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

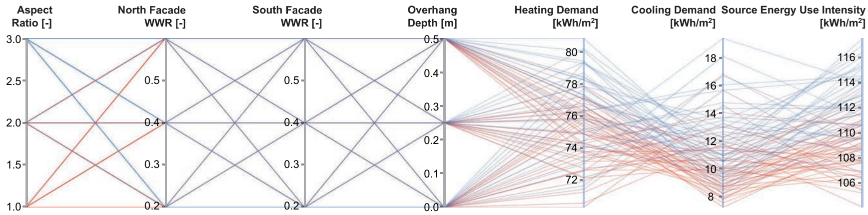

Figure 8.1 An example parallel coordinates plot depicting the mapping between design parameters (here, building aspect ratio, north and south façades window-to-wall ratio, overhang depth) and performance indicators (here, heating demand, cooling demand, source energy use intensity).

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 $x \in X\text{min } f(X)$ 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

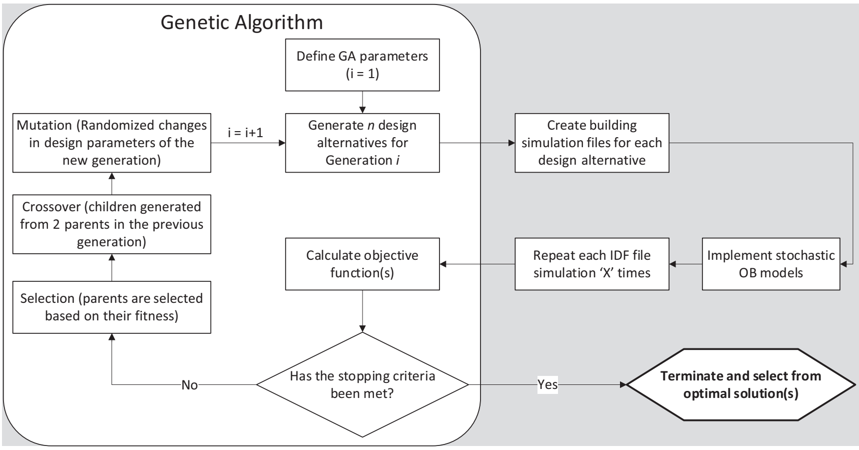

Figure 8.2 Overview of integrating stochastic occupant behavior in optimization using the genetic algorithm.

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

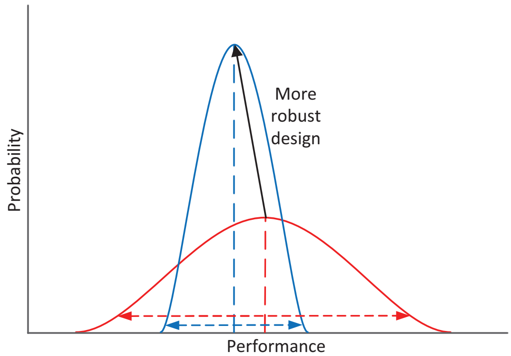

Figure 8.3 Probability distribution for two different design options. Robustness is indicated by the spread (variance) of the distributions. In this case, the design depicted by the narrower distribution is preferable because it is not only less uncertain but also has a lower mean predicted performance.

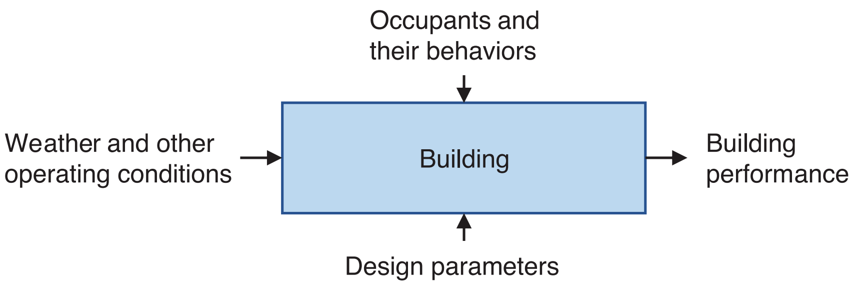

Figure 8.4 P-diagram for robust design applied to buildings and uncertainty from occupants.

