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A stepwise approach for assessing the appropriate occupant behaviour modelling in building performance simulation

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ABSTRACT

Occupant behaviour (OB) is recognized as a leading source of uncertainty in building performance predictions. Neglecting the potential influence of uncertainties on building performance could result in erroneous decision-making during the design phase. Therefore, it is essential that uncertainties are appropriately considered within building performance simulation (BPS) models. As for OB, there are various approaches to model occupant presence and actions in BPS tools. Literature shows that the appropriate modelling approach depends on the object and purpose of the simulation, which makes it difficult to favour a method over another \textit{a priori}. Moreover, there is very little support for selecting the most appropriate modelling approach. As a result, OB is modelled in practice in various ways, mostly dictated by intuition and habit. This study builds on previous literature to introduce and test a complete approach for appropriate OB modelling. The method can be generalized and readily applied to design questions.

1. Introduction

Energy consumption of buildings has dramatically increased over the past decade due to population growth, more time spent indoors, bigger floor area per capita and improved indoor environmental quality standards (IEA 2017). At the same time, the building sector offers great potential for energy savings. For these reasons, buildings have become a major frontline in our efforts to save energy. Global and local building policies set stringent energy goals for new and existing buildings with the aim of reaching near zero energy and carbon emissions. However, concerns exist about the comfort-related risks arising from low-energy, highly insulated buildings in a changing climate (Chvatal and Corvacho 2009; McLeod, Hopfe, and Kwan 2013; Sameni et al. 2015).

In this context, predicting, assessing, and verifying the energy and comfort performance of buildings has become vital at different stages of the building life cycle, from building design to operation.

Nowadays, buildings often include advanced technologies and materials that make them very complex. It is thus ever more challenging to design and operate energy-efficient buildings that do not compromise on indoor environmental quality (IEQ). Building performance simulation (BPS) software has emerged as a useful tool in supporting the design and operation of buildings.

BPS models are typically deterministic, i.e. they contain no random variables and no degree of randomness. These models have fixed input values that result in a corresponding set of outputs (for example, the amount of yearly energy use in kWh/m\(^2\) or the indoor temperature distribution in °C). However, it frequently occurs that not all input values are known with certainty by the user of the BPS tool.

The reliability of BPS tools’ outputs is dependent on the quality of the BPS models and on their input, following the \textit{garbage in = garbage out} principle. However, even though much effort may be put into the model, the BPS models may still be subjected to uncertainty. In particular, the following types of uncertainties are distinguished (de Wit and Augenbroe 2002):

- **Numerical uncertainty** arising from the numerical techniques, model discretization, and computational hardware used to run a mathematical model;
- **Modelling uncertainty** resulting from the fact that all models are imperfect representations of reality;
- **Input uncertainty** associated with the unknown or uncertain input parameters.

Input uncertainties are themselves categorized into two main groups: (i) \textit{epistemic uncertainties} (from Greek epistēmē, ‘knowledge’), which are potential inaccuracies connected to knowledge (Oberkampf et al. 2002) and can be reduced by gathering more data; and (ii) \textit{aleatory uncertainties}, which are associated with the unpredictable boundary conditions and use scenarios of a building, such as weather and occupant behaviour (OB).

1.1. Uncertainties in BPS due to OB

Numerous researchers have identified OB as the single most important source of uncertainty in BPS (e.g. Li, Hong, and Yan...
OB includes the physical presence of occupants, as well as their actions that have an influence on the energy use and thermophysical behaviour of a building, such as using plug-loads, operating windows and shading devices, setting thermostats, etc.

Figure 1 shows the difference between the highest and lowest consumers in heating energy (Figure 1a) and total energy (Figure 1b) in terms of ratio (building consuming most energy: building consuming least energy) in identical buildings where the sole difference are the occupants. The figures show that, indeed, how occupants behave within buildings can have a dramatic effect on the building’s energy and comfort performance.

Figure 1a includes two simulation studies (Gaetani, Hoes, and Hensen 2016a [1]; Lin and Hong 2013 [2]) and five field studies (Morley and Hazas 2011 [3]; Gram-Hanssen 2011 [4]; Maier, Krizczek, and Tejchman 2009 [5]; Gaunt and Berggren 1983 [6]; Andersen 2012 [7]), while Figure 1b presents the outcome of three simulation studies (Wang, Mathew, and Pang 2012 [8]; Hong and Lin 2012 [9]; Clevenger, Haymaker, and Jalili 2014[10]) and four field studies (Norford et al. 1994 [11]; Lutzenhiser 1993 [12]; Muroni et al. 2019 [13]; Sonderegger 1978 [14]).

A median ratio of about 1:2.4 (heating energy) and 1:2.2 (total energy) between the buildings using the least and the most energy was observed due to differences in OB alone. These values give an impression of the potential uncertainty of BPS output if variation in OB is not taken into account in a suitable way.

However, Figure 1 also shows the high variability of OB influence among different studies. The different studies investigated diverse buildings, climates, occupants, and available interactions between occupants and building. This research demonstrates that it is impossible to define a priori what the influence of OB on building performance may be. What is important to note, however, is that the influence of certain aspects of OB on building energy performance tends to increase as building envelopes and systems are optimized, technical performance standards become tighter and low-energy systems become more widespread (Clevenger and Haymaker 2006). In other words, the more energy-efficient the building, the more attention needs to be paid to the impact of certain OB aspects on building performance. Conversely, other OB aspects, such as the use of shading systems, might be less influential for the energy performance of buildings with high-performing glazing.

1.2. Occupant behaviour and BPS practice

A large survey was carried out among BPS users to determine if the uncertainty in OB and its modelling was also perceived as a relevant topic outside the academic community (O’Brien et al. 2016). The majority of the survey’s respondents agreed that OB was the most important source of discrepancy between BPS predictions and measurements in real buildings, confirming that this issue was also seen as relevant among practitioners (Figure 2).

Appropriate modelling of OB allows this type of aleatory uncertainty to be included in BPS to achieve reliable predictions. However, while BPS tools are advanced in predicting the functioning of building envelopes and systems, they are still lacking in the ability to properly address how occupants behave within buildings.

