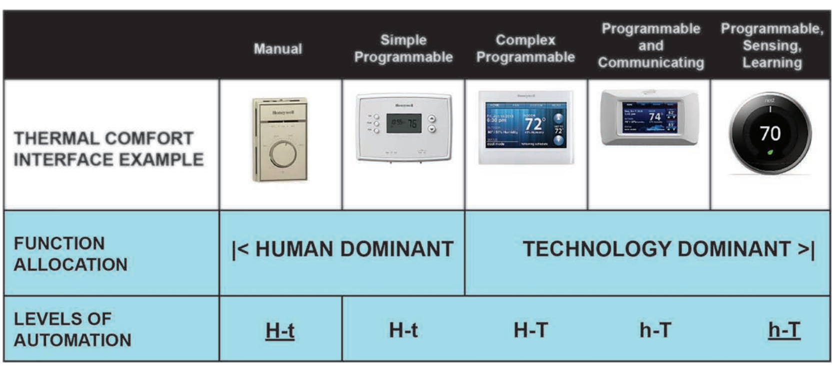


Figure 9.8 Understanding thermostat levels of automation by using function allocation.

better understand the often-invisible human-system relationships. Understanding these human-systems relationships is increasingly important with advancements in automated controls systems. Taking this view, operational savings are a byproduct of BAS, not the primary goal.

Once a designer or simulation user has allocated human-technology functions to support human performance, the next step is to understand how the user will use and/or accept the interface. In the section below, we offer a framework borrowed from UX and human factors research to help designers and simulators develop this understanding.

9.2 A Framework for Understanding HBIs in Simulation

It is important to integrate interfaces into building simulation due to the dynamic nature of HBIs. Before these interactions can be fully quantified, however, three aspects must be understood: (1) how humans process and receive information from interfaces, (2) how or to what level they might interact with buildings, and (3) what factors determine if a technology or interface will be accepted by a user. In this section, we describe two models from human factors and UX research—the Human Information Processing model and the Technology Acceptance Model—that provide a contextual framework in which to better understand the above list of key aspects of HBI and how they might inform the integration of interface use into building simulation.

The first model is Wickens *et al.*'s (2015) Human Information Processing (HIP) model, depicted in Figure 9.9, based on human factors theories of information processing. The model shows that when interacting with interfaces, users must process and perceive multiple stimuli and navigate response selection based on long- and short-term memory before executing a response. The multiple sensory inputs and varied attentional resources impact human's perceptions, decisions, input selections, and response(s).

The HIP model is helpful for understanding HBIs through the lens of human cognition. Notably, HIP is dynamic in that people have attentional resources that are ever-changing in response to stress, environmental conditions, mental workload, etc. In turn, these attentional resources impact people's ability to perceive and respond to environmental stimuli such as text or symbols on an interface. For example, a building user with adequate attentional resources will interact with an interface different than the same user with limited attentional resources due to stress or additional mental workload. In other words, people's interactions with their buildings and interfaces can be highly variable and not always predictable and thus difficult to accurately simulate. The dynamic nature of HIP is not currently represented in building performance simulation, and yet it must be considered by building designers and simulation users at the risk of designing building interfaces that are too complex (i.e., sensory inputs requiring too many attentional resources) and liable to being misused or not used at all.

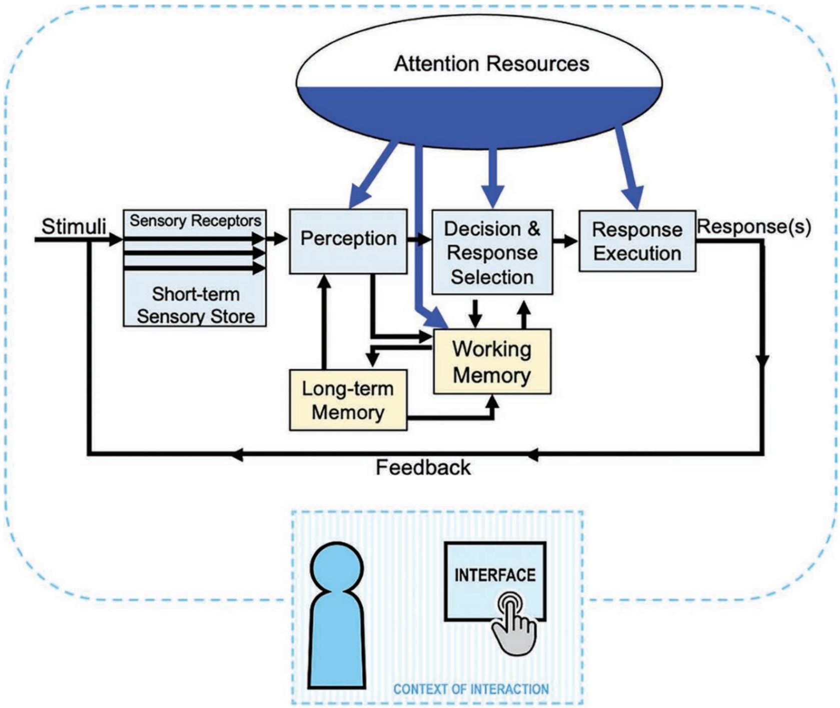


Figure 9.9 Human Information Processing (HIP) model.
Adapted from Wickens *et al.* (2015).

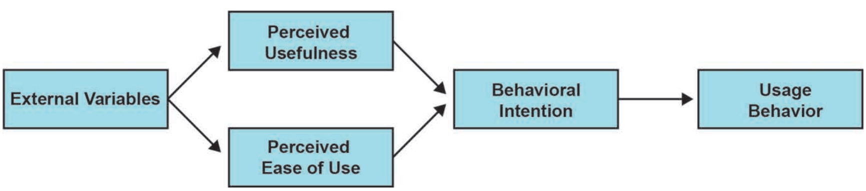


Figure 9.10 Technology Acceptance Model (TAM).
Image adapted from Venkatesh and Davis (1996).

The second model that helps to better capture HBIs in simulation is the Technology Acceptance Model (TAM) (see Figure 9.10). The TAM posits that users only accept a technology (such as an interface) if the system is perceived to be (1) useful and (2) easy to use (Davis *et al.*, 1989). This human-computer interaction theory provides the foundation for usability and UX research and can be leveraged in the design and development of useful and usable building interfaces and their integration into more robust simulation tools. For example, an app-based thermostat designed using the TAM would prioritize temperature control in the interface and would remove other visual clutter (e.g., time of day, weather conditions) that distract from detection of the temperature setting.

Both the HIP model and the TAM can help frame both building designers' and simulation users' understanding of human factors and UX in the built environment. This foundational knowledge is especially necessary to integrate HBIs into BPS. Integrating these models and lessons learned from other domains into the field of simulation can offer guidance to create more holistic and accurate simulations. If progress is not made in this regard, the current simulation gap will be compounded as (1) building automation becomes more ubiquitous and (2) stakeholders strive for higher levels of building performance. The BPS industry will no longer be able to focus exclusively on technology-centered outcomes (e.g., equipment efficiency, lighting power density, automation schemes motivated only by operational savings); they will also need to understand HIP and how building users perceive and interact with building interfaces. There is also a need to understand the impact of BAS on HBIs and to integrate this knowledge into both design and simulation.

The next section provides several specific recommendations for how the HIP model and the TAM can be used to better predict and define human needs and HBIs for simulation.

9.3 Defining and Translating User Needs and HBIs for Simulation

The TAM explains that users will only use a technology (e.g., an interface) that they perceive to be useful and easy to use; the HIP model reinforces this stance by stating that the more complicated the interface, the more attentional resources and cognitive load are needed to use it. In the case of building interfaces, to optimize their use for users and accurately predict how they will be used, interfaces should serve a clear purpose (i.e., be useful) and be designed well (i.e., be easy to use and demand few attentional resources). To meet users' needs, designers should follow a user-centered design process that facilitates the investigation, specification, and evaluation of interfaces in the context of users' physical, physiological, and psychological limitations. This shift is particularly important as some building designs are integrating more passive systems (in response to code requirements, occupant health, comfort, etc.) and requiring more active occupants. As buildings become more interactive, user-centered design processes will be critical to designing useful and usable building interfaces and to accurately capture user interactions with interfaces in building performance simulations.

The field of UX offers a design process for user-centered interface design to better understand the users, their needs, and the context of their interactions

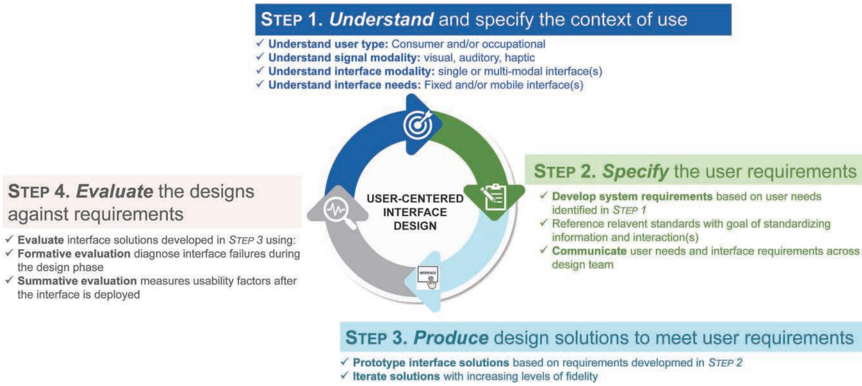


Figure 9.11 Iterative design approach.
Adapted from ISO 9241-210, Ergonomics of human-system interaction.

so these can better integrate into simulation workflows. The process includes the following four steps, which are further detailed in Figure 9.11:

- Step 1. Understand and specify the context of use.
- Step 2. Specify the user requirements.
- Step 3. Produce design solutions that meet use requirements.
- Step 4. Evaluate the designs against requirements.

It is critical for simulators to understand the context of use and users' needs when attempting to predict behaviors and HBIs. Steps 1 and 2, understanding and specifying the context of use and specifying user requirements, are particularly salient to some of the current gaps in BPS methods. Elements of Steps 1 and 2 are expanded below in relation to HBIs.

9.4 The Context of HBIs and User Requirements

As stated above, a user-centered interface design approach (e.g., as shown in Figure 9.11) emphasizes the importance of understanding the context of use for any given interface. In the case of simulation, the same sentiment applies; the context of HBI use and the environment must be understood to accurately predict use. The given setting, the types of signals available (e.g., touch, visual, haptic), the human attentional resources required (as per the HIP framework), and even the interface modality (e.g., fixed, wall-mounted, application-based) all drive the level of interface interaction and the range of interface use. Currently, differing conditions may be represented in simulation as binary inputs (on/off, low/high, present/absent), but these inputs likely do not represent how buildings are actually used.

Another important, but often overlooked aspect of HBIs, is the development of system and user requirements. For example, in a typical commercial building simulation, lighting use might be predicted based on a simple and basic occupancy schedule (9a-5p). However, lighting use and requirements might vary widely based on the type of building (school, office, weather station, etc.) and how the building is actually used. Other factors, such as plentiful windows and daylighting, or differing operation hours, might also impact lighting usage. In one study, occupants were frustrated when their night vision needs and 24-hour building operation schedule were not considered during lighting design or simulation, both of which adversely impacted their ability to do their jobs, and consequently, building energy use (Day and O'Brien, 2017).

System requirements distill the information collected in Step 1 of Figure 9.11 (i.e., interface context and use) into a list of interface requirements (e.g., features, functionality). System requirements also serve as communication tools for cross-functional teams and should be bound by the HIP and TAM frameworks. The development of system requirements enhances bi-directional information flow between users and markets and interface developers (Salvendy, 2012). There is no standard structure or outline for system requirements, but we the authors of this chapter suggest a single-page, weighted matrix of interface features and functionality that prioritizes and communicates interface requirements.

Figure 9.12 provides an example of system requirements for a user-centered interface for daylight controls. In the figure, a variety of daylight controls are noted, such as lighting switches, occupancy sensors, daylight apertures (i.e., windows), and daylight sensors (i.e., photocells).

	Lighting Response		Occupancy Controls (Sensors)			Daylight Aperture		Daylight Sensor		...
	Dimming	Bi, Tri, Multi-Level Switching	Ultrasonic	Passive Infrared	Dual	Side Lighting (Windows)	Top Lighting (Skylight)	Open Loop	Closed Loop	...
Space Type: Office										
Lobby	+	+	—	—	—	+	+	+	√	
Open Office Daylit	+	√	√	+	+	+	√	+	+	
Open Office Interior	+	√	√	+	+	—	—	—	—	
Daylit Enclosed Office	+	√	√	+	√	+	√	+	+	
Office w/o Daylight	+	√	√	+	+	—	—	—	—	
Conference Room	+	√	√	+	√	+	√	+	+	
Corridors	√	+	√	√	√	√	√	√	—	
Restrooms	—	+	+	√	+	—	—	—	—	
Storage	—	+	√	+	—	—	—	—	—	

LEGEND
+ = Best Practice
√ = Good Option
— = Not Typical and/or Not Recommended*

**Note: The inclusion of components should depend on the use and characteristics of the space. This matrix is based on typical space use characteristics but may not be applicable in all cases.*

Figure 9.12 Example of interface system requirements from Integrated Design Laboratory, Daylight Demo Curriculum, 2013. Image has been recreated and abbreviated.

There are certain applications where interfaces require some level of occupant control and interaction, and others where full automation is appropriate. The matrix in Figure 9.12 allows the designer to select a more appropriate interface based on the space type and how occupants might use that space. Of course, more information is needed to make the best decisions, and these selections might change based on specific projects, but tools like the one shown in Figure 9.12 can help designers better meet the needs of occupants while also better predicting how interfaces might be used.

It is essential to understand these different programmatic elements during the design and simulation of interfaces. Differences based on space type are just one aspect of the challenge of selecting the proper interface for buildings to best suit users' needs and requirements. For example, what building service does the interface serve (e.g., thermostat controls heating and cooling modes and temperature)? Are occupants expected to interact with the interface? What types of interactions will the occupant have with the interface and how often? Are the building design goals more focused on energy savings or occupant health and comfort, or both (*hopefully*)? What interface selections support these goals? These questions can also apply to differing building typologies (e.g., commercial, residential) and spaces (e.g., office, kitchen) within those typologies.

While there is no building interface standard, Table 9.1 provides an overview of relevant standards that may be consulted when designing and/or integrating interfaces into BPS.

Taken together, the steps outlined in the UX interface design process in Figure 9.11 and the standards in Table 9.1 can provide perspective on how other industries have aligned best practices for human-system interaction

Table 9.1 Selected relevant standards for building interfaces and occupant-centric controls.

Standard	*Domain*
ISO 9241-10 Ergonomic Requirements for office work with visual display terminals (VDTs)	Occupational
ISO 16982 Ergonomics of human-system interaction	Consumer/Occupational
ISO/IEC 13251 Collective Standard — Graphical symbols for office equipment	Occupational
IEEE P1621 Standard for User Interface Elements in Power Control of Electronic Devices Employed in Office/Consumer Environments	Consumer/Occupational
ISO 22902-6:2006 Road vehicles—Automotive multimedia interface—Part 6: Vehicle interface requirements	Consumer/Occupational
ANSI/HFES 100-2007 Human Factors Engineering of Computer Workstations	Occupational
ANSI/HFES 200-2005 Ergonomic Requirements of Software User Interface	Consumer/Occupational

and integration. As the world of occupant behavioral modeling and simulation evolves, it will be necessary and critical to learn from these and other domains to ensure that models reflect actual human behaviors in buildings. Other chapters in this book, such as Chapter 4, offer methods for gathering information about building occupants to better inform models and simulations.

Next, we present some of the challenges surrounding the incorporation of interfaces and HBIs into simulation as well as current occupant modeling and simulation tool capabilities.

9.5 Incorporation of Interfaces into Simulation and Current Challenges

There are many reasons why simulations might not (yet) reflect reality. For instance, most building simulations use historical data to predict the impacts of climate and weather on building performance rather than using data from observed and quantified HBIs. In heating/cooling-dominant end-uses, model predictions may be largely based on easily observable physical conditions, such as weather or building physics (e.g., *if the temperature is [X] degrees, and my building has [X] characteristics, then the heating/cooling will behave in this way*). This information is useful and needed, but it neglects how the people in the building might act or interact with the building based on these physical conditions. Adjusting occupant controls within simulation interfaces requires integrated workflows and iteration to predict the energy performance along indoor/outdoor environmental variations; however, existing BPS interfaces lack the ability to support such functions. Aside from the psychological and physiological aspects of human comfort (see Chapter 2), which are dynamic in nature, many BPS users are not aware of occupant-related behavioral aspects since there is no consensus on which modeling and/or simulation approach best represents *in situ* performance.

In addition, there is often a lack of knowledge of the actual user or user group(s) within the building and, therefore, in the building simulation. For example, a building owner or developer may design and build a building without having tenants lined up at the time of simulation or during the design phase. In these cases, building energy modelers often make assumptions about building use or occupancy without talking to or observing occupants. In cases where the tenants are known, information can be collected to better understand occupant needs (see Chapter 4).

Another reason that simulations may not reflect what is actually built and/or how a building is used is that programs and codes may dictate thermostat setpoints or default assumptions (e.g., ASHRAE Standard 140 “Standard Method of Test for Building Energy Simulation Computer Programs”), thereby bypassing actual use patterns, needs, etc.

Building interface design, context, and implementation are incredibly important to building performance, and yet, for the reasons outlined above (i.e., use of historical data instead of observed data, lack of knowledge about tenants, and/or code or standard requirements), they are rarely captured within simulation-aided design, let alone via other quantitative or evidence-based design methods (Day *et al.*, 2020). Accurate and realistic simulations of HBIs, across many interface modalities, will become important for designers and engineers as energy and health-related building codes and standards become more rigid.

Although the complexities of HBIs are not fully reflected in simulation methods, some progress has been made. In the next section, we outline current modeling and simulation tool capabilities, followed by a case study of private offices and lighting to illustrate how HBIs are being integrated into simulations.

9.5.1 Current Common Occupant Modeling Capabilities

As the previous sections have argued, understanding occupant behavior during BPS-aided design is essential for developing methods for modeling building interfaces. Currently, user behavior can be categorized into two types: (1) self-adaptive behavior, such as adjusting clothing level or changing positions in the space; and (2) interaction with various building interfaces to recover their comfort level, such as switching on/off lights, opening/closing windows, or adjusting thermostats setpoints, window shading, and water fixtures (e.g., turning on a tap, flushing toilets). Chapter 6 presents occupant modeling fundamentals, but it is not focused specifically on interactions with interfaces. Below we describe three types of occupant models in the interface context: (1) deterministic, (2) probabilistic, and (3) agent-based. We describe each approach in turn in the paragraphs that follow, though readers may opt to refer back to Chapter 6 for further detail.

First, deterministic approaches to representing occupant behaviors are available in common simulation tools. For example, occupants' interactions with lighting (turning on/off lights) are represented by a static lighting schedule that shows the fraction of lights that are turned on/off, the time when lights are turned on/off, and the fraction of lights that are left on during the unoccupied hours. Several BPS tools also have advanced lighting control scenarios, such as lighting control based on available daylight levels. Similarly, thermostats are typically represented by heating and cooling indoor temperature setpoints schedules.

Interactions with window blinds/shades are commonly neglected in the current BPS practices and assumed to be always open during modeling (O'Brien *et al.*, 2020). However, some BPS tools offer multiple options for modeling interactions with window blinds/shades, such as assuming that window blinds/shades closing actions are triggered by high solar radiation or high glare levels. The presence of operable windows is treated as means of ventilation, and the action of opening the window and the fraction of opening are set based on temperature, wind speed, and atmospheric pressure setpoints.

Second, probabilistic occupant behavior models are normally based on collected occupancy and operational data from existing sensing sensors in buildings. For example, Reinhart (2004) developed the Lightswitch-2002 model that predicts switching on lights and closing window blinds according to the level of available illuminance in the space. In another example, Haldi and Robinson (2009) modeled the probability of window opening behaviors according to weather. The data-driven nature of these models brings some semblance of reality.

One hindrance to the field of occupant behavior modeling has been the availability of reliable and generalizable occupant-related data. This issue is being addressed by initiatives such as the ASHRAE Global Occupant Behavior Database (Dong *et al.*, 2022). Although there have been remarkable research advances regarding accurately modeling occupants' presence and interactions with buildings, the uptake of these advances by BPS practitioners is almost nonexistent (Abuimara *et al.*, 2019; Ouf *et al.*, 2018). Modeling practitioners, as well as researchers, are still questioning the generalizability of these stochastic data-driven models as they were developed for single offices under certain conditions that do not apply elsewhere (Schweiker and Shukuya, 2011).

Lastly, agent-based models (ABM) allow each agent (e.g., occupant) to make a decision in relation to their environment based on a set of rules. ABMs consist of three main steps that can be coupled with one of the previous approaches: (1) defining agents and their interactions, (2) setting the relationships between those interactions, and (3) simulating the building environment in which the interactions are happening.

The implementation of these three different modeling approaches in current BPS tools is governed by the level of complexity required for each case and the resources and skills available to design practitioners (as discussed in Chapter 6). Given BPS practitioners' time and budget limitations, the implementation of stochastic (see Chapter 6) and ABM models will not be favorable unless they are required by codes and standards.

In the next section, we discuss in more depth how simulation tools can account for user interactions with building interfaces.

9.5.2 Simulation Tool Capabilities

In simulation, user interactions with building interfaces consist of two main actions: (1) sending actions through the interface (e.g., pushing a button) and (2) receiving feedback to satisfy the request (e.g., delivering sufficient lighting). This back-and-forth mechanism can currently be integrated into BPS tools in three discrete categories that formulate a BPS's inherent prediction capabilities:

1 **User behaviors as inputs:** Interfaces are used to deliver requests from users to building services that are acting as inputs to BPS tools. Often derived from standards (e.g., ASHRAE 90.1), prescribed schedules

are capable of modeling deterministic occupants' interaction with an interface as predefined values rather than time-varying interactions. However, there are methods to model occupants' interactions stochastically (e.g., built-in, user-customized controls), but these methods are limited to certain functions. For example, window interactions in EnergyPlus are limited to certain fixed or probabilistic indoor temperature thresholds. However, there are other features, such as window type and position on façade, that might change the occupant's interaction with interfaces to open/close the windows (Roetzel *et al*., 2010).

2 **Interfaces as control logic:** In BPS tools, to conceptualize the automated logic of an interface, implementing a control logic within a simulation workflow is necessary. This feature is feasible through co-simulation or user-customized controls such as Energy Management System (EMS) in the EnergyPlus simulation tool, which allows the inputs to be passed through a set of conditional deterministic/probabilistic assumptions of occupants' behavior when dealing with an interface in reality (e.g., thermostats) (Gunay et al., 2016; Tabadkani *et al*., 2020). For example, window blinds controls in EnergyPlus have been widely used to automate a shading system based on occupants' visual comfort (e.g., glare), assuming they override an automated action or control it manually.

3 **Feedback as outputs:** BPS tools are capable of illustrating interface feedback as time-dependent outputs and quantifying occupants' interactions with the interface. Depending on what has been controlled—such as light on/off switches based on an occupant's arrival/departure (e.g., wall-mounted interface) or daylight level (e.g., remote control)—BPS tools can characterize the implications of interfaces on three levels: (1) occupant level (e.g., task illuminance or light switching frequency), (2) space level (e.g., blind adjustments per day), or (3) building level (e.g., lighting load). Future occupant-centric developments in BPS should enable more reliable building performance predictions.

While much work is needed to more accurately reflect interfaces and interactions with buildings in simulation, the current BPS tools and their capabilities for understanding HBIs as outlined above (i.e., user behaviors as inputs, interfaces as control logic, and feedback as outputs) are a starting point. In the next section, we describe a case study example of lighting interface design and controls logic in private offices to offer insights into how simulation methods are emerging to begin to address the integration of interfaces, HBIs, and occupant behavior into simulation.

9.6 The Impact of Lighting Interface Design and Controls Logic: A Simulation Case Study

As indicated throughout this chapter, occupant models are generally not adequately detailed to quantify the impact of building interface design on

Table 9.2 Three different lighting control schemes that were modeled and explored

Name	*Light on controls*	*Light off controls*
Manual-on/manual-off	Occupant may turn on light (using Reinhart light use model)	Occupant may turn off light (using Reinhart light use model)
Manual-on/vacancy-off	(same as above)	Lights turn off after 15 min. of no detected occupancy
Occupancy-on/-vacancy-off	Lights turn on upon occupancy detection	(same as above)

user interactions. However, there are some models that are reasonably capable of quantifying the impact of interface design on building performance, such as lighting use behavior models. In this section, we provide a brief case study of private offices to illustrate the impact of lighting interface design and controls logic.

The three different lighting interfaces and control schemes that were modeled and explored in the case study (i.e., manual-on/manual-off, manual-on/vacancy-off, occupancy-on/vacancy-off) are compared in Table 9.2.

A south-facing private (single occupancy) office was modeled using the three schemes in EnergyPlus. The model is the same as that described in Chapter 8. In brief, it measures 4 m by 4 m, with a ceiling height of 3 m. It was modeled with a 50% window-to-wall area ratio, with the window centered on the wall. The Lightswitch-2002 (Reinhart, 2004) and Haldi and Robinson's (2010) model were implemented in EnergyPlus to predict the manual behaviors. These models predict whether occupants will turn on lights as a function of work plane illuminance and whether occupants will turn off lights at departure as a function of expected absence duration. The blind model predicts how occupants respond to daylight conditions. The Wang, Federspiel, and Rubinstein (2005) model was used to predict occupancy, which provides some randomness to arrival, departure, and break times. Occupancy is an important part of the simulation, since the lighting and shades use models depend on occupant-related events (e.g., arrival). Daylight-based control was not included, though the lighting and shades use models consider daylight.

Given that these models are stochastic, 50 simulations were repeated to quantify the distribution of predicted results. The reported output from the model is annual lighting energy and the number of times the lights were turned on by the occupant or by the automation system. The results (Figure 9.13) show profound differences in annual lighting electricity use and number of times the light is turned on for relatively subtle changes in human-interface interactions and the impact of automation on these interactions.

For both explored performance metrics (i.e., lighting electricity use and ratio of lighting on/off), the manual on and automatic (vacancy) off

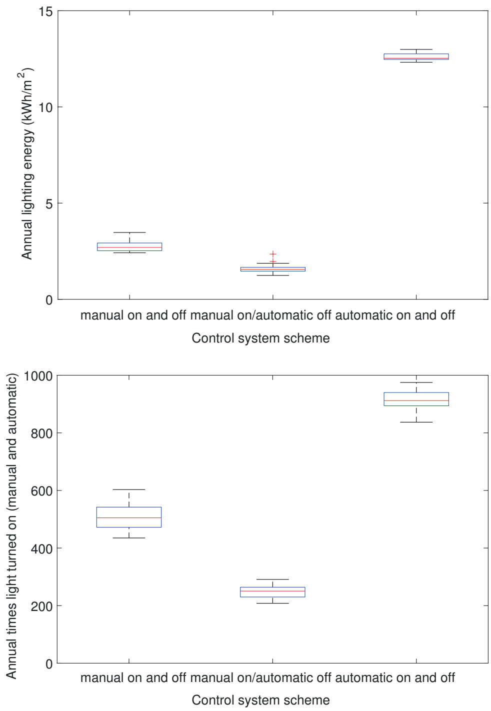


Figure 9.13 Results of different interface design/controls logic for lighting: annual energy use (top) and number of times light is turned on (bottom).

scheme performed best, likely because this perimeter office receives significant daylight, and the occupant often does not turn on the light upon arrival. According to both metrics, the vacancy off feature is valuable, as the Lightswitch-2002 model predicts that occupants will often leave lights on upon departure, particularly for shorter absences. Reinhart (2004) noted that such a feature makes occupants less likely to manually turn off lights and thus, in the current configuration, they stay on for 15 minutes after departure. However, the vacancy-off feature still appears to have a net benefit.

This short case study illustrates how relatively subtle interface and control design decisions can profoundly affect building performance. However, actual performance depended on validated occupant models that are based on long-term in situ measurement studies. A more detailed version of this case study, which includes a monitoring and model development phase, is presented in Gilani and O'Brien (2018).

In the final section, we offer summary recommendations for further exploring and integrating HBIs into building performance simulation and future research needs.

9.7 Final Recommendations and Future Research Needs

In this chapter, we presented an introduction to building interface theory, design, and considerations for integration into building performance simulation. We emphasized the importance of recognizing that user-centered building interface research and practice is an emergent but critical area. There are significant opportunities to understand, design, simulate, integrate, and evaluate building user needs into building interfaces and better understand the impact of interfaces on human and building performance (Day *et al*., 2020). With this in mind, we propose six steps to continue to advance knowledge regarding user-centered building interface research and practice to better provide accurate information and HBI inputs for simulations.

Step 1. Learn from user-interface simulation work in other domains/industries. For example, the aerospace and automobile industries have fully developed human–interface simulators with varying levels of fidelity (see Figure 9.14).

Considerable interface research has also been published in occupational settings such as mining, military, farming, and construction. For example, Thompson (2020) simulated human auditory localization capabilities (see Figure 9.15) and then developed a mobile interface evaluation tool to validate simulation findings in specific occupational settings.

Step 2: Develop higher fidelity approaches to modeling occupant-interface interactions. Higher fidelity modeling approaches will be necessary to better reflect emerging challenges related to human-building interaction. For example, the emergence of multimodal interfaces will require advanced understanding of human factors as well as account for smart interfaces that are increasingly reliant on automation and capable of learning user preferences for interactions.

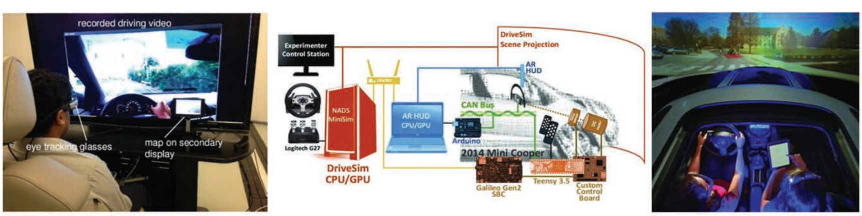


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Figure 9.14 Automobile interface research examples. (a) Low fidelity driver simulator, (b) schematic for head-up display (interface) simulator, (c) full-scale driver-interface study.

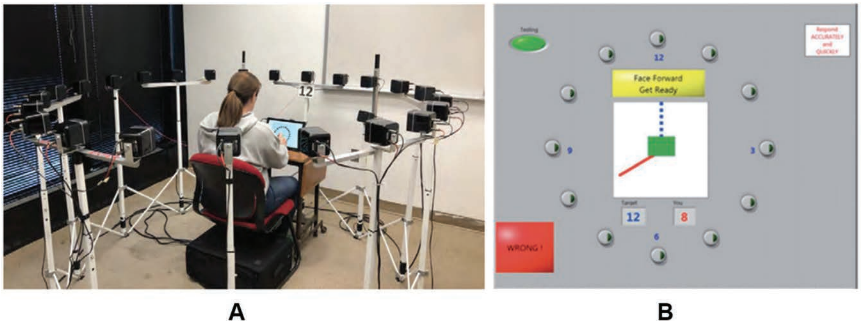

Figure 9.15 (a) Auditory interface being used for localization evaluation. (b) User interface developed to validate localization simulation assumptions.
Source: Thompson (2020).

Step 3. Validate simulations with data-driven models. With the growth of cost-effective sensing technologies, the ability to measure, analyze, and integrate data into building performance simulations to improve simulation predictions has grown exponentially. Iteratively simulating to predict and measuring to validate (and calibrate) should be the preferred approach to realize more user-centered outcomes. This is the current approach, but it is important to note that data-driven models are still not truly representative of interfaces and HBI.

Step 4. Account for and differentiate between high-interaction, low-performance impact interfaces (e.g., door handles) and low-interaction, high-performance impact interfaces (e.g., water heater setpoints). HBIs are diverse and dynamic. How can interactions be prioritized to better understand and simulate them? For example, building users in industrialized societies have four to 15 interactions with a toilet per day (or 1,460–5,475 interactions per year). The toilet interaction is an example of a high interaction, low energy performance impact interface. These interfaces and interactions matter for usability, but they do not significantly impact building energy performance.

Figure 9.16 represents two toilet interfaces: (a) has a single flush lever (top of left) and (b) has a dual flush interface. The dual flush interface was designed to reduce water consumption but does require additional human information processing (e.g., cognitive burden) prior to the user responding with a flush choice.

Step 5. Develop and validate experimental designs to support interface interaction models. A consistent challenge with integrating human-interface interactions into BPS is the lack of experimental designs that would

Figure 9.16 Toilets are high-interaction, low-performance impact human-building interactions. (a) Single-flush interface. (b) Dual flush interface (increases user cognitive burden, compared to single flush).

provide BPS developers with confidence regarding the validity and reliability of the human-interface assumptions. For example, increasingly, smartphone-based applications are accompanying building systems (e.g., smart thermostats, energy feedback displays). These applications integrate push notifications to send command and status signals. These push notifications increasingly inform human-building interactions, but they are not yet well understood in BPS.

Step 6. **Explore experimental designs that build upon behavioral economics**, specifically Thaler and Sunstein's (2009) work in "nudge" theory and choice architecture. For example, an energy-efficient system decision could be set as an interface default with other options presented to the user as well. The nudge, in this case, the energy-efficient default acceptance or rejection, could be studied as a true experiment (random sample, manipulation of independent variable(s), etc.). This type of study could also be adapted to measure user response from the choice architecture as well as the mental workloads associated with interface push notifications (see Figure 9.17).

9.8 Closing Remarks

In this chapter, we presented key human-building interaction research to provide a framework for understanding how humans process information and interact with buildings. We discussed the importance of defining user needs due to the dynamic nature of HBIs in relation to both the challenges surrounding the incorporation of interfaces and HBIs into simulation as well as current occupant modeling and simulation tool capabilities. We provided a brief case study example of lighting interface design and controls

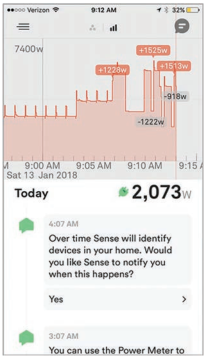

Figure 9.17 Mobile energy monitor interface.

logic in private offices to illustrate how simulation methods are emerging to address current challenges and gaps in simulation tools. Finally, we made six recommendations for the further exploration and integration of HBIs into building performance simulation. Ultimately, there is still much to learn in terms of interface characteristics, drivers for use and behaviors, and how to accurately reflect those aspects in simulation.

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10 Design of Sequences of Operation for Occupant-Centric Controls

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Summary

In this chapter, we will present basic classes of occupant-centric controls with illustrative examples developed using a real-world dataset. We will introduce workflows to study occupant-centric controls in building performance simulation. We will also discuss challenges related to the use occupant-centric controls in conventional sequences of operation by synthesizing findings from several field implementations.

10.1 Introduction

The development of sequences of operation is an essential phase in the design of a building since they detail how each building system, subsystem, and device will interact with each other to deliver building services efficiently (ASHRAE, 2018). This phase requires a system-level perspective that integrates the design team's vision of how individual pieces of equipment, solution, and technology will work together during the service life of a building.

If sequences of operation are not designed properly, energy-saving technologies and solutions may not work as intended; causing deviations in measured energy performance from the design intent by 30% or more (Wang *et al*., 2012; Zhang and Bannister, 2013; Gunay *et al*., 2019). However, the sheer number of interconnected systems, subsystems, and devices in a building makes the design of sequences of operation as one of the most challenging stages in the design process. For example, here, consider a variable air volume (VAV) terminal device's damper and reheat coil responding to zone-level heating and cooling demand. In turn, an air handling unit's (AHU) fan will respond to these changes in the terminal device dampers, AHU heating, and cooling coils will respond to heating/cooling demand from the various zones it serves, secondary and primary pumps will react to the demand from AHUs and VAVs, and so on. During the construction phase, control engineers codify the sequences of operation that regulate these different systems and then implement them into the building automation system (BAS). The outcome is a modern building with a network of

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devices automatically responding to a collection of *setpoints* and *schedules* prescribed in the sequences of operation.

Traditionally many of these setpoints and schedules are defined as constant or steady-periodic variables (Gunay, 2016). As design codes often leave the decision about these setpoints and schedules to the discretion of the design team, they are often selected conservatively to cater to an unrealistically high design occupancy that assumes occupants arrive and depart each day same time like clockwork. A few common examples of these conservative setpoints and schedules from the literature are as follows:

- Constant 22°C temperature setpoint year-round without a seasonal or daily setback (Gunay *et al.*, 2019);
- AHUs in office buildings scheduled to operate much longer than the actual occupied hours (Gunay *et al.*, 2019);
- Excessive over-ventilation due to high VAV terminal minimum airflow setpoint and AHU outdoor air damper minimum position setpoint (Cho and Liu, 2009; Pang *et al.*, 2017);
- Illuminance setpoints conservatively exceeding occupants' preferred illuminance levels (Gilani and O'Brien, 2018).

In reality, occupancy and occupant preferences of individuals using a building are diverse (Haldi *et al.*, 2017; O'Brien, Gaetani *et al.*, 2017; O'Brien, Gunay *et al.*, 2017). Any attempt to address this diversity with static and conservative setpoints and schedules means delivering building services blindly without knowing how many people are in a building, where they are in the building, what temperatures and illuminance levels they each prefer, and so on. Such attempts will inevitably waste energy and affect comfort as well as indoor environmental quality (IEQ).

Research using field-scale occupant data revealed that while individual occupancy events and adaptive actions of an occupant can be described as stochastic, the aggregate of many occupancy events and adaptive actions by the same individual are predictable and thus can be accurately modeled (Nicol, 2001; Haldi and Robinson, 2011). Beginning in the early 2000s, this finding initiated the following line of inquiry (Guillemin and Morel, 2002; Nagy *et al.*, 2015; Gunay, 2016): can data-driven occupancy and occupant behavior models be used to estimate optimal setpoints and schedules for HVAC and lighting controls? Currently, there are over 35 published field investigations documenting the viability of learning occupancy and occupant behavior patterns through occupant modeling to derive setpoints and schedules for HVAC and lighting controls (Park, Dougherty *et al.*, 2019). The approach has been termed occupant-centric controls (OCC). A recent position paper by the IEA EBC Annex 79 defined OCC as an indoor climate control paradigm whereby measured occupancy and occupant preference data are used in the sequence of operation of building energy systems (O'Brien *et al.*, 2020). In lieu of constant or steady-periodic conservative setpoints or schedules, OCC algorithms input occupant data and adapt the sequences of operation to the occupancy and occupant preferences in a building.

With the advent of ubiquitous occupant sensing and low-cost data archiving technologies, emerging data mining tools and techniques, and case studies documenting the energy savings potential, controls practitioners' interest in OCC has grown. The 2019 edition of ASHRAE Handbook HVAC Applications incorporated a standalone chapter on OCCs (ASHRAE, 2019). In parallel, commercial solutions tailored for OCC applications have begun to emerge. As the number of stakeholders in OCC research and development increases, so does the need for the present chapter that introduces a system of classification with real-world examples.

In this chapter, we first classify controls-oriented occupant data into different grades and provide examples for the most promising sensing technologies to acquire occupant data at these grades. Then, we describe and demonstrate controls-oriented occupant variables derived from occupant data with real-world examples. Next, we present the use of these variables inside a zone- and system-level controller. We then introduce approaches to integrate OCC algorithms into the building performance simulation (BPS)-based design process. Finally, we demonstrate the energy savings potential of OCCs through a simulation-based investigation.