(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

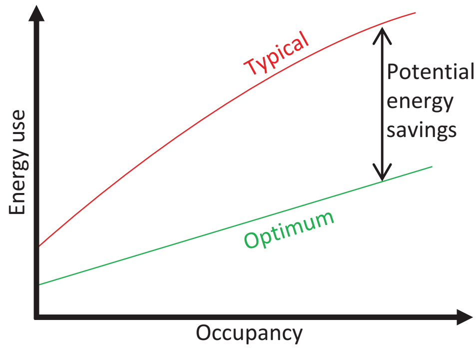

Figure 8.5 Conceptual representation of a building with adaptable features versus a building with traditional non-adaptive features.

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·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·K and profile width of 6 cm. The outside wall insulation's U-value was specified as 0.325 W/m^2·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

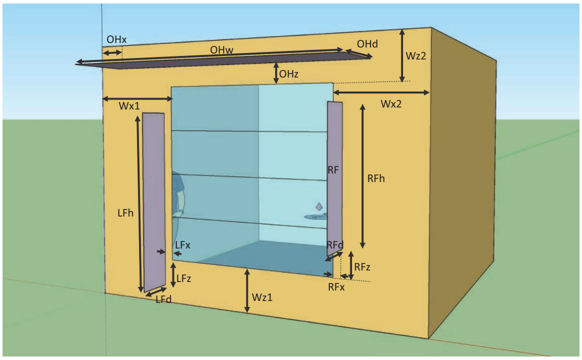

Figure 8.8 Parametric office geometry with variables for robust design test. Note that the window is modeled as four windows for the purpose of simulating partially closed shades.

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

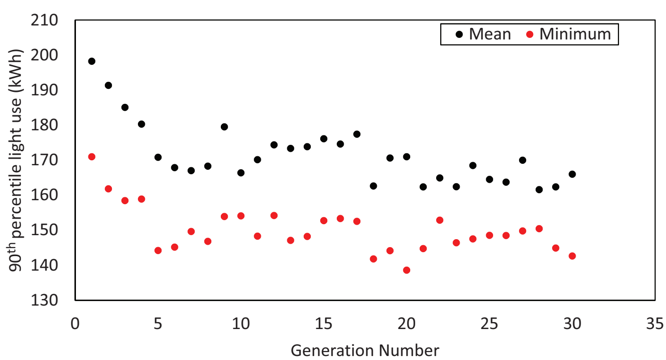

Figure 8.9 Optimization results through 30 generations.

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.

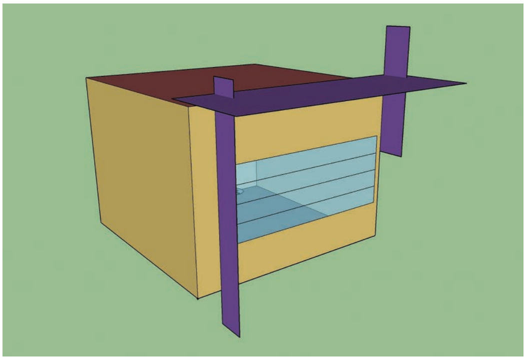

Figure 8.10 Optimal fixed shading design corresponding to the lowest predicted lighting energy use.

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

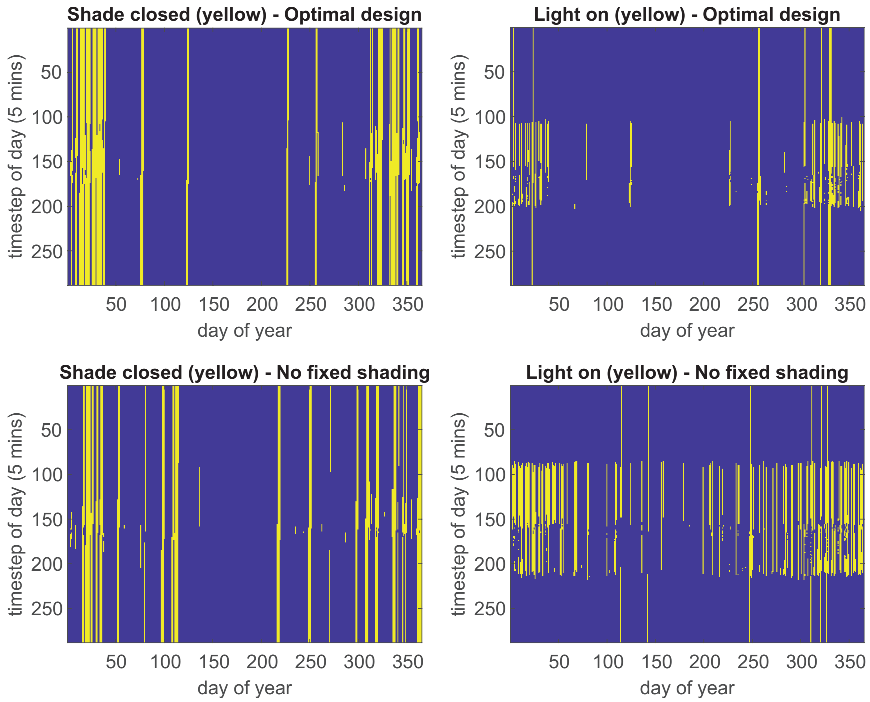

Figure 8.11 Comparison of light and shade states for a single simulation for both the optimal and no fixed shading cases.