Despite understanding the relevance of OB modelling in BPS, most simulation users still rely upon fixed, a priori schedules and other simple IF–THEN models to describe occupant presence and their behaviour. Schedules and IF–THEN models represent a
completely foreseeable, repetitive environment where changes only occur because of predefined shifts in one or more variables (typically, time or environmental triggers). They represent the lowest level of complexity of the OB sub-model, and are often dictated by standards such as ASHRAE 90.1 (ASHRAE 2013). Simulation experts agree that OB modelling features should be improved in BPS tools, but they object that there are no better available modelling options, nor guidance for model selection (O’Brien et al. 2016).

1.3. Occupant behaviour and modelling complexities

In response to these concerns, researchers have been developing a growing number of increasingly complex models (for example, stochastic, agent-based models), mostly derived from actual data (e.g. Haldi and Robinson 2010; Tanimoto et al. 2013; Yun and Steemers 2008; Page et al. 2008; Tanimoto and Hagishima 2005). Due to their conceptual differences, a distinction is made between the modelling formalisms used for presence, adaptive actions (actions performed as a reaction to indoor/outdoor variables, such as opening a window) and non-adaptive actions (such as the use of equipment). Currently, presence can be modelled using (standard or data-driven) occupancy schedules, discrete-time Markov models, and survival models. Adaptive actions are modelled as schedules, deterministic models, Bernoulli models, discrete-time Markov models, or discrete-event Markov models. Non-adaptive behaviour can be modelled using schedules, occupancy schedules or survival models. Such models can be broadly classified, according to their size and resolution, in terms of complexity: schedules and deterministic models, probabilistic models, and agent-based models (Gaetani, Hoes, and Hensen 2016a). Nevertheless, these models are subject to questions about their validity and seldom find application in practice (Mahdavi and Tahmasebi 2017). The few studies that compare different OB model complexities fundamentally disagree on which level of complexity delivers a better predictive ability (e.g. Mahdavi and Tahmasebi 2016; Tahmasebi, Mostofi, and Mahdavi 2015; Duarte, Van Den Wymeelenberg, and Rieger 2013; D’Oca and Hong 2014; Langevin, Wen, and Gurian 2014; Chapman, Siebers, and Robinson 2014; Azar and Menassa 2010; Yamaguchi, Tanaka, and Shimoda 2012), but they do align on the fact that more complex models are not always needed. Moreover, simulation users are not supported in the model selection for a specific case, which leads to a negligible application of research models in practice.

An oversimplified approach to OB modelling may lead to a number of pitfalls such as: designing buildings that do not achieve the desired performance; over- or under-sizing of building systems; and failing to optimize building design and control for actual occupant presence and behaviour. On the other hand, using complex, often stochastic models, currently requires specific expertise and large expenditures of time and money, which may not be justified by the improvement in the simulation’s output quality. Other applications that could benefit from an appropriate representation of OB include: risk assessment; controls and operations; demand-side management; building flexibility; occupant comfort analysis; and simulation-based occupant-feedback mechanisms.

1.4. Need for fit-for-purpose occupant behaviour modelling in BPS

Due to all of the reasons mentioned above, there is a need to bring together research and application by providing guidance for practitioners about OB model selection. Doing so would also increase the probability that the efforts made in the academic community to develop models are rewarded by the successful application of the models in practice. This paper presents the outcome of a research directed towards the development of an approach for fit-for-purpose OB modelling in BPS. A number of steps of this research are based on a body of previously published work (Gaetani, Hoes, and Hensen 2016a, 2016b, 2017, 2018), but the complete approach is presented in this paper for the first time as a comprehensive methodology that can be readily applied to a variety of case studies and design questions. While the previous works were focusing on different levels of sensitivity analysis to determine the influential aspects of OB, guidelines for modelling are provided here. The step-by-step approach is detailed in Section 2. Four single-occupant offices in Amsterdam are used as a simple case study to illustrate the FFP-OBm approach and to demonstrate its potential (Section 3). The results are presented and discussed in Section 5, while the conclusions are provided in Section 5.

2. The FFP-OBm approach

The model complexity should not be investigated for all aspects of OB in all simulation problems. It is possible to frame the relevance of OB by considering an uncertainty-impact matrix (see Figure 3). In those cases where the potential impact of an OB aspect on the simulation results is low, such aspect shall be modelled using the lowest possible complexity. If the potential impact is identified as high but the degree of uncertainty is low, the available knowledge should be used to model this particular OB aspect. The cases that should be investigated by means of the FFP-OBm approach are those characterized by a high degree of

![Figure 3. Uncertainty-impact matrix applied to OB model selection. Adapted from (Yan et al. 2017).](image-url)
uncertainty and a high potential impact on the simulation results (quadrant highlighted in Figure 3).

However, matters are complicated further. Firstly, various OB aspects may be interrelated, and this interrelation should be considered while modelling (e.g. occupant presence, which is a necessary condition for most behaviours; different presence statuses can also act as triggers for sub-models, such as in (Haldi and Robinson 2010)). Secondly, while the degree of uncertainty related to an OB aspect can be assessed using available knowledge, this may not be the case for the level of impact. The axis that separates high impact from low impact often cannot be drawn a priori.

Therefore, the FFP-OBm approach must include a method to assess whether an OB aspect is relevant or not for the results. Moreover, it should allow the user to input further information about OB aspects whose epistemic uncertainty (the uncertainty derived by lack of knowledge) can be reduced.

The proposed FFP approach is based on two fundamental concepts: (i) there is a trade-off between abstraction error and input uncertainty when increasing the modelling complexity, and (ii) the modelling complexity for each aspect of OB should depend on its relevance for the results.

The first concept essentially means that the most elaborate and inclusive predictive model is not necessarily the best for applied work, depending on the quality of the available input data; poorer data call for simpler models (Alonso 1968). Often, this concept is introduced graphically with visualizations such as Figure 4.

In the field of OB modelling, however, it is not yet proven that more complex models are characterized by a lower abstraction error (i.e. that they do offer a better approximation of reality), due to issues connected with model validation and verification (e.g. Mahdavi and Tahmasebi 2017). For this reason, this concept is currently confronted in the FFP-OBm approach by considering other uncertainty sources related to the model and comparing them with OB-related uncertainties. If the input uncertainties related to other aspects of the model (e.g. thermophysical properties uncertainty) outweigh the OB-related uncertainties, there is no sense in increasing the OB model complexity. This check is made in the Step 2 of the approach.

The second concept is based on the notion of building robustness to OB (Hoes et al. 2009). A key step of the approach is to separate influential and non-influential OB aspects. This goal is achieved by means of increasingly complex sensitivity analyses, as explained later in the paper.