10.2 Controls-Oriented Occupant Data

Controls-oriented occupant data can be broadly grouped into six grades, as shown in Figure 10.1. Occupant data grades (1) and (2) indicate absence or presence, grades (3) and (4) indicate occupant counts, and grades (5) and (6) indicate occupant activities. Grades (1, 3, 5) are for occupant data at the system/building resolution, and grades (2, 4, 6) are for occupant data at the zone/room resolution.

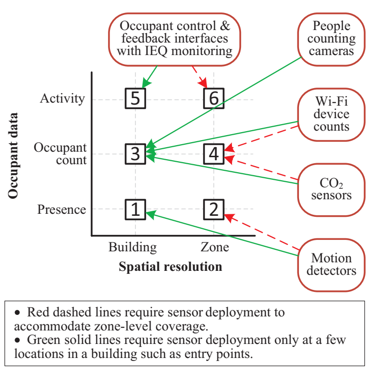

Figure 10.1 Grades of occupant data and the most promising sensing technologies to acquire occupant data at these grades.

Note that this categorization is adapted from Melfi *et al.* (2011). Melfi *et al.* grouped occupant data based on three dimensions: occupant, spatial, and temporal resolutions. Occupant resolution was grouped into four grades: presence, count, identity, and activity. Occupant resolution *identity* can be of practical use if an occupant's work location inside a building frequently changes, as a building's automation system can only learn a highly mobile occupant's preferences by monitoring them individually. This logic does not apply to spaces with transient occupancy characteristics (e.g., airports, hotels, restaurants) unless a globally available automation system can track all occupant actions individually in all space types. For OCC applications offering personalized comfort conditions, the general assumption is that the same group of occupants continuously use the same space; thus, anonymously monitoring their actions would provide insights into the preferences of occupants using a space. Hence, occupant resolution *identity* is found not necessary for common controls applications and omitted from this chapter. Spatial resolution was grouped into three grades: room, floor, and building. We adapted this as room/zone and system/building-level occupant data. As all controls-oriented occupant data must be generated at sub-hourly resolutions, temporal resolution grades are also not included.

While the list of commercially available occupant sensing technologies is constantly growing, Figure 10.1 presents the most promising and widely used: motion detectors, Wi-Fi, people counting cameras, and CO_2 sensors. Motion detectors (passive infrared and ultrasound) are the de facto standard in occupancy sensing, to the point that building codes and standards prescribe their use for lighting controls. Motion detectors output a binary present/absent signal over a timeout period of typically 5 to 30 minutes. They are available in most commercial buildings, albeit their coverage is often limited to only a fraction of the spaces. Motion detectors placed at main entry points can provide data at grade (1) (presence/absence at the building level). To acquire data at grade (2) (presence/absence at the zone level), motion detector coverage needs to be extended to all occupiable spaces.

CO_2 sensors are an implicit occupant count sensing solution. CO_2 sensors have been a method of controlling ventilation for decades using threshold-based CO_2 concentration to control outdoor air control (Brandemuehl and Braun, 1999; Emmerich and Persily, 2001). This method has been part of the performance-based criteria within the ASHRAE Standard 62.1 focused on indoor ventilation (Persily, 2015). CO_2 sensors are widely used at the system/building level, primarily to monitor AHU return air CO_2 concentration to facilitate this control. A more recent use of these sensors has been as an implicit occupant counting solution. CO_2 sensors do not count people directly, but instead detect occupants' impact on the CO_2 concentration. While there are several commercial thermostats and zone sensor hubs with built-in CO_2 sensors, zone-level CO_2 sensing is currently unavailable in all commercial buildings (Dong *et al*., 2019).

Wi-Fi device count is a very promising proxy for occupancy. Hobson *et al.* (2019) and Ashouri *et al.* (2019) demonstrate that Wi-Fi device counts exhibit a strong linear correlation with ground truth occupant counts. Both studies reported that occupants carry ~1.2 Wi-Fi-enabled devices each on average. However, the number of Wi-Fi-enabled devices per person is expected to exhibit some variation in different buildings depending on the building use case and occupant demographics. Therefore, if possible, ground truth occupant count data should be collected for calibration to achieve high accuracy. Both (Ashouri *et al.*, 2019; Hobson *et al.*, 2019) reported that two to three days of ground truth data are adequate for calibration. In a building with a centralized IT network, building/system-level Wi-Fi-enabled device count data can be accessed, often without any additional software and hardware. In facilities without a centralized IT network, standalone Wi-Fi probing devices deployed in the atria can be utilized for building-level occupant count estimation, albeit there will be some hardware and software costs.

Acquiring zone/room-level occupant counts from Wi-Fi requires redundancy in the Wi-Fi coverage. Indoor localization at the zone/room level requires each zone to remain within the coverage of multiple Wi-Fi access points (APs). Having this redundancy in Wi-Fi AP installations is needed to estimate the occupant counts at the zone/room level by analyzing the received signal strength indicator (RSSI) by each AP. Therefore, the use of Wi-Fi to estimate occupant counts at the zone/room level (grade (4) in Figure 10.1) will likely require additional Wi-Fi APs and specialized software for localization. Currently, there are several commercial solutions for zone-level occupancy sensing with Wi-Fi—either software-based solutions connecting to an existing Wi-Fi network through its API or hardware-based solutions with Wi-Fi probing devices. However, in most buildings, using the existing Wi-Fi network for zone-level occupant count sensing requires additional APs, which will have cost implications.

People counting cameras can also be used in occupant sensing. In most cases, these devices are manufactured with built-in computer vision capabilities. As such, they can count the number of occupants entering and leaving from a door, without streaming the video footage to a centralized server. The fact that the number of occupants, not the video, can be stored anonymously may alleviate privacy concerns, at least at the building level. People counting cameras deployed at each entry point to a building can provide an accurate low-cost estimate of the building-level occupant counts (grade (3)) and it can be a viable alternative to Wi-Fi-based occupant count estimation in commercial buildings without a centralized IT network. However, occupant count estimation at the zone/room level with a camera network will require a significant investment and likely cause considerable privacy concerns, given that cameras need to be deployed above each zone/room entry point.

Unlike occupancy sensing, occupant activity data require input from occupants. A common source of occupant activity data is the interactions with control and feedback interfaces such as thermostats and light switches. As adaptive actions (e.g., thermostat adjustments) restore comfort, adaptive behavior models developed with concurrent IEQ data provide insights into preferred temperature levels. These models can be used to identify building- or zone-specific temperatures that minimize the need for adaptive actions. A shortcoming of relying on unsolicited feedback from behavior patterns to acquire preference data can be the infrequent nature of occupant actions. Some occupants may use their thermostats only a few times over a year, deeming it nearly impossible to learn their preferences through passive observation.

An emerging approach to acquiring occupant activity data at the zone/room level is to solicit feedback with a higher frequency than can be captured from typical surveys. For example, smartwatch applications can facilitate the process for occupants to register preference feedback about their thermal, visual, and aural comfort (Jayathissa *et al.*, 2020). Such applications collect occupant preferences and motivations with miniature surveys to accelerate the occupant activity data collection process at the zone/room level. These studies have shown that large amounts of subjective occupant feedback can be collected from an individual in a short period of time from a diversity of spaces and conditions across a building. These smartwatch-based methods collect large and diverse datasets to create personalized comfort models in a way that has less risk of survey fatigue. Personalized occupant comfort models, which enable a practical way to collect previously stated identity data, open up possibilities for future building controls strategies driven by recommendation engines that guide occupants to decisions that best suit their preferences (Sood *et al.*, 2020). Personalized comfort models will be more appropriate for work environments in which occupants do not have a dedicated workspace; hence, preference learning cannot be achieved by anonymously monitoring actions and would require monitoring occupants individually.

10.3 Sequences of Operation Using Occupant Data

The grades of occupant data presented earlier are then used to compute OCC variables (i.e., analog variables of a BACnet communication protocol) listed in Figure 10.2. The earliest expected arrival and latest expected departure times ((a) and (b) in Figure 10.2) in a building are the two variables that can be computed from the lowest grade occupant data (grade (1)). These two variables can be used in scheduling the start and stop times for the *occupied mode* in a building. The third OCC variable ((c) in Figure 10.2) is the building-level occupant counts. At any time, only a fraction of the design occupancy is expected to be present in the building. This variable can be used to adapt the minimum outdoor airflow setpoint to occupant counts.

The four OCC variables that can be computed from grade (2) occupant data are the earliest expected arrival and latest expected departures times, the latest expected arrival times, and the longest expected duration of an intermediate break in a zone ((e)–(h) in Figure 10.2). Table 10.1 presents pseudocode summarizing how these variables can be used in the sequences of

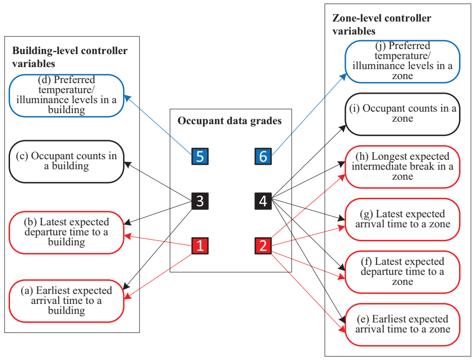

Figure 10.2 Controls variables computed from the occupant data grades listed in Figure 10.1.

operation. The earliest expected arrival and the latest expected departure times are intended for occupied weekdays, while the latest expected arrival time is intended for absent weekdays. For example, if the current time exceeds the latest expected arrival time of a zone/room (e.g., noon) and the zone/room remains vacant, we can safely assume that the zone/room will remain vacant until the end of the day. This simple midday setback logic can be quite effective in zones/rooms with frequent vacant days. The longest expected duration of an intermediate break is intended for partially occupied weekdays. For example, if a zone/room is occupied earlier in the day, but then vacated for longer than the longest expected break duration, the zone status *unoccupied* can be reinstated earlier. When a zone's status is switched to unoccupied, the minimum VAV airflow setpoint can be set to zero and unoccupied mode temperature setpoints can be applied. Note that relying on instantaneous presence/absence data to switch between the occupied and unoccupied states would not be appropriate considering the response time of the temperature of thermal mass. Thus, the control logic presented in Table 10.1 maintains a zone-occupied status occasionally, even though the zone is empty, considering the likelihood of occupants' arrival.

A fifth zone-level OCC variable can be computed with zone-level occupant count data ((i) in Figure 10.2). This variable is suitable for large multi-occupant thermal zones with VAV terminals. The minimum airflow setpoint of the zone can be adjusted with the number of occupants in the space. The ability to fine-tune ventilation based on occupant count data at the zone level, other than achieving energy savings, will improve the controllability of occupant-induced contaminants at the zone level (e.g., infectious aerosols, odor, CO_2).

The occupant activity data at the building and zone level (grades (5) and (6)) with concurrent IEQ data (e.g., indoor temperature, illuminance)

Table 10.1 Algorithm to integrate grade (2) occupant data into the sequences of operation to determine zone occupancy status

```
Input:
  motion detector

Variables:
  earliest expected arrival time
  latest expected arrival time
  latest expected departure time
  longest expected break

Process:
  if current time == midnight
    zone not yet occupied today = true
  end

  if motion detector = on
    zone not yet occupied today = false
    last time occupied today = current time
  end

  if current time > earliest expected arrival time
    zone status = occupied
  end
  if current time > latest expected arrival time and zone
  not yet occupied today = true
    zone status = unoccupied
  end
  if zone not yet occupied today = false
    if current time - last time occupied today > longest
  expected break
    zone status = unoccupied
    end end
  if current time > latest expected departure time
    zone status = unoccupied end
```

can be used to compute two other OCC variables: preferred temperature/illuminance setpoints at the building and zone level, respectively ((d) and (j) in Figure 10.2). These variables can be used to determine optimal setpoints that minimize the risk of occupant adjustments or complaints.

10.4 Estimation of OCC Variables

The OCC variables listed in Figure 10.2 can be estimated through online or offline learning approaches. The advantage of online learning is the ability to adapt to changes in occupancy and occupant preferences over time. Online learning can be executed in two different ways: batch learning or recursive learning. In batch learning, a server would periodically read the most recent data over a pre-set time interval (e.g., calling the most recent three months' worth of data once a week), compute the OCC variables using the dataset, and write to the OCC variables to the BAS. The server is expected to have the computational and analytical capabilities to undertake this batch learning task—e.g., maximum likelihood estimation to train a logistic regression model (Haldi and Robinson, 2011), reinforcement learning (Park and Nagy, 2020), and neural nets (Peng *et al.*, 2019).

Recursive learning approaches compute OCC variables with lightweight parameter estimation techniques inside zone VAV controllers in a distributed fashion, instead of using a centralized server. There are a few successful OCC field implementations with recursive learning of OCC variables by using stochastic gradient descend (Gunay *et al.*, 2018), recursive least squares (Nagy *et al.*, 2016), extended Kalman filter (Gunay, 2016), etc. For example, in Gunay (2016), during long absence periods (e.g., long vacations), the earliest expected arrival times were set to increase and the latest expected arrival times were set to decrease slowly until these two variables become nearly identical. However, it can be challenging to set up the hyperparameters in recursive learning approaches, particularly how much weight should be given to the new observations (e.g., new arrival events) in updating the OCC variables, and how fast distant information should be forgotten. As will be discussed in Section 10.6, BPS can play a vital role as a sandbox environment in the design of these learning algorithms.

In offline learning, the OCC variables are estimated with archived BAS data during retro/ongoing commissioning. Based on this analysis, the OCC variables are updated in the BAS database and remain constant. The involvement of a human analyst provides oversight on the data preparation (detection of outliers and data imputation) and parameter estimation process. However, as it is not a continuous process, OCC variables can become inappropriate should there be abrupt changes in the occupancy.

10.5 Illustrative Examples for the OCC Variables

In this section, we discuss the effectiveness of the OCC sequences presented earlier by considering examples built upon data collected from full-time office occupants in Ottawa, Canada. The dataset contains a year's worth of motion detector, temperature, and thermostat use data from 37 private offices at 15-minute intervals. The offices were served by multiple-zone VAV AHU systems, and the zones were equipped with VAV terminals with reheat and ceiling-mounted hydronic heaters. The occupants could change the temperature setpoints until midnight up to ±2°C. While the building from which the data were collected contained sensors necessary to implement OCC algorithms, they were not used in the sequences of operation. The occupied mode followed a constant schedule from 6h00 to 20h00 on weekdays.

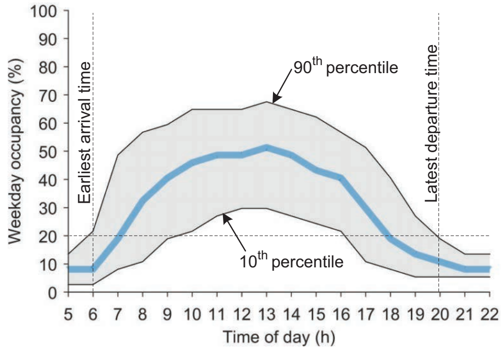

Figure 10.3 Building-level OCC variables highlighted on the weekday occupancy profiles. Note that earliest arrival and latest departure times are annotated where the 90th percentile profile intercepts with 20% occupancy.

The outdoor airflow was constant and determined for full occupancy. The temperature setpoints were 22°C year-round.

Figure 10.3 presents the building-level OCC variables on the weekday occupancy profiles. The 10th and 90th percentile occupancy profiles indicate the day-to-day variation of occupancy. The results indicate that at least 20% of the 37 occupants were present as early as 6h00 and as late as 20h00 on 10% of the days. These two values were treated as the first two building-level OCC variables, i.e., the earliest expected arrival and the latest expected departure times in a building. The 14-hour occupancy period between 6h00 and 20h00 results from inter-occupant diversity and underlines the difficulty of fitting everyone in an office building into a single operating schedule. While these two OCC variables inform the start and stop times for the AHU-occupied mode, due to the diversity of individual arrival and departure patterns, tuning the start and stop times for the occupied mode will not be very effective in achieving energy savings.

Although it is detrimental to the scheduling of AHU-occupied mode start and stop times, the diversity of occupancy patterns makes occupancy-based ventilation strategies a compelling OCC option. Recall that these occupancy-based ventilation strategies rely on building- or zone-level occupant count data (grades (3) and (4)). As shown in Figure 10.3, the highest expected number of occupants (with 90% confidence) did not exceed 68%. Particularly in extremely cold/hot climates, tuning ventilation rates to occupant counts can generate substantial energy savings, as will be discussed in the following section. Recall also that building-level occupant counts can be estimated from Wi-Fi-enabled device counts in buildings with a centralized IT network, Wi-Fi probing sensors in the atria, or people counting security cameras monitoring the building entry points.

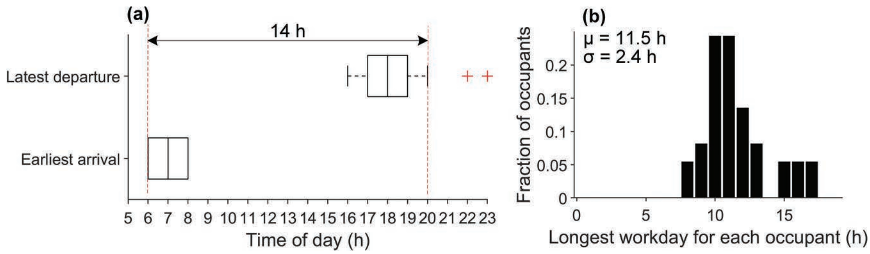

Figure 10.4 The distribution of (a) two of the zone-level OCC variables (latest expected departure and earliest expected arrival times), and (b) the longest expected workday for the 37 occupants. The longest expected workday is computed by subtracting the latest expected departure time from each zone's earliest expected arrival time.

Even if the outlying occupants are neglected, the earliest expected arrival time and the latest expected departure time in this example's small population of 37 occupants were spread over a two-hour and four-hour period, respectively, as shown in Figure 10.4a. The longest expected workday for individual occupants varied from 8 hours to 17 hours, with an average of 11.5 hours (see Figure 10.4b). With only these two control variables (earliest arrival and latest departure times), these zones can be maintained in the unoccupied mode on average for an additional 2.5 hours (11.5 hours instead of 14 hours), during which the unoccupied mode temperature setpoints can be applied and the minimum VAV airflow setpoints set to zero (i.e., no air is delivered unless it is necessary to meet the unoccupied temperature setpoints).

Other than four outlying occupants, the latest arrival times in this example's sample population were between 8h00 and 11h00 (see Figure 10.5a). Notably, this variable exploits the absent workdays, which have become increasingly common among office workers due to work-from-home, work-related travel, sick days, meetings outside the office, and so on. In this example's small sample of 37 occupants, on average, they spent one in every four workdays away from their offices (see Figure 10.5b). It is worth noting that the dataset used in this example was collected in 2017—i.e., long before the COVID-19 pandemic. As indicated in Table 10.1, this OCC variable is used to reinstate the unoccupied mode if occupants do not show up until their respective latest arrival times. This simple logic is estimated to reduce the average duration a zone needs to be maintained in the occupied mode by an additional three hours (from 11.5 to 8.5 hours).

For all but three occupants, the longest intermediate break duration was between 1.5 and 3.5 hours (see Figure 10.6a). This variable exploits workdays with short occupancy periods—e.g., dropping by for a meeting or to pick up an item. The occupied periods were two hours or less on more than 20% of the workdays (see Figure 10.6b). As indicated in Table 10.1, this OCC variable

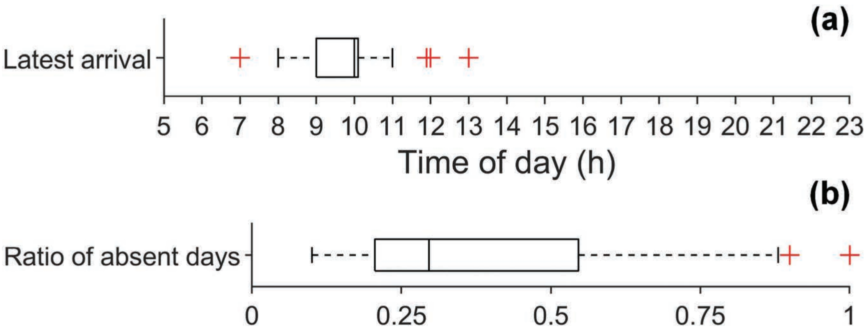

Figure 10.5 The distribution among the 37 occupants of (a) the zone-level OCC variable latest expected arrival time, and (b) the fraction of absent weekdays.

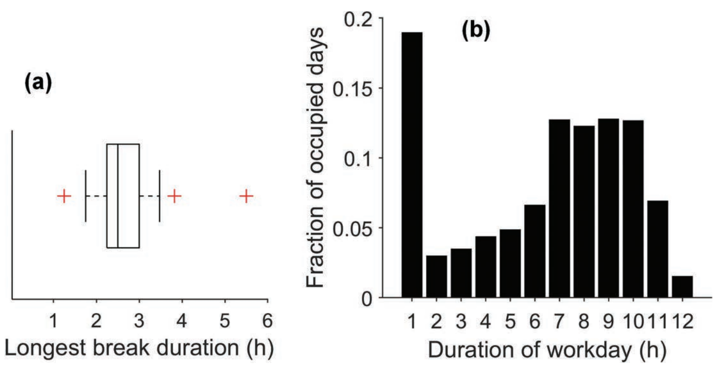

Figure 10.6 The distribution of (a) the zone-level OCC variable longest expected break duration for each occupant, and (b) duration of workday on occupied days. The duration of workday is the difference between the first arrival and the last departure on each occupied day.

can be used to reinstate the unoccupied mode before the scheduled end time if occupants leave their office and do not return for longer than their longest expected intermediate break duration. In this dataset, this logic is estimated to reduce the average duration a zone needs to be maintained in the occupied mode by two more hours (from 8.5 to 6.5 hours). Simply put, the four zone-level OCC variables, derived from grade (2) occupant data (only with motion detectors at the zone level), used as described in Table 10.1 could reduce the average occupied mode duration by over 50% (from 14 to 6.5 hours).

In this example's dataset, there were only 231 setpoint decrease events and 281 setpoint increase events by all 37 occupants over one year. There

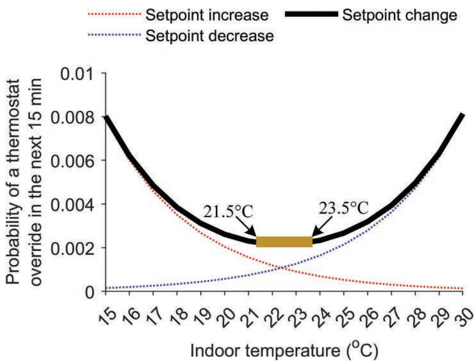

Figure 10.7 Univariate logistic regression models predicting the thermostat adjustment frequency.

were not many thermostat adjustments for each occupant, and so personalized occupant behavior models were not developed. *Logistic regression* (see Chapter 6), a common approach in occupant modeling, was employed to create two models for setpoint increase and decrease. When the two models were superimposed, the frequency of thermostat use was minimized between 21.5°C and 23.5°C for the 37 occupants (see Figure 10.7). These two values can be used to adapt the default temperature setpoints as 21.5°C and 23.5°C for the heating and cooling seasons, respectively, for this building during occupied periods. Notably, hot/cold complaints can be treated as a similar source of information about preferences at the building level. If occupant activity data are acquired frequently (e.g., via mobile or web applications actively seeking for the user input), similar models can be developed at the zone level and enable personalized indoor conditions.

10.6 Integration of OCC in the BPS-based Design Process

BPS tools provide a rapid testing environment for the sequences of operation using OCC variables prior to field implementations. Simulation-based testing of OCCs enables the assessment of the energy savings potential and the impact on indoor environmental quality prior to deployment. Aside from the sequences of operation, BPS offers an environment to study scenarios for different occupancy sensor deployment densities and configurations for use in OCCs. Early inclusion of this phase in the design process can also inform other design aspects that affect the OCC configuration, including HVAC and lighting zone sizing and interior design. For example, smaller HVAC zones with fewer occupants would make zone-level OCC algorithms relying on binary occupancy data (presence/absence) more favorable. In contrast, for large zones serving many occupants, the same types of OCCs may not be suitable. Simply put, some OCCs can make investments toward certain design decisions more favorable, should they be considered earlier in the BPS-based design process.

This section focuses on two different workflows to integrate OCCs into BPS. The first workflow is presented by Hobson *et al.* (2021) as a workflow in which OCC variables are estimated through functions implemented in R, and then the sequences using these OCC variables are incorporated within the EMS application of EnergyPlus (see Figure 10.8a).

The second workflow, by Ouf *et al.* (2020), provides an opportunity to determine the hyperparameters of the learning agents (i.e., estimators for OCC variables). The workflow includes an OCC variable learning agent, variables, and sequences, all implemented directly into a BPS tool—in this case, in terms of EMS programs in EnergyPlus. Occupancy and occupant behavior data can be generated in real time by stochastic occupant behavior models implemented into a BPS model; again, this can be through EMS programs (Haldi and Robinson, 2011; Gunay *et al.*, 2016). The OCC variable learning agent receives occupancy and occupant behavior data in real time from an EnergyPlus model and dynamically updates OCC variables such

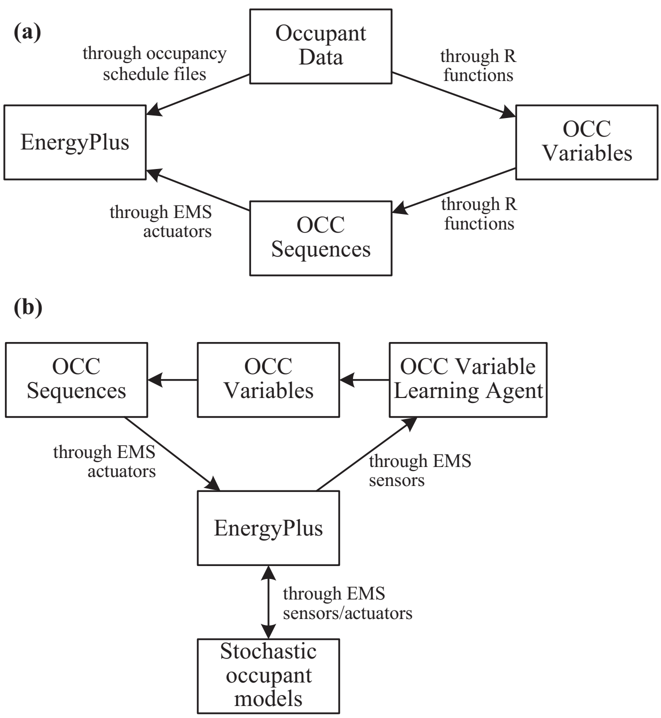

Figure 10.8 Example workflows to incorporate OCCs in BPS from the literature from (a) Hobson *et al.* (2021) and (b) Ouf *et al.* (2020).

as preferred illuminance and temperature setpoints. These OCC variables are then incorporated into a BPS model by overriding traditionally static or steady periodic setpoints or schedules, as shown in Figure 10.8b. Ouf *et al.*'s (2020) workflow was demonstrated using existing online recursive learning algorithms for illuminance and temperature setpoints (Nagy *et al.*, 2016; Gunay *et al.*, 2018). The results highlighted the importance of hyperparameter tuning and configuration of online recursive learning algorithms for OCC variables, especially given the diversity of occupant preferences. For example, Ouf *et al.* that the rate of changing temperature setpoints can vary significantly for occupants with a higher likelihood of adjusting thermostat setpoints than more tolerant occupants.

10.7 Energy Savings Potential of OCC and Impact on IEQ

The main goals of OCC are energy savings, occupant comfort, and IEQ. OCCs can improve the thermal and/or lighting conditions of the indoor environment by tailoring directly to the occupants' needs. OCCs can also improve indoor air quality (IAQ) by directing ventilation to spaces with high contaminant concentrations and/or are over-occupied. Other OCCs, such as those exploiting the earliest/latest expected arrival/departure times as described in Section 10.5, maximize energy savings in the absence of occupants; thus, the impact on IEQ should be negligible if implemented appropriately. Therefore, while most OCCs improve occupant comfort or IEQ, these interventions should, at worst, provide the same level of IEQ as traditional building controls while reducing energy use. A review on the field implementation of OCCs identified that OCCs either improve or do not have a significant impact on the IEQ (Park, Ouf *et al.*, 2019).

The impact of OCC on building energy use is affected by numerous factors including occupancy type, location (i.e., climate and orientation), building envelope properties, the number of occupants and their behaviors, as well as the meter data and sensing infrastructure available. In the latter case, BASs that are unhealthy (e.g., multiple hard/soft faults or inefficiencies) are poor candidates for OCC, as these faults may negate the benefits of any control interventions. For example, the minimum outdoor airflow setpoint of an AHU may never be achieved in the heating season if an appropriate supply air temperature setpoint reset logic is not implemented, diminishing the energy savings from occupancy-based ventilation strategies in heating-dominated climates. Additionally, the granularity of the sensing and metering infrastructure will dictate the data grade available for OCC implementation. Generally, more granular interventions produce higher energy savings and can provide more granular environmental control to match occupants' diverse preferences. For example, O'Brien and Gunay (2019) found that occupancy-based lighting controls could save 30% and 60% of lighting energy use when using single lighting control for 25 offices (i.e., grade (5) data) versus individual lighting control for each office (i.e., grade

(6) data), respectively. This enhanced granularity has also been shown to improve occupant comfort in terms of lighting utilization and quality (O'Brien, Gaetani *et al.*, 2017; O'Brien, Gunay *et al.*, 2017; Park, Dougherty *et al.*, 2019). Similarly, Gunay *et al.* (2015) found that using the earliest and latest expected arrival and departure times at the AHU level (i.e., grade (1) data) versus the earliest and latest expected arrival and departure times at the VAV level (i.e., grade (2) data) resulted in 7% and 27% HVAC energy savings, respectively. However, Gunay *et al.* (2017) found that this enhanced granularity had virtually no impact on occupant comfort. While granular controls generally result in higher energy savings at the building level, the energy use attributable to individual occupants is subject to wider variation based on occupants' behaviors and tolerances. Ouf *et al.* (2020) found that occupants with a higher tolerance to changes in the indoor environment resulted in more significant energy savings by OCCs. In contrast, sensitive occupants diminished energy savings or even increased energy use by OCCs in some extreme cases.

Hobson *et al.* (2021) performed a simulation-based investigation of OCC energy savings potential using data from the same offices described in the example in Section 10.5. Ten different combinations of nine occupants were randomly selected from the available data to populate a generic nine-office testbed (see Figure 10.9). Each of the ten different occupancy scenarios was simulated with various combinations of OCCs (see Table 10.2) in ASHRAE climate zones 4, 5, 6, and 7 and with three building envelopes: wall R-SI 2.5, window U-SI 3, and air leakage rate of 0.75 L/s·m^2 (poor); wall R-SI 3.3, window U-SI 2.5, and air leakage rate of 0.5 L/s·m^2 (moderate); and wall R-SI 4.2, window U-SI 2, and air leakage rate of 0.25 L/s·m^2 (good). The

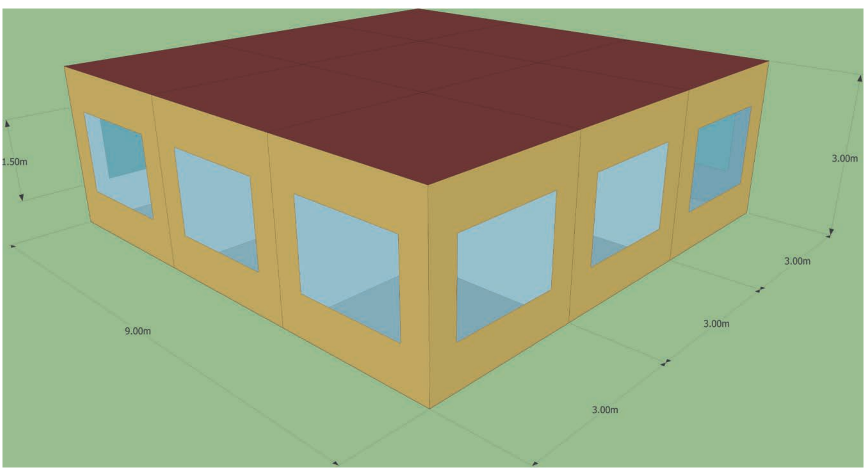

Figure 10.9 Generic nine-office testbed used to evaluate OCC energy savings potential.

Table 10.2 OCC interventions evaluated by Hobson *et al.* (2021) for energy savings potential

OCC combination	*Spatial resolution*	*OCC intervention*	*Average EUI reduction (%)*
1	Building	Occupancy-based AHU start/stop	–4%
2	Building	Occupancy-based AHU minimum outdoor air fraction	10%
3	Zone	Occupancy-based VAV start/stop and setback	24%
4	Zone	3 + individual occupants' preferred temperature setpoint	31% (+7%)
5	Zone	4 + individual occupants' preferred illuminance setpoint	35% (+4%)

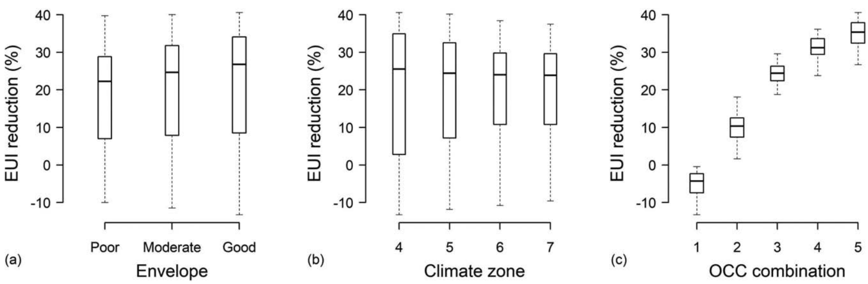

Figure 10.10 EUI reductions from OCCs for a variety of (a) envelopes, (b) climates zones, and (c) OCC combinations.

study found that occupants had a more considerable impact on energy use in buildings with better envelopes, resulting in higher average savings for OCC in these buildings (see Figure 10.10a). However, it should be noted that the average savings potential in buildings with even the poorest of envelopes can still be considerable.

Generally, relative savings were found to be higher in warmer climate zones (see Figure 10.10b) in two specific instances: (1) lower latitudes and longer days increase opportunities for daylight harvesting, which can increase the effectiveness of lighting-based OCC; and (2) tuning start and stop times for AHUs, which can increase equipment operating times due to inter-occupant diversity (i.e., occupants arriving before and departing after typical operating hours, as discussed in Section 10.5), had less of an impact on moderate climates where the differential between the indoor and outdoor temperature is less than that of extremely hot or cold climates. However, tuning start/stop times and temperature setbacks at the zone level (OCC combination 3, see Figure 10.10c) was found to reduce energy use across climate zones, and using occupancy-based ventilation at the system level to control outdoor airflow (OCC combination 2, see Figure 10.10c) significantly decreased energy use in colder climate zones (i.e., 15%–18%) compared to warmer climate zones (i.e., 3%–5%).

In brief, zone-level schedule-based OCC variables can provide the highest savings potential across a diverse set of climates. In contrast, OCC variables involving ventilation are most beneficial in extremely hot or cold climates. Lighting-based OCC offers higher savings in warmer climates with lower latitudes. While buildings that are well-insulated and relatively airtight benefit the most from OCC, buildings of all envelope quality in all climate zones can see significant energy savings from the introduction of OCC, especially those which use zone-level occupancy data grades (2, 4, 6).

In this section, we discussed the energy-saving potential of OCCs through examples involving office occupancy and using the data presented in Section 10.5. While general principles of OCCs are applicable to other building types, the readers can refer to Ye *et al.* (2021) and Pang *et al.* (2021a, 2021b) for the saving potential of OCCs in primary schools, hotels, and low-rise residential buildings, respectively.

10.8 Discussion

In this chapter, we treated OCC variables and sequences in exclusion of other steps of developing the sequences of operation. In reality, the success of OCCs hinges on the quality of sequences of operation as a whole—i.e., free from hard and soft faults and following a standard metadata model. For example, there are real-world examples demonstrating that a faulty supply air temperature reset or a faulty economizer logic can deem OCC sequences completely ineffective (Hobson, 2020). In brief, OCCs should be seen as an important piece of the puzzle and should be compatible with other aspects of the building design process.

ASHRAE Guideline 36 (2018) is one of the first formal efforts to standardize best-practice sequences of operation and has already been widely adopted by the HVAC controls industry. Integrating OCC algorithms into such industry guidelines, standards, and codes will enable rapid industry uptake. However, the industry uptake requires defining a standard taxonomy for base OCC categories and using terminology consistent with the existing guidelines, standards, and codes. The OCCs need to be compatible with sequences defining the state and mode of operation for common HVAC systems, as defined in these documents. Beyond ensuring OCC compatibility to common HVAC sequences of operation, further research is needed to seamlessly integrate OCCs into the model-based predictive control framework.

Moreover, occupants have diverse schedules. Each occupant has unique arrival and departure time patterns. Occupants also spend many days away from their offices, especially due to the recent increase in teleworking. This diversity challenges traditional schedule-based HVAC scheduling with constant ventilation rates designed for full occupancy. Two OCC variables in particular can contribute to achieving significant energy savings: occupant counts and the latest expected arrival time in a zone. Sequences using occupant counts take advantage of inter-occupant diversity to adjust the ventilation rates. Sequences using the latest expected arrival time in a zone take advantage of absent weekdays at the zone level by reinstating the unoccupied mode when a first arrival has yet to occur until a prescribed latest arrival time.

It is essential to consider the value of occupant data for controls, availability of data infrastructure in existing buildings, and the ability to generate occupant information without causing privacy concerns for the practical deployment of OCCs. Motion detectors at the zone level and Wi-Fi device count or people counting cameras at the building level appear to be the most promising occupant sensing technologies to achieve these objectives. If the project budget permits, zone-level people counting that relies on CO_2 sensors or Wi-Fi-based localization should be considered, as they would be effective in improving the indoor air quality and provide higher energy savings. Evidently, societal and technological changes, public perception about occupant sensing, and changes in indoor environmental quality standards may lead to the development of new and more robust occupant sensing solutions for the built environment.

Evidence from case studies involving OCCs with different OCC variable estimation/learning methods accumulates from different climates and building archetypes. However, these studies reported that energy, cost, and comfort benefits vary considerably (Park, Ouf *et al.* 2019). Methods to estimate/learn OCC variables are still an active area of research. Researchers are exploring emerging machine learning techniques to improve the representativeness of OCC variables. In parallel, there is growing interest in user control and interface design (Huchuk *et al.*, 2019), which will likely increase the volume of occupant activity data and improve data quality.

10.9 Closing Remarks

In this chapter, we introduced occupant-centric controls as an indoor climate control approach whereby occupant information is directly used in operation. We introduced six grades of occupant data representing three tiers for the resolution of occupant information (i.e., presence/absence, count, and action) and two tiers for spatial resolution (i.e., at the zone/room level vs. building/system level). We presented different occupant sensing technologies to acquire occupant data at these resolutions and introduced OCC variables as calculated analog variables of a building controller. These OCC variables are the earliest and latest arrival, and latest departure times, occupant counts, and preferred indoor temperature and illuminance setpoints. These variables can be learned online within a controller or estimated offline periodically by a supervisory energy management system. We described base OCC sequences as controls programs using the OCC variables and presented two alternative workflows to integrate OCCs into BPS tools. Finally, using a real-world dataset, we provided illustrative examples to discuss the efficacy of each OCC sequence.

