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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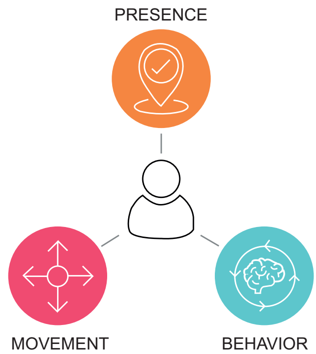

Figure 7.1 The three categories of people modeling.

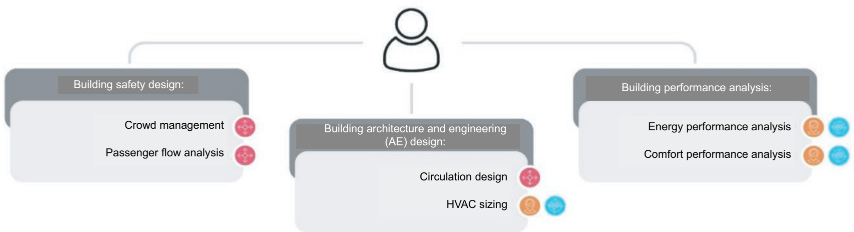

Figure 7.2 Applications of people modeling during the building design phase.

- *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

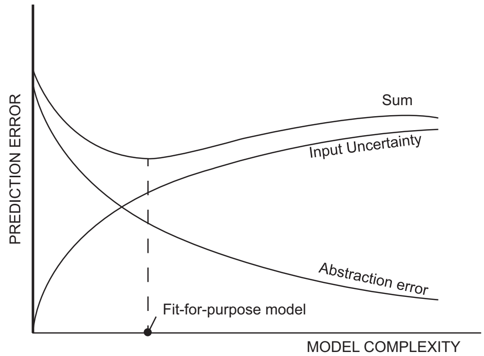

Figure 7.3 Model complexity versus prediction error.
Adapted from Alonso (1968).

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

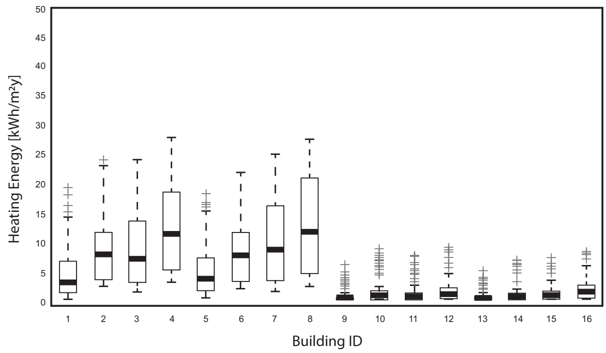

Figure 7.4 Variation in heating energy use due to high/low patterns for uncertain aspects of occupant behavior; see text for explanation of legend and results.

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.

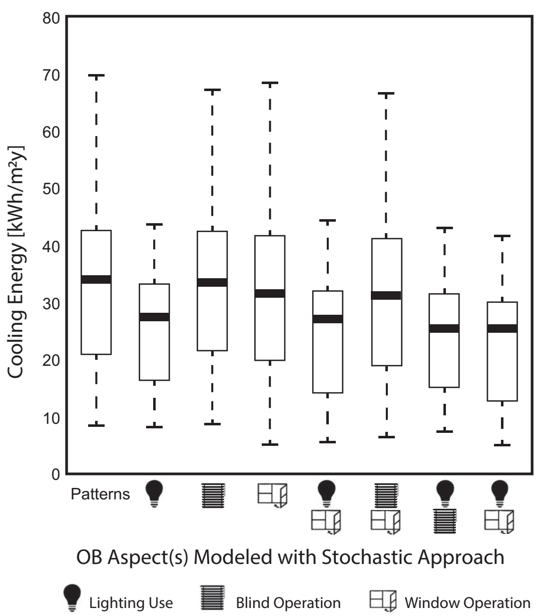

Figure 7.5 Effect in cooling energy use distribution by changing the modeling approach for influential aspects of OB (light switch behavior) and non-influential aspects of OB (shading devices and window operation), as well as all possible combinations; see text for explanation of legend and results.

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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