The methods presented in (Gaetani, Hoes, and Hensen 2016b) and (Gaetani, Hoes, and Hensen 2018) (namely the Impact Indices Method and the Diversity Patterns Method including the Mann–Whitney $U$ test), form the core of the FFP-OBm approach and allow for the identification of OB influential aspects. Then, the user of the stepwise approach can decide to reduce the epistemic uncertainty connected with such aspect(s) (where possible), or to refine the OB model.

In this section, the overall approach is presented, starting with the problem at hand and ending with the fit-for-purpose occupant behaviour model for each OB aspect.

Figure 5 is the resulting FFP-OBm approach. The approach is composed of a number of steps. A detailed description of each step follows hereafter.

- **Step 1 / Start: Problem definition**

The starting point for each study must be the acknowledgement of the objectives and scope of the study itself. Besides building, climate and phase in lifecycle, it is important that the user of the approach is aware of the purpose of the study (e.g. choice among alternative designs, or energy and comfort performance prediction). In turn, the purpose of the study commands the performance indicators (PIs) and the temporal granularity of the required results. A use scenario (e.g. lighting power density) must also be envisioned, where possible. It is important to note that some simulation questions can be answered only by means of specific models; in cases where there is a unique match between a simulation problem and a model formalism, it would be superfluous to proceed with the FFP-OBm approach.

- **Step 2: Choice of building model complexity**

Once the purpose of the study is clear, the building model complexity is chosen. In fact, building performance related problems may be solved with a range of methods, spanning from rules-of-thumb, to steady-state calculations, to transient (sub-)hourly dynamic simulation (CIBSE 2015). This is a general simulation problem and it does not strictly relate to occupant behaviour modelling.

While it is important to highlight that the building model complexity should derive from the purpose of the study, a deep analysis of such a choice goes beyond the scope of this paper. It is worth mentioning that often this step is solved based on experience, rather than after a rigorous analysis. Other studies exploring this topic are available in literature (e.g. Hensen 2004; van Enk 2016) and CIBSE offers practical guidelines for selecting the appropriate building model complexity (CIBSE 2015). During this step, the user of the approach must become aware of the uncertainties connected to the model, such as those in the thermophysical properties (Rezaee et al. 2015). If no information about the model’s uncertainty is available, an uncertainty analysis should be conducted. This step is necessary to put uncertainties related to OB into perspective.
Figure 5. Fit-for-purpose occupant behaviour modelling (FFP-OBm) approach overview.
Supposing it is concluded that the problem should be solved by means of BPS and other model uncertainties do not outweigh OB-related uncertainties, the remaining steps of the approach, introduced below, should be followed.

- **Step 3: Impact Indices screening method**

This step is supposed to be a fast screening method to avoid running an unnecessary number of simulations, for example by formulating scenarios for OB aspects that are non-influential for the results. The Impact Indices Method (see Gaetani, Hoes, and Hensen 2018) is used in the approach as a first, simplified screening method. The method is based on a number of indicators (impact indices or II) that allow for the quantification of the influence of various aspects of OB without requiring the formulation of scenarios, but instead using the already available information provided by one simulation run. The indicators are developed in the form of ratios among the various contributors of the building energy balance, which were obtained by the simulation run. Figure 6 is a representation of impact indices for a generic heat gain corresponding to an OB aspect (for example, heat gains derived by equipment use) during heating. Figure 6a shows that if the considered heat gain (e.g. equipment use heat gains) is negligible if compared with the total heat gains (which include all sources of heat gains, such as occupant presence, light use, solar heat gains through windows, heat gains from interzone air flow, infiltration and ventilation), there is a balance between heat gains, losses and heating energy; in this case, the ratio would be 1 and the resulting II for the specific aspect of OB is zero. Hence, the minimum value of the impact index is 0, which would occur if a type of behaviour has no potential influence. Instead, if the considered heat gain is non negligible, the resulting II is positive (Figure 6b). The more relevant the share of gains imputable to the considered aspect of OB (e.g. equipment use), the higher the values of the corresponding II (Figure 6c). The higher the specific impact index, the more likely the considered aspect of OB has an impact on the building heating energy use. The high-end cap depends on the ratio between heat losses and heating demand.

At present time, the II are developed to test the influence of a number of OB aspects on building heating and cooling energy demand only. However, similar screening methods could be developed for different OB aspects and performance indicators, including comfort. Currently, if the user is interested in considering also the comfort performance (which is certainly recommended), he/she is re-directed to Step 4. In some cases, the information obtained by the screening method could be sufficient for decision-making; the simulation user would then be directed to the end and the lowest OB model complexity would be identified as fit-for-purpose. Instead, if the simulation user is not able to make a decision based on the screening method’s results, he/she is directed towards the next step.

- **Step 4: Definition of diversity patterns**

In this step, the diversity patterns are defined. In this study, diversity patterns are defined as perceptual structures to describe different attitudes in various aspects of OB. The term ‘diversity patterns’ indicates (high/low) possible variations of uncertain aspects of OB to mimic diversity, and are implemented by means of simple schedules or other built-in deterministic software assumptions. Applying diversity patterns to a building model equates to testing the possible sensitivity of the results to a particular aspect of OB (Gaetani, Hoes, and Hensen 2016b). This step is highly relevant as the sensitivity of the results to the various aspects of OB will be strictly related to the assumptions made here. The reason behind formulating such diversity patterns is to perform preliminary testing on the influence of different aspects of OB on a performance indicator. All possible combinations of the diversity patterns are to be investigated. The assumptions made in formulating the high/low variations have necessarily a great impact on the results of the sensitivity analysis. Where possible, the user of this methodology should validate his/her assumptions with data, so that the diversity patterns are representative for possible variations of OB for a specific building. However, in some cases (typically, during the design phase) it might be difficult to validate assumptions because of a lack of data. In such instances, data from similar buildings or standard deviations from building codes might be taken. This methodology encourages a shift in mindset from considering only one possible set of behaviours to scenario analysis through the diversity patterns. In all cases, the user of the methodology should observe maximum transparency about the assumptions when presenting the end results. It is also important to note that the very implementation of the patterns through simple schedules or other built-in software assumptions de facto excludes the influence of behaviour stochasticity. This exclusion does not compromise testing the effect of various behaviours on PIs that are highly integrated and do not include energy production. Conversely, particular care should be applied when testing e.g. energy-matching indicators. In this case, the patterns should

![Figure 6. Visual representation of the II concept (heating). Balance (a), lower impact index (b), and higher impact index (c).](image-url)
be tailored to reflect the importance of the timing of a given behaviour. The patterns cause results to move from single values to a range of values (in case the selected PI is sensitive to the modelled aspects of OB).