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11 Detailed Case Studies

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Summary

In this chapter, we will unite the theory and the practice of occupant-centric design through an analysis of seven unique case study buildings. The case studies are diverse in several ways, including geographic location, type, size, and project phase. We will offer our key insights drawn from qualitative and quantitative analysis in order to support researchers and industry practitioners alike.

11.1 Introduction

In this chapter, we demonstrate the real-world application of the occupant-centric design methods and principles developed and presented in the previous chapters of this book. We provide an analysis of seven unique case study buildings that demonstrate how occupant-centric design can assist in developing better designs that suit occupants' needs and preferences while meeting clients' needs and energy targets. The selected case studies demonstrate alternative methods and approaches for considering occupant behavior and occupant-related assumptions throughout the building design process. These real-world examples illustrate the strengths and shortcomings of current occupant modeling approaches and assumptions in the design process. The case studies also provide examples of various qualitative and quantitative research approaches to evaluate both technical and nontechnical aspects of occupant modeling and representation. Our analysis involves simulation, field studies, surveys, and interviews with design stakeholders and occupants.

We selected the case studies in this chapter based on the following criteria: (1) authors' access to information about the cases, (2) breadth of design/construction phases represented among the cases, and (3) usability of analysis outcomes for advancing occupant modeling approaches during building design. The case studies are diverse in terms of project phase,

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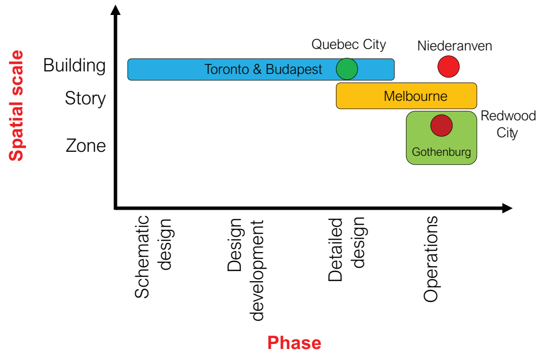

Figure 11.1 A conceptual diagram illustrating the range of the case studies with regards to project phase and spatial scale.

Figure 11.2 Geographical distribution of the case studies.

location/climate zone, building type and size, and analysis approach. Collectively, our analysis of the selected case studies covers approximately the whole life cycle of a building, including design, construction, and operation (see Figures 11.1 and 11.2).

In the Toronto and Budapest case studies (Case Studies 1 and 2), we demonstrate alternative methods of representing occupants during design (see also Chapter 3). In the Quebec City, Melbourne, Redwood City, Niederanven, and Gothenburg case studies (Case Studies 3–7), we focus on post-occupancy conditions, aiming to evaluate design approaches and provide recommendations for occupant-centric design and operation. The seven case studies are summarized in Table 11.1.

Table 11.1 Summary of the seven case studies

Case study	*Location (Köppen climate classification)*	*Building size and type*	*Project phase*	*Case study objectives*
Case Study 1: Toronto	Toronto, Canada (Dfa, humid continental)	Mid-rise office building	Design	• Document occupant modeling approaches during design • Develop a method for handling occupant-related uncertainty during design
Case Study 2: E-co-housing	Budapest, Hungary (Dfb, warm summer continental)	Mid-rise multi-unit residential building	Design & construction	• Explore and leverage synergies between people and the built environment in all dimensions of sustainability • Bridge qualitative participatory co-design methods and simulation for higher fidelity energy models
Case Study 3: Cité Verte	Quebec City, Canada (Dfb, warm summer continental)	Mid-rise multi-unit residential building	Post-occupancy	• Evaluate the feasibility of low-energy buildings • Assess the impact of occupants on achieving low-energy goals
Case Study 4: Gillies Hall	Melbourne, Australia (Cfb, temperate oceanic)	Six-story student residence	Post-occupancy	• Assess occupants' comfort and well-being as well as energy saving potentials from passive house strategies when coupled with performance-based modeling • Assess the benefits of deploying low-cost sensing techniques in passive house design

Table 11.1 Continued

Case study	*Location (Köppen climate classification)*	*Building size and type*	*Project phase*	*Case study objectives*
Case Study 5: Stanford Redwood City	Redwood City, USA (Csb, dry-summer subtropical/ Mediterranean)	Mid-rise office building	Post-occupancy	• Optimize building layouts to maximize occupants' productivity and collaboration while achieving energy efficiency
Case Study 6: Goblet Lavandier & Associésa headquarter	Niederanven, Luxembourg (Cfb, temperate oceanic climate)	Mid-rise office building	Post-occupancy	• Derive occupant-centric rules for optimal exterior shading design
Case Study 7: Samhällsby-ggnad 1	Gothenburg, Sweden (Cfb, marine west coast)	Institutional office building	Post-occupancy	• Enhance indoor environmental quality (IEQ) and energy savings potential based on an evaluation of occupants' satisfaction in energy efficient buildings

11.2 Case Study 1: Toronto, Canada

Tareq Abuimara, William O'Brien, Burak Gunay, Juan Sebastián Carrizo

11.2.1 Summary

This case study is a mid-rise office building located in Toronto, Canada. The analysis of this case study includes implementing alternative methods for occupant considerations during building design (as detailed in Chapter 3). The occupant-centric analysis of this case study building covers the entire design phase of the building and aims to document the current practices of occupant modeling throughout the simulation-aided building design process and investigate possible improved approaches. The analysis included documenting occupant-related design assumptions and the implications of these assumptions on design outcomes.

The analysis was performed using qualitative (workshop and interviews) and quantitative (simulation-based investigation) approaches. The qualitative analysis included documenting occupant modeling approaches and assumptions through the analysis of design documents and interviewing

design stakeholders of the case study. The quantitative analysis was a simulation-based investigation to assess occupant assumptions and propose alternative approaches for modeling occupants and quantifying their impact on design decisions. The simulation-based investigation included occupant-centric parametric analysis, design optimization, and comfort analysis.

The findings of the qualitative analysis indicated the absence of a standardized and consistent occupant assumptions sharing mechanisms among design stakeholders. Further, these findings indicated that the adoption of an integrated design process (IDP) could have assisted in avoiding discrepancies among design disciplines.

The findings of the quantitative simulation-based investigation indicated that occupant assumptions are influential in terms of selecting optimal energy conservation measures (ECMs) and determining optimal design solutions. Additionally, the occupant-centric comfort analysis indicated the need to consider comfort at the occupant and building zone level rather than at the building level.

Overall, the findings of this case study analysis can contribute to occupant-centric building design by providing insights to building designers on how to handle occupant-related uncertainty throughout the simulation-aided building design process. Additionally, the findings can inform relevant building codes and standards on advancing requirements to improve the quality of assumptions and efficiently manage occupant-related uncertainty.

11.2.2 Building Description

The Toronto building is a mid-rise commercial building located in Liberty Village to the west of downtown Toronto, Canada. The building consists of four similar office floors, a retail ground floor, and two levels of underground parking. The building has a gross floor area of 7,940 m^2 (including the underground parking). The building is in ASHRAE climate zone 6A (cold-humid) with overcast cold winters and hot-humid summers.

The above grade floors were constructed using mass timber and nail laminated timber (NLT) panels, and the main design objective was to create a building that is sustainable, aesthetically pleasing, and cost-effective by returning to the use of heavy timber. Figure 11.3 shows the building shortly after construction and Table 11.2 summarizes key performance specifications.

11.2.3 Methodology

In this study, both qualitative and quantitative data collection and analysis approaches were used as described in the sections below.

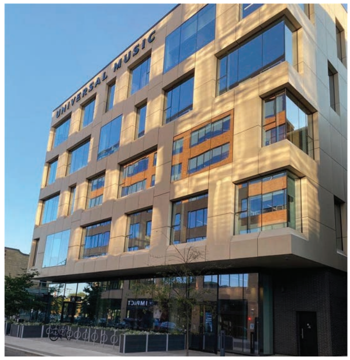

Figure 11.3 Toronto case study building.

Table 11.2 Toronto case study description

1.1.1. *Item*	*Description*
Typical office floor area	1,728 m^2
HVAC	Rooftop package unit with zone level variable air volume (VAV) reheat Hydronic baseboard heating
Cooling coefficient of performance (COP)	3.5
Boiler (space heating)	Type: Condensing boiler Fuel: Natural gas Nominal thermal efficiency = 0.9
Heat recovery	Air-to-air heat exchanger Sensible effectiveness at 100% heating /cooling airflow = 70% Sensible effectiveness at 75% heating/cooling airflow = 85%
Outdoor air minimum flow rate	0.000435 $m^3/s.m^2$
Windows	U-factor = 1.9 $W/m^2{\cdot}K$; SHGC = 0.33 WWR (overall) = 46.5% WWR (south) = 85% WWR (north) = 12% WWR (east) = 41% WWR (west) = 41%
Walls	U-value = 0.245 $W/m^2{\cdot}K$

11.2.3.1 Qualitative Analysis

The qualitative analysis sought to document occupant assumptions and occupant modeling approaches throughout the case study building's design process. In brief, the process included semi-structured interviews about current practices with four key design stakeholders: the owner representative, the architect, the mechanical engineer, and the energy modeler. First, written questionnaires were sent to each stakeholder, with each questionnaire customized to the stakeholder's scope of work and design objectives. Then, questionnaire responses were analyzed qualitatively, and the findings were used as the basis for a set of interview questions. Next, interviews were conducted to obtain depth and clarification. Finally, all the questionnaire and interview responses were analyzed qualitatively, and conclusions were drawn.

11.2.3.2 Quantitative Analysis

The quantitative analysis took the form of a simulation-based investigation that included a parametric analysis, optimization study, and comfort study. For this purpose, an energy model for a typical office floor of the case study building was created using EnergyPlus (see Figure 11.4). Custom scripts in MATLAB were used to automate simulations. Each step of analysis is described below.

11.2.3.2.1 OCCUPANT-CENTRIC PARAMETRIC ANALYSIS

The first step of the simulation-based investigation was to use a parametric analysis to evaluate the impact of occupant assumptions on the ranking

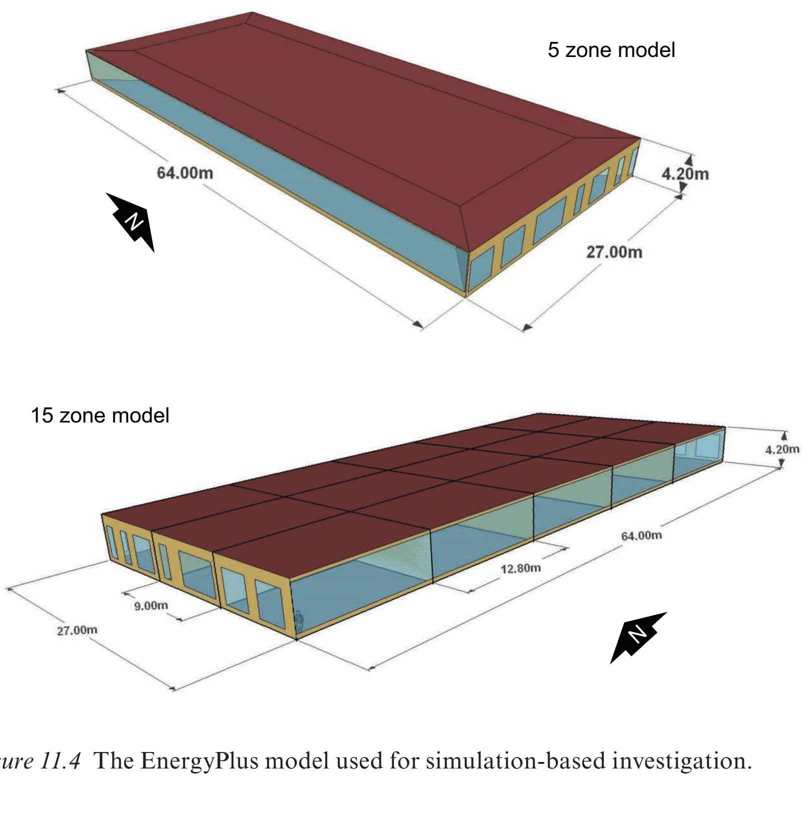

Figure 11.4 The EnergyPlus model used for simulation-based investigation.

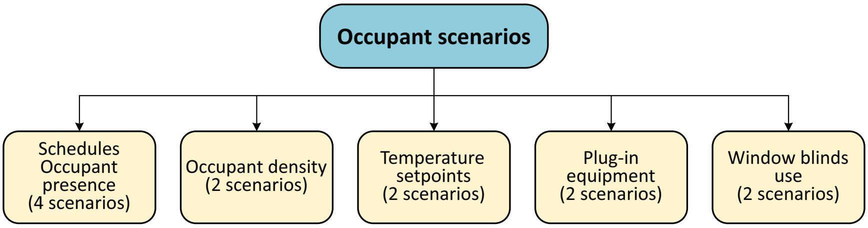

Figure 11.5 Occupant scenarios used in parametric analysis.

Table 11.3 List of design parameters/energy conservation measures used in the parametric analysis

Systems-related parameters	**Envelope-related parameters**
Cooling COP	Window-to-wall ratio (WWR)
Water boiler efficiency	Window properties (U-factor & SHGC)
Lighting power density (LPD)	Wall insulation
Plug-in equipment loads	Roof insulation
Water pumps efficiency	Air infiltration
ERV efficiency	

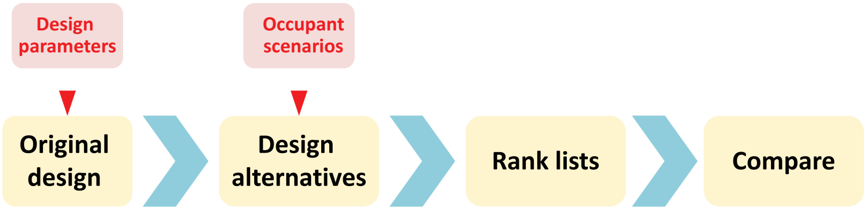

Figure 11.6 The parametric analysis workflow.

and the saving potential of energy conservation measures (ECMs)/design parameters (DPs). The case study model was simulated using a parametric analysis and EnergyPlus under 12 occupant scenarios (see Figure 11.5).

In the parametric analysis, 12 ECMs and DPs were considered, as shown in Table 11.3. Multiple values for each ECM/DP were used. The simulation workflow is shown in Figure 11.6.

11.2.3.2.2 OCCUPANT-CENTRIC DESIGN OPTIMIZATION

The second phase of the simulation-based investigation was an optimization study. The objective of the study was to evaluate the impact of occupant

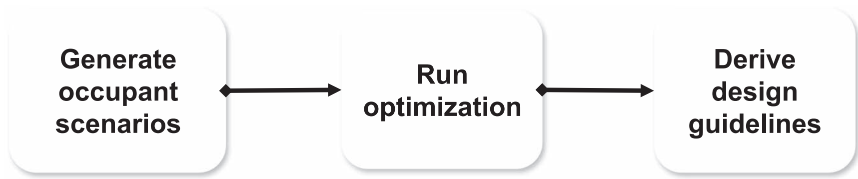

Figure 11.7 The three-step approach followed in the optimization study.

assumptions on the outcomes of building design optimization. The optimization study was performed following the three-step approach, as shown in Figure 11.7.

Step 1 was generating occupant scenarios by using multiple occupant presence scenarios and varying the relationship between occupant presence schedules and lighting and equipment schedules. Four different occupant presence schedules were used: default (as per ASHRAE Standard 90.1), low occupancy (40% occupancy at the highest), morning peak (90% morning and 40% in afternoons), and afternoon peak (40% morning and 90% in afternoons). For each occupancy schedule, four altered lighting and equipment schedules were generated. A total of 64 occupant scenarios were created (4 occupancy × 4 lighting × 4 equipment).

Step 2 was to run the optimization using the genetic algorithm (GA) in MATLAB. The objective function was set to minimize the HVAC energy use intensity (kWh/m^2). A penalty was applied to the objective function for design solutions that have unsatisfactory comfort conditions (i.e., more than 300 unmet hours). Ten different ECMs/DPs were considered in the optimization including WWR, window material, and exterior shading (overhangs and sidefins).

Finally, Step 3 was training decision trees using MATLAB "*fitctree*" function. Decision trees are a useful method to visualize the optimization outcomes and derive occupant-centric design parameters selection rules.

11.2.3.2.3 OCCUPANT COMFORT ANALYSIS

The comfort analysis was focused on investigating the impact of occupants' spatial distributions on comfort and energy performance of the building. To this end, the following steps were followed:

1 The building typical floor model zoning was adjusted to have 15 thermal zones instead of five (see Figure 11.8). The intention was to have a more realistic zoning strategy that included a variety of zone orientations

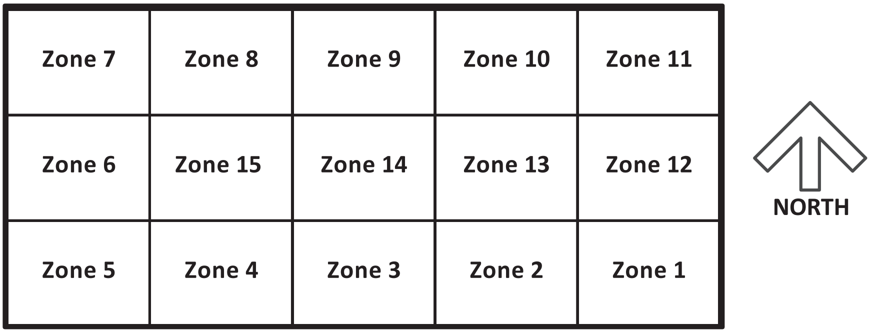

Figure 11.8 Case study model plan demonstrating thermal zones and their orientations.

(south-facing, north-facing, east-facing, west-facing, core, and corner offices). Further, the model HVAC equipment and flow rates (air and water) were hard-sized based on a sizing run using default ASHRAE Standard 90.1 values for occupant density and schedules. The equipment hard-sizing was done to mimic reality, as real buildings' equipment has preset maximum capacities.

2 Seventy-five occupant distribution scenarios (ODSs) were created for the use in simulations. An ODS refers to the distribution of building occupants across building zones. The same total number of occupants was maintained in all the ODSs. The ODSs were generated by sampling from uniformly distributed large population using a custom script in the programming language R.
3 The hard-sized model was simulated in EnergyPlus under the 75 ODSs. A MATLAB custom script was used to automate the process.
4 The simulation was repeated with the demand-controlled ventilation (DCV) to evaluate the impact of using building adaptive technologies (e.g., DCV) on comfort and energy performance.

Several performance metrics were evaluated in this analysis. For energy use, energy use intensity (EUI) was used, as it is a commonly used metric in the architecture, engineering, and construction (AEC) industry. For comfort, unmet hours, as defined by ASHRAE Standard 90.1, were used. However, a limitation of unmet hours is that it does not consider the number of occupants who suffer from discomfort. Thus, a new comfort metric was developed for this study. The new thermal comfort metric is called occupant discomfort hours (ODH). ODH indicates the annual share of each occupant at a given zone of discomfort hours. Further details about this metric and how it is calculated are available in Abuimara *et al.* (2021).

11.2.4 Results and Discussion

11.2.4.1 Design Process Documentation

The design process documentation was classified and summarized under four main groups of findings: (a) type and source of occupant assumptions during design, (b) design workflow, (c) communicating occupant-related assumptions, and (d) challenges and limitations throughout the design process. Each group of findings is described in turn below.

11.2.4.1.1 TYPE AND SOURCE OF OCCUPANT ASSUMPTIONS DURING DESIGN

The Toronto building was designed without a specific target tenant; instead, the client had a general vision of the total number of occupants the building would host. Due to the lack of specific information about occupants, the architect sourced occupant assumptions from Ontario Building Code (OBC). The OBC occupant density of 20 m^2/person was used by the architect's in-house energy modeling using Sefaira software. The mechanical engineer used conservative occupant assumptions for designing and sizing the mechanical equipment. It is common practice among HVAC designers to size HVAC equipment to supply the highest expected heating and cooling loads (Djunaedy *et al*., 2011).

The energy modeler was somewhat involved early in the design process in a design charrette. At this early phase, the energy modeler used the ASHRAE Standard 90.1 values for occupant density, lighting power density (LPD), and equipment power density (EPD) for creating an energy model of the building. Once the design development phase started and the energy modeler was reengaged, several of the original assumptions had to be refined to align with the current design (e.g., the LPD was adjusted based on the selected lighting fixtures, from 8 to 3.9 W/m^2).

Overall, the design team's occupant assumptions were sourced from codes and standards, including, for example, OBC, NECB, and ASHRAE Standard 90.1. Additionally, some assumptions (e.g., the mechanical engineer's) were based on experience.

Sourcing occupant assumptions from codes and standards or from experience can limit or narrow occupant representation during building design. In particular, occupant assumptions in codes and standards (densities and schedules) tend to be conservative and outdated, as many were developed in 1980s and based on a small set of data (Abushakra *et al*., 2004).

11.2.4.1.2 DESIGN WORKFLOW

Initially, this building's design process was intended to be an integrated design process, as all design stakeholders participated in a design charrette early in the design process. However, as the design progressed, the process became characterized by a traditional design process, where different design stakeholders performed their tasks independently at different times throughout the process. For example, although the energy modeler was involved in the early design charrette, they were not involved again until late in the design development phase when most of the critical design decisions (e.g., type of HVAC system) had already been made. This intermittent or delayed involvement of energy modelers is typically driven by the client's unwillingness and/or misunderstanding of the role of energy modeling during the design process (Oliveira and Marco, 2018).

Additionally, the energy modeling scope was not integrated into other scopes, such as the mechanical engineering scope (e.g., HVAC selection and sizing). The HVAC system type was selected and designed by the mechanical engineer using their conservative occupant assumptions, and then the equipment sizing was handed to the energy modeler who performed energy modeling using their own occupant assumptions. This inconsistency of occupant assumptions may have led to suboptimal design decisions and/or missed design opportunities.

11.2.4.1.3 COMMUNICATING OCCUPANT-RELATED ASSUMPTIONS

The Toronto building's design team members reported that they communicated through regular phone calls, emails, and bi-weekly meetings. Drawings, reports, and computer models were shared. No specific information-sharing platform or mechanism was reported.

Although the design team members reported that they communicated regularly, a deeper investigation of the design documents and models (along with information obtained during the interviews) revealed discrepancies in some of the basic occupant assumptions made and used by different design stakeholders, as shown in Figure 11.9.

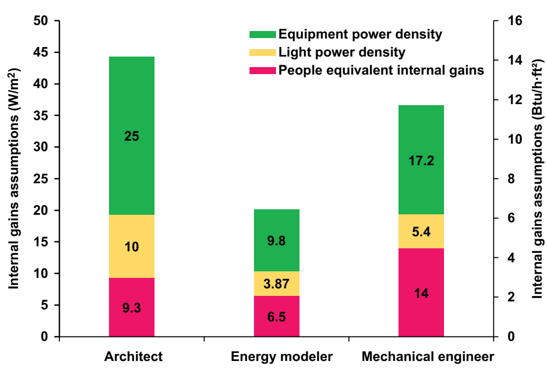

Figure 11.9 Assumptions made by the different design team members of the Toronto case study building.

The lack of information-sharing mechanisms may have led to these discrepancies in assumptions and constitutes a fundamental issue in the design process. Effective communication throughout the design process is widely recognized as fundamental for successful building design (Arditi and Gunaydin, 2002).

11.2.4.1.4 CHALLENGES AND LIMITATIONS THROUGHOUT THE DESIGN PROCESS

One of the major challenges that the Toronto building designers faced was time, including the time each team member was involved in the design process and the time assigned to complete the design task. The former is typically out of a design team's control, as it is determined by the project owner. The latter is a common practice in the AEC industry, where a specific timeline is assigned to design tasks. For example, in the case of the Toronto building, the modeler was hired to perform the main modeling scope late in the process when they had limited impact on design outcomes because all critical design decisions had already been made and approved by the owner.

Another major challenge the Toronto building design team faced was the cost limitation of the project (capital cost and added engineering costs). For example, when asked why adaptive ventilation technologies were not considered, the mechanical engineer reported that cost was the main driver for selecting HVAC and any additional technologies were not considered by the owner.

11.2.4.2 Occupant-Centric Parametric Analysis Results

The first phase of the quantitative analysis was an occupant-centric parametric analysis. Figure 11.10 presents the results of the parametric analysis under different occupant scenarios. Overall, the results presented in Figure 11.10 indicated that occupant scenarios affect the energy-saving potential of ECMs/DPs. Some ECMs/DPs such as implementing DCV were sensitive to occupant scenarios and demonstrated drastic changes in energy savings potential (1%–12%). However, ECMs/DPs such as increasing wall and roof thermal resistance (i.e., R-value) demonstrated robustness to changing occupant scenarios, as the energy saving potential was only moderately affected (6%–8%). The energy-savings potential of adjusting the WWR also demonstrated moderate sensitivity to changing occupant scenarios (2%–6%).

The results shown in Figure 11.10 also demonstrated the insensitivity of some ECMs/DPs, such as cooling COP, to occupant presence. According to the results, the ECMs/DPs saving potential was highly sensitive to assumptions about temperature setpoints. Further, the results indicated the impact of plug-in equipment assumptions on the energy-saving potential of different ECMs/DPs. These variable sensitivities of ECMs/DPs to occupant scenarios point to the importance of occupant assumptions during building design. In other words, variable sensitivities to occupant scenarios affect design decisions of selecting ECMs/DPs.

Design parameters

Occupant scenarios	Roof_RSI = 11 $m^2 \cdot K/W$	Roof_RSI = 9 $m^2 \cdot K/W$	Roof_RSI = 7 $m^2 \cdot K/W$	Wall_RSI= 7 $m^2 \cdot K/W$	Wall_RSI= 5 $m^2 \cdot K/W$	Wall_RSI= 4 $m^2 \cdot K/W$	[U=1.62, SHGC=0.388]	[U=2.036, SHGC=0.584]	[U=1.467, SHGC=0.245]	WWR = 30%	WWR = 50%	WWR = 70%	Boiler eff. = 0.95	Pump eff. = 0.95	ERV eff. [0.88, 0.78]	Infl = 0.15 ach	Blinds (Solar Ref.=0.6, Solar Trans= 0.15)	COP = 5	COP = 4	DCV
Schedules * (0.4)	8%	6%	3%	3%	2%	1%	7%	7%	4%	2%	2%	1%	3%	0%	1%	2%	0%	3%	1%	9%
Schedules * (0.6)	8%	7%	4%	3%	2%	1%	6%	6%	4%	3%	2%	1%	3%	0%	1%	2%	0%	3%	1%	8%
Schedules * (0.8)	8%	6%	3%	3%	2%	1%	6%	5%	4%	3%	2%	1%	3%	0%	1%	1%	0%	3%	1%	7%
Schedules * (1.2)	6%	5%	3%	2%	2%	1%	4%	3%	3%	3%	2%	1%	2%	0%	1%	1%	0%	3%	1%	4%
Setpoints [clg 26.7, 22°C],[htg 15.6,22°C]	7%	5%	3%	2%	2%	1%	5%	4%	4%	4%	2%	1%	2%	0%	1%	1%	0%	3%	1%	5%
Setpoints [Always 22°C]	6%	5%	3%	2%	2%	1%	5%	3%	4%	5%	3%	1%	3%	0%	1%	1%	0%	3%	1%	3%
50% of People density [40 m^2/person]	8%	7%	4%	3%	2%	1%	5%	4%	4%	4%	3%	1%	2%	0%	1%	2%	0%	3%	1%	1%
150% of People density [13.3	6%	5%	3%	2%	1%	1%	4%	4%	3%	3%	2%	1%	2%	0%	1%	1%	0%	3%	1%	12%
Original design [Blinds always on]	7%	5%	3%	2%	2%	1%	5%	1%	5%	6%	1%	2%	2%	0%	1%	1%	1%	3%	1%	7%
Blinds triggered by solar radiation	7%	6%	3%	2%	2%	1%	5%	2%	5%	5%	3%	2%	2%	0%	1%	1%	1%	3%	1%	6%
75% of Plug-in load [7.4 W/m^2]	8%	6%	3%	3%	2%	1%	5%	5%	4%	3%	2%	1%	2%	0%	1%	1%	0%	3%	1%	6%
150% of Plug-in load [14.8 W/m^2]	5%	5%	3%	2%	1%	1%	4%	3%	3%	3%	2%	1%	2%	0%	1%	1%	0%	3%	1%	5%

More savings — Less savings

Figure 11.10 Design parameters' ranking and energy use savings under multiple occupant scenarios.

Overall, the parametric analysis results highlight the impact that occupant assumptions have on the savings and ranking of ECMs/DPs. Likewise, the results emphasize the importance of accurately considering occupant assumptions during the building design process and support the use of more occupant-centric parametric analysis when selecting ECMs/DPs.

11.2.4.3 Occupant-Centric Design Optimization Results

The second step of the quantitative analysis was occupant-centric design optimization. The design optimization was performed under 64 occupant scenarios. Figure 11.11 presents the results of the 64 optimization runs where GA was used to search for optimal design solutions. Overall, Figure 11.11 demonstrates that occupant scenarios had a substantial impact on the outcomes of the 64 optimization runs. The results also indicated that even with the same occupancy scenario, varying lighting and plug-in equipment schedules can impact the HVAC energy use intensity significantly and lead to different optimal design solutions. The box plots in Figure 11.11 show that the median of the cost function fluctuated drastically with different occupant scenarios. Figure 11.11 also indicates that there were several outlier solutions outside the interquartile but no outliers on the lower side of the population, which means that there were many poor design solutions but few optimal and semi-optimal solutions. This result offers the insight to building designers that considering families of optimal and near-optimal solutions offers flexibility in choosing ECMs/DPs that better suit each project constraint (e.g., budget, time).

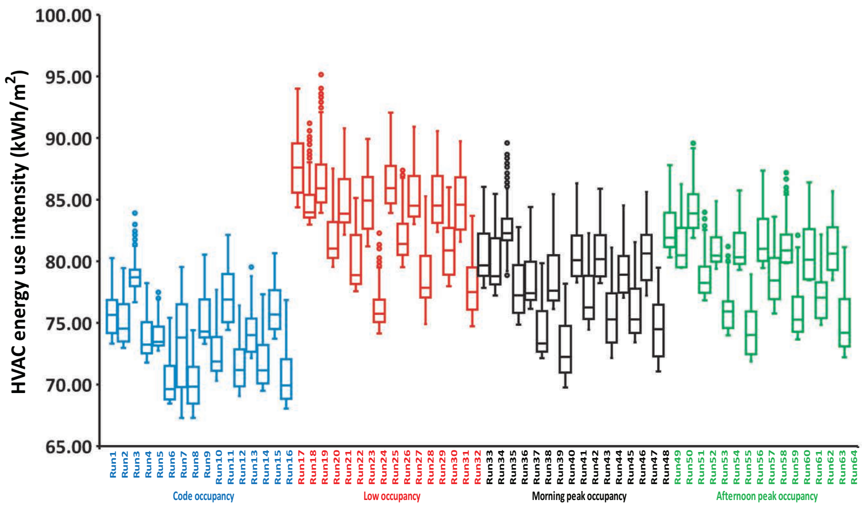

Figure 11.11 Optimization results for the 64 different occupant scenarios.

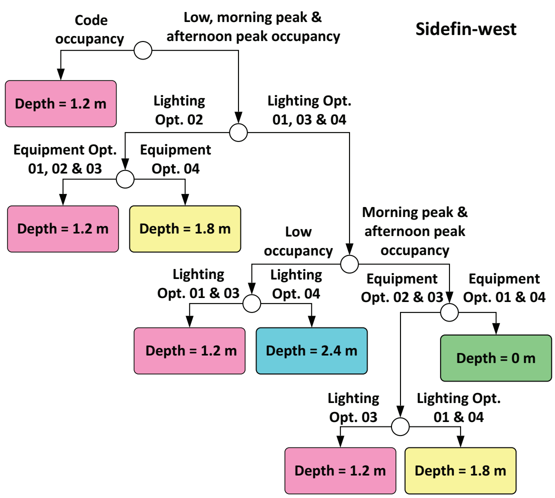

Figure 11.12 Example classification tree demonstrating sensitivity to occupant assumptions.

Decision trees were used to better understand and visualize the final results of the optimization. Figures 11.12 and 11.13 are examples of the decision trees that were trained using the 64 optimization runs results. Figure 11.12 represents a case were the DP (i.e., size of window sidefin shading on west-facing windows) was highly sensitive to occupant assumptions.

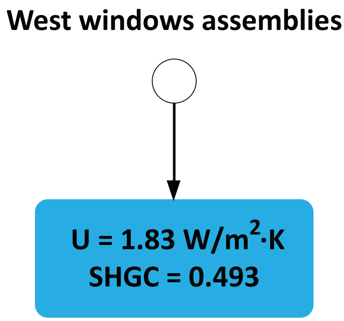

Figure 11.13 Example classification tree demonstrating robust design parameter to occupant assumptions.

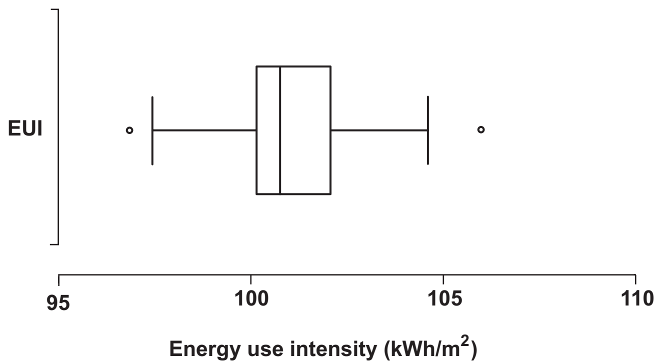

Figure 11.14 EUI of the 75 simulations.

Figure 11.13 demonstrates an example of a DP (i.e., window U-factor and SHGC) that is robust to occupant scenarios. Decision trees are very useful in occupant-centric design optimization, as they can assist designers in classifying and grouping ECMs/DPs based on their sensitivity to occupant scenarios.

11.2.4.4 Occupant-Centric Comfort Analysis Results

The third phase of the quantitative analysis was evaluating the impact of occupants' distributions scenarios (ODS) on comfort and energy performance. The case study building was simulated under 75 ODSs.

Overall, the results indicated that occupants' spatial distributions had a high impact on comfort and a moderate impact on energy use. Figure 11.14 demonstrates the range of EUI reported from the 75 simulations. It is evident

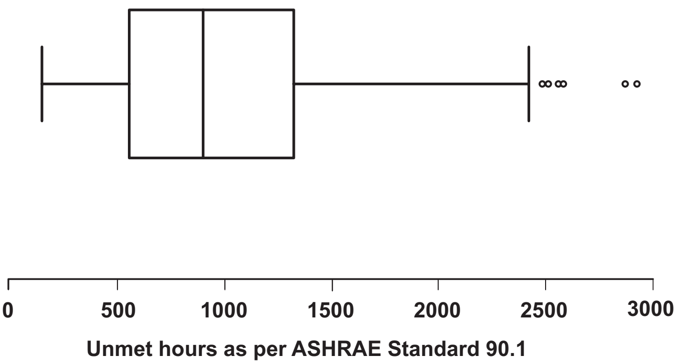

Figure 11.15 Unmet hours as per ASHRAE Standard 90.1 under multiple occupant distribution scenarios.

that ODSs were modestly influential on energy use, as EUI experienced changes in the range of 5–10 kWh/m^2/yr. The hard-sized HVAC equipment and flow rates likely contributed to limiting the changes in EUI.

On another front, Figure 11.15 presents the range of the unmet hours as per ASHRAE Standard 90.1 for the 75 simulation runs. The ODSs had a substantial impact on the number of unmet hours (i.e., thermal comfort). The unmet hours ranged from 150 unmet hours with the standard code ODS (i.e., homogeneous occupants' distribution across building zones) to about 3,000 unmet hours with some extreme ODSs where some zones were overpopulated.

To evaluate comfort at zone and occupant level, overheating and overcooling ODH were reported. Figure 11.16 presents the overheating ODH. It is clear from Figure 11.16 that different zones had different values of ODH. Further, the zones that were south- and west-facing and core zones (zones 1–5 and zones 13–15; see Figure 11.16) experienced a wider range of ODH. South-facing zones had a higher WWR (85%) and were subject to longer periods of direct solar gains compared to the east- and north-facing zones. The high WWR made south-facing zones more likely to experience overheating, especially with the increased internal gains from occupants. Core zones are also generally known to experience overheating, as they have minimal heat exchange with surrounding zones and the effect of infiltration is negligible. In the Toronto building, the wide range of ODH in south-facing, west-facing, and core zones indicates sensitivity to occupant distributions, where the higher the occupant density, the more discomfort levels will be in a given zone.

Figure 11.17 demonstrates the reported overcooling hours for the different building zones. Generally, overcooling ODH was not reported to be substantially sensitive to ODSs, as the highest overcooling ODH was observed

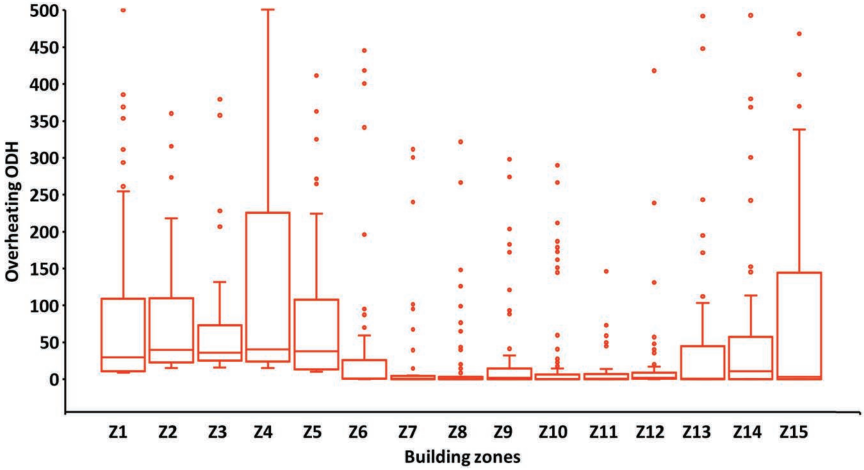

Figure 11.16 Overheating occupant discomfort hours (ODH) (Zones 13–15 are core zones).

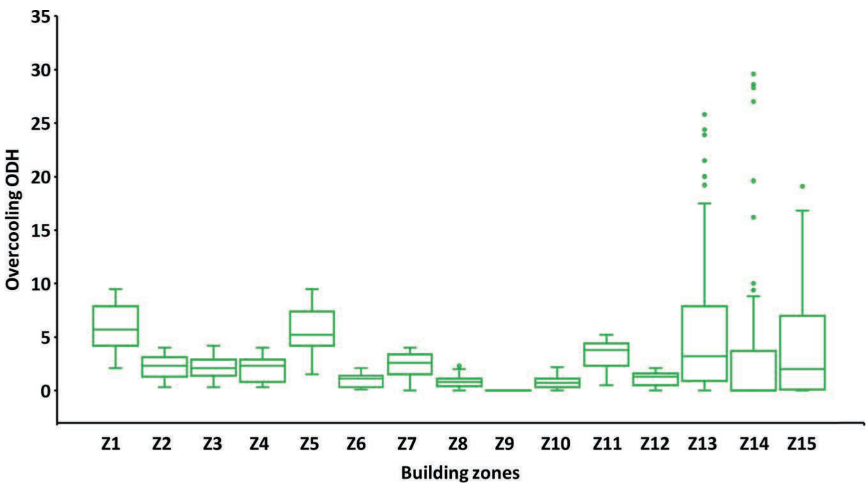

Figure 11.17 Overcooling occupant discomfort hours (ODH) (Zones 13–15 are core zones).

in core zones 13, 14, and 15. Upon further investigation, these core zones were found to be under-occupied (only one or two occupants) and surrounded by zones that were also under-occupied.