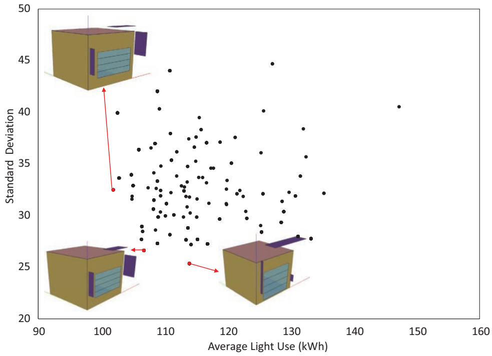

Figure 8.12 Pareto-optimal design alternatives for minimizing average annual light use and standard deviation.

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.

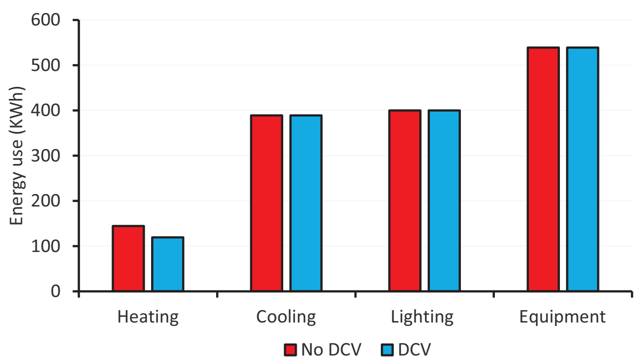

Figure 8.13 Energy use by category obtained from the building model with deterministic occupancy models with and without DCV.

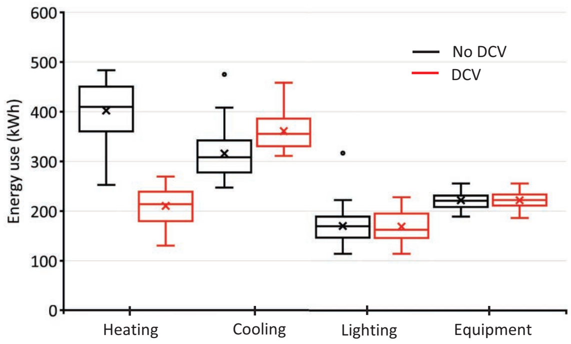

Figure 8.14 Energy use by category obtained from the building model with stochastic occupant models. The results demonstrate the energy use benefits of deploying adaptive technologies such as DCV.

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

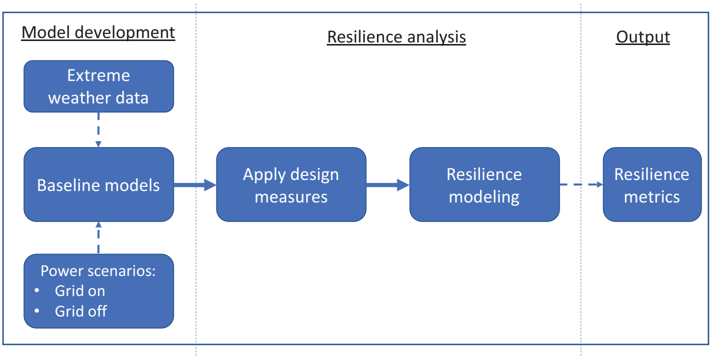

Figure 8.15 Workflow of resilient design simulation.