Once the simulations are run and the results are processed, the simulation user can assess whether the given range allows him/her to make a decision, or whether further investigation is needed to check if refining the modelling technique might help decision-making.

- **Step 5: Identification of influential OB aspects with Mann–Whitney U test**

In case a decision cannot be made based on the initial range of the results due to the patterns, for the first flowchart iteration, or \( n = 0 \), a refined sensitivity analysis takes place to identify the decidedly influential aspects of OB. This step is a further refinement of the results obtained with the Impact Indices Method, and it allows relevance to be ascribed only to the aspects that truly affect the results for a specific case. As presented in (Gaetani, Hoes, and Hensen 2016b), this sensitivity analysis is achieved by means of the statistical Mann–Whitney U test. This nonparametric test is used to assess whether two independent groups are significantly different from each other. Here, the two groups are characterized by all scenarios with the same pattern for an uncertain aspect of OB. For example, all scenarios formulated in Step 4 characterized by 'low' occupant presence are compared to those characterized by 'high' occupant presence. The aim of the sensitivity analysis is to ultimately assess which aspects of OB are responsible for the spread in the results so that more attention can be drawn to modelling such aspects. However, matters are complicated further. Various OB aspects may be interrelated, and this interrelation should be considered while modelling (let us think of occupant presence, which acts as a trigger for most behaviours).

- **Step 6: Epistemic uncertainty reduction for influential OB aspects**

If an aspect of OB appears to be influential, it should be verified whether the epistemic uncertainty connected with the OB aspect can be reduced. This operation allows the simulation user to ensure that the range of the diversity patterns previously assumed is not too extreme and indeed represents the case at hand. Typically, such uncertainty could be reduced by gaining further information and analyzing operational data, where possible. During the design phase, reducing epistemic uncertainty may mean collecting or accessing data from similar buildings to act as a benchmark. Moreover, the epistemic uncertainty could be reduced by limiting the degrees of freedom of people concerning influential OB aspects, such as imposing a maximum possible variation of the temperature setpoint. Finally, specific design choices could also contribute to reducing uncertainty, e.g., if the blind operation is found to be influential, the building designer may choose to apply automated solar shading systems rather than manual ones to reduce the uncertainty connected to this behaviour (however, manual overrides should still be considered). If the epistemic uncertainty can be reduced, the diversity patterns are updated and the simulations are run again.

Nonetheless, epistemic uncertainty cannot always be reduced. In some cases, one or more aspects of OB may be identified as influential, but there may be no possibility to decrease the epistemic uncertainty connected with such behaviour(s). In those cases, an alternative is to refine the modelling approach with the aim of achieving a more representative/realistic modelling formalism.

- **Step 7: Check on possible model complexities for influential OB aspects**

If the epistemic uncertainty of the influential aspects cannot be reduced, the next step is to check whether the modelling formalism can be refined (see Step 6). This check is reliant on an OB modelling database that should be integrated in the software, and where possible modelling complexities should be filtered out according to the case under investigation (e.g., in the conceptual design phase it should not be possible to implement an agent-based model, as the uncertainty due to estimation of input parameters would be too high). Moreover, the OB modelling database should contain information regarding interrelations among different OB aspects. While this type of research is to date not available, the issue of interrelations is here considered by maintaining the diversity pattern variations for all OB aspects, including those that were not identified as influential for the results. The models within the database are also filtered out according to the uncertainty analysis that was conducted in Step 2. For example, if the purpose of the simulation is a design decision among alternatives, and the decided parameter uncertainty is higher than the scenario uncertainty due to OB, there is no sense in increasing the model complexity. In the future, this step should include a quantitative analysis of the trade-off between input uncertainty and abstraction error when increasing the model complexity.

- **Step 8: Increasing model complexity of influential OB aspects**

If a different model complexity can be used, the simulations are run again with more refined models for the influential OB aspects (\( c_{n+1} \)). If a more detailed or accurate model is not available (for example, because of the early stage of the building design phase, there might be no use in increasing complexity beyond a certain level, or the maximum complexity has already been reached), the user is led to the end. In this case, the fit-for-purpose model complexity (\( c_{FP} \)) is the previous one, i.e., the diversity patterns in the first flowchart iteration. It is important to note that the levels of complexity reported in Figure 5 are a simplification; in reality, a category (e.g., stochastic models) can be characterized by different complexities according to the model’s size and resolution.

- **Step 9: Decision-making**

As for the second and further iterations, if the user is still unable to make a conclusive design decision, the stepwise approach will evaluate if the current run led to the same decision if compared to the previous. If not, it might be necessary to increase complexity for the influential OB aspects again, because it means that the design decision is extremely dependent on the modelling.
of the influential OB aspects. Otherwise, if the design decision is the same as in the previous iteration with less complex models, the user is led to the end via the box ‘increasing complexity does not help decision-making’. It is important to note that simulation is not a design tool, but a design-support tool. In each decision-making step of the methodology (i.e. ‘Can take decision?’ blocks) a human is still needed to interpret results and make appropriate decisions. The refinement of OB modelling should make the simulation user aware of the importance people and their behaviours can have on the performance of the chosen design.

- Step 10 / End: Fit-for-purpose occupant behaviour model complexity

The user is led to the end in the following cases: (i) a decision could be taken; (ii) increasing model complexity does not help decision-making; and (iii) influential OB aspects’ modelling formalism/complexity cannot be changed. In the second and third cases, the user may have to evaluate other performance indicators, change design to achieve the desired results, or limit the freedom of occupants concerning influential OB aspects. In fact, in cases ii and iii, the problem does not concern OB model complexity, or no alternative OB modelling formalism is available.

The following section provides a practical demonstration of the steps mentioned above by means of a simple case study for illustration purposes. It is important to note that all steps included in the methodology presented above are based on standard output of BPS tools and on postprocessing of such output. The postprocessing can be easily done with computing environments such as MATLAB or Python. The prerequisites for the methodology to be applicable is to have a BPS file (such as .idf) and to use a BPS tool that allows for batch simulation. If these prerequisites are satisfied, the methodology can be easily generalized and applied to any building, climate or purpose of the simulation.