The simulations under the 75 ODSs were repeated with DCV enabled; then, the results were compared to the previous run results. Figure 11.18 presents the EUI results for both simulations under the 75 ODSs with and

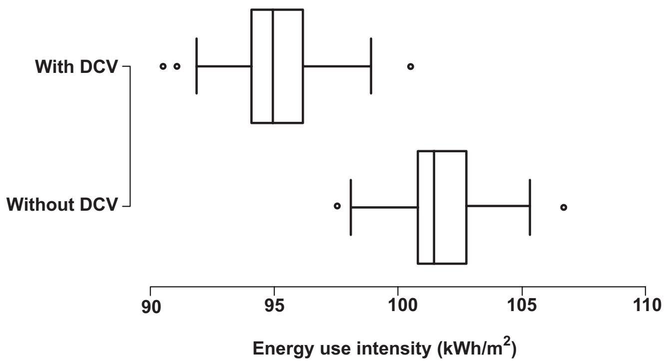

Figure 11.18 EUI with and without demand-controlled ventilation (DCV) under the 75 ODSs.

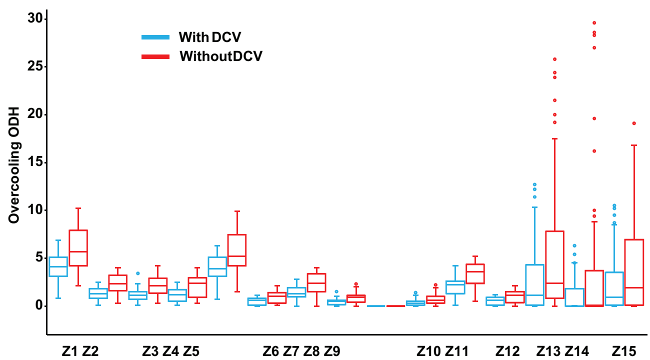

Figure 11.19 Overcooling ODH with and without DCV (Zones 13–15 are core zones).

without DCV. Incorporating DCV was beneficial in terms of saving energy; however, it demonstrated a similar range of sensitivity to ODSs.

Figure 11.19 demonstrates a comparison between the overcooling ODH with and without DCV. The results indicated that deploying DCV was beneficial in reducing overcooling ODH by about 50%. Using DCV also reduced the unnecessary ventilation of under/unoccupied zones.

11.2.5 Concluding Remarks

To summarize, this occupant-centric documentation and analysis of the Toronto case study building design process included: (1) interviews with four design stakeholders (owner, architect, mechanical engineer, and energy modeler) and (2) a simulation-based investigation, including an occupant-centric parametric analysis, an occupant-centric optimization, and a comfort study that analyzed the impact of occupants' spatial distributions across the building on comfort and energy performance.

The findings of the building design process documentation (via interviews) indicated that occupant-related assumptions were not a primary design input that influenced design outcomes. The design team typically sourced occupant assumptions from codes and standards and from their experience. Additionally, their design practice lacked an effective communication mechanism, which may have been responsible for discrepancies between occupant-related assumptions.

The simulation-based investigation indicated that occupant assumptions can be critical for selecting ECMs/DPs as well as influential on design outcomes (i.e., different occupant assumptions can lead to different optimal solutions). An evaluation of the impact of ODSs on building performance revealed that ODSs can yield different comfort and energy performance. Overall, the analysis indicated that in order to achieve more accurate design predictions and reach optimal design solutions, occupants and occupant assumptions should be given more attention during the design process in terms of consistency and accuracy of assumptions. In addition, designs should be evaluated using alternative occupant scenarios to predict building performance and inform design decisions.

11.3 Case Study 2: Budapest, Hungary

Attila Kopányi, Viktor Bukovszki, András Reith

11.3.1 Summary

An apartment building with 27 units, a community hall, and a shared laundry room will be constructed in downtown Budapest, Hungary, as part of the E-co-housing project. This case study demonstrates a method to create occupancy schedules based on use-pattern extraction through participatory design (also referred to as *co-design*), which refers to making design decisions through a problem-oriented mutual learning process involving occupants and architects. The two main research questions were therefore as follows: (1) How can a participatory design methodology be integrated into the building energy modeling workflow? (2) Does integrating participatory design result in significant differences in energy demand outputs compared to standard modeling workflows?

To assess the possibility of acquiring additional information regarding occupancy behavior from the participatory design process, occupancy schedules for the building energy simulations were created based on focus group interviews. The energy modeling outcomes using these co-design schedules were compared to those applying schedules from national guidelines. A difference of over 10% heating energy use intensity (EUI) was found in the apartments, and a difference of between 46% and 86% in heating EUI was found in the community hall. This difference is achieved through the differentiation between the use of living and common areas and between active and passive occupancy.

11.3.2 Building Description

E-co-housing is an experimental building for a novel social housing policy spearheaded by the 14th district of Budapest, developed as part of a UIA (Urban Innovative Actions) research project by the same name. The main goals of the project are to provide methods and evidence of just, sustainable transition in housing and to inform policymakers of how a holistic approach to sustainable housing development offers a financially viable, environmentally friendly, and socially sensitive alternative to alleviate housing poverty. As part of the project, an apartment building with 27 units and two common areas (i.e., community hall and laundry room), with a total floor area of 1,950 m^2 will be constructed in downtown Budapest, Hungary by 2022 (see Figures 11.20 and 11.21). Hungary is in a warm summer continental climate zone, and the building itself will be in a dense urban area characterized by perimeter blocks with attached buildings. The building has four stories, divided into two detached tracts connected by a network of suspended corridors. This arrangement separates an inner courtyard and a larger backyard from the street. The estate is legally owned by the municipality, with the apartments rented out at a subsidized rate to residents who live in housing poverty.

The E-co-housing project follows a combination of the co-housing model, zero-energy building principles, and continuous occupant engagement with

Figure 11.20 3D model of E-co-housing.

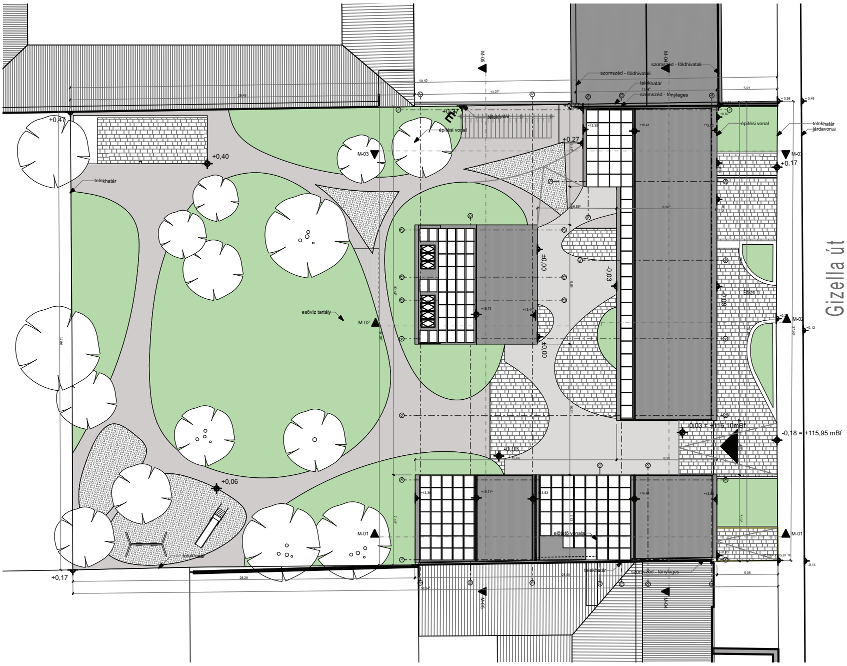

Figure 11.21 Site plan of E-co-housing (ABUD Mérnökiroda Kft, 2020).

the objective of minimizing operational expenditures to achieve a viable business model for affordable housing. In practice, this model entails a wide range of shared facilities, a strong community development program, collaborative facility management, and predictable and minimized energy demand and load curves. To that end, an initial energy simulation conducted during the design phase by the design team predicted an EUI of 54.7 kWh/m^2, while the heating and cooling EUI were 6.9 and 10.6 kWh/m^2, respectively. This simulation was based on standard Hungarian engineering practice, which uses standard occupancy data from conventional buildings. However, relying on standard data neglects two occupant behavior-centric challenges:

1 a demographically varied occupant pool of people living in housing poverty, and
2 a range of unconventionally used rooms and facilities.

The first challenge stems from the building project's goal to create a support network of occupants built on a synergistic occupant pool. This pool includes single, elderly, disabled, family, student, and social worker tenants.

The heterogeneity of expected occupants means that there is a challenge in accurately estimating when and how different apartments and shared facilities will be used, which in turn decreases confidence in projections for energy demand and load curves. This effect is critical since a core tenet of the business model is to have a reliable and predictable reduction of operational expenditures.

The second challenge is that the co-housing model translates to shared facilities with unconventional occupancy patterns. For example, the project includes a 107 m^2 community hall, and a 20 m^2 shared laundry room. The energy demand of these spaces is not insignificant, and their use will highly depend on the simultaneity of diverse occupant motivations, which adds an extra layer of uncertainty to predicting building operation.

In response to these two challenges, a co-design process involving occupants in the building's architectural design was conducted. This process provided an opportunity to access specific occupancy data, which can be used to simulate shared facilities and account for occupant heterogeneity.

The aim of the present case study is to showcase how these challenges/opportunities were addressed during the design phase of the project—in particular, how co-design was leveraged to navigate the complexities related to occupant behavior.

11.3.3 Methodology

This case study methodology followed an alteration of the standard simulation approach to include participatory or co-design (see Figure 11.22). The role of participatory design in this approach was to produce simulation-ready occupancy schedules, thus adding new data-collection and new data-preprocessing steps. The design steps were as follows: (1) defined and organized focus groups representative of potential building occupants, (2) interviewed focus group members during a design workshop to understand their daily routines, (3) aggregated daily routines for overall occupancy schedules, and (4) translated the schedules using occupant metadata. This exercise deviated from standard occupancy schedules by providing metadata to differentiate occupancy patterns of different social groups and by detailing activities that constituted occupancy. The research questions were addressed by using the new occupancy schedules together with a selection of standard schedules in the same building energy modeling (BEM) engine and comparing the outputs.

11.3.3.1 Participatory Design

The participatory design process consisted of three design workshops with a focus group (n=16). To approximate the future building occupants as much as possible, the municipality recruited focus group participants from among a pool of residents who were already tenants in municipal social housing.

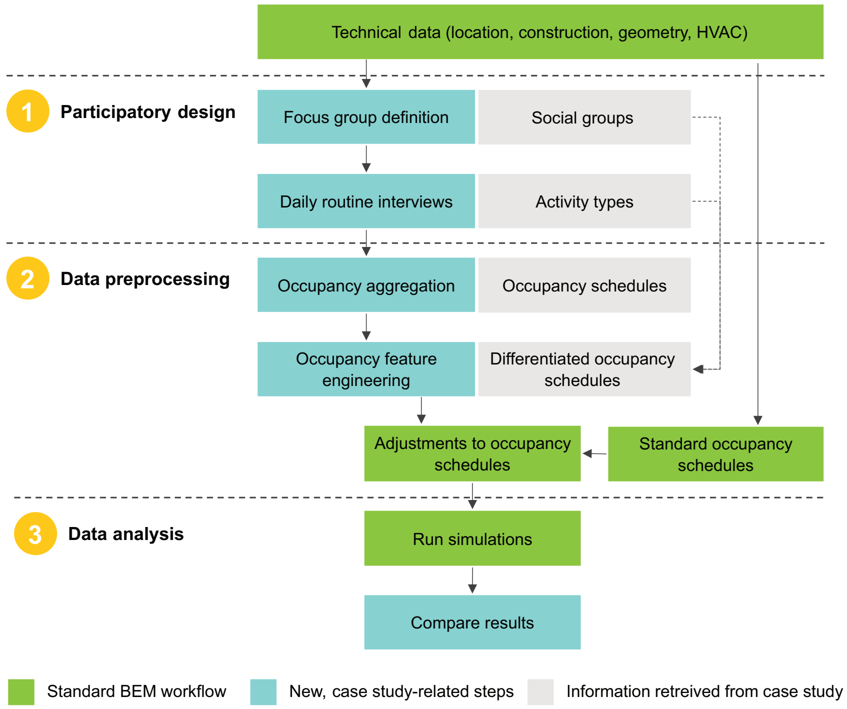

Figure 11.22 Case study design in the context of the standard BEM pipeline.

The residents were joined by a group of social workers, co-housing experts, and architects from the E-co-housing consortium. The former "target" group (n_t=8) and the latter "expert" group (n_e=8) together formed the final focus group. To fulfill the project goals of synergistic housing community composition, this focus group was selected to provide a mix of age, sex, family status (single, couple, etc.), education level, and employment status were selected (see Table 11.4). The age distribution among the focus group participants represented the national average, and the sex balance was roughly equal (male = 7, female = 9). Compared to the national average, family and employment status were more evenly distributed, while the education level of the target group was lower. During the workshops, participants used pseudonyms (used throughout this case study).

The information relevant to occupancy patterns was collected in the second workshop, where the focus group was partially present (n_t = 8, 100%; n_e = 3, 38%). This workshop focused on individual habits and behaviors and, to a lesser extent, specific design solutions. Each respondent drew up their individual daily routine chart for typical weekdays at an hourly resolution (see Figure 11.23), differentiating between four activity categories: sleeping, work/activities outside the house, at-home leisure, and at-home chores. This

Table 11.4 Composition of the focus group, row-by-row for: age, sex, family status, education, employment status

Between 18 and 30	*Between 30 and 65*	*Older than 65*			
Female	Male				
Single	Couple	Single parent	Family with fewer than 3 children	Family with 3 or more children	
Elementary	Vocational	Other secondary	Post-secondary education		
Unemployed	Seasonal	Part-time	Full-time	Self-employed	Retired

Darker colors indicate a larger cohort population, where each row shows proportions independently.

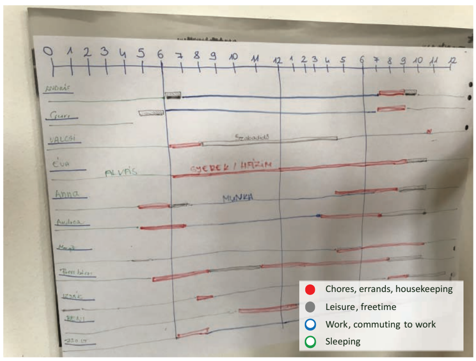

Figure 11.23 Registering of daily routines during participatory design workshop #2. Participants' activities were color-coded per hour (scale on top) as a Gantt chart.

level of differentiation and resolution was necessary for architectural design and served as a pre-processing logic for occupancy schedules.

The occupancy schedules were generated through the aggregation of daily routine schedules. The aggregation method in each case involved taking the mean of responses. Two types of occupancy schedules were created: (1) a general schedule and (2) an active vs. passive occupancy schedule. For the general schedule, all activity types except for work were included equally. Separate active and passive occupancy schedules were generated by considering only chores and leisure activities for the former and sleeping for the latter. In the context of this case study, active and passive occupancy were differentiated in terms of occupant heat load.

11.3.3.2 Building Energy Modeling

To evaluate the impact of using the occupancy schedule created based on the co-design methodology, a BEM was created using EnergyPlus 9.2 and simulated applying different occupancy schedules. Along with the occupancy schedule

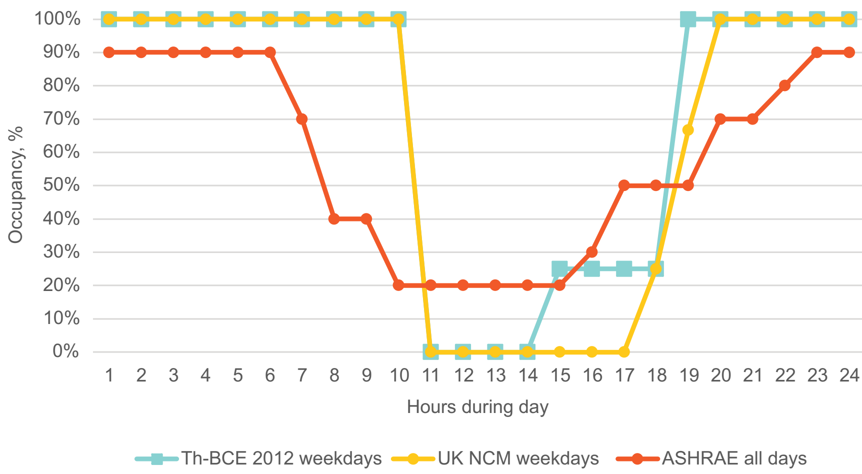

Figure 11.24 Residential occupancy schedules based on different standards.

created using co-design approaches, three other schedules from national guidelines and standards were used, as described in the paragraphs that follow.

Based on a review of the available standards and guidelines of European countries, the authors only found hourly occupancy schedules for residential buildings in the French Th-BCE 2012 (2012) and the UK NCM Database (2018); therefore, only these were used in the study as European schedules. The residential occupancy schedule provided by ASHRAE Standard 90.1 (2019) was applied as well, as it is widely recognized and used in the energy modeling industry worldwide.

The residential occupancy profiles provided by these three standards are shown in Figure 11.24. Notably, ASHRAE uses the same schedule for all days, and in the Th-BCE 2012 and the UK NCM guidelines, the weekend occupant schedule is 100% throughout the whole period. The Th-BCE 2012 standard weekday values are averages, as it has a different profile for Wednesdays. The UK standard provides occupancy schedules on room level. Since in the created BEM each apartment represented one thermal zone, the room-level schedules had to be aggregated into an apartment-level profile. This aggregation was accomplished by assuming the number of occupants for each area based on its function.

In the BEM, 3.88 W/m^2 equipment power density was used with an average 66% diversity, while the lighting power density was assumed to be 2 W/m^2.

11.3.3.3 Occupant Heat Load Profile of the Living Areas

Using the schedules from the co-design process, it was possible to differentiate between active and passive occupancy when creating the hourly occupancy heat load profile for the living areas (i.e., private apartments). This profile was calculated as a weighted average of the active and passive heat loads, where the weighting factors were the probabilities of the active and passive occupancy based on the focus group interview results (see Equation 11.1).

$$q_{\text{Co-design}} = p_a \cdot q_a + p_p \cdot q_p \tag{11.1}$$

where:

$q_{\text{Co-design}}$: occupant heat load in the living areas, W/person
p_a: probability of active occupancy
q_a: heat load of active occupant, W/person
p_p: probability of passive occupancy
q_p: heat load of passive occupant, W/person

When calculating the heat load used in the co-design schedule, a 72 W/person heat load was used for each passive occupant, corresponding to the heat load of an average person while sleeping, as per the ASHRAE 55-2010. When considering active occupancy, 100 W/person was assumed, corresponding to the metabolic rate of a seated, relaxed person (International Organization for Standardization, 2006).

When determining the heat load profile based on the Th-BCE 2012, UK NCM, and ASHRAE occupancy schedules, no differentiation was possible regarding active and passive occupancy; therefore, the schedule value was always multiplied by 100 W/person, including during the nighttime.

11.3.3.4 Occupant Schedule and Heat Load Profile of the Common Areas

Since participants were not asked about their weekend habits during the co-design focus group workshops, information about weekend occupancy was not available. Therefore, in the co-design schedules for the living areas (i.e., private apartments) and common areas (i.e., community hall and laundry room), the same weekend occupancy was used (as in the case of the Th-BCE 2012 and UK NCM standards, i.e., a constant value of 100%).

The co-design schedule of the common areas was created using assumptions regarding the probability that an occupant will use the common rooms for either chores/work or leisure. The assumed probability values are summarized in Table 11.5. The overall probability (at each hour) of the common area usage was then determined as the average of the probability values of the respondents. The occupancy ratio values were then determined proportionately to the probability values, with 100% occupancy assigned to the highest probability value.

In case of the Th-BCE 2012 and UK NCM standards, no specific guidelines were given for the occupancy of common areas; therefore, the same schedules were used for the living areas. The ASHRAE standard provided

Table 11.5 Assumed probability values for the occupancy of the common areas

	Community hall	*Laundry room*
Probability of using the area for chores or work	10%	10%
Probability of using the area for leisure	50%	50%

start hr	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
András	1	1	1	1	1	1	2	3	3	3	3	3	3	3	3	3	3	3	3	4	4	2	1	1
Gyuri	1	1	1	1	2	2	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	1	1	1
Valcsi	1	1	1	1	1	1	4	4	2	2	2	2	2	2	2	2	3	3	3	3	3	3	1	1
Éva	1	1	1	1	1	1	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	2	2	1
Anna	1	1	1	1	4	4	2	3	3	3	3	3	3	3	3	3	3	3	3	4	2	2	1	1
Andrea	1	1	1	1	4	4	4	3	3	3	3	3	3	3	3	4	4	4	4	2	2	2	2	1
Margit	1	1	1	1	2	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4	1
Józsi bácsi	1	1	1	1	1	4	4	4	2	2	2	4	4	4	4	4	4	4	4	4	2	2	2	1
Izsák	2	1	1	1	1	1	1	4	3	3	3	3	3	3	3	3	3	3	3	3	4	4	2	2
Beni	1	1	1	1	1	1	1	1	1	1	2	4	4	3	3	3	3	2	2	2	2	2	2	2
Zsolt	1	1	1	1	1	1	4	4	3	3	3	3	3	3	3	3	3	4	4	4	4	1	1	1

Figure 11.25 Daily routine charts. Activities were coded as 1=sleeping, 2=at-home leisure 3=away, 4=at-home chores.

the same occupancy profile for common areas in residential buildings as for the living areas. When determining the occupant heat load based on the schedules for the common areas, the 100 W/person metabolic rate used in all standards was used for co-design calculations.

11.3.4 Results

The E-co-housing case study results are presented below as follows: first, the daily routine charts drawn at the design workshop #2; then, the general, active-passive, and shared facility occupancy schedules; finally, a comparison of the simulation outcomes following the three selected standards.

11.3.4.1 Co-Design Daily Routines

Daily routines were broken down by activity type, as shown in Figure 11.25. The average times for key activities included waking up at 5h43; leaving the house at 8h53; arriving home at 18h20; and going to sleep at 22h38. Notably, 4 out of 11 respondents spent all their morning hours at home, and two stayed at home all day. These respondents explained their sporadic occupancy patterns mostly by their employment status. For instance, four respondents were self-employed, unemployed, seasonally employed, and a pensioner. Also, many respondents reported temporary, short-term, and volatile employment conditions, overtime working, multiple workplaces, and seasonal jobs. On average, respondents spent seven hours sleeping, roughly eight hours out of the house, around 5.33 hours spending free time at home, and the remaining 3.5 hours doing chores. Regarding differences in sex, female respondents slept over 1.5 hours less than male respondents, but almost two hours more being active at home than male respondents. Differences in age and family status yielded no discernible patterns in occupancy.

11.3.4.2 Co-Design Occupancy Schedules

Overall occupancy of the apartment units (Figure 11.26) dropped from 100% to around 40% between 4h00 and 8h00 and rose to 100% between 16h00 and 22h00. The schedules plateaued in the morning hours until noon, with some movement in the afternoon.

However, not all occupancies were the same from an energy perspective. The active and passive occupancies were equal at around 5h00 and 22h00, respectively. Between these two points, more people were awake than sleeping. Sleep times varied from 20h00 to midnight, and wake times ranged between 3h00 and 10h00. This means that there was a passive occupancy component in the schedule for about 58% of the day. Likewise, active occupancy clearly showed a morning and evening peak at 6h00 and 19h00, respectively. In between those times, most but not all occupancy was active.

Time spent on active, at-home daily activities in the common areas took away from time spent on the same activities in private apartments. This pattern was shown by a truncated inverted trajectory of common hall occupancy versus apartment occupancy (see Figure 11.27). As the share of passive occupancy in overall occupancy increased, people spent more time in their apartments than in the community hall. The laundry room occupancy is flatter, with minor peaks at 9h00 and 21h00, compared to the plateau

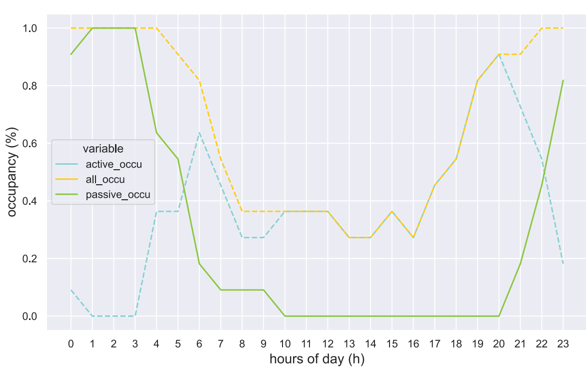

Figure 11.26 Daily occupancy by the level of activity. All occupancy is the sum of active and passive occupancies.

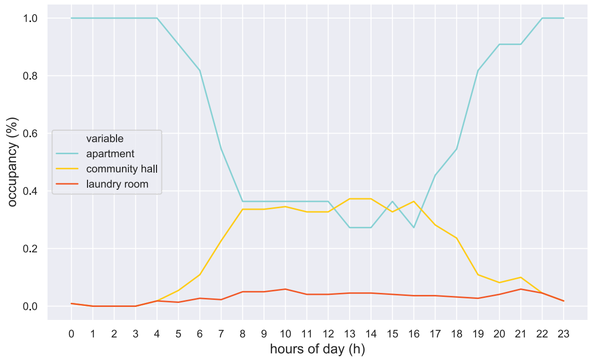

Figure 11.27 Daily occupancy in private apartments vs. common areas (community hall and laundry room).

between 8h00 and 16h00 for the community hall. This flattening is due to the smaller overall assumed coefficients, and the peaks can be explained by a higher prevalence of chores (in the case of the laundry room).

11.3.4.3 Occupant Heat Load Profiles

The daily occupant heat load profiles based on the analyzed standards and the co-design workshop results are summarized in Figure 11.28. Due to the application of a lower heat load for occupants during night hours, the co-design heat load profile shows generally lower values during this time. The root mean squared error (RMSE) between the co-design occupant weekday heat load profile and the other profiles for the living areas is summarized in Table 11.6. The heat load profile based on the ASHRAE occupant schedule shows the highest similarity to the co-design profile.

In the case of the common areas, the occupant heat load profiles showed significant differences. The co-design heat load profiles of the community hall and the laundry room showed higher values during daytime, which reflects the assumption that occupants are more likely to use these areas during this period.

11.3.4.4 Impact on Energy Modeling Outputs

The heating EUI, cooling EUI, and total EUI of the living areas modeled using the co-design occupancy schedule were 6.0, 12.4, and 66.1 kWh/m^2, respectively. The comparison of these values with the outcomes of applying the other analyzed occupancy schedules is shown in Figure 11.29. The largest deviation can be seen in the heating EUI, followed by the cooling EUI, while the total EUI shows a very small difference, <1%. The heating

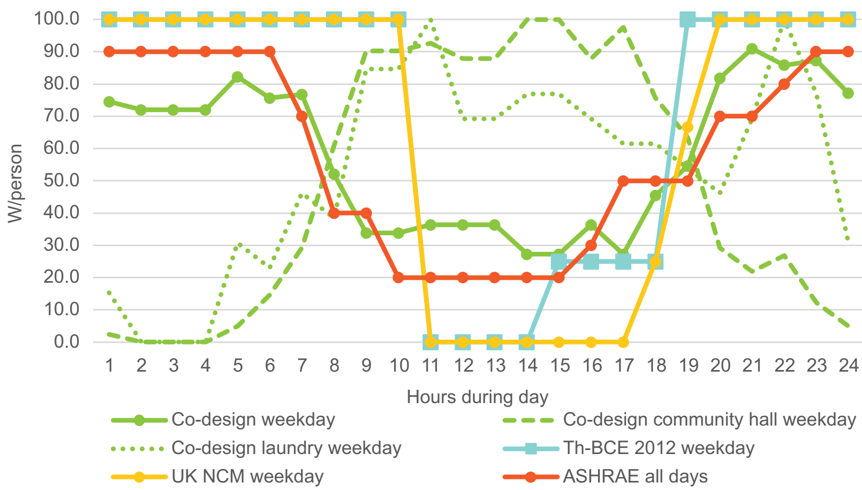

Figure 11.28 Occupant heat load profiles used in the analysis. Different profiles were created for the living areas, the community hall, and the laundry room in the co-design methodology; for the other schedules, the same profile was used in every zone. The weekend heat profile was a constant 100 W/person in the co-design, Th-BCE 2012, and UK NCM cases; for ASHRAE, the same heat profile was applied for each day.

Table 11.6 RMSE between the co-design weekday heat load profile and the other analyzed occupant load profiles of the living areas

	Th-BCE 2012	*UK NCM*	*ASHRAE*
RMSE, W/person	31.7	33.6	13.2

consumption was predicted to be lower and the cooling consumption higher based on the Th-BCE 2012 and UK NCM standards; in case of ASHRAE, the results were the opposite.

In the community hall, when considering the co-design schedule, the cooling EUI was 119.5 kWh/m^2, the heating EUI was very low (only 0.42 kWh/m^2), and the total EUI was 125.7 kWh/m^2. The comparison between the heating, cooling, and total EUI applying different schedules is shown in Figure 11.30. All energy results were predicted to be lower in the Th-BCE 2012, UK NCM, and ASHRAE cases.

Figure 11.31 depicts the differences in the heating and total EUI of the laundry room using different occupancy schedules (no cooling system was designed for the laundry room). Figure 11.31 shows a similar pattern, with larger differences regarding the heating EUI. Both the heating and total

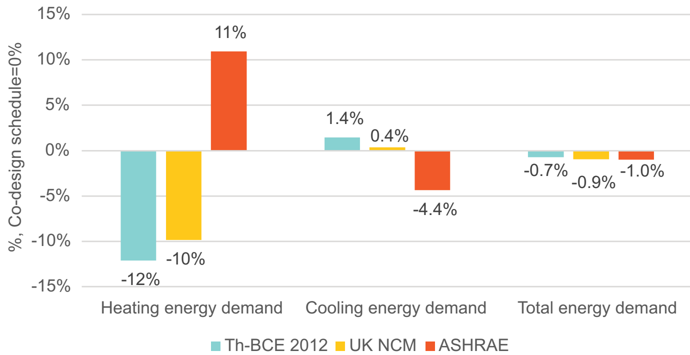

Figure 11.29 Heating, cooling, and total EUI of the living areas modeled with different occupancy schedules. The reference points are the results based on co-design schedule.

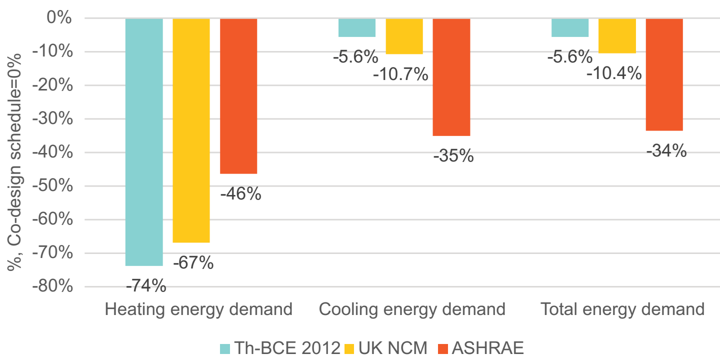

Figure 11.30 Heating, cooling, and total EUI of the community hall modeled with different occupancy schedules.

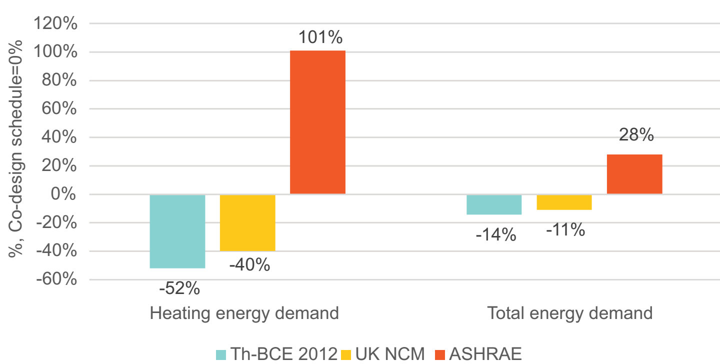

Figure 11.31 Heating and total EUIs of the laundry room modeled with different occupancy schedules.

EUI were predicted to be lower based on the Th-BCE 2012 and UK NCM standards; in case of ASHRAE, the results were the opposite.

11.3.5 Discussion

In the living areas, the difference in the heating and cooling EUI can be attributed to the disparity in the average occupant heat loads (see Figure 11.32). When applying the Th-BCE 2012 and UK NCM standards, the average heat load was slightly higher; yet, when applying the ASHRAE standard, it was lower. This discrepancy could be due to the heating EUI being lower and the cooling EUI higher in the case of the Th-BCE 2012 and UK NCM standards, while the opposite was true for the ASHRAE standard. In the living areas, the heating and cooling EUIs represented only a small part of the total EUI. The large differences in the heating and cooling EUIs compared to the total EUI might be explained by the occupant heat load, which directly affects the heating and cooling demand.

In the community hall, the cooling constituted the largest share of the total demand, hence the difference in the total demand; the cooling demand showed a similar pattern. The heating consumption was very low in all cases, which could have caused larger differences.

The difference in the cooling EUI of the community hall when applying different schedules can be explained by the variation in the daily profile of the occupant heat loads. As shown in Figure 11.33, the co-design-based occupant heat load increased during the daytime and significantly contributes to the rise in cooling demand in the community hall on a typical summer day. Yet, the occupant load profile based on the ASHRAE standard showed a decrease during the day, causing the cooling EUI to remain at almost a constant value throughout the day.

Moreover, in the laundry room, only the heating and total energy EUIs could be analyzed since no cooling was designed for this space. The

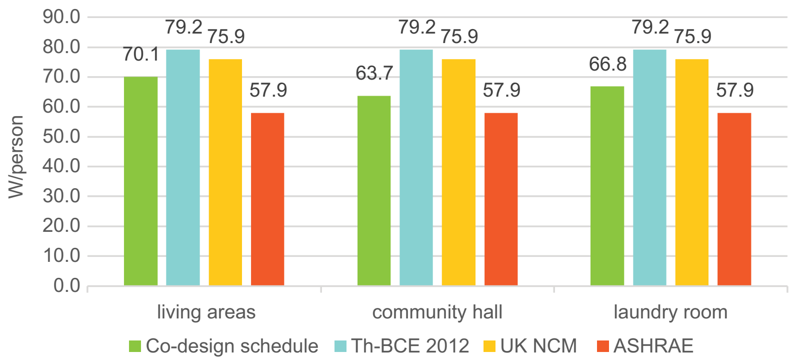

Figure 11.32 Average occupant heat load values in the three analyzed areas: living areas, community hall, and laundry room.

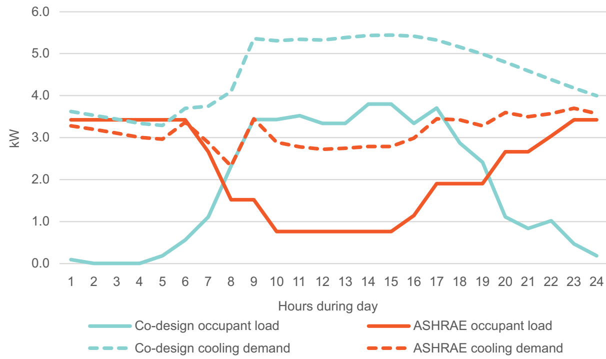

Figure 11.33 The occupant heat loads and the cooling energy demand of the community hall using the co-design schedules and ASHRAE standard, considering a typical summer day.

difference in the heating EUI of the analyzed models can be explained by the changes in the occupant heat loads. All the models resulted in lower heating consumption while having higher occupant heat loads.

Limitations of this case study stem from: (1) uncertainties in BEM, (2) assumptions made prior to modeling, and (3) the co-design methodology. In the case of BEMs based on the Th-BCE 2012 and UK NCM standards, the occupancy schedule of the living areas was used for the common rooms as well, assuming an energy modeler would follow a similar path. While this approach is purely speculative, it draws attention to the uncertainties designers face because of a lack of accurate model inputs. Also, the results were limited to weekday analyses only, as weekend schedules were not collected during the focus groups. This case study was likewise limited to analyzing the effect of changing the occupancy schedule only, whereas other sources of internal heat gains (e.g., equipment, lighting) may have been relevant as well. Additionally, in certain cases, the analyzed energy demands had very low absolute values, such as the heating demand in the laundry room and the community hall.

Regarding assumptions, the occupancy of these rooms was based on assumptions about the proportion of chore/leisure time that would be spent there. These assumptions, however, were not informed by focus group interviews. Furthermore, the calculations did not consider the facilities provided by the rooms, nor the number of people living in the building. Both factors heavily influenced common room occupancy. The comparison of these results may have been less insightful as a result.

Finally, the co-design process used in this project was intended to support architects, not BEM. Weekend schedules were thus not collected, and the focus group included only a limited sample size of people currently living in housing poverty. Retrieving occupancy schedules during co-design is time-consuming, and so future larger studies should consider a more streamlined method.

11.3.6 Concluding Remarks

In this case study, participatory design was used as a tool for constructing more detailed and more accurate occupancy schedules compared to schedules from the three selected standards. Overall, between 13.2 and 33.6 W/person differences in heat load profiles were observed compared to standard occupancy schedules. While these differences did not translate to significant differences in overall energy EUI, it yielded over 10% heating EUI difference in apartments and between 46% and 86% heating EUI difference in the community hall. The difference in the EUI was achieved through the differentiation of active and passive occupancy and the ability to tell exactly how people are using the building beyond simply occupying it. Forecasting how occupants use the building could especially be significant for predicting occupancy in shared facilities and common areas, which are prevalent features of co-housing.

This case study analysis also showed that people living in social housing occupy buildings differently than standards predict (albeit this claim could be specific to this case study), potentially due to higher volatility in their employment schedules. The employment schedules for this study's participants were closer to the standard "9-to-5" work schedule for male occupants and less so for female occupants, but further research is required to explore the association between sex, work schedules, and occupancy patterns to understand how social housing occupancy may be distinct from conventional residential buildings. Overall, this study's findings suggest that participatory design may be a viable tool to depart from generic standards toward higher specificity in BEM as well as a valid research method to explore different factors of occupancy, which could potentially contribute to development of more inclusive standards in the field.

11.4 Case Study 3: Quebec City, Canada

Jean Rouleau, Louis Gosselin

11.4.1 Summary

In the mid-2010s, a 40-unit, four-story social housing building called *Les Habitations Trentino* was constructed in Quebec City, Canada (lat. 46.78°N, lon. 71.29°W), in an eco-neighborhood called La Cité Verte. The climate in Quebec City is characterized by significant variations throughout the year: cold and snowy winters (HDD18 = 4,843°C-day), and relatively warm, humid summers. The stakeholders wanted to reach a high level of energy performance for this building. During the design phase, building performance simulations (BPS) and life-cycle analyses were performed to test different options to inform the decision-making process.

A partnership with the Chaire industrielle de recherche sur la construction écoresponsable en bois (CIRCERB) from Université Laval was established to analyze the behavior of this case study building. Researchers from Université Laval analyzed the energy performance of the building from the beginning of operation and found that occupants had a strong influence on the energy performance of the building. The researchers also found a substantial energy performance gap for this building, where the energy demand that was predicted prior to construction differed from the actual demand.