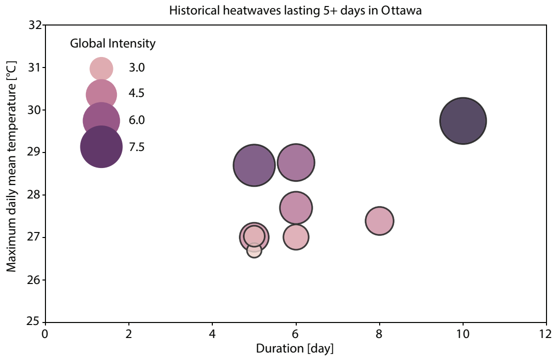

Figure 8.16 Historical heat waves that lasted longer than five days in Ottawa. Note: The size of each bubble represents the global intensity of a heat wave. Global intensity is defined by the cumulative difference between the temperature and the S_{deb} threshold during the event, divided by the difference 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

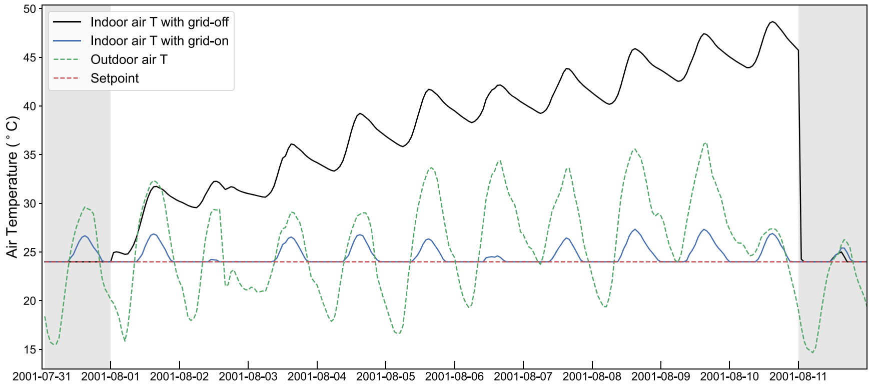

Figure 8.17 Comparison of outdoor and indoor air temperature under power-on and power-off scenarios. The greyed-out periods are one day before and one day after the heat wave under normal operation to illustrate the impact of the heat wave.

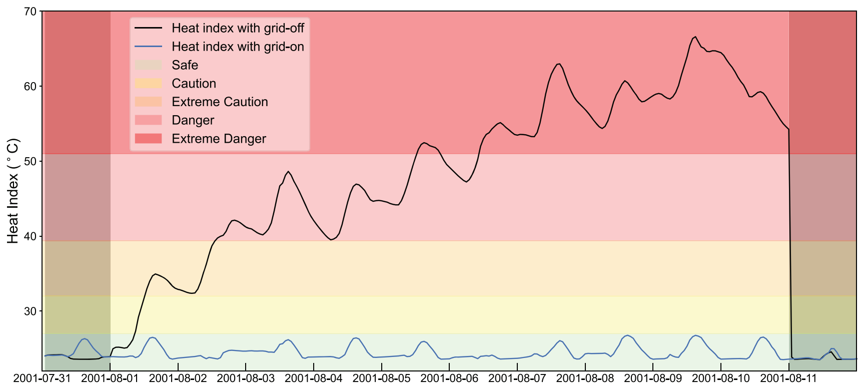

Figure 8.18 Hourly indoor Heat Index, with and without grid power. The greyed-out periods are one day before and one day after the heat wave under normal operation to illustrate the impact of the heat wave.

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.

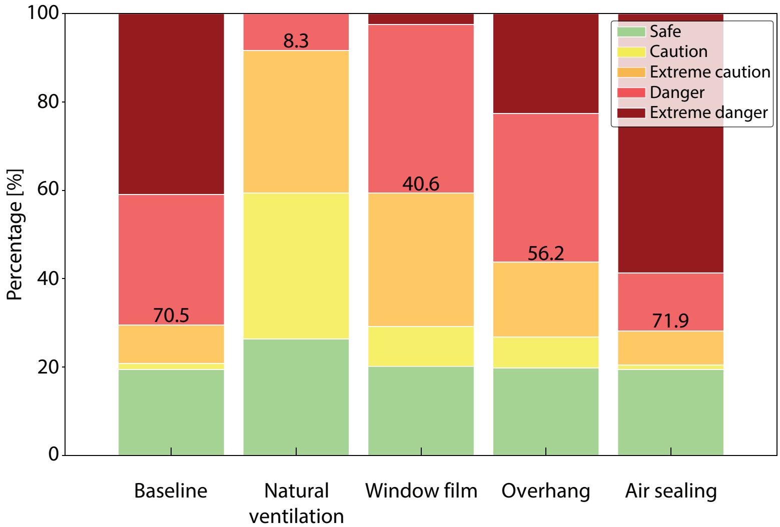

Figure 8.19 Heat hazard occurrence distribution of the baseline and design measures (labeled numbers refer to the total percentage of "Danger" and "Extreme danger" occurrences).

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 onsite 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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