### 3. Description of the demonstration case study / problem definition (step 1 / start)

#### 3.1. Case study

Four offices are used as a case study. The four offices have dimensions of 5 m × 5 m × 3 m, they are characterized by different window-to-wall ratios (WWR) and different wall constructions for the southern façade facing the outdoor environment (see Figure 7). Floor, ceiling, and all facades but the southern one are assumed to be adiabatic, as if the office was surrounded by other spaces in thermal equilibrium with it.

#### Table 1. Physical properties of the office variants.

<table>
<thead>
<tr>
<th>Wall R-value [m²K/W]</th>
<th>Window U-value [W/m²K]</th>
<th>g-value [-]</th>
<th>Visible transmittance [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low thermal insulation</td>
<td>1.3</td>
<td>3</td>
<td>0.73</td>
</tr>
<tr>
<td>High thermal insulation</td>
<td>4</td>
<td>1.1</td>
<td>0.29</td>
</tr>
</tbody>
</table>

Four case studies are assessed:

- Case 1: WWR 40% – low thermal insulation
- Case 2: WWR 80% – low thermal insulation
- Case 3: WWR 40% – high thermal insulation
- Case 4: WWR 80% – high thermal insulation

The physical properties corresponding to the terms ‘low thermal insulation’ and ‘high thermal insulation’ are given in Table 1.

The heating, ventilation and air-conditioning (HVAC) system is supposed to be ideal, but was capped in size following preliminary simulation runs.

#### 3.2. Climate

The virtual offices are located in Amsterdam, the Netherlands.

#### 3.3. Use scenario

The use scenario for lights and equipment is assumed to be the ASHRAE default 10.76 W/m². The HVAC system keeps the indoor environment between 21°C ($T_{sp,heating}$) and 24°C ($T_{sp,cooling}$) on weekdays between 6 am – 10 pm and on Saturdays between 6 am – 6 pm. Outside of these hours, the setback temperatures are 26.7°C for cooling and 15.6°C for heating. Each office is assumed to be occupied by one person.

#### 3.4. Purpose of the simulation and performance indicators

The purpose of the simulation is to identify the best performing shading strategy for the four offices among: (i) no shading, (ii) fixed overhang (0.5 m depth), and (iii) manual shading device. In this example, the yearly energy for cooling and for heating is the performance indicator to be optimized. While the authors acknowledge that additional indicators are in place when making a decision concerning blinds (typically, comfort indicators ought to be considered), this work is supposed to provide a simple example application of the proposed methodology. Multiple performance indicators should be adopted in practical applications.

![Figure 7. Impression of the investigated variants.](image-url)
3.5. Phase in the building lifecycle

This design question may typically concern a rather advanced stage of the design process. No real data or information is available as this is a virtual experiment.

4. Demonstration of the fit-for-purpose approach

- Step 2: Choice of building model complexity

As mentioned above, a deep exploration of the reasoning behind the choice of building model complexity is beyond the scope of this paper. For the presented case study, it was decided to answer the problem by means of dynamic simulation as the design question is typical of a rather advanced stage of the building design. The four office variants were modelled using the software EnergyPlus V8.7.

To become familiar with the uncertainties connected to the model, a preliminary uncertainty analysis on the decided parameters was conducted considering the uncertainty due to thermophysical properties’ variations as given in (Hopfe 2009) and reported in Appendix A. The distribution assigned is a normal distribution. The Latin hypercube sampling (LHS) method was used to generate a near-random sample of 200 office variants derived from a multidimensional distribution of thermophysical parameter values.

First, the three shading options were investigated for the four office variants in a traditional fashion. As for blind operation, the shading devices were modelled with the function OffNightAndOnDayIfCoolingAndHighSolarOnWindow integrated in EnergyPlus. This choice was dictated by the findings of (O’Brien et al. 2016), where the majority of survey respondents stated that thermal and radiation considerations motivated their modelling strategy for blind operation. It is important to note that modelling the blind operation in such a manner does not actually represent manually operated blinds, but it is indeed a typical manner to do so in practice. Figure 8 shows the impact of the two shading strategies on the four investigated offices. It can be noted that, as expected, the shading strategies were much more effective in limiting the cooling energy in the two variants characterized by poor thermal insulation and high U-value, g-value and visible transmittance (Case 1 and Case 2). In Cases 1 and 2, the designer would be inclined to choose to apply blinds, as they seem to have been the most efficient strategy. Instead, a decision cannot be made as easily for Cases 3 and 4, where all solutions performed very similarly.

As a next step, the influence of the uncertainty of the decided parameter was investigated for all variants (Figure 9). Generally speaking, it was evident that the uncertainty of the thermophysical properties was especially pronounced in poorly performing offices (Case 1 and Case 2). For both Case 1 and Case 2

![Figure 8](image8.png)

**Figure 8.** Energy demand for cooling and heating of the four investigated offices with changing shading strategy; state-of-the-art OB modelling (lowest complexity).

![Figure 9](image9.png)

**Figure 9.** Influence of the uncertainty of thermophysical properties on the energy demand for cooling and heating.
the preferred shading strategy remained manual blinds, while for Case 3 and Case 4 all solutions again showed a similar performance.

- Step 3: Impact Indices screening method

The Impact Indices (II) screening method presented in (Gaetani, Hoes, and Hensen 2018) was applied to the current case study to quickly evaluate whether some aspects of OB are non-influential for the results. The hypothesis is that if some OB aspects are identified as non-influential for the performance indicator under investigation, they can be modelled with the simplest model complexity. Certainly, an OB aspect that is identified as non-influential for a PI could turn out to be essential to another PI, so it is essential to clearly map all PIs of interest. In this paper, the operation of applying the II method was performed solely with respect to cooling energy, which covers the largest share of the demand, as illustrated in Figure 8.

Figure 10 shows the impact indices for occupant presence, light use, equipment use and blind operation (cooling energy). The results for blind operation are represented with a dotted line in the Base and Overhang cases as these solutions do not actually include shading systems.

Figure 11 shows the impact indices for temperature setpoint setting on cooling energy. The impact indices for temperature setpoint setting are shown also separately because of the different nature of the indices themselves (see Gaetani, Hoes, and Hensen 2018).