The objectives of the present case study analysis were thus (1) to explain the reasons behind this energy performance gap and assess if it was caused by an inaccurate representation of the occupants in simulation, and (2) to develop a method to assess the full influence of occupants on the performance of multi-unit residential buildings (MURBs). The analysis also aimed to find appropriate ways to incorporate occupant behavior into BPS to improve the design of MURBs and reduce the energy performance gap. Studied occupant behavior included occupancy, space heating, hot water and electricity consumption, setpoint temperatures, and the use of operable windows for ventilation. In brief, the study found that the performance gap was mainly caused by differences between the assumptions regarding occupants in the BPS and the actual occupant behavior observed in the building.

11.4.2 Building Description

Construction of *Les Habitations Trentino* took place in 2015 (see Figure 11.34). Although pre-construction BPS assumed a building population of 125 people, the total number of occupants in 2016 was 90. Energy bills for heat and electricity are included in the lease. The floor area of each unit varies between 70 and 80 m^2. The window-to-wall ratio (WWR) is 16%, with operable triple-glazed windows. A special feature of the building is that part of it was constructed with a cross-laminated timber (CLT) system, and a light-framed wall system was used for the other side. The thermal resistance (RSI value) of the opaque portion of the envelope is 6.32 m^2K/W for both construction systems. The air tightness of the envelope was measured to be 0.6 ACH at 50 Pa.

Heating is provided by a biomass-based district heating system. Each apartment is equipped with three or four hot water radiators. The energy supply for producing domestic hot water comes from the district heating network. A 100% fresh air ventilation strategy is used. Each dwelling has a switch to turn the mechanical ventilation on or off (with a heat recovery ventilator (HRV) efficiency of 85%). No mechanical cooling was installed.

Building data have been collected since the beginning of building occupancy (i.e., October 2015). Data on the consumption of electricity, domestic hot water, and heating is collected. Indoor temperature and humidity,

Figure 11.34 Picture of the building and floor plan.

window openings, mechanical ventilation control, and exhaust fan operation (kitchen hood, dryer, bathroom fan) are also monitored for some units. Overall, more than 500 data points are monitored, with, for the most part, an acquisition every 10 minutes.

At the building level, the annual EUI of the heating, electricity, and domestic hot water (DHW) in 2018 was 38.4, 48.1, and 51.3 kWh/m^2, respectively, for a total EUI of 137.8 kWh/m^2. These figures are a significant improvement compared to the typical total EUI observed for this type of building in Quebec, i.e., 250 kWh/m^2 (Whitmore and Pineau, 2021). The improvement is mostly due to the quality of the envelope that contributes to reducing the heating needs. Monitoring of the building from 2015 to 2020 showed that the annual energy consumption for heating and DHW was consistent over time, but electricity consumption increased over the last few years.

Figure 11.35 presents the annual EUI of all dwellings in the case study building, ranked from the lowest to the highest consumers. The most striking element of this figure is the large variation of energy consumption from one dwelling to another, despite their similar features. The EUI varied by a factor of 11 from 23.2 to 267.3 kWh/m^2 across dwellings. Very weak correlations between the DHW consumption and the number of occupants in

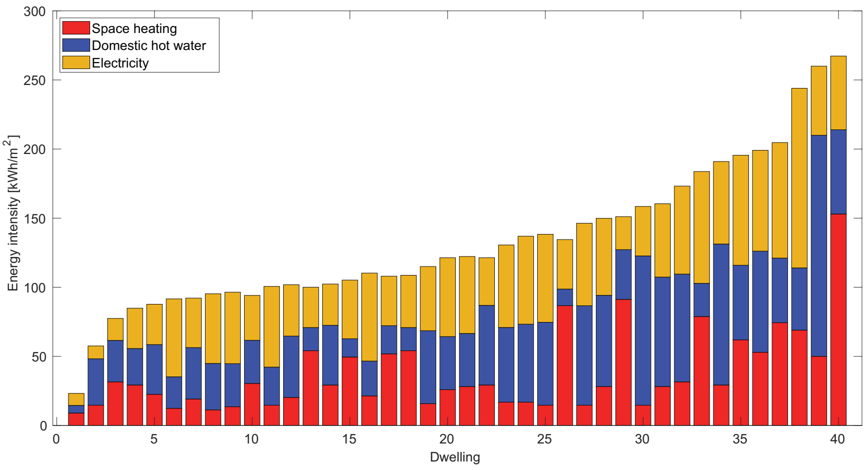

Figure 11.35 Annual energy intensity in each dwelling in 2018.

each dwelling and between the space-heating demand and the floor level were noted, but other factors such as orientation, construction system, etc., did not explain the variability of the EUI (Rouleau *et al.*, 2018). In fact, most of the observed variance appeared to be due to differences in occupant behavior.

Thermal comfort during summer was also studied. A portion of the dwellings exhibited overheating (Rouleau and Gosselin, 2018), with an indoor temperature above the limit provided by the adaptive comfort model of ASHRAE Standard 55. In other units, the indoor temperature stayed within the limits of acceptable conditions. Once again, most of the variability was linked to occupant behavior.

11.4.3 Methodology

Since this analysis had two distinct objectives, the methodology was divided into two sections: one to evaluate the impact of occupant behavior on the energy performance gap and the other to develop a novel occupant behavior model. Details of the methodology are provided below.

11.4.3.1 Occupant Behavior Assumptions during Design

During the design phase of the building, BPS was performed to assess the impact of different design options in terms of construction costs and energy savings. Different envelope assemblies were simulated with the Passive House Planning Package (PHPP) software (Feist, 2012), leading to the design previously presented above, which offered a good trade-off between cost and energy performance. In these simulations, occupants were accounted for by static schedules that relied on fixed assumptions regarding occupancy, heating setpoint, etc. These were the default schedules supplied by the PHPP software.

For the purposes of this study, the PHPP model was examined thoroughly, and the assumptions of the initial energy model were compared to the monitored data. This step allowed for the identification of inaccurate assumptions. The initial energy model was modified to account for divergences between the model and the actual building. Changes in the total energy use predicted by the model were tracked as those changes were applied.

11.4.3.2 Occupant Behavior Simulation Model Development

A versatile integrated occupant behavior model was developed. To develop the model, existing models that simulated different facets of occupant behavior were adapted and assembled. The unified model provided sets of possible coherent schedules that served as inputs for the BPS.

The main requirements for the model were:

- *Integrated several facets of occupant behavior*: The model should provide schedules for the most influential types of occupant behavior with respect to energy consumption and thermal comfort (occupancy, electricity consumption, DHW consumption, heating setpoint, window opening).
- *Ensured coherence between sub-models*: The model should provide schedules that are coherent with one another. For example, if the occupancy schedule indicates that no one is present, the DHW and electricity consumption should be adapted accordingly.
- *Provided high time and space resolution*: The model should provide representative schedules at the level of a single dwelling. It should provide daily or yearly schedules, with a time step that could be as small as 10 minutes.
- *Replicated observed variance*: The model should generate schedules that properly match the observed unit-to-unit variance, as well as the day-to-day variability observed in the dwellings. The model should be probabilistic: two different runs lead to two different sets of schedules, both of which would still be within the observed variance for each type of occupant behavior.

For the occupancy, electricity, and domestic hot water sub-models, modifications were made to existing models to account for various factors. First, models were created using data from foreign countries (United Kingdom and USA); then, adjustments were made so the models better represented behaviors observed in Canada (Rouleau *et al.*, 2019). Another modification was to add a "diversity" factor that was randomly assigned to each simulated dwelling to ensure that the dwellings had diverging behaviors (i.e., that the simulated occupant profiles were different between households) so the full range of observed occupant behaviors was reproduced. Finally, the sub-models communicated with each other to make sure that the generated schedules for occupancy, electricity, and hot water were coherent with one another. The methodology to develop each sub-model is described below.

11.4.3.2.1 OCCUPANCY

The daily occupancy profiles generator developed by Richardson *et al.* (2008) was used as the basis for the model. The generator assigned the number of active occupants (i.e., present and not sleeping) in the simulated dwelling at a 10-minute frequency. Occupancy schedules were generated and then forwarded to other sub-models.

11.4.3.2.2 ELECTRICITY CONSUMPTION

Richardson *et al.* (2008) model was also used to generate schedules for the use of electric appliances (Richardson *et al.*, 2010). Another model was also used for the usage of artificial lighting (Armstrong *et al.*, 2009).

11.4.3.2.3 DOMESTIC HOT WATER CONSUMPTION

The domestic hot water sub-model used the yearly DHW event schedule generator developed by the National Renewable Energy Laboratory (NREL) in the United States (Hendron *et al.*, 2010). The hourly NREL model was adjusted so it would fit with the desired time resolution of 10 minutes.

11.4.3.2.4 HEATING SETPOINT

A probability distribution function that copied the distribution found in Canadian houses (National Resources Canada, 2011) was used to assign the heating setpoint of the heating system. The setpoint was treated as a static parameter that remains constant throughout the year.

11.4.3.2.5 WINDOW OPENING

The state of the windows (opened/closed) was calculated based on the outdoor and indoor temperatures using a logit equation to estimate the probability of window opening (when closed) and window closure (when opened). This equation was developed with the monitored data from the case study building. The equations that calculated the states were based on coefficients that varied for each simulated dwelling. Unit-to-unit variance was thus ensured.

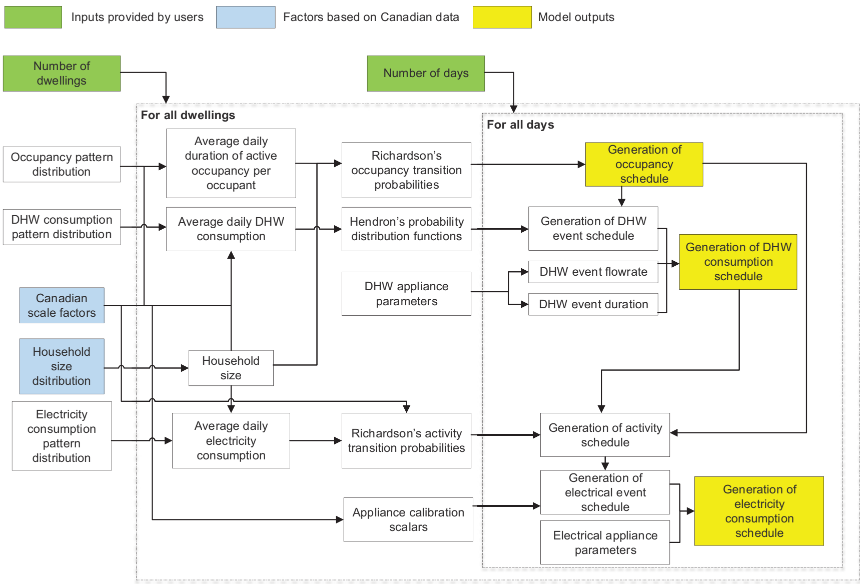

Figure 11.36 Architecture of the occupant behavior model showing the relationship between all sub-models.

More details on these occupant behavior models are available in Rouleau *et al.* (2019) and Rouleau and Gosselin (2020). The interactions between these different sub-models are presented in Figure 11.36.

Since the occupant behavior model described above could generate many different schedules that were representative of possible occupants, it offered the possibility to run Monte Carlo simulations. For this type of simulation, a large number of schedules can be created by running the model repeatedly. Then, these different schedules can be introduced into BPS tools. The results of this procedure will be probability distributions for important model outputs (e.g., energy consumption, thermal comfort, overheating, peak demand). These distributions can indicate the likeliness of achieving a certain level of performance while considering the full extent of possible occupant behaviors.

The abovementioned approach can also be used to size HVAC equipment. For instance, the methodology was used to study the sizing of hot water systems. The case study building's hot water consumption was simulated 100 times with the occupant behavior model. These 100 building consumption profiles were forwarded to a numerical model of a hot water system to find the optimal size of the system (storage water tank volume and heating capacity of the system). If an instantaneous water heater had been installed in the building, the methodology predicted that the ideal heating capacity for the building ranged between 192 and 497 kW, depending on how much hot water the occupants in the building use. On the other hand, with a water tank of 2,000 L, the ideal heating capacity was between 33 and 77 kW.

11.4.4 Results and Discussion

The results of the case study analysis are presented and discussed in the sections below.

11.4.4.1 Occupant Behavior Assumptions during Design

According to these prior-to-construction simulations, the predicted annual heating EUI was 16.6 kWh/m^2 and the annual total EUI (summation of heating, electricity, and DHW) was 74.3 kWh/m^2. As shown in Figure 11.37, these values departed significantly from the actual average energy consumption observed in the building.

The assumptions of the initial energy model and the measurements were compared and analyzed to explain the discrepancies. Three notable sources of discrepancies were:

- i *Window opening*: The original model did not include window opening during the heating season. However, it was observed that windows were opened 9.4% of the time during the heating season, and so the infiltration rate of the building was adjusted to include this behavior. The relatively high rate of window openings obviously increased the heating demand compared to predictions.
- ii *Heating setpoint*: The heating setpoint was originally assumed to be 20°C. In practice, the actual temperature in the units tended to be much higher, around 23.9°C, which again increased heat consumption compared to predictions.
- iii *Domestic hot water*: A daily consumption of 25 L/person was assumed, but the measured consumption was much higher, around 58.3 L/person.

Other changes applied to the energy model following the monitoring of the building included (continued from the list above): (iv) using the "true" weather data, (v) modifying the HRV efficiency from 85 (expected value by the HRV supplier) to 70 (estimated value from monitored data), (vi) reducing the building population from 125 to 90 people, (vii) considering the internal heat gains generated from the hot water recirculation loop, and (viii) using the "true" electricity demand. Implementing these changes in the original energy model achieved simulation predictions much closer to measurements, thus reducing the performance gap. As shown in Figure 11.37, changes in the model were applied cumulatively.

This exercise illustrated the challenge of making accurate assumptions about occupant behavior prior to construction. At the same time, the study

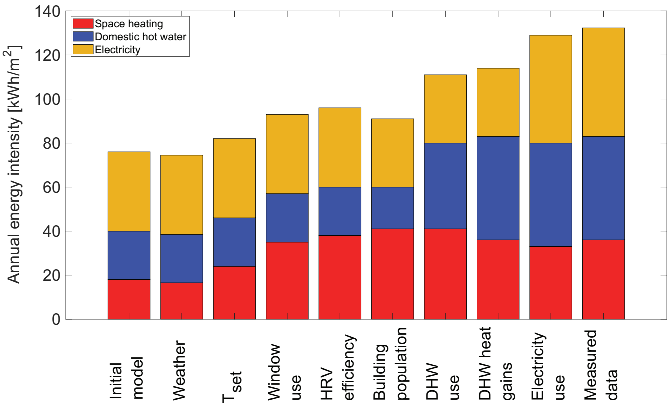

Figure 11.37 Revisiting assumptions related to occupant behavior to close the energy gap between predictions and measurements.

revealed the significant impact that these assumptions might have on energy predictions and, potentially, on design choices. In addition, the BPS used during the actual design phase only accounted for the "average occupant" and did not consider the full spectrum of possible occupants (as highlighted in Figure 11.35). Thus, there is a need to develop an integrated model encompassing the different facets and inherent variability of occupant behavior as well as design methods to exploit these kinds of models.

11.4.4.2 Occupant Behavior Simulation Method

The results presented in this section include the simulation outputs of an energy model of a single dwelling located in the case study building. Monitoring data were used to calibrate this numerical model to make sure the simulations adequately reflected the real building in terms of annual heating demand and thermal comfort. A total of 1,000 annual occupant profiles were then generated and provided to the dwelling model to generate probability distributions for the heating demand, total energy use, and thermal comfort (for more details, see Rouleau *et al*., 2019). This approach is useful for assessing the robustness of the building design for use by different occupants.

The average annual heating EUI across the 1,000 simulations was 36.6 kWh/m^2 with an average total EUI of 110.2 kWh/m^2 when adding hot water and electricity use. In terms of thermal comfort, a mean value of 2,429 hours per year was deemed as not comfortable according to ASHRAE 55 (ASHRAE, 2017). Figure 11.38 provides the overall distribution observed from all simulations for the three performance indicators and illustrates the wide range of possible building outputs. For example, the heating EUI in the simulated dwelling went from 10 to 150 kWh/m^2 depending on which

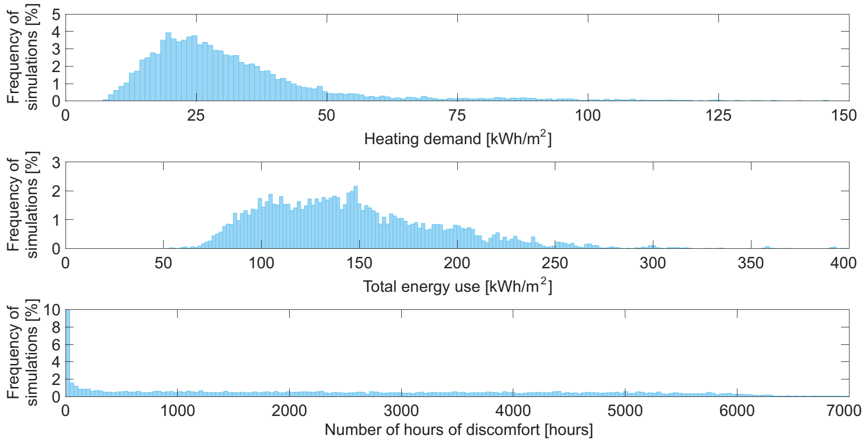

Figure 11.38 Projected distribution of various energy performance indicators depending on occupant behavior.

occupant profile was used. Note that in the monitored building, the space heating demand per dwelling ranged from 13 to 146 kWh/m^2, which was similar to the range obtained with the simulations. The same result was true for thermal comfort. On the one hand, there were multiple profiles that had close to zero hours of thermal discomfort. On the other hand, some profiles endured uncomfortable conditions for most of the year. The large range of energy consumption and thermal comfort conditions displayed in Figure 11.38 was similar to that observed in the actual dwellings.

For the three distributions shown in Figure 11.38, an important proportion of the simulations was located near the bottom boundary of the distribution where the contribution of each unit was small. This means that the overall energy consumption of the case study building was not as driven by the consumption of the majority of people in the dwellings as it was (at least to some extent) by its highest-consuming households. For instance, the average heating EUI in the biggest 15% of consumers was 77.4 kWh/m^2 versus 29.4 kWh/m^2 for the remaining 85% of households. This difference suggests that the current building design is sensitive to high levels of energy demand for certain types of behavior.

The distributions shown in Figure 11.38 were obtained for a single dwelling at the level at which a high diversity of behaviors was expected, which translated to a widespread of possible energy demands and thermal comfort. When more units were considered simultaneously (i.e., when the sample size increased), extreme behaviors canceled out and the variability of possible energy intensity and comfort level was reduced. This result suggests that large MURBs should be more robust in terms of energy performance with respect to occupant behavior.

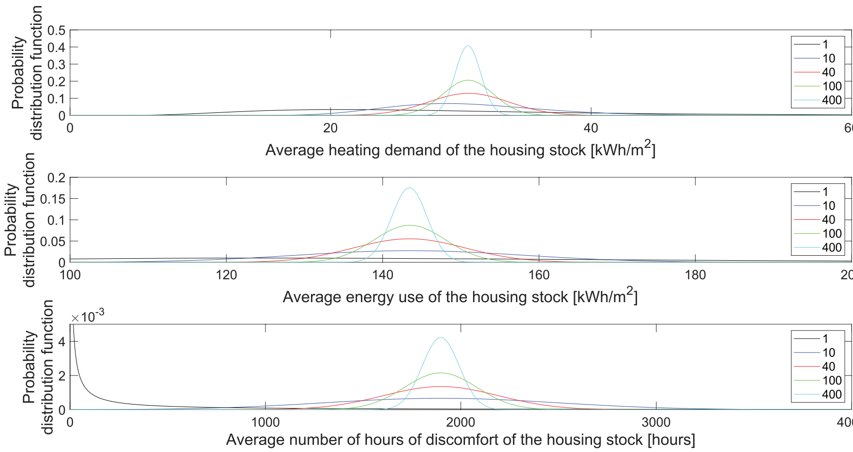

Figure 11.39 Impact of the number of units on the probability distribution of possible energy consumption, space heating consumption, and discomfort.

The energy and comfort distributions obtained from housing stocks of 1, 10, 40, 100, and 400 dwellings were considered. For each of these housing stock sizes, 10,000 combinations were randomly chosen from the simulations of the dwelling under different occupant behavior. The resulting distributions are displayed in Figure 11.39. The widest probability distribution function on each subplot corresponds to the distribution for a one-dwelling housing stock, and then the distributions become narrower as the housing stock increases, where the most cramped distribution is for a 400-dwelling housing stock. The case study building has 40 dwellings, and so the distribution projects that the annual heating EUI should be between 25 and 45 kWh/m^2, which is roughly what was observed year after year.

To improve the energy robustness of the building, it will be important to evaluate the reasons behind its high sensitivity to occupant behavior. In Figure 11.40, the outputs of each simulation are represented in multiple grids of 30 × 30 pixels. The color of a pixel conveys the average value of an aspect of occupant behavior for all simulations located within the pixel. For example, for simulated households with a heating demand between 75 and 100 kWh/m^2, the average frequency of opened windows is approximately 50% of the time.

At this point, the heatmaps were only produced for the actual building design, but the methodology can be applied to future building designs. Different configurations of building designs can be tested to assess their robustness regarding occupant behavior. One might envision robust design optimization, where the design is optimized not for a single occupant behavior profile but for various profiles to ensure that its high level of energy

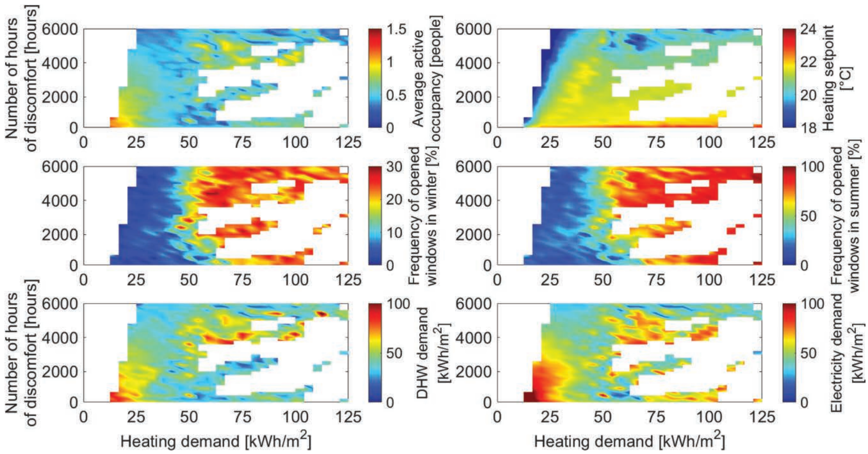

Figure 11.40 Heatmaps representing the influence of various aspects of occupant behavior on the heating demand and comfort performance of the building.

performance is sustained for the full array of possible occupant behaviors. Parametric-based studies are also possible, where designers can change values for a specific parameter (e.g., WWR) in the building model to see the changes in the distributions for the energy performance.

Robust design assessment offers additional information that can be provided to the building stakeholders with the generation of probability distributions. As discussed, typical pre-construction simulations yield only a single value of expected heating demand (or peak demand, thermal comfort, etc.). While this single expected value can be useful when comparing different designs, it regularly differs from reality; its predictive value is minimal. Generating probability distributions helps in that regard by providing a full range of possible outputs, which gives stakeholders a better idea of the range of performance that the building might exhibit.

Robust design assessment can also help building designers and owners identify behaviors that can drive up energy consumptions and to understand how the building responds to such behaviors. In this case study analysis, for instance, high window opening rates during the heating season were found to increase the heating EUI up to 100 kWh/m^2. If designers are not satisfied with this level of consumption, they could target designs that yield better performance with high window opening frequency (e.g., decrease WWR, increase mechanical ventilation rate to decrease the use of windows, inform occupants).

11.4.5 Concluding Remarks

This case study analysis demonstrated the significant influence that occupants can have on the energy performance of their dwellings. It is also another example of the much-discussed energy performance gap (i.e., actual energy consumption differs from projected energy consumption during the design phase of the building). This analysis showed that the energy performance gap in this case study building was mainly caused by a misrepresentation of occupants in the energy simulations. Occupant behavior is a highly uncertain parameter, especially in residential buildings where behaviors change from one household to another; it is practically impossible to accurately forecast this variable in the simulations used to design a building.

For these reasons, multiple occupant behavior profiles are recommended when designing buildings. This method can be used to guide the decision-making process during the design phase. For example, the method can be applied to energy simulations with different levels of insulation or different WWRs, and the resulting probability distributions can be observed for energy consumption. In addition to considering the most likely or average value of energy consumption, the designer could also consider the possibilities of achieving extreme values depending on how occupants use the building systems

11.5 Case Study 4: Melbourne, Australia

Ye Kang, Jenny Zhou

11.5.1 Summary

This case study building was the first large-scale timber structure built to Passivhaus standard in the southern hemisphere. This case study analysis evaluated the interactional behavior between occupants and the building, multi-story student accommodation. Design specifications and in situ performance were compared to identify misalignments in three occupant-centric variables: presence profile, interaction with electrical appliances and lighting, and thermal comfort. Compared to a fixed value defined by the Passivhaus simulation model, the actual occupant presence varied significantly between in-semester and semester break, between weekdays and weekends, and between private rooms and shared spaces. The simulation underestimated the use of electrical appliances and lighting and overlooked its time dependency. The building also suffered from overheating problems that had not been identified in the design stage. The result of this study can contribute to a deeper understanding of human behavior and thermal comfort in Passivhaus buildings. The measured data can also help to refine the parameter setting for human factor variables in the future occupant-centric design.

11.5.2 Building Description

The case study building (see Figures 11.41–11.43) is a Passivhaus-certified six-story student accommodation building that is located in the mild temperate climate zone of Melbourne, Australia. The PH building has a gross floor area

Figure 11.41 Photograph of the building exterior.

Figure 11.42 Photograph of the studio room.

Figure 11.43 Photograph of a communal space.

Table 11.7 Thermal transmittances (U-value) and total areas of the Melbourne building envelope

Components	*Average U-value (W/m² K)*	*Total area (m²)*
Wall system	0.308	2,814
Roof system	0.135	1,139
Ground floor system	0.843	1,009
Window	1.322	1,010

of ~5,200 m^2 that includes 150 independent studio rooms and various communal spaces. Each studio consists of a bedroom, an open-plan living/kitchen area, and a bathroom. The living/kitchen area is outfitted with a range of electrical appliances (cooktop, microwave, fridge, etc.). The communal spaces contain recreation rooms, communal kitchens, and a laundry room.

The building is of lightweight structure, with external walls and roofs built from cross-laminated timber (CLT) and a ground floor built from concrete panels. Rockwool and rigid foam insulation and triple-glazed windows were used to improve the thermal performance of the building envelope. The characteristics of the building envelope are summarized in Table 11.7. The building is equipped with three mechanical ventilation equipment with heat recovery (MVHR) units. The building management system (BMS) modulates air dampers to adjust the ventilation rate of the studios. The damper position remains in minimum mode (3.5 L/s) when the studio is vacant, and it adjusts to the max mode (10 L/s) and boost mode (25 L/s) based on the signal from the room key and bathroom light, respectively. When the average temperature of the floor exceeds 25°C for 10 minutes, the BMS will also activate the boost mode for the entire floor. The MVHR units are equipped with thermal batteries (via hot water) to provide tempered outdoor air to the student accommodations; the building has no active cooling systems. The building was occupied in February 2019.

11.5.3 Methodology

This section is arranged into three different sub-sections: (1) model and input variables, (2) in situ performance data collection and (3) TM52 method for overheating assessment, to address the objectives of this analysis.

11.5.3.1 Model and Input Variables

The Passive House Planning Package (PHPP) Version 9 simulation tool was used during the design stage to predict the building performance. PHPP is the only authorized software in the Australian context for PH certification (Australian Passive House Association, 2021). Similar to other building energy simulation tools, the PHPP is built upon energy conservation principles and heat balance equations, but it models the entire building as one single zone and generates simulation results on a monthly basis owing to the limitation of the spreadsheet computing environment (Passive House Institute, 2015).

The simulation required a range of inputs from weather data to building service equipment. This work focused on three occupant-centric variables:

- *Presence profile*: The occupancy fraction (i.e., percentage of time that a space is occupied) was used to describe the presence profile. In the PHPP simulation, the indoor spaces were assumed to be occupied all the time with the occupancy fraction of 1.
- *Interaction with electrical appliances and lighting*: The energy demand was calculated from three variables; power rate, use frequency, and the total number of occupants (Eq. 1) (Passive House Institute, 2015). The PHPP manual (Passive House Institute, 2015) provided default settings for the first two variables (Table 11.8), and the last parameter was estimated based on the building use: one occupant per studio and eight additional residents for building management. The simulation was unable to capture the time variance of the appliance and lighting use because the PHPP applies a "per year" rate to the power rate or use frequency.

$$E_{el} = V_{\mathrm{Norm}} \cdot h \cdot G \tag{11.2}$$

where
V_{Norm} is the power use of the appliance or lighting;
h is the use frequency of the appliance or lighting;
G is the total number of occupants.

- *Thermal comfort*: The PHPP applies overheating frequency (i.e., the percentage of time that the indoor temperature is above 25°C) to evaluate the thermal comfort of the building (Passive House Institute, 2015). When the annual overheating frequency exceeds 10%, the space is classified as overheating. To simplify the calculation, the PHPP database only specifies monthly average temperatures (Table 11.9) and a fixed

Table 11.8 The power rate and use frequency of electrical appliances and lighting

	Power rate	*Use frequency*
Dishwashing	0.8 kWh/use	65 use/(person-year)
Refrigerator	0.78 kWh/person-day	365 days/year
Cooktop	0.22 kWh/use	500 use/(person-year)
Television	80 W	1.5 hours/(person-year)
Small appliances	0.14 kWh/person-year	365 days/year
Lighting	10 W	8 hours/(person-year)

Table 11.9 Monthly average outdoor air temperature in Melbourne in the southern hemisphere

	January	*February*	*March*	*April*	*May*	*June*	*July*	*August*	*September*	*October*	*November*	*December*
T (°C)	20.6	20.8	19.0	15.8	13.0	10.7	10.1	11.0	12.7	14.6	17.1	18.8

Data were extracted from the PHPP database (Passive House Institute, 2015).

daily temperature swing (10°C). The PHPP evaluation completed for the case study building identified an overheating frequency of 6%, which meant there were no overheating concerns in the design stage.

In this case study analysis, the simulation results from these three occupant-centric variables are compared to in situ performance data to evaluate the interactional behavior between occupants and the multi-story student accommodation built to the Passivhaus standard.

11.5.3.2 In Situ Performance Data Collection

The building management system (BMS) and a wireless sensing platform were applied to collect in situ data for eight months from August 2019 to March 2020. The BMS recorded the energy use of the case study building and exterior temperature on an hourly basis. The indoor temperature and carbon dioxide (CO_2) concentration of indoor spaces were detected every 30 seconds using the wireless sensing platform. The monitoring devices were calibrated against standard reference instruments and displayed the accuracy of ±0.6°C for temperature and ±11 ppm for CO_2 concentration. Before the final data analysis and visualization, the sensor data were aggregated to hourly intervals to facilitate the comparison. Permission was granted to access 12 spaces in the building for device installation (Table 11.10). The 12 spaces spread over three floors and covered both studio rooms and communal spaces. Data collected by the BMS and the sensing platform were applied to pursue the three occupant-centric variables, as described below.

- *Presence profile:* The CO_2 concentration of indoor spaces recorded by the sensor nodes was used to determine the occupancy status and to generate the presence profiles. When the hourly CO_2 concentration

Table 11.10 The indoor monitoring stations and room characteristics

Room number	*Floor*	*Room type*	*Window orientation*
103	1	Communal	Northwest
108	1	Communal	Northwest
309	3	Studio	Northwest
314	3	Studio	Southwest
324	3	Studio	Southeast
327	3	Studio	Northeast
332	3	Communal	Northwest
609	6	Studio	Northwest
614	6	Studio	Southwest
624	6	Studio	Southeast
627	6	Studio	Northeast
632	6	Communal	Northwest

exceeded 550 ppm, the space was considered occupied. The 550 ppm was a cut-off value obtained from a four-day dataset measured during the Christmas holiday. It should be noted that this is a simplified approach as the indoor CO_2 concentration could be influenced by window operation and occupant behaviors. CO_2-based dynamic occupancy detection algorithms could further improve the accuracy of the outcomes.

- *Interactions with electrical appliances and lighting*: The BMS system disaggregated the energy use data of the case building into plug load, lighting, and other building service functions. The human interaction with electrical appliances and lighting was inferred from the BMS energy breakdown data.
- *Thermal comfort:* Considering the limitation of the fixed benchmark (25°C) in the PHPP tool (Fletcher *et al.*, 2017), the TM52 method (Chartered Institution of Building Services Engineers, 2013), an adaptive method derived from EN 15251 (CEN, 2007), was applied in this study to assess the overheating risk of the building. The TM52 method is further detailed in the following section.

11.5.3.3 TM52 Method for Overheating Assessment

The TM52 method defines three criteria for overheating assessment. All three criteria, listed below, are associated with the exceedance (ΔT), which refers to the difference (rounded to the nearest integer) between the operative temperature of the indoor space and the TM52 benchmark. A space is classified as overheated when it fails any two out of three criteria specified by the TM52 approach.

- Criterion 1: Hours of exceedance, H_e, should not exceed 3% of the occupied hours ($H_e \leq 3\%$). H_e represents the total number of hours that the ΔT is greater than 0°C between November and March (typical non-heating season in the southern hemisphere).
- Criterion 2: Daily weighted exceedance, W_e, should be no more than 6°C-hours in any one day ($W_e \leq 6$°C-h). W_e refers to the hours when the indoor temperature is above the benchmark ($\Delta T \geq 1$°C) during occupied hours, weighted by a factor that is a function dependent on how many degrees the benchmark has been exceeded (Equation 11.3).

$$W_e = \sum (h_e \times W_F), \tag{11.3}$$

where the weighting factor $W_F = 0$ if $\Delta T \leq 0$°C; otherwise, $W_F = \Delta T$, and h_e is the number of hours when $W_F = \Delta T$.

- Criterion 3: Maximum exceedance, max_ΔT, should be less than or equal to 4°C (max_$\Delta T \leq 4$°C). The max_ΔT represents the highest value of exceedance.

The determination of the exceedance (ΔT) and the TM52 benchmark (T_{ben}) is based on the exponentially weighted running mean outdoor temperature (T_{rm}) (Equations 11.4–11.6).

$$\Delta T = T_{op} - T_{ben} \tag{11.4}$$

$$T_{ben} = 0.33T_{rm} + 21.8 \tag{11.5}$$

$$T_{rm} = \begin{pmatrix} T_{out-1} + 0.8T_{out-2} + 0.6T_{out-3} + 0.5T_{out-4} + 0.4T_{out-5} \\ +0.3T_{out-6} + 0.2T_{out-7}) / 3.8 \end{pmatrix} \tag{11.6}$$

where,

T_{op} is the operative temperature of the indoor space, considering the thermal uniformity of the case study building, indoor air temperature (T_{in}) is a reasonable approximation for operative temperature (T_{op}) (Tabatabaei Sameni *et al.*, 2015).

T_{ben} is the benchmark.

T_{rm} is the exponentially weighted running mean outdoor temperature.

T_{out-1}, T_{out-2}, T_{out-3}, T_{out-4}, T_{out-5}, T_{out-6}, and T_{out-6} are the daily mean external temperature for the previous day, the day before, and so on.

11.5.4 Results and Discussion

A range of analyses was conducted to evaluate the interactional behavior between occupants and the case study building. The results are broken down into four sub-sections: (1) occupant presence, (2) use of electrical appliances and lighting, (3) thermal comfort, and (4) recommendations to improve the PHPP software. Each is discussed in turn below.

11.5.4.1 Occupant Presence

Figure 11.44 shows the occupancy fraction of the studio rooms (marked as orange) and communal spaces (marked as blue) of the case building. The occupancy data were disaggregated by in-semester/semester break and weekday/weekend designations. In contrast to the default setting in the PHPP tool (i.e., the building was assumed to be always occupied), the actual occupancy fraction of the measured spaces fluctuated.

There were significant differences between in-semester and semester break occupancy. The studio rooms had occupancy fractions ranging from 0.32 to 0.79 (with an average of 0.56) during the semester, but the values were decreased to 0.03–0.09 (with an average of 0.07) during the break. Similarly, the off-peak occupancy fraction (0.01–0.68, with an average of 0.35) was much lower than the in-semester values (0.01–0.18, with an average of 0.10) in communal spaces. The decrease in occupancy fraction during the semester break could be attributed to the increased vacancy in student accommodation during the semester break.

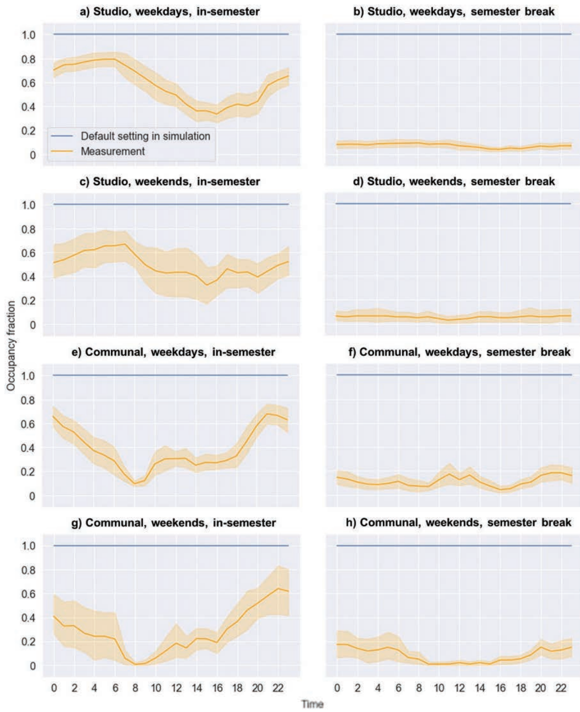

Figure 11.44 Measured occupancy fraction of the studio rooms on (a) weekdays, in-semester, (b) weekdays, semester break, (c) weekends, in-semester and (d) weekends, semester break, and communal spaces on (e) weekdays, in-semester, (f) weekdays, semester break, (g) weekends, in-semester, and (h) weekends, semester break. The uncertainty bounds represent the standard deviation. Semester: August 2019 to November 2019, March 2020; Semester break: December 2019 to February 2020.

The occupancy schedules also varied between weekdays and weekends during the semester. In studio rooms, a slight reduction in occupancy fraction could be found on weekends (0.32–0.67, with an average of 0.50; Figure 11.44c) compared to weekdays (0.34–0.79, with an average of 0.58; Figure 11.44a). A similar trend could be observed in communal spaces (0. 10–0.68, with an average of 0.38 for weekdays; Figure 11.44e; 0.01–0.64, with an average of 0.28 for weekends; Figure 11.41g). The decreasing occupancy fraction on weekends could be associated with the fact that the students had more opportunities to attend off-campus activities during this period and thus left their studios for a considerable amount of time. Considering the constantly low occupancy fraction (<0.2) of the case study building during the semester break, no discernible discrepancy in occupancy profiles could be discovered between weekdays and weekends.