To put the results concerning the II, Tsp into context, Figure 12 shows a one-at-a-time (OAT) sensitivity study that correlates the impact indices with the effects of changing the temperature setpoint for cooling. Figure 12 shows a strong correlation (coefficient of determination R^2 ~ 0.85) between the impact indices and the average change in cooling energy when increasing/decreasing the temperature setpoint by 2 °C.

Generally speaking, Figure 10 highlights how Case 3 and Case 4 (the office variants with high thermal isolation) were similarly influenced by OB, apart from the influence of blind operation, which of course was only present in the solutions with blinds. Alternatively, Case 1 and Case 2 (the office variants with low thermal isolation) present a marked difference between the potential influence of OB on Base and Overhang case, and the potential influence of OB on the solution with blinds. Both in Case 1 and Case 2, the solution with manual blinds seems less robust to OB. In line with expectations, all variants with higher window U-value and g-value (Case 1 and Case 2) showed a higher potential influence of blind operation compared with variants with lower window U-value and g-value (Case 3 and Case 4). Conversely, highly isolated offices were generally more prone to behavioural impacts for other behaviours (e.g. highly isolated offices are always characterized by higher R^2 for temperature setpoint setting than their low isolation counterparts).
Figure 12 shows a strong correlation between temperature set-point impact indices and OAT sensitivity analysis, which confirms the significance of the II for temperature setpoint setting.

As far as influential and non-influential aspects, the only seemingly non-influential aspect was occupant presence, which may nevertheless be taken into consideration as a trigger for OB. Light use and equipment use are generally identified as influential. All OB aspects for the four analyzed cases are therefore taken to the next step (Step 4).

- **Step 4: Definition of diversity patterns**

No information is available about possible OB characteristics, therefore the diversity patterns to test the potential influence of OB are standard and defined as in Table 2. It is important to note that the diversity patterns defined in Table 2 should be agreed upon with all interested parties. Ideally, the agreed diversity patterns should represent (high/low) possible variations of uncertain aspects of OB. In this illustration, for example, there is a decisive difference among the patterns developed for equipment use (where the original schedule is simply modulated) and the patterns developed for light use (where the introduction of daylight control resembles a design choice). The patterns proposed for light use are therefore more extreme than those proposed for equipment use. Moreover, Pattern A for blind operation assumes that the blinds are not operated at all and are always left in open position. This assumption is in line with findings from (O’Brien et al. 2016) but may nevertheless be considered extreme. These choices are very important as they influence the final outcome of the analysis. All pattern combinations resulted in a total of \(2^4 = 64\) (assuming that blinds are present, and 24 otherwise).

Simulations were run and the results are shown in Figure 13. Figure 13 shows how considering the potential influence of OB generally led to greater uncertainty than decided parameter uncertainty. In particular, it is now not evident which shading strategy should be chosen for all cases. For example, in Case 1 the solutions with overhang and manual blinds have the same median value for cooling plus heating energy (ca. 60 kWh/m²y), but the solution with overhang presents a much smaller uncertainty and it is hence more robust to OB. In the solution with manual blinds occupants naturally have more influence on the performance, and hence OB causes more uncertainty. For Case 1, it would therefore seem reasonable to choose the solution with overhang. For Case 3 and Case 4 an investigation of the potential influence of OB did not lead to greater insights into the performance of the offices. This result can be explained as the windows of Case 3 and Case 4 are highly performing and reduce the impact of different shading strategies. Instead, there seems to be potential for the application of blinds in Case 2. Case 2 is the only case where the median value of the solution for blinds is lower than the median value obtained with overhang. Still, the uncertainty of the solution with manual blinds appears to be higher than the one of the solution with overhang. As a decision could not be made using the results, Case 2 was selected to test the remaining steps of the FFP-OBm approach.

- **Step 5: Identification of influential OB aspects with Mann–Whitney U test**

In the first flowchart iteration, \(n = 0\), the sensitivity analysis by means of Mann–Whitney U test is used to identify the influential OB aspects. The influence of various aspects of OB is verified only for cooling energy as it covers the vast majority of the demand. The results of the sensitivity analysis for the three shading strategies are reported in Figure 14. An aspect of OB is considered influential if the \(p\)-value < 0.05. As a reminder, this and the following steps are only investigated for Case 2, as for all other cases it was possible to take a design decision without increasing OB model complexity (see Step 4).

The Mann–Whitney U test shows that all shading solutions are influenced by lighting switch on/off behaviour and by the cooling temperature setpoint. The solution with manual blinds is

### Table 2. OB diversity patterns (adapted from (Lin and Hong 2013)).

<table>
<thead>
<tr>
<th></th>
<th>Pattern A</th>
<th>Pattern B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Occupant Presence</strong></td>
<td>Mon–Fri 10–12 am and 1–4 pm</td>
<td>Mon–Fri 8–12 am and 1–6 pm</td>
</tr>
<tr>
<td><strong>Equipment Use</strong></td>
<td>90% when occupied; 30% when non-occupied</td>
<td>100% when present; 60% before arrival and after departure</td>
</tr>
<tr>
<td><strong>Light Use</strong></td>
<td>ON when occupied; daylight control</td>
<td>ON when occupied; lunchbreak; no daylighting control</td>
</tr>
<tr>
<td><strong>Tsp, heating</strong></td>
<td>18°C</td>
<td>23°C</td>
</tr>
<tr>
<td><strong>Tsp, cooling</strong></td>
<td>22°C</td>
<td>26°C</td>
</tr>
<tr>
<td><strong>Blind Operation</strong></td>
<td>Always open</td>
<td>Close if high solar on window</td>
</tr>
</tbody>
</table>

Figure 13. Influence of OB on energy demand for cooling.
significantly dependent on the operation of the blinds. It is worth noting that equipment use, which scored higher than light use in the initial impact indices screening, does not turn out as influential in this analysis. This is because of the assumptions made for the patterns, as highlighted at Step 4. This result further highlights the importance of the assumptions made while defining the diversity patterns.

- Step 6: Epistemic uncertainty reduction for influential OB aspects

As the considered buildings are virtual buildings, it is assumed that it is not possible to reduce the epistemic uncertainty of the influential OB aspects in any way. Therefore, the simulation user would proceed to the next step of the approach; namely, to assess available modelling complexities.