The discrepancy in occupancy profiles between studio rooms and communal spaces also needs to be considered. During the weekdays of the semester (Figure 11.44a), the studios displayed the highest occupancy fraction (ranging between 0.7 and 0.79) between 00h00 (midnight) and 6h00 because most occupants preferred to stay in the studio and sleep during this period. Then, the values reduced significantly until 16h00 (occupancy fraction of 0.34), likely because students woke up and left their studios to attend various courses and activities.

After 16h00, people began to return to their studios and the occupancy fraction increased to 0.65 at 23h00. In contrast, a significant reduction of the occupancy fraction could be found from 0.66 to 0.10 between 00h00 and 8h00 in communal spaces (Figure 11.44e), as individuals left communal spaces and returned to their studios for sleeping. After that, the value rose to 0.30 at 11h00 and then fluctuated between 0.25 and 0.31 until 18h00. In the evening, as individuals entered the communal spaces for entertainment and group activities, the occupancy fraction escalated again and reached the maximum value (0.68) at 21h00. Later, the value declined until 23h00. The discrepancy in occupancy profiles between studio and communal spaces could also be observed on weekends of the semester and during the semester break.

11.5.4.2 Use of Electrical Appliances and Lighting

Figure 11.45 shows the power density of electrical appliances and lighting. Similar to occupancy profiles, the on-site data related to electrical appliances were categorized by in-semester/semester break and by weekday/weekend. In comparison to the default settings in the PHPP tool (1.9 W/m^2 for electrical appliances; 0.1 W/m^2 for lighting), the measured power density of electrical appliances and lighting ranged from 1.0 to 5.5 W/m^2 (an average of 2.7 W/m^2) and from 0 to 2.9 W/m^2 (an average of 1.7 W/m^2), respectively.

As expected, the power density of electrical appliances and lighting was much higher during the semester as compared to the semester break. Electrical appliances in-semester value (2.6–5.5 W/m^2, with an average of 3.6 W/m^2) was approximately three times the off-peak data (1.0–1.8 W/m^2, with an average of 1.3 W/m^2). A similar trend was observed for lighting, the case study building required 0.5–2.9 W/m^2 (with an average of 2.1 W/m^2) for lighting during the semester, and the power density was reduced to 0–2.1 W/m^2 (with an average of 1.0 W/m^2) during the break. The significant reduction in power density during the semester break could be attributed to the increased vacancy, as mentioned in the previous section.

The variation in the power density of the electrical appliances could also be observed between weekdays and weekends during the semester. The power density of the electrical appliances decreased from 3.6 to 2.7 W/m^2 between 00h00 and 5h00 (Figure 11.45a) as individuals stopped using electrical appliances and fell asleep. When students woke up, the value

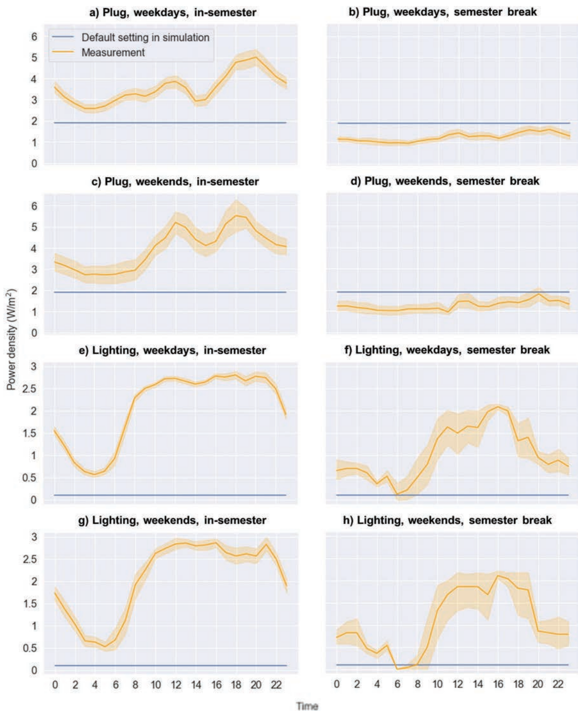

Figure 11.45 Power density of electrical appliances on (a) weekdays, in-semester, (b) weekdays, semester break, (c) weekends, in-semester and (d) weekends, semester break and lighting on (e) weekdays, in-semester, (f) weekdays, semester break, (g) weekends, in-semester and (h) weekends, semester break. The uncertainty bounds represent the standard deviation. Semester: August 2019 to November 2019, March 2020; Semester break: December 2019 to February 2020.

increased and reached the first peak (3.9 W/m^2) at 12h00 (lunchtime). Then after another reduction (12h00 to 14h00) and growth (14h00 to 20h00), the power density reached the second peak (5.2 W/m^2) at 20h00 (suppertime). The two peaks could be attributed to the cooking and corresponding energy demand related to kitchenware (e.g., microwave oven and cooktop). During the weekends, the electrical appliances were found to consume more energy than on weekdays (Figure 11.45c). The power density reached 5.2 and 5.5 W/m^2 at 12h00 (first peak) and 18h00 (second peak). The higher energy consumption during the weekends can be related to the fact that students did not have any courses during this period and could spend more time cooking. During the semester break, no significant difference in the power density of electrical appliances was observed between weekdays and weekends due to high vacancy.

There was no discernible discrepancy in the lighting power density between in-semester weekdays and weekends, despite the increased vacancy during the weekends (see the previous section). Considering the utility expense was amalgamated into the fixed rent, some vacant studio rooms might have had the lights left on during the weekends by less energy-conscious occupants. During the weekdays (Figure 11.45e), the power density of the lighting diminished from 1.6 to 0.6 W/m^2 between 00h00 and 4h00, as students fell asleep and turned off the lights. Then the value rose to 2.7 W/m^2 at noon with occupants getting up. After that, the power density fluctuated between 2.6 and 2.8 W/m^2 until 21h00, which was likely because individuals (who were not responsible for the energy bills) preferred to keep the lights on. After 21h00, the occupants began to rest, and the value dropped again. A similar profile was observed during the weekends (Figure 11.45g). No obvious variation was discovered in the lighting power density between weekdays and weekends during the semester break. It should be noted that considering the lights in the communal spaces were always on during the daytime, the lighting power density was observed to exceed 1 W/m^2 even during the semester break.

11.5.4.3 Thermal Comfort

The thermal comfort results based on the TM52 method are displayed in Table 11.11. It is worth mentioning that this table only shows data for five months (November 2019 to March 2020), which covered the non-heating season in the southern hemisphere. The remaining months were not in the scope of the TM52 analysis.

Although the PHPP simulation tool reported no overheating risk in the case study building, all 12 selected spaces were observed to have overheating

Table 11.11 TM52 analysis result summary

Room number	*TM52 method*			*Overheated (at least two criteria failed)*
	H_e (%)	*Annual max We (°C-h)*	*Annual max_ΔT (°C)*	
103	0	0	0	No
108	0	0	0	No
309	0.17	40	5	Yes
314	0.08	56	5	Yes
324	0.08	64	4	Yes
327	0.15	76	6	Yes
332	0.09	28	5	Yes
609	0.12	32	7	Yes
614	0.08	27	4	Yes
624	0.04	25	4	Yes
627	0.13	50	8	Yes
632	0.12	29	5	Yes

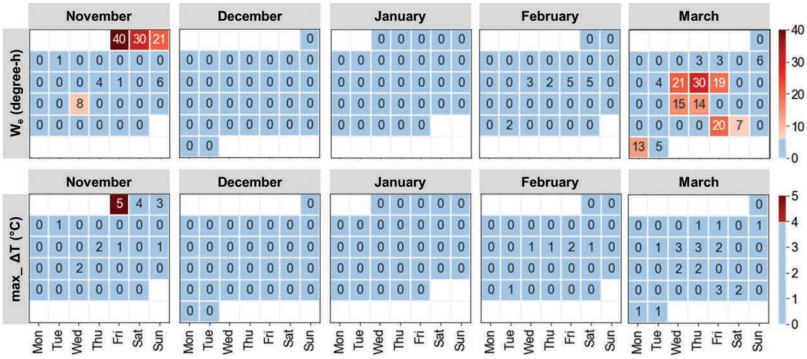

Figure 11.46 Daily weighted exceedance (W_e) and daily maximum exceedance (max_ ΔT) of room 309 between November 2019 and March 2020 in the southern hemisphere.

problems with the annual overheating frequency above 10%. Additionally, all the selected spaces on the third and sixth floors were classified as overheated based on TM52 analysis, as they failed both Criterion 1 and Criterion 2. Some occupants in the case study building also reported overheating problems. The overheating problem is likely because the PHPP recommended inputs underestimated the heat emitted from electrical appliances and lighting. As shown in Figure 11.46, the daily weighted exceedance (W_e) of room 309 was found to be higher than the threshold specified by the TM52 method (6°C-h) during the semester (i.e., November and March), likely because the in situ energy consumption for electrical appliances (with an average of 3.6 W/m^2, see Figure 11.45a and c) and lighting (with an average of 2.1 W/m^2, see Figure 11.45e and g) was much higher than that considered in the PHPP (1.9 W/m^2 for electrical appliances and 0.1 W/m^2 for lighting). The uncertainty in weather could also be a contributor. The maximum exceedance (max_ΔT) of room 309 was observed to reach 5°C, higher than the TM52 threshold (4°C), on the 1st of November (see Figure 11.46). In the PHPP software, the average monthly outdoor temperature in November was assumed to be 17.1°C (see Table 11.9) and a fixed value (10°C) was applied to represent the diurnal temperature fluctuation. In contrast, the maximum outdoor temperature recorded on the 1st of November reached 34°C. The maximum outdoor temperature measured on-site higher than that simulated in the PHPP software could be the main reason contributing to the high exceedance (ΔT) of room 309 on the 1st of November. Similar trends were observed in all the other selected rooms.

11.5.4.4 Recommendations to Improve the PHPP Software

The following strategies are proposed to reduce the performance gap of the Passivhaus case study building:

- The monthly quasi-steady state method in the PHPP software could be substituted by a dynamic building simulation model. The dynamic simulation could consider the variation of outdoor temperature and human interaction with plug load and lighting on an hourly basis. Thus, it could deliver more accurate simulation outcomes than the monthly calculation method. Additionally, the incorporation of dynamic simulation with the TM52 model could provide opportunities to better predict the overheating problems of the case building.
- A feedback loop could be integrated into the PHPP software to bring the predicted outcomes closer to reality. It is because the feedback mechanism could enable the incorporation of variations in occupant behavior and different building electrical appliance profiles into the PHPP simulation tool. The feedback loop could be used to better inform building design by identifying common mistaken assumptions. This process could be supported by various advanced methods, such as low-cost sensing techniques and post-occupancy evaluation.

11.5.5 Concluding Remarks

To summarize, the performance of a recently constructed Passivhaus student accommodation in the operational stage was compared to the corresponding PHPP simulation in the design stage to develop an in-depth understanding of occupant behavior in large Passivhaus buildings. The temporal schedule of occupancy, the human interaction with electrical appliances and lighting, and thermal comfort were analyzed and discussed.

The PHPP simulation assumed that spaces were always occupied, but this simplification does not work well, as evident by the fluctuating occupancy fraction. Discernible variation can be found between in-semester and semester breaks and between weekdays and weekends. The fluctuation of the occupancy fraction can be attributed to the discrepancy in occupants' activities. The design prediction underestimated the use of electrical appliance and lighting. The use frequency defined by the Passivhaus authority would have been a valid assumption for small family dwelling cases but not for the examined student accommodations. In addition, the occupants of the student accommodation may have been less energy-conscious with their appliance and lighting use since the utility expense was amalgamated into the fixed rent. There were also serious overheating issues that had not been identified in the design stage. The increased heat emission from electrical appliances and lighting and uncertainty in weather data contributed to the discrepancy in thermal comfort assessment.

Considering the limitation of the classical PH design applied in this study, adopting a dynamic building simulation model and feedback loop to recognize the context-dependent features of human behavior is suggested. Future occupant-centric building design should also consider the energy-consciousness of occupants, as it is a factor that can significantly affect occupant-building interactions and, consequently, building performance

11.6 Case Study 5: Redwood City, USA

Andrew Sonta, Thomas Dougherty, Rishee Jain

11.6.1 Summary

This case study considers the question of leveraging information on occupant behavioral patterns to optimize a commercial building's layout in terms of seat assignments in an effort to save energy. The case-study building is a three-story commercial office building located in Redwood City, California, USA, in a warm-summer, Mediterranean climate. Real-time data collected from one floor of the building was used to establish a correlation between zone-level lighting energy consumption and diversity in occupant behavior, where *diversity* refers to the level of differences in space use among occupants within a particular building zone. A data-driven surrogate simulation model was used to estimate lighting energy consumption as a result of changes to the building's layout. Both clustering-based and genetic algorithm optimization routines were introduced to find the layout that reduced lighting energy as much as possible. Through simulation, it was found that optimizing the building's layout can reduce lighting energy consumption by 5% compared to the existing layout. This study demonstrates the ability to use low-cost ambient sensing infrastructure to reconsider the layouts of existing buildings based on the past behavioral patterns of its occupants.

11.6.2 Building Description

This case study building is a three-story commercial office building located in Redwood City, California (Figure 11.47). The building is owned and operated by Stanford University and largely houses university operations staff. The building was completed in 2019. Plug load energy sensors were installed at each workstation on the third floor of the building (164 workstations) in June 2019, just before occupancy began (see sensor details in "Plug load energy sensors" below).

These plug load energy sensors enabled analysis of occupancy patterns. Workers were each assigned their own workstation, which did not change over the study period. The office design can be characterized as open plan, with large, shared office spaces in addition to meeting rooms of various sizes. Generally, occupants used the spaces during standard, but flexible, business hours: 7h00–19h00 Monday through Friday. Through the building management system's application programming interface (API), the energy consumption of the lighting system (see details in "Lighting system and zones" below) was also collected. The lighting system is controlled with infrared sensors by zone; 11 of the lighting zones service the 164 workstations in this office building. The data-collection period spanned August 1, 2019 to February 29, 2020. Due to sensor outages at the beginning of data collection, data collected between August 1 and September 30, 2019, was

Figure 11.47 Stanford case study building.

discarded. Data collected between December 16, 2019, and January 4, 2020, was also discarded due to irregularities during the university's winter holiday break. The analysis therefore included 132 full days of data. The collection of highly granular occupancy data alongside lighting energy data enabled analysis of the relationship between occupant behavior and energy consumption.

11.6.2.1 Plug Load Energy Sensors

Installed at each workstation on the third floor of the building were Zooz SmartPlugs, which communicated using Z-Wave technology to a Samsung SmartThings hub. A schematic of the sensing strategy is shown in Figure 11.48. The sensors reported power consumption values any time the power consumption varied by more than 0.1 W. Consistent with previous work (Sonta *et al*., 2018; Sonta and Jain, 2020), the power consumption was aggregated to 15-minute intervals. This 15-minute scale offered insight into occupant behavioral patterns while reducing noise.

11.6.2.2 Lighting System and Zones

The building is equipped with an automated lighting system that operates using infrared occupancy sensors, daylighting sensors, and schedules. This system is controlled by zone (as shown in Figure 11.49). The occupancy sensors turn on the lights in the zone if they sense any motion in the past

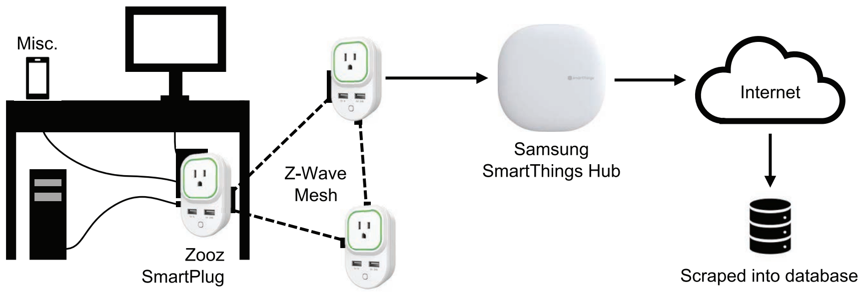

Figure 11.48 Schematic of plug load sensing data collection.

Figure 11.49 Floorplan diagram, with open office areas shown in white, workstations and meeting rooms in blue, and the ten lighting zones servicing workstations in red.

20 minutes (10 minutes on the weekends). Eleven of the lighting zones service all 164 workstations. There are other lighting zones that service the small, shared spaces of the building (e.g., meeting rooms, break areas), but analysis was restricted to the zones that service workstations, as this study focused on how workstation space use impacts lighting energy for those spaces. This lighting energy data were scraped for each fixture at one-hour intervals.

11.6.3 Methodology

This section describes the methodology for optimizing the layouts of existing buildings by leveraging individualized occupancy data, that is, data ascribed to each individual occupant (as outlined in Figure 11.50). First, the time series plug load energy data at each workstation was used to model occupancy schedules. The methodology introduced by Sonta *et al.* (2018)

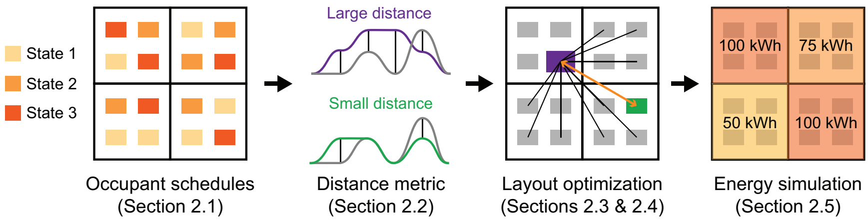

Figure 11.50 Methodology overview: Occupant schedules were used to measure zone diversity, which enabled layout optimization. Energy simulation was used to estimate the impact of layout optimization.

was leveraged to abstract the raw time series data into activity states, which describe patterns of space use and individual schedules. A distance metric, referred to as zone diversity, was introduced to describe the level of differences among the occupants' schedules within each lighting zone. This metric allowed the characterization of the relationship between zone diversity and empirical energy data, which has been theorized in the literature to be a positive relationship (Yang *et al*., 2016). Given this theoretical relationship, two optimization routines were developed to rearrange the occupants' seat assignments. One optimization spatially clustered occupants in a manner that reduced zone diversity. The other, a genetic algorithm, leveraged a data-driven surrogate model for simulating energy consumption based on the layout. This surrogate model used both the occupant layout and the individualized occupant behavior data to estimate the energy consumption of the building's lighting system.

11.6.3.1 Individualized Occupant Schedules from Plug Load Energy Data

This section briefly describes the process for abstracting data streams from plug load monitoring devices into individualized occupant schedules. The key insight that enabled this process was that time series plug load energy signatures provide information about how occupants are interacting with their workstations. For example, higher energy consumption indicates that occupants are interacting with the electronic equipment at their workstations and are therefore likely to be actively using their workspaces. Lower energy consumption indicates that occupants have stopped interacting with this equipment and are likely away from their workstations. In this case study, the time series plug load data was defined as $\mathbf{X}_{i,\ d}$, where i is the occupant index and d is the day index. Each entry in $\mathbf{X}_{i,\ d}$ is a vector $\{x_1,..., x_T\}$ where T is the number of time steps during the day (here, $T = 96$). The method described in detail in Sonta *et al.* (2018) was used to map this raw data onto the abstracted occupant schedules: $\mathbf{X}_{i,\ d} \rightarrow \mathbf{S}_{i,\ d}$. This mapping leveraged a variational Bayesian Gaussian Mixture Model to cluster the raw time series data into discrete states. As in Sonta *et al.* (2018), a two-step process was used, whereby the data for each occupant for each day was first clustered into two components, effectively clustering out the low-energy data (data near 0 W). The higher energy data was then clustered again, as this data generally maintains higher variability. As in past work, the higher energy data was clustered into two further components, giving three components in total: low energy, medium energy, and high energy ($\mathbf{X} \rightarrow \mathbf{S}$, where $s_{i,\ d}^{t} \cdot \in \cdot \{1,2,3\}$). Hereafter, these time series of clustered states are referred to as occupant schedules.

11.6.3.2 Zone Diversity

Given these individualized occupant schedules, a method was adapted from the building operation literature for characterizing the similarities and differences in the behavioral patterns of all occupants within a zone. These similarities and differences are referred to as *zone diversity*, with a higher zone diversity indicating a greater level of differences in behavior. Based on the work of Yang *et al.* (2016), this diversity metric was computed as the Euclidean distance among all vectors containing the occupant schedule data. It should be noted that other distance metrics could have been used (e.g., Manhattan distance, cosine similarity), but it was found that the specific distance metric did not have a meaningful impact on the analysis. With the schedule data defined as $\mathbf{S}_{i,\ t}$, where i is the occupant index and t an arbitrary time index, the distance between any two occupants i and j was computed via Equation (11.7):

$$d_{i,\ j} = \sqrt{\sum_{t=0}^{T} \left(\mathbf{S}_{i,\ t} - \mathbf{S}_{j,\ t}\right)^2} \tag{11.7}$$

The distances between all pairs of occupants were computed within each zone, which formed a distance matrix. This matrix was normalized by the total number of entries (excluding the diagonals, because the distance between occupants and themselves is 0). This normalized value is the overall *zone diversity*. Then, zone diversity computed over the course of a single day (i.e., $T = 96$) was compared to the energy consumption of the lighting system summed over a single day.

11.6.3.3 Optimizing Layouts: Naïve Clustering

The zone diversity metric quantifies the level of differences in occupant dynamics within each building zone. Given that higher zone diversity can be expected to cause more energy consumption, a clustering algorithm was developed to change the occupant layout in an effort to reduce the diversity. A challenge in working with time series data is that the dimension of the vectors used for the distance calculation can grow quickly (e.g., 35,000 signals per year per occupant in our case). Distance metrics are known to be costly to compute and to potentially lose meaning when applied to data of such high dimensionality—often referred to as the curse of dimensionality. Therefore, singular value decomposition (SVD) was used in this study to reduce the dimensionality of the occupancy data without losing valuable information. SVD was applied to the occupant schedule data matrix **S**, which has dimension $I \times D \cdot T$. The user can choose the number of dimensions d retained, up to I (in this case, 151), so that the resulting matrix is $I \times d$ with $d \le I$. It should be noted that the zone diversity metric can be computed for either the unreduced data or the reduced data.

The data in **S** (reduced or otherwise) can then be used to cluster occupants. The next paragraphs describe the stochastic optimization routine used in this study for reducing zone diversity based on past occupancy data. This particular clustering problem had the real-world constraint that each building zone had a predefined size (i.e., number of workstations). Therefore, the resulting cluster sizes needed to match the sizes of the zones, which prevented the use of standard clustering algorithms such as *k*-means. The clustering algorithm simulated occupant "swaps", whereby two individuals swap locations, and then the resulting zone diversity was calculated.

Figure 11.51 outlines the algorithm. First, a random occupant, with replacement, was selected. Then, the effect on overall zone diversity across all building zones was simulated when the selected occupant was swapped with all other occupants in the building. The swap that produced the largest reduction in overall zone diversity was completed. This swap could include the null action of swapping the occupant with itself. The process was repeated by manually setting an iteration limit, beyond which no further improvement in overall zone diversity was seen. It should be noted that this stopping criterion could be automated if desired.

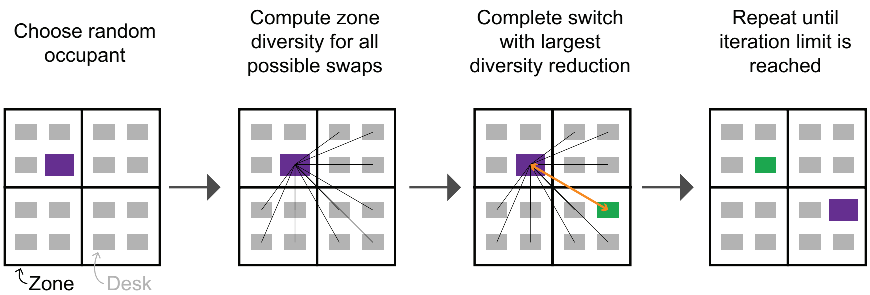

Figure 11.51 Occupant clustering algorithm.

11.6.3.4 Optimizing Layouts: Genetic Algorithm

The spatial optimization problem considered in this case study has an extremely large solution space. In an effort to fully explore the solution space and gain confidence in our clustering approach, an optimization routine that made direct use of our expected energy outcomes was also implemented. The clustering approach was designed to reduce zone diversity efficiently, but it does not explicitly consider energy consumption of building systems. It assumes that reducing zone diversity will have the effect of reducing energy consumption because these two concepts are hypothesized to be related. However, in this study, to optimize explicitly for energy, a simulation engine was required for predicting energy as new layouts are produced. The genetic algorithm optimization approach used to explicitly optimize for energy reduction is described here, and the data-driven surrogate simulation model is described in the following subsection.

Genetic algorithms belong to a class of evolutionary optimization algorithms originally inspired by the process of natural selection. They make use of a fitness function, which in our case study was expected energy consumption. This study's genetic algorithm routine started with a set of random design points x—in this case, occupant layouts—in an initial population **P**. The energy consumption of each design point was evaluated, and the **B** best performing designs were chosen as well as **R** random designs in order to maintain diversity. A key step in genetic algorithms is the recombination of selected designs in order to produce a new generation of designs based on the previous generation. For a pair of selected designs, this recombination was done c times. The first step is crossover, whereby a random selection of the two occupants in the two "parent" designs was selected for each desk location. The next step in recombination is mutation, which occurred with probability m. If mutation did occur, a random occupant in each zone was swapped with a random occupant in another random zone. This recombination was repeated until a new generation was formed. This overall process repeated G times. Figure 11.52 represents the algorithm and a visual summary of the crossover and mutation steps.

11.6.3.5 Data-Driven Surrogate Energy Simulation Model

To evaluate the impact of the occupant layout on energy consumption, a simulation engine that considers the key features of occupant layout and historical occupant schedule data was implemented. There are two major categories of building energy simulation: physics-based thermodynamic models (e.g., EnergyPlus), and data-driven "surrogate" models. Thermodynamic models can be particularly helpful when modeling heat flows, such as in the case of HVAC systems. However, these models are also quite complex and can be prohibitively time-intensive when evaluating many different

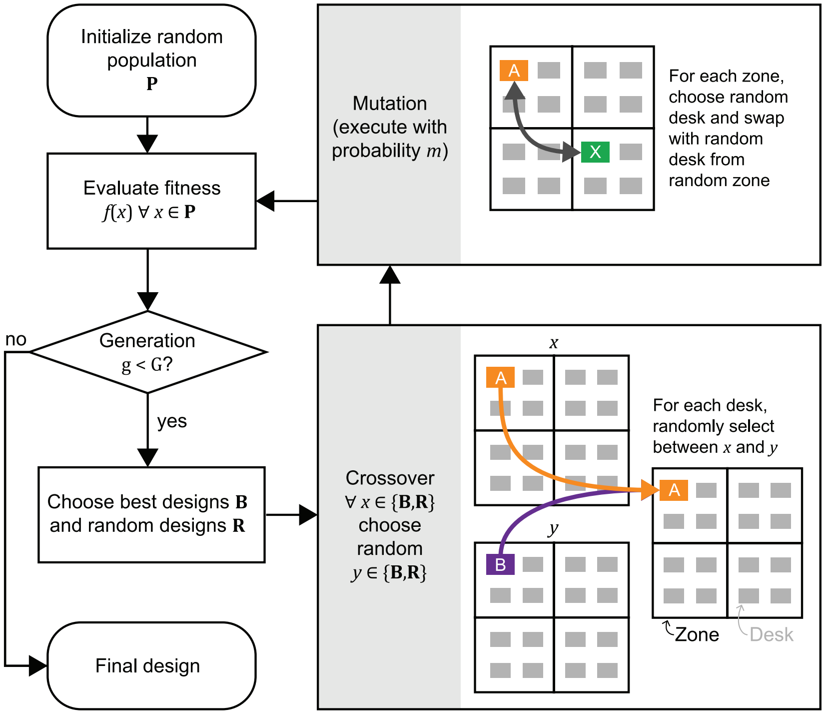

Figure 11.52 Genetic algorithm adapted for building layout optimization.

alternatives. Data-driven simulation models are growing in popularity for a variety of tasks and significantly reduce the time cost of prediction.

Because the present case study considers the lighting system, which is controlled through simple on/off sensors, a data-driven surrogate model was chosen for simulation. This surrogate modeling approach amounted to a machine learning problem that considered the study's key features (layout and schedules) to predict lighting energy consumption. We tested several models—multiple linear regression (MLR), support vector regression (SVR), random forests (RF), and artificial neural networks (ANN)—to determine the most robust model for the study's purpose. Each of these models has been applied to energy prediction tasks in the past (Ekici and Aksoy, 2009; Jain *et al*., 2014; Ahmad *et al*., 2017; Wang *et al*., 2018). Key aspects of the surrogate modeling tests are listed below.

- **Features:** Seven specific features for this prediction task were identified:
  - s_1, s_2, s_3: the occupant energy states as described above, for each occupant in each zone.
  - Hour of day (0–23)

- Day of week (0–6)
- Weekend/weekday indicator (0 or 1)
- Zone number (0–number of zones)

It should be noted that the inclusion of both the day or week feature and the weekend/weekday feature can introduce multicollinearity. While this may reduce confidence when conducting hypothesis testing, it does not negatively impact the power of the machine learning algorithms. For the non-tree-based models (i.e., MLR, SVR, and ANN), the day of week and zone number features were one-hot encoded. For these models, the hour-of-day feature was also transformed using sine and cosine transformations to preserve cyclicity. Lastly, the state count features were transformed using a sigmoid function, as there are diminishing returns to having increasing occupants in each state. All features were scaled to fall between 0 and 1. These transformations are not required for the RF model, as the decisions on the trees in the model are invariant to this scaling.

- **Training and testing:** The data was split into a training set and a test set, using fivefold cross validation on the training test for model development. The training/test split was 80%–20%, and the choice was made to preserve the time-series order in this split so that the time-series nature of the predictions could be visualized.
- **Hyperparameter tuning:** For the high-performing models, any hyperparameters were tuned using fivefold cross validation on the training set. The specific hyperparameters for the high-performing models are discussed in "Data-driven prediction of energy consumption" below.

With this surrogate modeling approach defined and the layout optimization routines discussed above, simulation-based results from layout optimization can be analyzed.

11.6.4 Results and Discussion

This section describes the key results from the case study analysis and discusses their significance for occupant-centric design. The results are broken down into three sections: (1) analysis of zone diversity and energy consumption, (2) data-driven surrogate model performance, and (3) analysis of occupant layout optimization.

11.6.4.1 Energy Consumption versus Zone Diversity

A regression analysis was completed between the lighting energy consumption and the zone diversity metric. The analysis involved each of the 11 zones using energy and diversity data aggregated by day over the data-collection period. Zone diversity was computed using the Euclidean distance of the 96-dimensional vectors for each zone for each day, and the average lighting

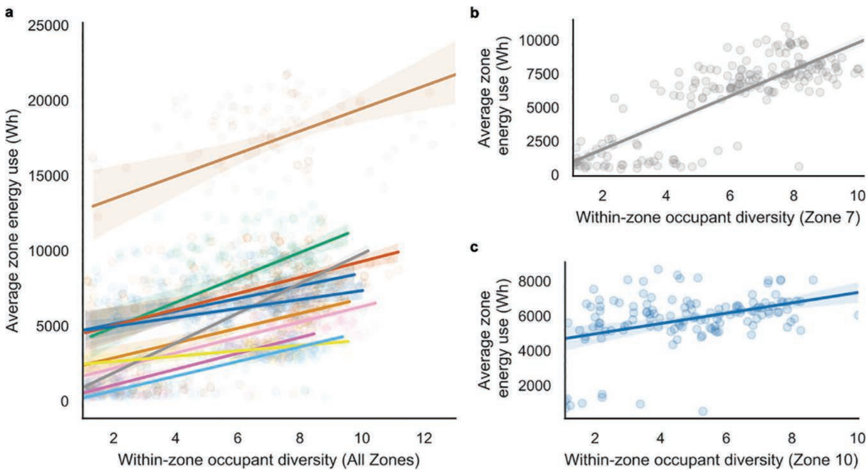

Figure 11.53 Relationship between zone diversity metric and energy consumption along with regression fits and confidence intervals for (a) all zones—with colors representing different zones, (b) zone with the largest regression coefficient (zone 7), and (c) zone with the smallest regression coefficient (zone 10).

consumption was computed across lighting fixtures within each zone. The regression analysis found that there exists a positive relationship between energy consumption and zone diversity for each zone, with the *p*-values for the *t*-statistics being significant at the 0.001 level for all zones. Figure 11.53 shows the data along with the regression lines for (a) all zones, (b) the zone with the strongest relationship in terms of the regression coefficient (zone 7), and (c) the zone with the weakest relationship (zone 10).

This result suggests that reducing zone diversity would be a means to reduce the energy consumption of the lighting system. The following sections present the results for simulating energy consumption based on occupant schedules as well as optimizing building layouts in order to reduce this energy consumption.

11.6.4.2 Data-Driven Prediction of Energy Consumption

The four models described above (MLR, SVR, RF, and ANN) were tested using the fivefold cross-validation methodology. Table 11.12 shows the performance of each model, as estimated through cross validation, using standard metrics, as well as the time required for both training and prediction in this case. The RF model performed the best in terms of MAE, while the ANN performed the best in terms of MSE and R^2. Therefore, these two models were chosen for hyperparameter tuning. Again, fivefold cross

Table 11.12 Energy prediction model results on fivefold cross-validation

Model	*Mean absolute error (MAE)*	*Mean squared error (MSE)*	*Explained variance (R^2)*	*Time for training (s)*	*Time for prediction (s)*
Multiple linear regression	9.55	141	0.534	0.0311	0.00198
Support vector regression	7.13	118	0.614	30.9	4.38
Random forest regression	6.11	98.2	0.678	2.82	0.0983
Artificial neural network	6.29	88.7	0.710	54.8	0.0105

Table 11.13 Energy prediction model results after hyperparameter tuning on both fivefold cross-validation and final test set

Model	*Errors on CV*			*Errors on test set*	
	Mean absolute error (MAE)	*Mean squared error (MSE)*	*Explained variance (R^2)*	*Explained variance (R^2) Hourly*	*Explained variance (R^2) Daily*
Tuned random forest regression	6.27	87.1	0.715	0.740	0.834
Tuned artificial neural network	6.28	88.5	0.710	0.734	0.817

validation was performed, and these parameters were tuned using a grid search. The final parameters for each model were as follows:

- ANN: single hidden layer of size 100, tan*h* activation function, Adam solver, learning rate of 0.01.
- RF: 200 trees, minimum split size of 50, minimum samples per leaf of 2, maximum depth of 300, bootstrap used in model training.

Model performance after training is shown in Table 11.13. The RF model outperformed the ANN model after hyperparameter tuning. In addition to calculating R^2 for hourly lighting energy prediction values, the data by day was also aggregated and the R^2 for these daily values computed. Prediction improved for both models, especially the RF model, after this aggregation.

Figure 11.54 shows the actual vs. predicted energy consumption (using the tuned RF model) for the first seven days in the test set for zone 1. The model, while not perfect, accurately captured the major jumps between low energy and high energy consumption. One of the benefits of the RF model is that

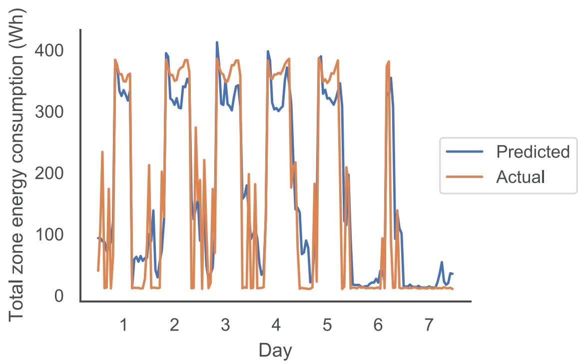

Figure 11.54 Example predicted (using tuned RF model) versus actual energy consumption data for the first seven days of data in the test set for zone 1.

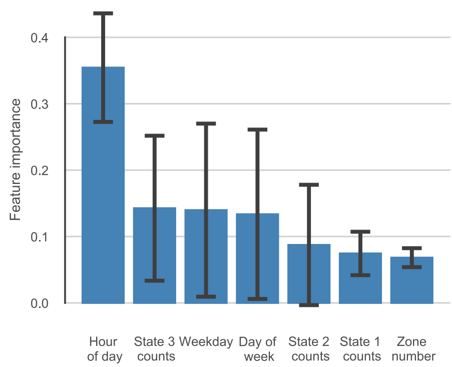

Figure 11.55 Feature importance for the final tuned random forest regression model.

it is quite interpretable in that the importance of each feature in the model can be quantified. The feature importance was calculated using the Gini importance metric, which can be interpreted as the relative number of times tree decisions involved a particular metric (see Figure 11.55). The number of occupants in state 3, the high-energy state, was the second most important feature. This finding may explain why the jumps between high and low energy consumption were accurately captured in the simulation model: the presence of occupants causes the lights to turn on, and this was accurately captured in the model.

11.6.4.3 Occupant Layout Optimization

The surrogate simulation model was leveraged to estimate the energy consumption of the lighting system for the existing occupant layout using the full

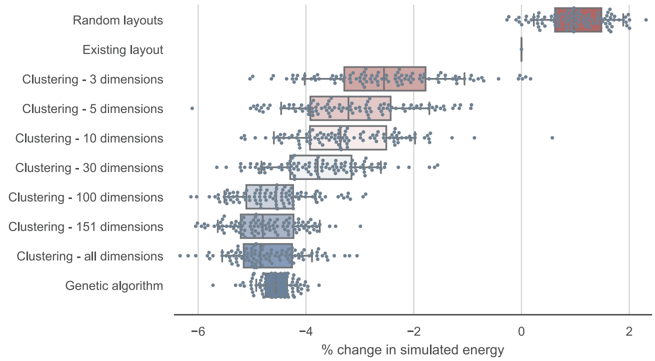

Figure 11.56 Simulated energy consumption (expressed as % change from the existing layout) for random and optimized building layouts.

132 days of data, which serves as a baseline. One hundred random occupant layouts were also produced and energy consumption was estimated again. Then, the clustering-based algorithm was applied using increasing dimensionality (3, 5, 10, 100, 151, and full dimensionality without reduction). The genetic algorithm was also implemented, which explicitly used the surrogate model in its optimization. For each optimization option, the algorithm was executed 100 times to produce 100 layouts, and the expected energy consumption was simulated for each. The results are shown in Figure 11.56. The 100-dimension clustering, 151-dimension clustering, full-dimension clustering, and the genetic algorithm all performed very similarly, resulting in a 5% reduction in expected energy compared to the existing layout and a 6% reduction compared to random layouts. An important result to highlight is that the distance-based clustering algorithm performed about the same as the genetic algorithm, which suggests that high-performance layouts can be generated without designing an optimization routine that explicitly considers energy consumption.

It is interesting to note that the random layouts performed slightly worse than the existing layout. There are many possible explanations for this. One likely explanation is that people tend to align their behavior to those around them, as documented in previous work (Chartrand and Bargh, 1999). In other words, individuals' actions could be influenced by what they see their physical neighbors doing. For example, a particular occupant might be inspired to take a coffee break when they see their neighbor doing so instead of going at a random time, which would have the effect of reducing the zone diversity metric. This possibility has notable implications for the interpretation of this study's results because the results were based on the assumption that occupants' behavior would not change when their seat assignments changed. While this possibility is unlikely to be completely true (and is therefore a limitation of this study's approach), an important question is what the direction of the impact would be if individuals did in fact change their behavior. If occupants tend to assimilate their behavior to those around them, as this study's random versus existing results suggested, then it is quite possible that given new layouts, people will again assimilate to those around them, and thus an even further reduction in energy consumption might be expected. It is also possible that people would change their behavior after reassignment in other ways. Therefore, future work is recommended to test the empirical effects of true layout changes in office buildings.