- Step 7: Assessment of available model complexities for influential OB aspects

This step implies checking whether a better representation of the influential aspects of OB exists. In other words, whether a higher complexity model is available. In this case, the resulting influential aspects were: lighting switch on/off behaviour, cooling temperature setpoint setting and operation of the blinds. For lighting switch on/off behaviour higher complexity models exist, while no validated model is available for cooling temperature setpoint setting (Gaetani, Hoes, and Hensen 2016a). It is important to reiterate that the assumption that higher complexity models lead to more realistic results is to date not verified. However, it can be presumed that the database of OB models coupled with the approach introduced here will, in the near future, only include validated models, whose validity range is well defined and specified.

- Step 8: Increasing model complexity of influential OB aspects

For the purpose of this study, two stochastic models were applied to increase the model complexity of the manual operation of the blinds and the light switch on/off behaviour. The implemented models are well-established stochastic models taken from literature: Reinhart’s discrete-event Markov model Lightswitch-2002 (Reinhart 2004) for light use and Haldi and Robinson’s discrete-time Markov model for blind operation (Haldi and Robinson 2010). These models were developed for cellular offices in climates different than the one considered in this study, and there is no evidence that their combined use leads to representative results. However, they have been extensively used in conjunction for several buildings and climates (Gunay, O’Brien, and Beausoleil-Morrison 2016; Gilani et al. 2016) and represent the state-of-the-art in OB modelling literature.

The models are fitted as a logistic function, so that the probability \( P \) that the blinds or lights at timestep \( t \) are in state \( S \) is equal to:

\[
P(S_t | S_{t-1}, x) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}},
\]

where \( \beta \) are the parameters of the model and \( x \) are the predictors. The models were implemented in EnergyPlus V8.3 using the Energy Management System (EMS) as in (Gunay, O’Brien, and Beausoleil-Morrison 2016). The parameters that were used for each model were taken from (Gunay, O’Brien, and Beausoleil-Morrison 2016) and are reported in Table 3. The parameters were not altered as that would equal to altering the model itself. The prescribed time-step size of 5 min was adopted. 50 simulations were run to ensure that the mean and standard deviation of the performance indicator resulting from multiple runs of a stochastic model were stabilized (Gunay, O’Brien, and Beausoleil-Morrison 2016).

- Step 9: Decision-making

Figure 15 shows the results of applying a higher complexity model for lighting use in Case 2, NoShading and Overhang, and a higher complexity model for lighting and blind use in Case 2, Blinds. While this may currently not be the case due to the relative immaturity of the research field, let us assume that in the near future the results of the higher complexity models will be more representative than the OB patterns (e.g. it is never the case that people simply do not operate the blinds and leave them always open). The decision-maker can thus finally choose to apply blinds as the most efficient shading strategy for Case 2 (see Figure 15). If decision-making had not been possible despite the refinement of the modelling formalism, a further refinement (e.g. to agent-based models) would have been recommended. However, for the sake of the demonstration of this methodology, agent-based models are not considered as they are deemed too uncertain and lacking validation (Mahdavi and Tahmasebi 2017).

- Step 10 / End: Fit-for-purpose occupant behaviour model complexity

Figure 14. Mann-Whitney \( U \) test results: \( 1 – p \)-value. Darker bars represent influential behaviours.
Table 3. Parameters used in the lighting and blinds use models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Type of action</th>
<th>$a$</th>
<th>$b_1$</th>
<th>$x_1$</th>
<th>$x_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Reinhart 2004)</td>
<td>Predicting light switch-on action at arrival</td>
<td>1.6 ± 0.3</td>
<td>−0.009 ± 0.002</td>
<td>Workplane illuminance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Predicting light switch-on action during intermediate occupancy at 5 min time-step size</td>
<td>−3.9 ± 0.5</td>
<td>−0.002 ± 0.0005</td>
<td>Workplane illuminance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Predicting light switch-off action at departure and lunch break</td>
<td>−1.3 ± 0.3</td>
<td>0.003 ± 0.001</td>
<td>Duration of absence</td>
<td></td>
</tr>
<tr>
<td>(Haldi and Robinson 2010)</td>
<td>Predicting blinds closing action at arrival</td>
<td>−7.4 ± 0.16</td>
<td>−0.0010 ± 0.0001</td>
<td>Workplane illuminance</td>
<td>Unshaded window fraction</td>
</tr>
<tr>
<td></td>
<td>Predicting blinds closing action during intermediate occupancy at 5 min time-step size</td>
<td>−8.0 ± 0.1</td>
<td>−0.0008 ± 0.0001</td>
<td>Workplane illuminance</td>
<td>Unshaded window fraction</td>
</tr>
<tr>
<td></td>
<td>Predicting blinds opening action at arrival</td>
<td>−1.54 ± 0.1</td>
<td>−0.0007 ± 0.0005</td>
<td>−3.14 ± 0.07</td>
<td>Workplane illuminance</td>
</tr>
<tr>
<td></td>
<td>Predicting blinds opening action during intermediate occupancy at 5 min time-step size</td>
<td>−3.6 ± 0.03</td>
<td>−0.0003 ± 0.0002</td>
<td>−2.7 ± 0.04</td>
<td>Workplane illuminance</td>
</tr>
</tbody>
</table>

Figure 15. Effects of increasing model complexity for light and blind operation.

The approach enabled the identification of the fit-for-purpose model complexity for the 4 investigated cases. In particular, in two cases (Case 3 and Case 4) the FFP-OBm approach allowed us to quickly determine that increasing model complexity of OB would be useless. For these two cases (Case 3 and Case 4, higher thermal insulation of envelope and glazing), the FFP-OBm complexity was the lowest, and therefore used simple schedules and built-in controls. The cooling demand for these cases was hardly affected by the shading strategy. In Case 1 (smaller windows, leakier envelope), applying an overhang is deemed to be a more robust and equally efficient shading strategy compared to manual blinds. For Case 1, the FFP-OBm complexity was the diversity patterns for all OB aspects except for occupant presence, for which simple schedules sufficed.

In Case 2 the potential of manual blinds was identified and confirmed by a more complex OB modelling formalism. The FFP-OBm complexity for lights and shading devices (and, ideally, cooling temperature setpoint) use was identified as stochastic models.

Without the method, manual blinds would have been identified as the preferred solution for Case 1, Case 2 and Case 4, while applying an overhang would have resulted as the preferred solution for Case 3. The method identified the FFP-OBm complexity for various OB aspects in all cases. In particular, all cases but Case 3 and Case 4 turned out to have a different FFP-OBm complexity.

5. Conclusions

The overall flowchart presented in Section 2 is divided into 6 categories: start or problem definition, Impact Indices Method, Diversity Patterns Method, Mann–Whitney U test application, dealing with influential OB aspects, and end or FFP-OBm. The essential prerequisites to start a well-posed problem were identified, as well as the expected end results. The numerous decisions within the flowchart can easily be automated, should this method become mainstream. However, the methodology is a design-support tool, hence the design choice should typically be taken by a human supported by BPS. The methodology is fundamental to make the BPS user aware of the implications of people and their behaviours (and consequently their appropriate modelling) on the building performance. The vision of the authors for the strategy is for it to become embedded in BPS tools, possibly not requiring any effort or additional expertise from the simulation user, apart from supervising the decision-making process. The method is partly based on scenarios (typically, in the Diversity Patterns Method part), therefore the robustness of the method to the assumptions should be assessed.

The case study successfully illustrated how the presented method is far from being theoretical, but it can instead be readily applied in simulation-aided design processes. Four variants of a single-occupant office were studied to apply the method on a range of different built environments. Indeed, decision-making concerning the best performing shading strategy was possible.
for all four variants, and the method delivered the appropriate OB modelling complexity in all cases. In some cases, simple schedules or Diversity Patterns were deemed sufficient to achieve reliable decision-making. This result underlines the importance of the method and challenges the application tout court of higher complexity models. At the same time, the results demonstrate that a more informed design decision-making is achievable by means of the method.

The proposed FFP-OBm approach is developed as an attempt to support the simulation user who is interested in appropriately representing OB in BPS.

The proposed approach is an important step towards achieving fit-for-purpose modelling of OB in BPS. While a number of studies investigated the sensitivity of building performance to OB, this paper is the first example of an actionable, ready to use approach for appropriate OB modelling in BPS. The validity of the approach is subjected to the validity of the models which are included in the database.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

List of pictograms

- Occupant presence
- Light use
- Blind operation/Shading with manual blinds
- Window operation
- Temperature setpoint setting heating (red) and cooling (blue)
- Equipment use
- Absence of shading
- Shading with overhang

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References


**Appendix A**

Table A1. Thermophysical properties variation ($t$ = thickness [m], $\lambda$ = thermal conductivity [W/mK], $\rho$ = density [kg/m$^3$], $c_p$ = specific heat capacity [J/kgK], $\mu$ = mean value, $\sigma$ = standard deviation).

<table>
<thead>
<tr>
<th>Material</th>
<th>$t$ [m]</th>
<th>$\lambda$ [W/mK]</th>
<th>$\rho$ [kg/m$^3$]</th>
<th>$c_p$ [J/kgK]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>External Wall (LOW TI)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel</td>
<td>$\mu$ 0.005</td>
<td>50</td>
<td>7800</td>
<td>480</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.0005</td>
<td>0.75</td>
<td>25.74</td>
<td>19.2</td>
</tr>
<tr>
<td>Fibre quilt</td>
<td>$\mu$ 0.046</td>
<td>0.04</td>
<td>12</td>
<td>840</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.0046</td>
<td>0.0032</td>
<td>1.08</td>
<td>56.28</td>
</tr>
<tr>
<td>Concrete block</td>
<td>$\mu$ 0.2</td>
<td>1.41</td>
<td>1900</td>
<td>1000</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.02</td>
<td>0.1269</td>
<td>28.5</td>
<td>106</td>
</tr>
<tr>
<td><strong>External Wall (HIGH TI)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel</td>
<td>$\mu$ 0.005</td>
<td>50</td>
<td>7800</td>
<td>480</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.0005</td>
<td>0.75</td>
<td>25.74</td>
<td>19.2</td>
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<tr>
<td>Fibre quilt</td>
<td>$\mu$ 0.174</td>
<td>0.04</td>
<td>12</td>
<td>840</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.0174</td>
<td>0.0032</td>
<td>1.08</td>
<td>56.28</td>
</tr>
<tr>
<td>Concrete block</td>
<td>$\mu$ 0.2</td>
<td>1.41</td>
<td>1900</td>
<td>1000</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.02</td>
<td>0.1269</td>
<td>28.5</td>
<td>106</td>
</tr>
<tr>
<td><strong>Internal Wall</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gypsum</td>
<td>$\mu$ 0.019</td>
<td>0.16</td>
<td>800</td>
<td>1090</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.0019</td>
<td>0.024</td>
<td>25</td>
<td>163.5</td>
</tr>
<tr>
<td>Air cavity</td>
<td>$\mu$ 0.15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.01</td>
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<tr>
<td>Gypsum</td>
<td>$\mu$ 0.19</td>
<td>0.16</td>
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<tr>
<td></td>
<td>$\sigma$ 0.019</td>
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<td>25</td>
<td>163.5</td>
</tr>
<tr>
<td><strong>Internal Floor</strong></td>
<td></td>
<td></td>
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<tr>
<td>Acoustic tiles</td>
<td>$\mu$ 0.0191</td>
<td>0.06</td>
<td>368</td>
<td>590</td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.00191</td>
<td>0.0198</td>
<td>64.4</td>
<td>63.42</td>
</tr>
<tr>
<td>Air cavity</td>
<td>$\mu$ 0.18</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>$\sigma$ 0.012</td>
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<td></td>
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<tr>
<td>Lightweight concrete</td>
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<td>0.53</td>
<td>1280</td>
<td>840</td>
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<tr>
<td></td>
<td>$\sigma$ 0.01016</td>
<td>0.0477</td>
<td>192</td>
<td>89.04</td>
</tr>
<tr>
<td><strong>Window (LOW TI)</strong></td>
<td>$U$-value</td>
<td>$g$-value</td>
<td>Visible transmittance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\mu$ 3</td>
<td>0.73</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.15</td>
<td>0.073</td>
<td>0.075</td>
<td></td>
</tr>
<tr>
<td><strong>Window (HIGH TI)</strong></td>
<td>$U$-value</td>
<td>$g$-value</td>
<td>Visible transmittance</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\mu$ 1.1</td>
<td>0.29</td>
<td>0.48</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.055</td>
<td>0.029</td>
<td>0.048</td>
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<tr>
<td><strong>Air tightness</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Air Changes per Hour (ACH)</td>
<td>$\mu$ 0.12</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\sigma$ 0.04</td>
<td></td>
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</table>