11.6.5 Concluding Remarks

This case study demonstrated how capturing data on individualized occupant dynamics within existing buildings can be helpful for improving spatial design throughout the building's use phase. Using ambient plug load energy sensors at the desk level, individual schedules of behavior were captured. Higher diversity (i.e., more differences) in behavior within individual lighting zones correlated with higher energy consumption of the zone's lighting system. Two novel optimization methods were applied: (1) a naïve clustering approach that used only the occupant schedule data, and (2) a genetic algorithm that actively made use of a data-driven energy simulation engine. For this surrogate model, a random forest model was able to accurately predict the lighting system's energy consumption. Both spatial optimization routines could reduce lighting energy consumption by 5% compared to the existing layout and 6% compared to a random layout. Overall, this case study demonstrated the added value of reconsidering commercial buildings' spatial designs after occupancy has begun. This approach offers new opportunities for achieving sustainable energy targets in existing buildings and ensuring that buildings perform well throughout their life cycle.

11.7 Case Study 6: Niederanven, Luxembourg

Ghadeer Derbas, Karsten Voss, Tugcin Kirant Mitic

11.7.1 Summary

This case study presents the methodology and key findings of a field study conducted on a mid-rise office building located in Niederanven, Luxembourg. The study focused on the building's automated shading system activation and the interaction between occupants and the shading system with the aim of identifying occupant-centric rules for optimal shading design solutions. The study included a design investigation, data monitoring statistical analysis, a questionnaire, and a simulation-based analysis. The design investigation included an interview with the building designer to better understand the shading system design characteristics and selection criteria. The data monitoring was performed under summer conditions in 2019, and the questionnaire was conducted in 2021 under similar conditions. Finally, the simulation-based analysis evaluated the daylighting and energy performance of the shade control strategy.

Contrary to expectations and previous studies' findings (Reinhart and Voss, 2003, Meerbeek *et al.*, 2014), the present study found relatively few interactions between the occupants and the shading system, though more interactions occurred when the occupant was located closer to the button for manual shade adjustment. Building orientation, social constraints, and time of day were found to influence the manual activation of shading systems. The statistical analysis of the monitoring data showed the low performance of a regression model and the superior performance of data mining techniques. The main takeaways from this study for designers and researchers include: (1) the use of internal/external shading systems can lead to optimal results (i.e., fewer override actions), (2) the definition of control thresholds is essential, and (3) the deployment of lighting sensors is beneficial. On the operation level, simple and robust shade control strategies are recommended.

11.7.2 Building Description

The case study building was the new Headquarters Goblet Lavandier, a five-story office building located in Niederanven, Luxembourg. The building received DGNB (Deutsche Gesellschaft für Nachhaltiges Bauen) Platinum certification in 2018. The building is located in a temperate oceanic climate (Cfb) with a mild marine winter and warm summer with no dry season. The building is a quadrilateral concrete structure (25 m × 25 m) with a galvanized metal sheet façade (see Figure 11.57). It consists of three underground parking floors, a ground floor, and four upper floors (the fourth floor is rented). The building core includes circulation and washrooms and creates a naturally daylit office zone and passive night cooling. The moderate use of transparent surfaces (fenestration) in combination with external Venetian blind and inner textile screen play a central role in the energy efficiency and daylight concepts of the building design. Table 11.14 provides further details about the building.

11.7.2.1 Monitored Offices

Forty-seven offices were monitored over 66 working days from June to mid-September 2019. The majority of the offices are located along the quadrilateral perimeter facing one of the four cardinal directions (see Figure 11.58). The offices are situated on three floor levels and are occupied by an average of two to six workers per office (see Figure 11.59). The offices' windows are the same in width and height. Each window is equipped with a double

Figure 11.57 Perspective view of Luxembourg building, Christian Bauer & Associés Architects.
Source: Jürgen Leick from Goblet Lavadier.

shading system with an external Venetian blind (type Warema E80) and an inner textile screen operated manually to avoid glare discomfort.

11.7.2.2 Configuration of Automated Shading System

The automated external blinds combined with inner glare protection are a reflection of design considerations such as more individual workplace control and passive solar gains in winter. Due to the extra cost, this "double system approach" (see Figure 11.60) is not common. The designer was interviewed and the design briefs and architectural documents were investigated in-depth in order to define the design characteristics and selection criteria of the shading systems (more details in "Design Investigation" below).

The shading control strategy was developed based on the designer's experience. The external shading system is operated automatically based on light and temperature control thresholds. Occupants can override the blind position and tilt the slat angle to different positions (horizontal slat equal to 0°, 60°, and 80°). Any manual interventions disable the automated

Table 11.14 Luxembourg building general characteristics (Lichtmess, 2018)

Item	*Description*
Net floor area (NFA)	2,600 m^2
Area-to-volume ratio	0.31 m^{-1}
Window-to-wall ratio (WWR)	43% per façade
No. of employees in offices	138 employees (30–40 employees during the COVID-19 pandemic, July and August 2020)
Year of completion	2018
Thermal insulation	U-walls: 0.13 W/m^2 K, U-roof: 0.13 W/m^2 K, U-floor: 0.17 W/m^2 K
Windows	U-value: 0.75 W/m^2 K, g-value (SHGC): 0.49, color rendering: 96%
Ventilation	11,000 m^3/h total air volume control depending on CO_2 concentration, individual air volume control in meeting rooms. Highly efficient heat recovery 80.8%
Shading systems	• External Venetian blind (upper threshold if irradiance on the façade exceeds 400 W/m^2, lower threshold 250 W/m^2), g-tot = 0.07 • Inner textile screen (T_s = 8%, R_s = 12%, A_s = 80%)
Cooling system	• Passive night cooling to cover 20% of the cooling energy demand • Passive ground cooling to cover 80% of the rest of the cooling demand • A heat pump can be switched on only in hot weather
Heating system	Geothermal heat pump with an array of vertical probes (i.e., liquid-filled tubes installed in the drilled hole)
Electricity demand and generation	23.7 kWh/(m^2 a), PV = 14.5 kWh/(m^2 a)

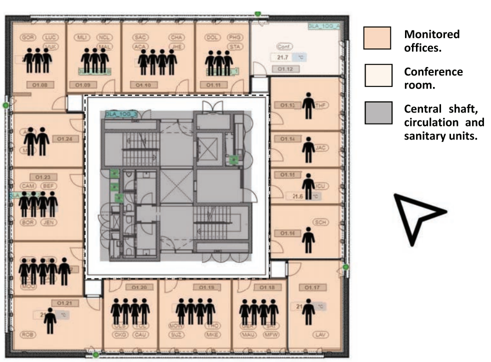

Figure 11.58 Typical offices plan view (Goblet Lavandier & Associés Navigation).

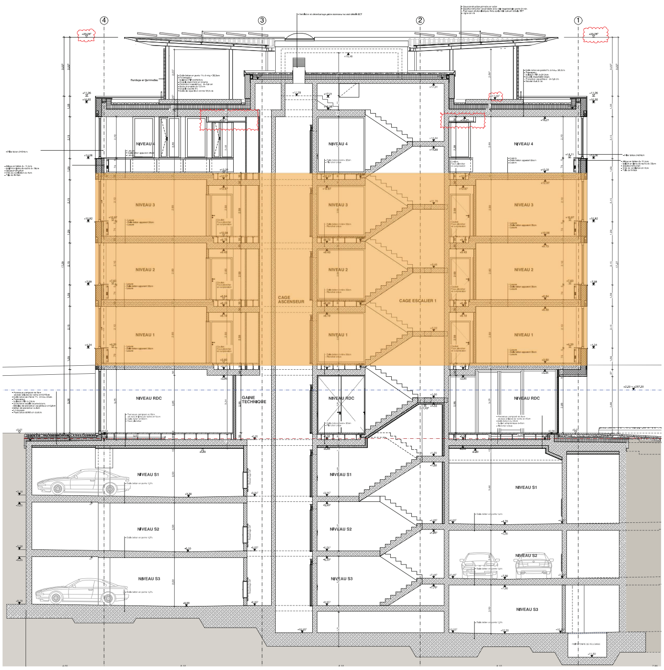

Figure 11.59 Section view of the building, where shaded areas indicate monitored offices (Goblet Lavandier & Associés Navigation).

system until it resets at 11h00 and 15h00. The KNX Elsner sensor controls the blinds in each facade. The blinds are automatically raised (closed) when wind speed exceeds 12 m/s. The blinds are lowered when the irradiance on the façade exceeds 120 W/m^2, and the outdoor temperature is above 5°C without any delay time. When the irradiance is below 50 W/m^2, the blinds are retracted after 60 minutes. During the operation phase, the established thresholds were modified. The lowering threshold is set up to 250 W/m^2 with a horizontal slat position to maximize the view to the outside. When the irradiance exceeds 400 W/m^2, the slat angle inclines up to 15° instead of 80° to provide sufficient daylight. Thresholds values can also be increased (e.g., a temporary cloudy sky) for less disruptive blind movements.

11.7.3 Methodology

Figure 11.61 outlines the methodology of the study. This study began with a design investigation via a written interview with the designer who was involved during the design and operation phase of the shading systems. Then,

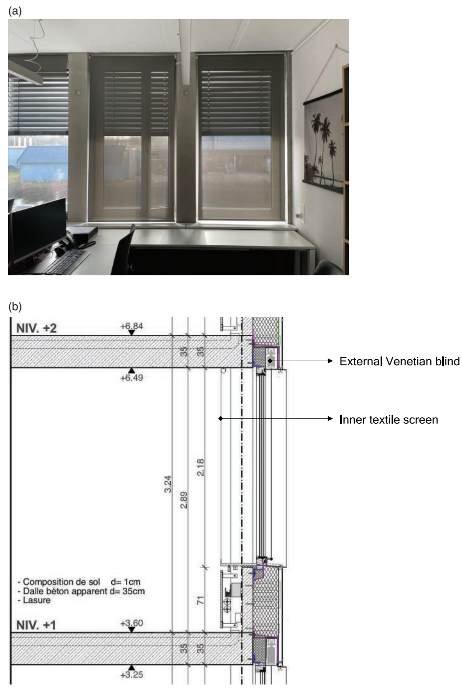

Figure 11.60 The double shading system approach. Left: Interior view. Right: Section view.
Source: Jürgen MÜLLER, https://www.golav.lu/.

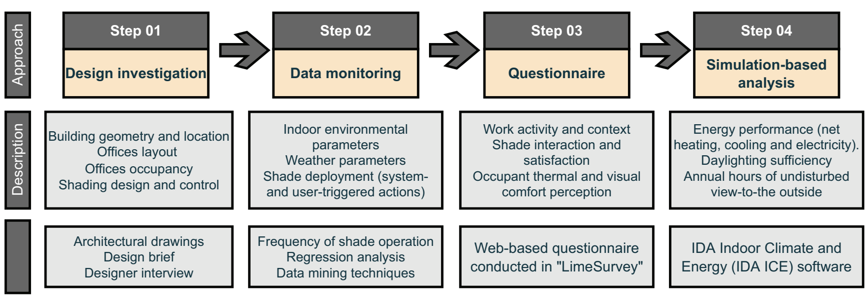

Figure 11.61 Methodology of the study.

a post-occupancy evaluation (POE) was performed using data monitoring and data collection (via a web-based questionnaire) to explore occupants' interaction, satisfaction, and preferences regarding the shading systems. Finally, a simulation-based analysis was performed. Each of these steps is presented and described in the sections that follow.

11.7.3.1 Design Investigation

A written, structured interview with the building's designer was conducted via email to explore if any of the questions below were considered during the shading system design. To streamline the interview, potential responses were provided for many of the questions (in brackets below).

- a *Which solar shading scenarios were proposed before the final shading design selection?* (Internal roller shades, fixed, dynamic, vertical, complex, combined).
- b *Which selection criteria were considered during the shading design?* (Environmental and climatic parameters, energy concern, aesthetics, safety, privacy, cost, user comfort, codes, etc.).
- c *What was the basis for the selection of shading control strategy?* (Codes, guidelines, literature, design brief, designer experience).
- d *Which occupant assumptions were considered during the shading design?* (Number of occupants, demographic, occupancy, work activities, preferences, etc.).
- e *Did the simulation specialist consider any simulation-based evaluation for the selection of the optimal shading design? If yes, which metrics were used?*
- f *Was there any cooperation between stakeholders (designer, client, energy modeler, etc.) with regard to shading selection and design?*

The designer's feedback provided clarity on the shading system design process and selection criteria and a better understanding of the quantitative findings of the monitoring study and the questionnaire analysis.

11.7.3.2 Data Monitoring

Monitored datasets were extracted from the building's KNX-based building management system (BMS). Data preprocessing was performed on the raw datasets, including cleaning, removing outliers, interpolation, and normalization (rescale a variable to have a value between 0 and 1).

The monitored weather parameters included global irradiance (I_{gl}, W/m^2), outdoor vertical illuminance (E_{out}, lux), air temperature (T_{out}, °C), solar azimuth, and altitude. The outdoor parameters were measured using a weather station mounted on the rooftop of the building. Indoor parameters included air temperature (T_{in}, °C), relative humidity (RH%), and CO_2 concentration (ppm). The indoor parameters were measured with Netatmo data loggers distributed in 11 workspaces throughout the building. Shading system-triggered actions and user-triggered actions were recorded as event-based measurements. The external Venetian blind position—activated by the automated system—was expressed as 0% fully open and 100% fully closed. The datasets were resampled every five minutes using an Excel tool (i.e., HisKNX_V1_2_17_BETA.xlsb, developed by Jürgen Leick from Goblet Lavadier) to unify intervals. For analysis purposes, the range of data was limited to daytime work hours, between 6h00 and 20h00.

The study analyzed two shade deployment datasets using statistical analysis methods: (1) system-triggered datasets and (2) occupant-triggered datasets. The preliminary behavioral patterns were analyzed in terms of the "rate of change" of blind use. The "rate of change" was defined as the number of user-shade override adjustments (UOAs) per day per office. Logistic regression was applied to the given datasets to identify associations between the physical measurements and user-shade interactions and predict the likelihood of UOAs. Alternatively, clustering analysis and association rules mining (ARM) were used on the given dataset to allow more accurate assumptions on complex and diverse behavior in big office buildings. Clustering analysis was used to obtain distinct behavioral patterns using *K*-means algorithm. The frequent pattern growth algorithm (FP growth) was employed to mine the association rules. Both regression and clustering analysis were performed in IBM *SPSS* (version 21.0) software, while Rapid Minor, an open-source data mining program, was used for the ARM analysis.

11.7.3.3 Questionnaire

A cross-sectional web-based questionnaire using LimeSurvey was distributed to the building's occupants to examine subtle and non-physical triggers behind blind adjustments and better understand the findings of the monitored datasets. The questionnaire was distributed in the summer of 2021 to ensure that occupants had experienced the same thermal and visual conditions as those studied during the monitoring period. The questionnaire was distributed via email to the building's occupants on July 30, 2021, and followed by a reminder three weeks later. The questionnaire included questions about participants' demographic details, mood, work activity, contextual environment (e.g., window orientation, size, location), thermal and visual discomfort, and interaction with the shading systems, and their satisfaction and preferences regarding shading system performance. A total of 32 participants (25% of the population) working in single-occupancy offices completed the questionnaire. Employees who were working from home due to the COVID-19 pandemic were excluded from the population sample.

11.7.3.4 Simulation-based Analysis

Daylighting and energy performance of the automated shading control strategy was evaluated using a simulation-based analysis using IDA Indoor Climate and Energy (IDA ICE) software. Annual heating, cooling, and lighting demand (kWh/m^2) were calculated under five shading control strategies, including low (S01: irradiance on the façade exceeded 100 W/m^2), and high (S03: irradiance exceeded 450 W/m^2), S02 was the established design lowering threshold (irradiance exceeded 250 W/m^2), S04 (fully closed) and S05 (fully open) were added to the analysis for benchmarking. Useful daylight illuminance (UDI) was used for the daylighting performance assessment. Achieved UDI% is defined as the annual occurrence of illuminances across the work plane where the illuminance is within the range of 300–3,000 lux (Nabil and Mardaljevic, 2005).

11.7.4 Results and Discussion

The main findings of the study are presented and discussed in the following sections.

11.7.4.1 Design Investigation

According to the designer's interview responses, the external and internal shading systems were proposed from the early stages of the building design. The design of the systems was based on different environmental and climatic parameters, thermal and visual comfort, energy concerns, aesthetics, safety and maintenance, budget restrictions, and building codes and standards. A simulation-based analysis had been conducted by the designer to find the optimal shading control strategy in terms of thermal and visual comfort as well as energy performance. However, according to the designer, occupant assumptions were not considered in their analysis.

The designer indicated that the intention of the shading design was to maximize users' satisfaction and comfort in their workspaces, which aligns with the notion of occupant-centric design, that is, placing occupants and their well-being as a top priority throughout the building life cycle. The designer's details about the shading design were helpful in better understanding the quantitative results of the monitoring and questionnaire analysis, described below.

11.7.4.2 Data Monitoring

Shade patterns are explored in terms of system- and user-triggered actions to differentiate their behavior regarding office orientation and shade control strategies.

11.7.4.2.1 SYSTEM BEHAVIOR

A total of 576 system-triggered actions (287 fully raising actions and 289 fully lowering actions) were recorded—an average of 8.72 blind changes per day. Figure 11.62 shows that the highest frequency of system-triggered actions was in west-facing offices, while the lowest was in east-facing offices. In contrast, the highest frequency of UOAs was in the east-facing offices, while the lowest was in the west-facing offices. The high rate of system-triggered

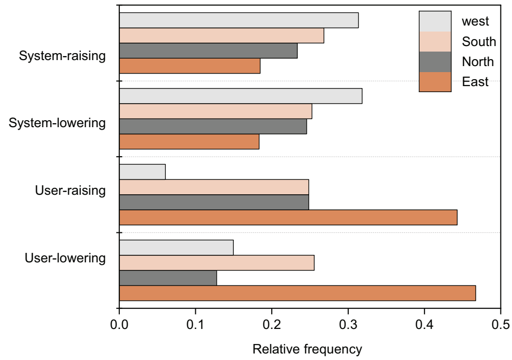

Figure 11.62 Relative frequency of system- and user-triggered actions for each façade.

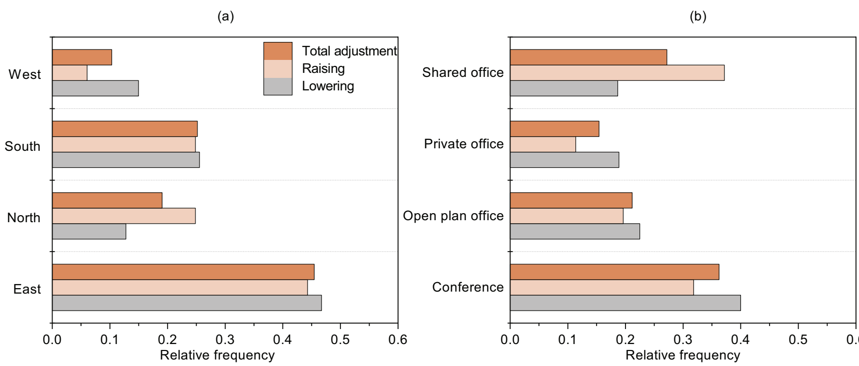

Figure 11.63 Relative frequency of UOAs in terms of (a) office orientation and (b) occupancy level.

actions in the west and south elevations can be explained by (a) the average daily high irradiance on the facade (above 400 W/m^2) and (b) the users (i.e., occupants) occasionally correcting the system.

11.7.4.2.2 USER BEHAVIOR

A total of 1,148 blind position changes were recorded over the 66 working days in the 47 monitored offices. The users triggered approximately 49% of the blind movements (fully and intermediate), 274 lowering actions, and 298 raising actions. The average daily rate of blind use was 0.184 per office. Figure 11.63a shows that the highest rate of UOAs was in the east elevation, where an average of 3.93 adjustments per day occurred. Fewer interactions were observed in the west and north elevations compared to the east and south. This result can be explained by the significant variations of global irradiance and indoor work plane illuminance in offices in different elevations. To reduce the visual discomfort and blind-triggered actions in the east and south elevations, smaller window size and fixed shading could be adapted in the building envelope design, as suggested by O'Brien and Gunay's (2015) robust design strategies.

Figure 11.63b shows a higher frequency of UOAs observed in shared offices, with an average of 0.19 changes per day per office compared to single-occupancy and open-plan offices. Most of the shared offices are located in north-east elevation close to a nearby building. This result is not in agreement with O'Brien *et al.* (2013), who found that, due to social pressure and constraints, occupants tend to be more reluctant to control their environment if others are present.

Figure 11.64 shows that the shades in the east and south facades were adjusted more frequently in the morning than during the rest of the day, while the opposite occurred in west-facing offices. This result is in line with previous studies (Inoue *et al.*, 1988; Haldi and Robinson, 2010b) that found that occupants interact more with blinds immediately upon arrival to the space. In north-facing offices, occupants tended to raise the blinds all day and in the evening.

Overall, the daily rate of change of UOAs was relatively low compared to the findings of previous studies. For comparison, Reinhart and Voss (2003) reported a mean of 3.7 blind movements per day per office over 174 weekdays in 10 south-facing offices, which is 20 times the present study's findings. In another study by Meerbeek *et al.* (2014), an average of 0.86 blind adjustments per day per office were recorded over 100 working days in 40 offices, which is five times this study's findings. Considering these studies were conducted in temperate climate zones same as the present case study, the difference in

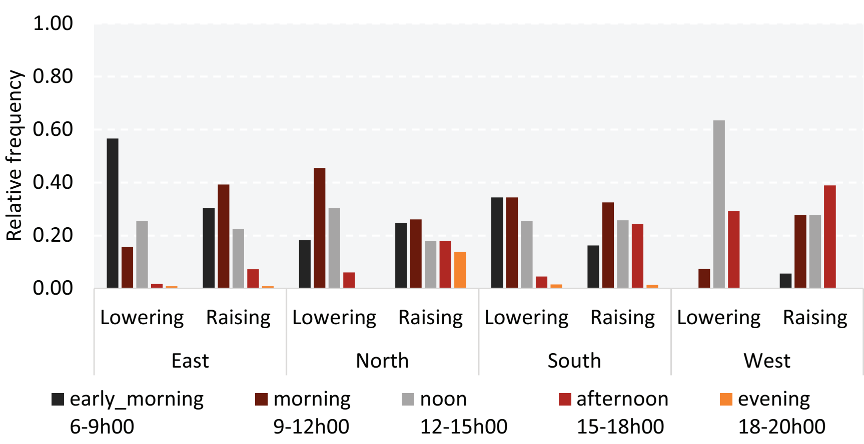

Figure 11.64 Relative frequency of UOAs during the day per façade.

findings may be explained by the case study building having both (a) appropriate and acceptable shade control thresholds and high-quality light sensor performance, and (b) additional inner glare protection, which requires less effort to prevent glare. Additionally, the daily profile of CO_2 concentration was analyzed in nine offices in the case study building to estimate occupancy presence; based on the results, the offices were occupied approximately 97% of the study period. Thus, the low rate of blind use is unlikely to be related to occupant absence. Instead, the findings suggest that the automation system performance met occupants' preferences and expectations.

11.7.4.3 Regression Analysis

The initial aim of the present study was to derive occupant behavior models, as a high rate of shades adjustments was expected based on previous studies (Reinhart and Voss, 2003, Meerbeek *et al.*, 2014). Thermal and visual stimuli were identified by earlier research as influencing blind use (Haldi and Robinson, 2010a; Mahdavi *et al.*, 2008). Accordingly, this study used logistic regression to predict the probability of UOAs as a function of several explanatory variables:

$$\begin{aligned}\text{Logit} = {} & \beta_0 + \beta_1\left(E_{\text{out}}\right) + \beta_2\left(I_{\text{gl}}\right) + \beta_3\left(T_{\text{out}}\right) + \beta_4\left(\tan\_d\right) \\ & + \beta_5\left(T_{\text{in}}\right) + \beta_6\left(\text{Rh}\right) + \beta_7\left(\text{CO}_2 \text{ concentration}\right) \\ & + \beta_8\left(\text{AOV\%}\right) + \beta_9\left(\theta_{\text{slat angle}}\right) + \beta_{10}\left(\text{time of the day}\right)\ldots\end{aligned} \tag{11.8}$$

where tan_d is the tan of solar profile angle, AOV% is the average occlusion value of the blind (0% fully open and 100% fully closed), $\theta_{\text{slat angle}}$ is the slat angle degree (0°, 60°, 80°), β_0 is the intercept, and β_n is the variable coefficient.

Separate analyses were conducted to predict the probability of UOAs (lowering and raising actions) for each façade (E, S, N, W), including eight sub-models. The forward regression method was used to select the explanatory variables that have a statistically significant influence on the value of the dependent variable (p-value < 0.05). Further details about the statistical analysis process are available in Derbas and Voss (2021).

The regression results had a considerably low Nag. R squared (in other words, the proportion of the variance for a dependent variable was close to zero) of all sub-models for shade lowering and raising actions. Moreover, a weak relationship between the model predictions and the physical parameters was found. The developed sub-models were all incapable of predicting UOAs. The limitations of the monitored parameters such as indoor work plane illuminance and glare probabilities, which are the primary triggers behind blind use, may explain why the models could not accurately explain the actions. Based on these results, it can be concluded that in this case, this commonly used modeling approach was not successful for explaining occupant behavior. This limitation justified an alternative approach for analyzing the observed patterns, as discussed in the next section.

11.7.4.4 Data mining Analysis

Data mining techniques, including clustering analysis and association rules mining, were considered an alternative methodology to provide more accurate assumptions of complex and diverse individual behavior in big office buildings and overcome the limitations of the regression models. The results of the two techniques are described in turn below.

11.7.4.4.1 CLUSTERING ANALYSIS

First, interactivity patterns clustered occupant behavior based on the frequency of UOAs per day. The user-control ratio was calculated by dividing the number of user-triggered adjustments per office by the total number of adjustments (system- and user-triggered actions) for that office. The activity ratio was calculated by dividing the total number of user-shade override adjustments for an office by the average number per 47 offices. Figure 11.65 shows 47 offices labeled by numbers and plotted, where the x-axis indicates the activity ratio and the y-axis represents the user-control ratio. The following interactivity behavioral patterns were clustered in the given dataset:

- Passive adjustments [C01]: 66% of offices assigned (range of 0–0.17 times per day).
- Neutral adjustments [C02]: 21% of offices assigned (range of 0.18–0.36 times per day).
- Active adjustments [C03]: 13% of offices assigned (range of 0.44–0.58 times per day). The offices assigned to this cluster have common design features: they are all shared offices and face north-east.

Second, motivational patterns clustered the factors that drive users to override the automated shading systems. Three clusters of shade-lowering actions and two clusters of shade-raising actions were defined (see Figure 11.66a and b). The clusters were based on each variable's impact factor (regression coefficients) that influenced the UOAs. Accordingly, logistic regression was performed to define the most statistically significant variables in each office. Patterns of user-shade lowering were clustered in 25 offices, and user-shade raising was clustered in 30 offices. The rest of the offices were excluded since they had the lowest frequency of UOAs.

Based on the motivational patterns, five clusters were induced as follows:

- Shade lowering cluster 01 [C01_L]: 12% of offices were assigned and associated with the time of the day (early morning and morning) and outdoor weather conditions (T_{out}, tan_d).

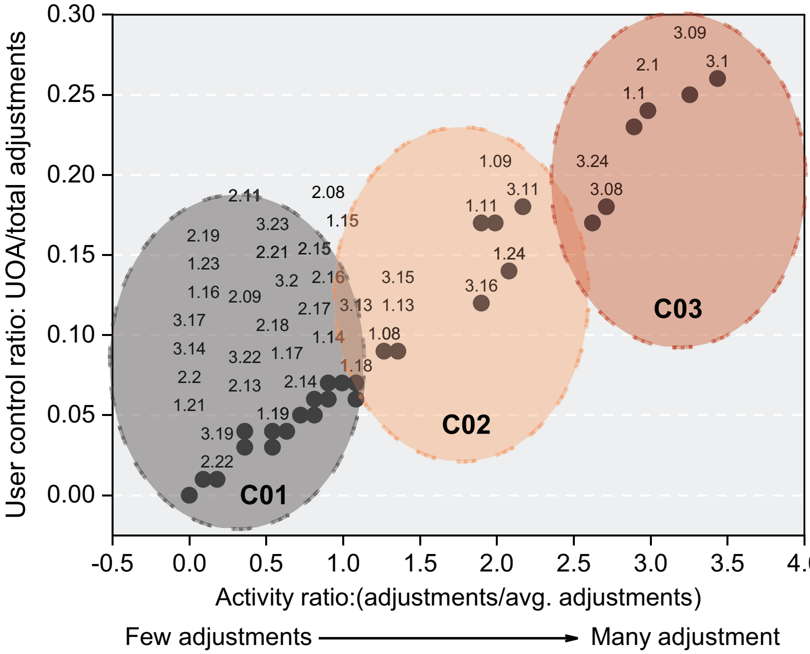

Figure 11.65 User-shade clusters based on interactivity patterns.

- Shade lowering cluster 02 [C02_L]: 24% of offices were assigned and associated to the time of the day (early morning until afternoon) more than physical drivers.
- Shade lowering cluster 03 [C03_L]: 64% of offices were assigned and appeared to be more influenced by slat angle position than physical and time-related drivers.
- Shade raising cluster 01 [C01_R]: 63% of offices were assigned and appeared to be more influenced by the slat angle position and time of the day (noon and afternoon) than physical drivers.
- Shade raising cluster 02 [C01_R]: 37% of offices were assigned and associated to the time of the day and indoor air temperature.

The clustered patterns constitute a base for association rules classifying the building occupants into typical office user profiles as described in the next section.

11.7.4.4.2 ASSOCIATION RULES MINING (ARM)

Based on the 20 rules mined, two working user profiles (user *ß*, user *µ*) were drawn in this study:

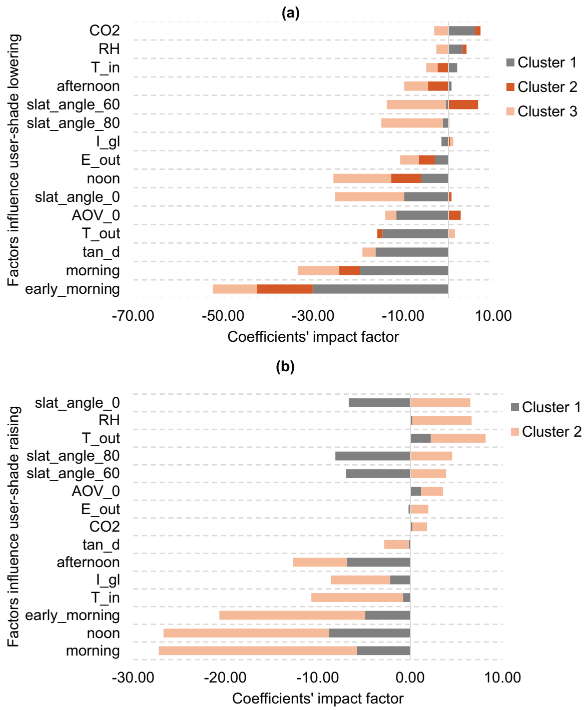

Figure 11.66 User shade (a) lowering and (b) raising clusters based on motivational patterns.

- User type (β) represents the passive user who tends to override the automated shading system on average 0.09–0.17 times per day (passive adjustments). User β is mainly influenced by the time of day and the current blind state for both lowering and raising adjustments.
- User type (μ) represents the medium user who tends to override the automated shading system on average 0.18–0.36 times per day (neutral adjustments). User μ is mainly influenced by the time of day and the current blind state only for raising adjustments.

11.7.4.5 Questionnaire

In total, 32 of the case study building's occupants completed the questionnaire, 71.9% of whom identified as male and 28.1% as female. Regarding employee role, 68.8% of participants performed professional jobs (e.g., engineer, specialist planner), 18.8% were in managerial positions, and 12.5% were administrators. The main results of the questionnaire are presented and discussed in the sections that follow.

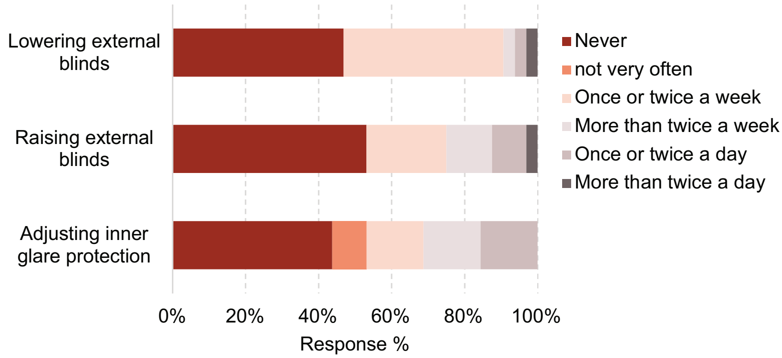

Figure 11.67 Relative frequency of user interactions with inner glare protection and external blinds.

11.7.4.5.1 USER-SHADE INTERACTION, SATISFACTION, AND PREFERENCES

About 75% of the participants reported never opening or adjusting the external blind once per week, whereas 10% closed the external blind a few times per day or week (see Figure 11.67). Overall, a low level of manual overrides to the automated shading system was observed, which is in line with the quantitative results from the study's monitoring analysis. More than half of the occupants indicated that there was no need to adjust the external blind, 20% reported that the blinds are fully open all the time, and 20% preferred the automatic position. Roughly 25% of the occupants chose to adjust only the inner glare protection because it is faster and easier to avoid glare (compared to waiting for the external blind to move). However, 34.4% of the occupants preferred the external blinds to the inner glare protection, while 28% liked both systems equally and 12% did not like either.

Approximately half of the occupants were satisfied with the performance of the automated shading system with an average of 3.68 on a 5-point scale (0 = very dissatisfied, 5 = very satisfied). Some participants explained that the automated shading systems are much more efficient than the glare protection and simple to operate via a push button. Most participants (93.8%) were satisfied with their ability to control both shading devices, that is, the "double approach", with an average satisfaction rating of 4.43 (see Figure 11.68).

11.7.4.5.2 INFLUENCE OF CONTEXTUAL FACTORS ON BEHAVIORAL PATTERNS

Figure 11.69 shows the relative frequency of shade lowering and raising actions in terms of floor level, office orientation, WWR, and window to a desk position. Few occupants (15%) whose offices are located on the first floor raised the external blind once or more per day. Fewer raising actions

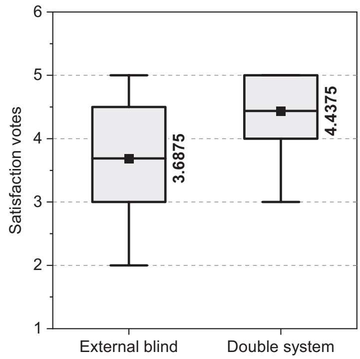

Figure 11.68 Satisfaction rating of the performance of external blind and the ability to control “double systems”.

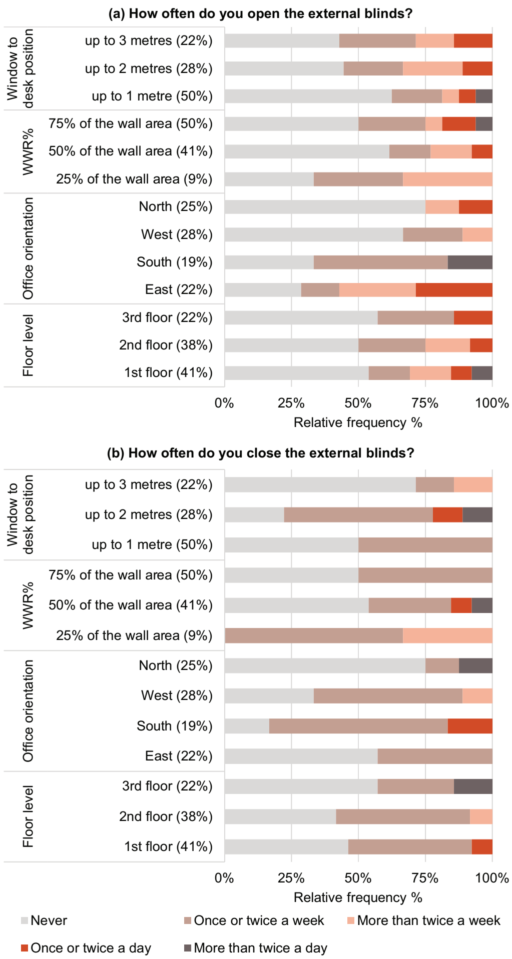

Figure 11.69 Influence of contextual factors on shade behavioral patterns.

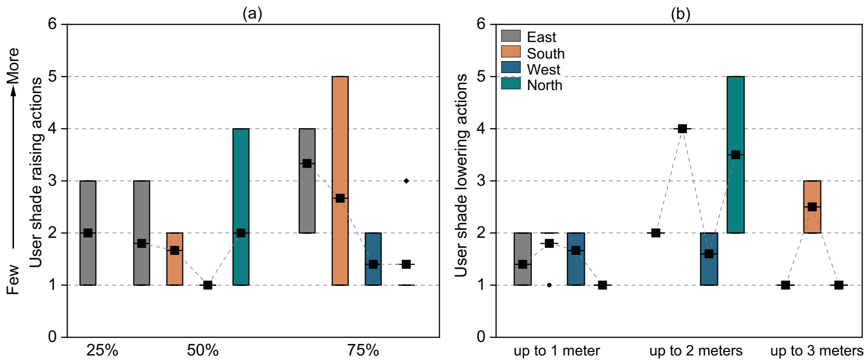

Figure 11.70 User shade raising action in terms of (a) WWR% and (b) window to desk position per each façade.

were noticed on the upper floors, while more closure actions occurred on the third floor. In the east- and south-facing offices, occupants opened the external blinds more frequently than in the north- and west-facing offices. This finding is in line with the findings from the data monitoring analysis.

In Figure 11.70a and b, considering that 0 on the *y*-axis refers to "never adjusted" and 5 refers to "more than twice a day", occupants who sit about 2 m from the window adjusted the external blinds more frequently than those sitting closer to the window. This difference could be due to (a) ease of access to the push button for the automatic blinds (next to the office door), and (b) most of these offices faced north (see Figure 11.70b). In the east- and south-facing offices with large window areas (WWR=75%), occupants opened the external blinds more frequently than those in offices with smaller windows (WWR=50% and 25%) (see Figure 11.70a). Therefore, moderate window size (50%) and desks farther from the window (more than 2 m) in east and west elevations may decrease UOAs. Based on these results, it is recommended that building designers set the first row of desks several meters back from the façade, such that the work planes will rarely receive direct solar radiation. Furthermore, moderately sized window areas are recommended in east and south elevations to decrease the number of shade interventions.

11.7.4.6 Simulation-based Analysis

The daylighting and energy performance of the different shading control strategies (based on irradiance threshold) were simulated. The impact of inner glare protection was ignored in the analysis since insufficient information about the usage of the system (e.g., number of lowering and raising actions) was known during the study period. Figure 11.71 demonstrates that UDI% values were the highest under S01 and S02 (original design) control

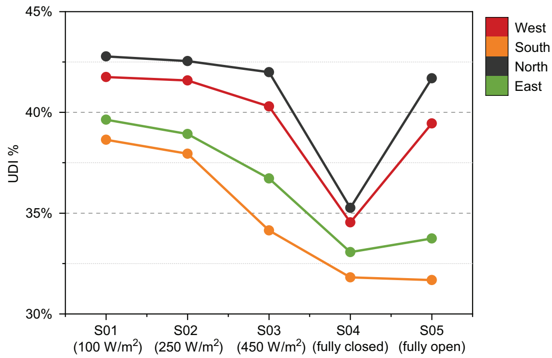

Figure 11.71 UDI% (300–3,000 lux) distribution on the work plane under different shading control strategies.

strategies in west- and north-facing offices with slight differences. This result is expected since the shade-lowering irradiance threshold exceeds 100 W/m^2 in S01 and 250 W/m^2 in S02. The lowest UDI% values were in the south elevation when irradiance thresholds exceeds 450 W/m^2 (S03), and the blind is fully closed or open.

Figure 11.72 shows the annual heating, cooling, and lighting demand in the building offices under different shading control strategies (S01–S05). Lighting demand was hardly affected by the different control strategies since the lighting was turned off if the work plane illuminance was above 500 lux. More significant differences were found in the heating demand, where the difference between the original design (S02) and the lowest demand (S05) reached up to 9.2 kWh/m^2. The total energy demand of S02 was higher than S01 by 43.74 kWh/m^2 and lower than S03 by 76.82 kWh/m^2. The main difference was in the cooling demand. Overall, the established shading control strategy seems to provide sufficient daylighting and views to the outside (note that the blind is closed 40% of annual working hours) as well as keep the energy use close to the minimum compared to other control strategies.

11.7.5 Concluding Remarks

The case study presented a successful example of automated shading system design and utilization. Based on the monitored datasets results, the daily rate of change of UOAs (i.e., occupants' interaction with the systems) was relatively low compared to previous studies (Reinhart and Voss, 2003; Meerbeek *et al.*, 2014). The regression analysis, a commonly used modeling approach, did not successfully explain the occupant behavior in this case. Using data mining techniques as an alternative methodology might be an improvement in terms of exploring occupant behavior patterns and

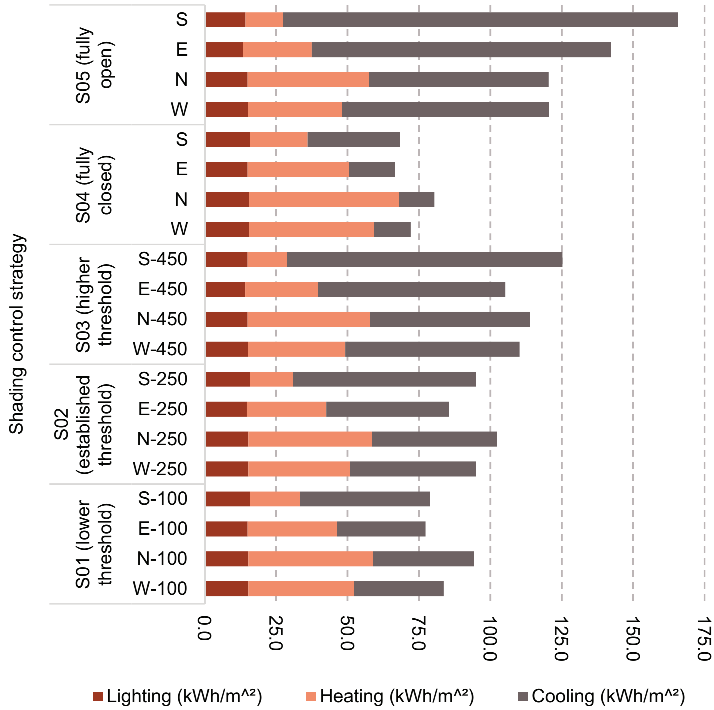

Figure 11.72 Annual heating, cooling, and lighting demand (kWh/m^2) using different shading control strategies.

allowing more accurate assumptions of complex and diverse behaviors in big office buildings. Similar results were found in the questionnaire analysis, where more than 50% of the occupants indicated that they rarely or never adjusted the automated external blinds.

This case study provides building designers and operators with potentially valuable insights about shading design features and operation strategies that may increase occupant comfort and satisfaction. Key insights include:

1 Use double shading system approach (internal/external).
2 Apply an acceptable range of established shade control thresholds. For instance, low irradiance thresholds (250–400 W/m^2) are recommended for shade control in south- and east-facing offices with moderate window size or fixed shades. In contrast, high irradiance-lowering threshold (above 400 W/m^2) can be adopted in north- and west-facing offices.
3 Use high-quality and accurate light sensors.
4 Quiet and infrequent movements while operating the automated shading systems can increase occupant satisfaction.

Further research is needed to develop comprehensive guidelines for occupant-centric shading design—for example, studies exploring various building types in different climatic zones and with long-term monitoring.

11.8 Case Study 7: Gothenburg, Sweden

Quan Jin, Holger Wallbaum

11.8.1 Summary

This case study, A-building, is a newly renovated office building in Gothenburg, Sweden. The building is certified Miljöbyggnad Silver (version 2.2), which aims to achieve both better indoor comfort and low energy use. This occupant-centric analysis focused on the operation phase and examined the indoor environmental performance predicted during design. The findings indicated both conformities and discrepancies between the designed performance and the actual performance as perceived by the occupants. On the one hand, the design enhanced the building's performance regarding, for example, daylight, ventilation, and energy savings. On the other hand, occupant surveys revealed that performance gaps exist between what was targeted and what was perceived regarding, for example, satisfaction with the indoor temperature and window screen and preference for daylight and indoor climate control. The findings of this study can contribute to closing performance gaps by examining how occupants perceive and experience the office environment.

11.8.2 Building Description

The A-building is an office building hosting the Department of Architecture and Civil Engineering on the Chalmers University campus in Gothenburg, Sweden (see Figures 11.73 and 11.74). The building was built in 1968 and extensively renovated in 2016 and 2017. A significant challenge during the building renovation was the preservation of the historical features of the building. The building was reoccupied in 2018 and is currently fully operational as of May 2022. It is located in the marine west coast climate zone according to the Köppen Climate Classification and features mild summers and cool but not cold winters.

The building consists of five stories with lecture halls and work studios on the first and second floors, staff and faculty offices on the third and fourth floors, and a kitchen and study rooms for students as well as a lunch and coffee room with a kitchen for employees on the fifth floor. In this case study, only the office floors (i.e., third and fourth floors) were the subject of analysis. The total floor area of the office floors is approximately 4,925 m^2. The study was conducted in 2018 after the building had been reoccupied for a year post-renovation.

Figure 11.73 Photo of the A-building exterior space.

Figure 11.74 Photo of the A-building interior office space.

The newly renovated A-building was certified as Miljöbyggnad Silver (version 2.2) by the Sweden Green Building Council. Miljöbyggnad is a Swedish system for the environmental certification of buildings (new and existing buildings as well as buildings in operation) that aims to provide comfortable and safe environments for people to work and live. The system certifies buildings at three levels—Bronze, Silver, and Gold—with regard to energy, indoor environment, and materials/chemicals. The case study building's Silver level is awarded when a building is designed to perform better than the reference values in the Swedish building regulation in terms of, for example, lower energy use, a higher daylight factor, and a lower predicted percentage of dissatisfied (PPD) value. The A-building specifically addresses low energy consumption, a comfortable indoor environment, and creative workspaces. The main energy-efficient features include sun shades, energy-efficient windows, a low U-value of wall, and a mechanical variable air volume (VAV) ventilation system. Since the renovation of the A-building was so extensive, the certification process followed the (stricter) certification requirements required for new buildings.

11.8.3 Building Design Parameters

The focus of the renovation design was to create a building that contributed to different sustainable perspectives, including energy conservation and an improved indoor environment. The heating, cooling, and electricity are intended to be controlled based on internal load variations from people, equipment, and the outdoor climate. Table 11.15 shows the design parameters for the renovation of the A-building.

The building envelope was a classical brick-and-mortar double-wall with a cavity gap in between, as was very popular in Sweden in the 1960s. During the renovation, the building exterior was kept similar, and additional inorganic insulation was added from the inside. By adopting this strategy, the historical features of the building were preserved and better thermal performance of the exterior wall achieved by reducing the heat flows from the indoor to the outdoor environment.

The windows were also renovated. All the windows in the building were replaced with energy-efficient windows with a low thermal transmittance (U-value). The windows are now operable, triple-pane casement windows. Exterior screens (i.e., awnings, a sheet of canvas, or other material stretched on a frame and used to keep the sun off the windows) were also installed to further reduce solar heat gain and protect from glare. All sunlit rooms facing south, west, and east were provided with effective exterior screens. The screen is automatically controlled based on the solar radiation level and outdoor temperature. Curtains were also added on the inside of the windows to be controlled manually by occupants.

The ventilation system was replaced by a mechanical variable air volume (VAV) ventilation system with heat recovery. The ventilation system is controlled based on the presence of occupants in each room by adjusting the

Table 11.15 Design parameters for the renovation of the A-building

Exterior wall	*$U = 0.44$ W/m²K*
Window	Triple pane casement $U = 1.04$ W/m² K including window frame SHGC (g-value) = 0.4 Light transmission, 60%
Exterior screen	Awning, fabric g-value screen: 0.21–0.24
Ventilation	FTX with VAV Maximum four outlets × 5 m³/s in office room

Figure 11.75 Photo of the A-building's exterior screens.

Figure 11.76 Photo of one of the A-building's triple pane windows and screens.

airflow rate according to the signal of presence as well as the indoor temperature. Figures 11.75–11.77 show each of the components mentioned above (exterior screens, windows, and ventilation).

11.8.4 Methodology

Energy performance is a topic frequently addressed in building renovations and green building design. However, there are still many newly renovated buildings that regularly receive complaints from their occupants, especially concerning the indoor environmental conditions (Lee *et al*., 2019). In other words, there are often gaps regarding occupant satisfaction between the designed and the actual conditions. The purpose of the present case study was to examine the A-building's post-renovation performance in terms of indoor environmental quality (IEQ)—specifically, the extent to which the

Figure 11.77 Photo of the A-building's ventilation inlet.

building's design achieved the target of a comfortable indoor environment based on occupants' perceptions of the building's performance.

To achieve this purpose, the study included three parts. The first part involved reviewing the building's design parameters and simulation results of its energy performance and indoor comfort (thermal comfort and daylight). The second part was a post-occupancy evaluation (POE) based on the smart and sustainable office (SSO) User Insight Toolbox (Cordero *et al.*, 2017; Jin *et al.*, 2019) that collected occupant feedback on indoor environmental quality (IEQ) and behaviors related to indoor comfort and individual control over indoor climate. The third part was a comparison of the original building design and the occupant survey results and a reflection on the development of an occupant-centric design concept (see Figure 11.79). Each part is described in turn below.

11.8.4.1 Building Design Simulations

In this study, simulation was used in the early stage building design and to support the implementation of the Miljöbyggnad certification. There are 13 aspects and up to 16 indicators in the Miljöbyggnad certification that need to be rated individually and then aggregated to grade a building as Bronze, Silver, or Gold. The goal of the A-building renovation was to achieve Miljöbyggnad Silver. To achieve this goal, the renovation could not only focus on the energy performance but also needed to reach high-performance level of IEQ related to occupant comfort and health. This goal was achieved by performing comprehensive simulations of the building's energy demands, thermal comfort, and daylight. A detailed building model was created using the software IDA Indoor Climate and Energy (IDA ICE) to predict the building energy and indoor environment performance (see Figure 11.78). The results of this simulation were used for comparison with the results of the POE, described below.

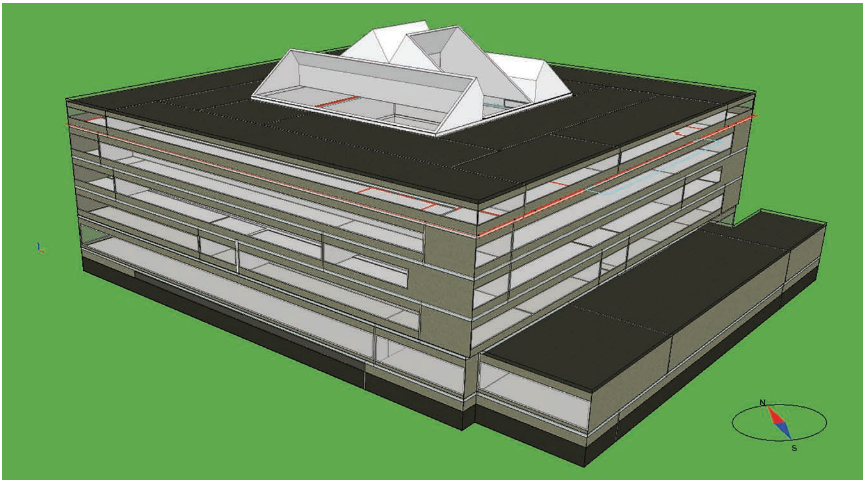

Figure 11.78 3D model for the structure of A-building.

Energy simulation was performed to ensure that the specific energy use, which refers to the supplied energy to building's service and energy system distributed over the floor area heated above 10°C, meet the requirement of 75% of the energy use of BBR (2017).

Indoor thermal comfort in winter and summer were simulated as well, and PPD index was calculated. To meet the Miljöbyggnad requirements, representative floors and worst cases were studied. The representative floor stands for the type of the entire building or a few floors (i.e., office or classroom). The worst cases are considered, such as lower floors for daylight simulation, the risk of overheating and cooling for thermal comfort in summer and winter, and full exposure toward north- and south-west. In this case, for the thermal comfort simulation, floor 4 was selected as the representative floor of office space, and for daylight simulation, floor 3 was selected as the representative floor, considering it bad for good daylight.

Occupant-related information and assumptions such as internal loads and occupancy were taken into account as they are of significance for the indoor climate. The basis of the set up for these parameters is based on the national guideline on determining the building energy use (BEN 2) and the default values provided by IDA ICE. The following Table 11.16 shows detailed information about these parameters.

11.8.4.2 Post-occupancy Evaluation

POE is frequently used to evaluate building performance and gather data from building occupants. When conducting POE, useful knowledge is

Table 11.16 Occupant-related parameters and setpoint (the third and fourth floors)

Cooling setpoint	23°C at presence, 25°C no presence
Heating setpoint	22°C at presence, 20°C no presence
Person heat	80 W/person
Clothing, activity	1.0 clo winter; 0.5 clo summer; 1.2 MET
Occupancy	Varying attendance between 7:00 and 17:00 Occupancy density: 0.07 person/m^2

assembled to improve the design and operation of both new and renovated buildings. POE is essential to examine and motivate occupant-centric building design. There are various ways to implement POE depending on the complexity and depth of evaluation. Surveys are a commonly used method to assess occupants' satisfaction levels—for example, the Building User Satisfaction (BUS) survey and UC Berkeley's Center for the Built Environment (CBE) survey on office IEQ satisfaction (Leaman and Bordass, 2001; Zagreus *et al*., 2004). These two surveys include detailed questions about occupants' comfort, health, and productivity.

For the preset case study, POE was conducted using the SSO User Insight Toolbox (Cordere *et al*., 2017; Jin *et al*., 2019). This toolbox relies on a holistic mixed methods approach based on qualitative and quantitative measures to capture a broad range of office occupants' comfort- and health-related factors, including current and general well-being. The empirical evidence can help identify implementation strategies for a new generation of user-oriented and resilient building design solutions for future offices. One of the main goals of the SSO User Insight Toolbox is to put users at the center of office design by collecting their experiences and needs—in this case, regarding the A-building's indoor environment, individual control, energy use, and social aspects of building use.

In addition to IEQ measurements, the SSO User Insight Toolbox includes the following tools:

- Web-based SSO Survey
- Web-based SSO Diary App
- Observation studies
- Individual and focus group interviews
- Reporting tool

The web-based survey (see Figure 11.79) is a tool to gain a holistic impression of a user's experience with the environment. The survey includes a series of questions around broad themes, such as general satisfaction, stress, and preferences, as well as more specific themes, such as mood and job and life satisfaction. Information about users' energy-related behavior, perceived health, and self-reported work performance is also gathered, as are details about individual contextual factors (e.g., nature of work). As the other tools

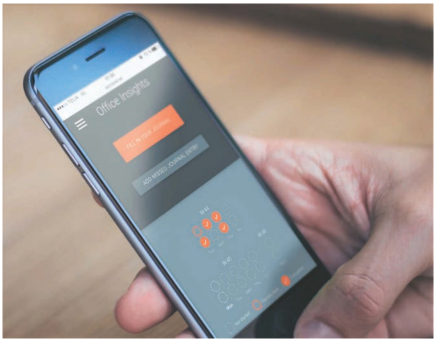

Figure 11.79 Image of the SSO User Insight Toolbox's web-based survey accessed via smartphone.

of the SSO User Insight Toolbox are not the focus of this chapter, the detailed description can be found in the study (Jin *et al*., 2019).

In the present study, a POE adapted from the SSO User Insight Toolbox focusing on the web-based survey was conducted over a two-week period in August and September 2019, one year after occupants' return post-renovation. In brief,

- A total of 283 permanent employees (i.e., long-term contracts) working in occupying offices on the third and fourth floors were invited to complete the web-based SSO survey; 160 (57%) participated in the survey, although around 40 chose not to answer all of the questions. Data were collected from occupant experience and satisfaction on IEQ, behavior, and individual control over indoor environment. The survey asked occupants a range of questions about their perceptions (i.e., experience and satisfaction) about the building's performance, including several factors of the indoor environment (glare, daylight, temperature, etc.) and adaptive behaviors for indoor comfort.
- Observations of the offices took place four times a day during three working days and three times a day during two working days to better understand how the spaces were used.
- A total of 46 in-depth individual interviews and two focus group interviews were conducted with a selection of the employees to gain a deeper understanding of individual needs.

For the purposes of this chapter, we will present and discuss only the survey findings because the study focuses on occupant perceptions of the actual indoor environments and the building design. See the study (Jin *et al*., 2020) for more results of the POE. The diary app and the reporting tool will be introduced in the future study.

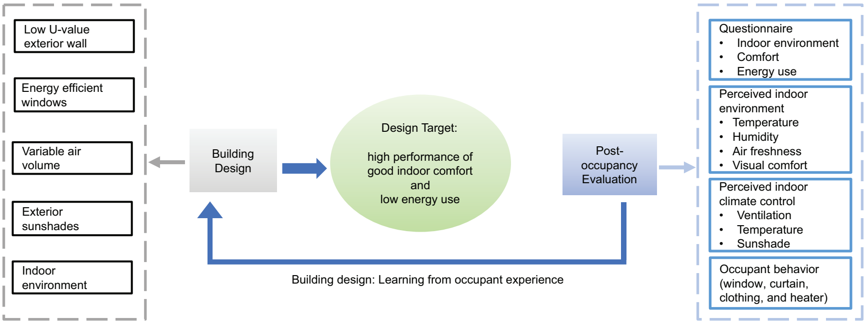

Figure 11.80 Building design concept: learning from occupant experience in the A-building.

11.8.4.2.1 COMPARISON OF THE BUILDING DESIGN AND SURVEY RESULTS

The target of the original building design is to achieve a high performance of good indoor environment and low energy use. The survey results from the study will be analyzed to examine the building's real performance and compare with the building design and simulation results. See Figure 11.80.

11.8.5 Results and Discussion

This section begins with the results of the building simulation from the early design phase, followed by key findings from the survey from the POE. Then, the simulation and survey results are compared and discussed alongside reflections on the development of an occupant-centric office design concept.

11.8.5.1 Building Simulation Results

The following sections describe the simulation results for the original model for the A-building's renovation, with a focus on energy performance, thermal comfort, and daylight.

11.8.5.1.1 ENERGY

Specific energy use intensity (EUI) for the whole building was calculated as 57.4 kWh/m^2 A_{temp} per year, which meets the requirement of Miljöbyggnad Silver (60 kWh/m^2 A_{temp} per year). The term A_{temp} defines the floor area for which the building's primary energy use is to be calculated. A_{temp} is the sum of the interior area for each floor, attic, or basement that is heated to more than 10°C. With the exterior screen installed, the solar heat load was reduced to less than 43 W/m^2 A_{temp}, which is rated as Miljöbyggnad Gold.

11.8.5.1.2 THERMAL COMFORT

The simulation results showed that the PPD in summer was lower than 10% in all simulated offices on the fourth floor. In the Miljöbyggnad rating system, this indicator of summer indoor climate was rated as Miljöbyggnad Gold. The simulation results also showed that the PPD in winter was lower than 10% in all simulated office spaces. This result means that the indicator of winter indoor climate was rated as Miljöbyggnad Gold as well. Figure 11.81 shows the PPD values on the fourth floor in a cold winter from the simulation by IDA ICE.

11.8.5.1.3 DAYLIGHT

The simulation results for daylight showed that the daylight factor (DF) was ≥1.2% for more than 21% of the total heated floor area on the third floor (see Figure 11.82). Only 3% of the total heated floor area was calculated with the DF of 1.0%. For all the office rooms on plan 3, most of the rooms were rated

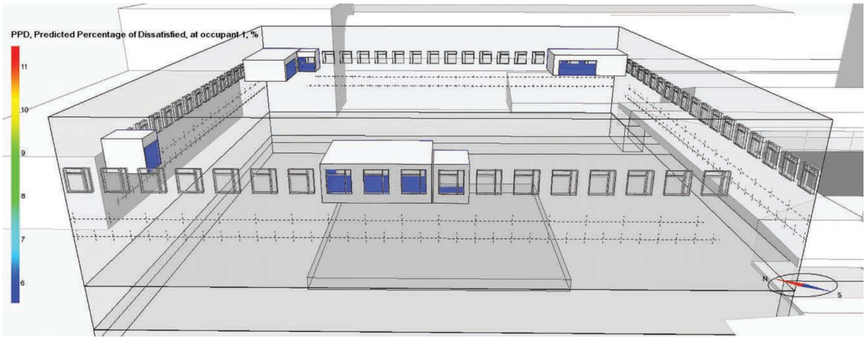

Figure 11.81 A selection of simulation result of the PPD on the fourth floor.

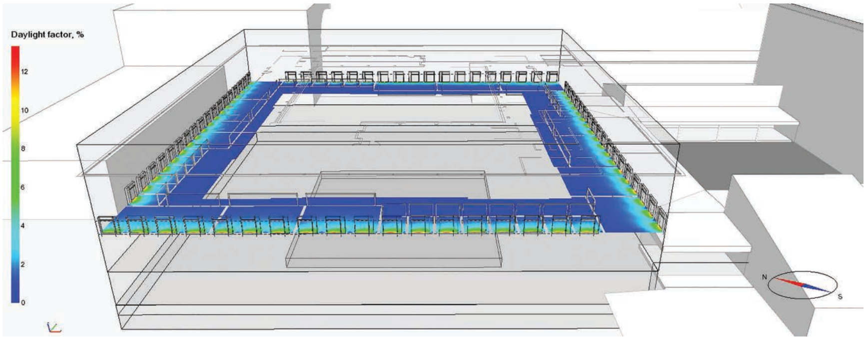

Figure 11.82 Simulation result of daylight factor on the third floor.

as Miljöbyggnad Gold, and one room was rated as Miljöbyggnad Bronze. The final grade for the DF was rated as Miljöbyggnad Silver.

11.8.5.2 Post-occupancy Evaluation Results

Figure 11.83 shows the levels and percentages of occupants' satisfaction with eight factors of the indoor office environment based on the survey results from the POE. In general, most of the factors were perceived as satisfactory by most of the occupants, except the screen and indoor temperature. The satisfaction rate for the overall indoor climate was about 70%. The amount of light and glare had a satisfaction rate higher than 80%, and other factors (air quality, daylight, air movement, and access to outside views) had a satisfaction rate of 70%. The most dissatisfactory factors were the air temperature and the screen.

Figure 11.84 shows occupants' satisfaction with the level of individual control of the indoor climate. In the survey, occupants were asked about their perceptions of daylight, ventilation, and indoor temperature since

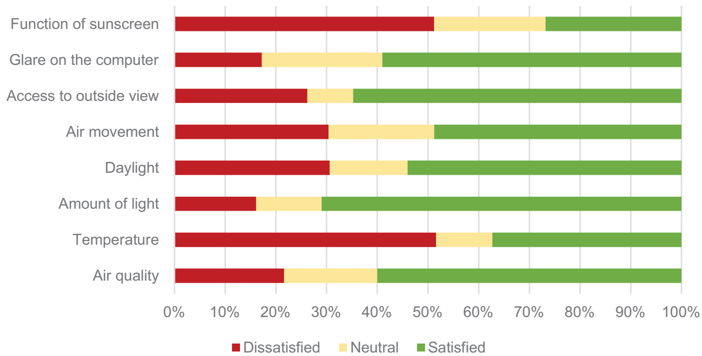

Figure 11.83 Percentage of occupant satisfaction with eight factors of the indoor environment.

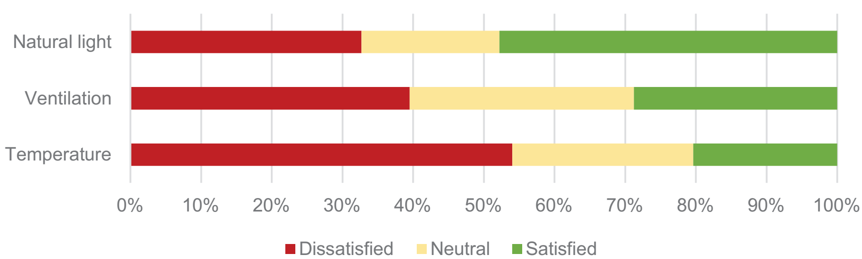

Figure 11.84 Percentage of occupant satisfaction for individual control of the indoor environment.

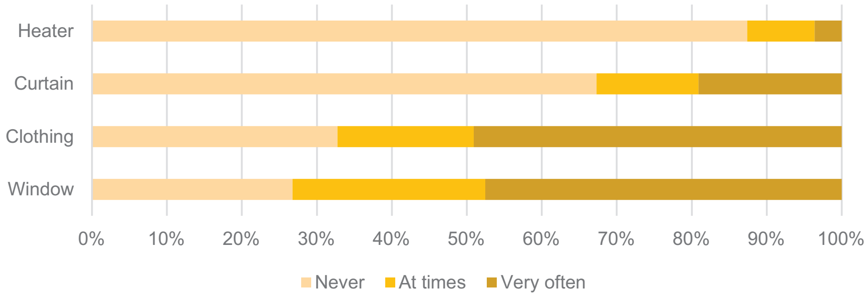

Figure 11.85 Frequency of occupant behavior for individual comfort.

these can be controlled to some extent by occupants. For example, glare/daylight can be blocked by a curtain, airflow can be controlled by either opening or closing a window, and indoor temperature can be controlled by operable windows. The screen cannot be operated manually by the occupants. In general, the satisfaction rates for all three components were relatively low, where more than 30% of occupants reported feeling dissatisfied. A majority of occupants expressed dissatisfaction with the control possibilities regarding indoor temperature.

Figure 11.85 shows the frequency of occupants' adaptive actions to improve comfort. It was observed that about half of the occupants reported operating the windows "Very often" in the office, and, in total, more than 70% of the occupants reported operating the windows at least "At times". Another factor related to occupant behavior was clothing: about 70% of the occupants reported adjusting their clothing to improve their thermal comfort.

11.8.5.3 Comparison of the Building Design Performance and the Perceived Performance

The original design for the renovation of the A-building met the design requirements of Miljöbyggnad Silver with a good indoor environment and low simulated energy consumption. In this case study analysis, the design information was collected and compared with data collected from occupant surveys. The results showed that the design enhanced the building's performance regarding daylight, ventilation rate, and energy saving, among others. Some indicators, such as daylight factor and PPD, were simulated and met the requirements for the Miljöbyggnad Gold level. Additionally, the exterior screen both reduced specific energy use in the A-building and contributed to high occupant satisfaction against the glare on their computer screens.

However, the survey results pointed to gaps between the designed performance and perceived building performance. Thermal comfort was not perceived to be satisfactory by the majority of the occupants even though the PPD was simulated to be less than 10% with a thermal sensation around neutral. The majority of occupants indicated a preference for a warmer indoor environment. Simultaneously, 30% of the occupants were not satisfied with the air movement, as drafts were perceived in some rooms. Yet, the reported occupant satisfaction with perceived air quality was at a good level with VAV ventilation.

Furthermore, the function of the screen was not perceived to be satisfactory by more than half of occupants, where many occupants preferred more daylight and felt that the screen blocked daylight and outside views, and it cannot be operated manually. Thus, 30% of the occupants felt dissatisfied with daylight levels, even though the amount of light was sufficient according to the measured values (Jin *et al.*, 2020). Likewise, occupants were not satisfied with the level of individual control of the indoor climate, such as room temperature, mechanical ventilation, and natural light.

These gaps may be because of design decisions and/or control strategies in the operation phase. For example, the airflow rate, which varies with presence, might be set too high and it cannot be controlled by occupants. Alternatively (or additionally), the setup value of solar radiation for daylight might be too low. The color and transparency of the screen material might be another influential factor.

When considering energy conservation in a building renovation, occupant demand and preference need to be addressed. In the A-building, the exterior screen was energy efficient; however, it reduced daylight and outside views. A better solution is needed to balance energy savings and visual comfort. Likewise, occupants' control of the indoor climate must be considered. With the possibility of ventilation and screen control, for example, occupant satisfaction might be improved.

11.8.6 Concluding Remarks

The A-building is an example of a building renovation that was designed to perform well in terms of indoor environment and low energy consumption. Energy-efficient solutions were applied, including high-performance windows, low U-value exterior walls, exterior screens, and a VAV with heat recovery. Yet, there were notable discrepancies between the A-building's designed and actual performance during operation and its occupants' perceptions of indoor comfort. Occupants' insights, collected through an extensive POE using the SSO User Insight Tool, included occupant satisfaction with IEQ, indoor climate control, and occupant behavior. The study found several instances of occupant dissatisfaction with the indoor environment that reinforce the need for more occupant-centric building design processes.

For example, in the A-building, opening windows happened frequently compared to other interventions, such as interactions with heaters and curtains. Enabling occupants to control the indoor climate, particularly the temperature and the shading situation, may have significantly increased occupant satisfaction. However, these aspects were not sufficiently considered in the building design, nor are they considered in building regulations or building certification schemes. Early-phase design and building control strategies need to better consider occupants' indoor comfort and preferences alongside energy consumption. Conducting occupant surveys can increase stakeholders' awareness of occupant-centric building design and performance. A pre-intervention survey or POE should be conducted for building renovations as well as new building designs, and the collected information and feedback should be integrated into the building planning and design process.

The next step of this case study is to provide recommendations to the A-building owner and facility managers to further improve occupants' satisfaction regarding IEQ. A further point to make is for the office design of the future, we need to better understand not only the factors to negatively affect occupants' comfort and well-being but also the positive factors, for example, salutogenic design (health-promoting potential), drawing on sense of coherence (SOC) theory (Antonovsky, 1987; Eriksson and Lindström, 2006; Allen *et al.*, 2019; Forooraghi *et al.*, 2021).

11.9 Closing Remarks

In this chapter, we presented occupant-centric analyses of seven case study buildings to demonstrate the benefits of recognizing occupants and their behavior during the design process and throughout the building life cycle. The buildings were of different types and located in different countries and climates, and in different phases of the building life cycle. Likewise, the studies represented different design and analysis approaches including participatory design, parametric and sensitivity analysis, optimization, operational data analysis, and statistical modeling. Considering the lessons learned from each case study, we can conclude the chapter with the following:

- Undertaking occupant-centric design requires information to be shared effectively among design stakeholders. The traditional linear design process is problematic, as it can lead to discrepancies in design assumptions and, consequently, to suboptimal or overlooked design solutions.
- Assumptions about occupants can be influential when performing design parametric analysis. Different occupant-related assumption can lead to a different savings potential of ECM/DP. Additionally, occupant assumptions can influence the outcomes of the design optimization process.
- Occupant assumptions can also influence the comfort performance of buildings, as current comfort metrics used by practitioners do not consider comfort at the occupant and zone levels. New occupant-centric comfort metrics should be developed and used instead.
- Occupant participation in the design process (i.e., co-design) is beneficial in achieving a more accurate representation of occupants' presence

and activities. Co-design can reduce performance gaps and improve energy efficiency.

- Increasing occupants' consciousness of their energy-intensive behaviors is an important factor in achieving energy efficiency.
- Collecting occupant-related data on individualized occupant dynamics post-occupancy can be helpful for improving spatial design (i.e., optimized layouts) and energy efficiency. More broadly, such data collection is useful to understand performance gaps between predictions during design and actual performance.
- The analyses highlighted the importance of post-occupancy data collection through occupant surveys, sensing infrastructure, and interviews with building design stakeholders.

Note

Figures 11.50, 11.51, 11.52, 11.53, 11.54, 11.55, 11.56, and Tables 11.12, 11.13 reprinted from Energy and Buildings, Vol 238, Andrew Sonta, Thomas R. Dougherty, and Rishee K. Jain, Data-driven optimization of building layouts for energy efficiency, Copyright (2021), with permission from Elsevier.

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12 Conclusion

Farhang Tahmasebi and William O'Brien

This is the first known book to focus on occupant-centric building design with an emphasis on quantitative and simulation-aided approaches. It builds upon decades of research on a variety of topics ranging from indoor environmental quality and design theory to occupant modeling and simulation. Starting in 2018, over 100 researchers from around the world converged to form the collaborative *International Energy Agency's (IEA) Energy in Buildings and Communities (EBC) Annex 79: Occupant-centric building design and operation*. The Annex 79 researchers were mid-way through writing this book when the COVID-19 pandemic began and the world gained a heightened appreciation for the critical role that buildings play in occupant health and well-being. As the virus spread through ducts and other pathways within buildings, and entire organizations and institutions shifted operations to work-from-home, interest in occupant-centric design and operation suddenly became widespread. In a way, this unfortunate event in history served as a catalyst to fundamentally rethink the way buildings are designed and operated for occupants. This book provides researchers and practitioners with concrete knowledge and guidance to build on this momentum and make significant improvements to the field.

In the first half of the book, we provided an overview of indoor environmental quality (IEQ) fundamentals and took a critical look at pertinent standards. We then addressed the challenges of integrating consideration of occupants into the building design decision-making process and proposed occupant-centric design patterns that could support the recording and transfer of the required information in this process. Arguing that occupants can greatly inform building designers and operators, we discussed methods for actively engaging occupants in design processes. Next, we established the need for and presented a suite of occupant-centric building performance metrics and targets. These metrics and targets represent a paradigm shift by positioning occupants as the central consideration – rather than merely one of many – of building performance.

In the second half of the book, beginning with Chapter 6, we focused our attention on building simulation and its applications. First, we introduced occupant modeling and a wide range of occupant model types, from

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traditional schedules to sophisticated agent-based models. We then discussed different approaches to identifying fit-for-purpose occupant models for different building performance queries, and we described and tested a number of simulation-aided design methods incorporating occupant behavior at their core. Next, we presented the interfaces and sequences of building systems operation and control as essential elements in the design of occupant-centric buildings. Lastly, to provide relatable details to a broader audience, we documented seven case studies of occupant-centric design that showcased a range of the considerations and strategies we discussed throughout the book.

12.1 Further Research

By addressing occupant-centric simulation-aided building design from different perspectives, we, the authors of the book, have collectively identified considerable potential for advancement in the field, including several key areas for further investigation within the research community. To begin, at a fundamental level, future research should continue to provide a better understanding of occupants' expectations, perceived and actual control, multi-IEQ-domain influences contributing to occupant-building interactions, and the balance between manual and automated building interfaces. Most modeling and simulation efforts focus on quantifying energy performance and, rather coarsely, several types of IEQ (particularly thermal comfort). However, future simulation should simultaneously consider all four domains of IEQ, the interrelationships between them, and other occupant needs (e.g., views, privacy, ergonomics, etc.).

As evidenced by the detailed case studies in Chapter 11, more efforts are needed within the design practice ecosystem to facilitate the effective transfer of information regarding occupancy and occupant behavior throughout the decision-making process and among different stakeholders. There is still much room for improvement in terms of engaging occupants in the processes of designing buildings. Although the ultimate occupants of a building are often unknown at the time of design, designers and other stakeholders are nonetheless responsible for delivering healthy and comfortable buildings. Enhancing occupants' awareness of the buildings' environmental control possibilities and collecting and analyzing post-occupancy data could also contribute significantly to realizing occupant-centric design visions.

With regard to occupant behavior modeling, access to large-scale occupant-related data remains a barrier to the development of more reliable, inclusive, and widely applicable models. In particular, the representation of different groups of occupants (with their specific preferences, needs, and behaviors) would add noticeable value to design. Realizing this potential, however, would demand a comprehensive set of occupant behavior models developed based on sizable and geographically diverse occupant-related datasets. Even if this data were to be obtained, occupant behavior modeling efforts would still need to go beyond thermophysical conditions to include occupant health and well-being more thoroughly. Other relevant areas of future work include enhancing the feasibility of integrating a new generation of occupant models into simulation-aided design workflows and establishing building design workflows that accommodate simulation-aided performance investigations in a more influential manner. Furthermore, occupant-centric building control is an active area of research that explores emerging machine learning techniques toward a more effective use of occupant information in operation of buildings.

Finally, understanding building interfaces, their design, and how users interact with them remains a critical research area with potentially substantial impact on the efficient operation of buildings and occupants' health, comfort, and well-being. Despite building interfaces playing an important role in both providing occupants with greater opportunities to control their environment and promoting pro-environmental behavior, the state of research in human factors and building interfaces is noticeably behind that of other consumer and industry products.

While leading and ambitious practitioners and building projects will continue to aim to surpass the status quo, a large portion of the building industry will aim only to achieve code compliance. It is therefore essential that researchers continue to contribute to building codes and standards to translate knowledge into mandated requirements – for all aspects and life-cycle stages of occupant-centric buildings.

12.2 Future Prospects

In the conclusion of *Exploring Occupant Behavior in Buildings* (Wagner *et al*., 2018) – which can be seen as a predecessor of this book – the authors suggested that occupant behavior research was at its peak and likely to go through a phase of disillusion to face new real-world challenges. Arguably, this premonition has actually happened. The research community is now much clearer that the mere inclusion of a few sophisticated probabilistic occupant behavior models in a building performance model does not in itself bridge the so-called "performance gap", nor does it automatically solve any other major problem in the building industry. In fact, in the present book, our focus on the application of occupant modeling to the building design process is based on the understanding that occupant behavior research is very much in need of finding its role within the rapidly evolving building design and operation practice.

But make no mistake, while the research community now sees the impact of narrowly defined occupant behavior models more clearly and more realistically (and as a piece of the puzzle in occupant-centric design), the need for further research on occupant behavior and its application in building design and operation practice is greater than ever. In recent years, we have seen ever-increasing threats of climate change, extremely wide-ranging and unequal effects of a global pandemic, the development of deeper automation systems with vast potential and correspondingly vast concerns, a global refugee crisis, increased impacts of disinformation and so-called "alternative facts", and exceedingly destructive wars that necessitate the accommodation of large, dislocated populations and reconstructing demolished cities from scratch. These are problems that must be addressed globally by systems thinkers and with a continued trust in environment-friendly and human-centered science and technology. These challenges (and opportunities) require building designers to address environmental problems and societal problems in tandem and much more consciously. To this end, we believe a holistic approach to understanding occupants' preferences, needs, and behavior will continue to play a key role in realizing truly occupant-centric buildings and communities.

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