International survey on current occupant modelling approaches in building performance simulation

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Abstract

It is not evident that practitioners have kept pace with latest research developments in building occupant behaviour modelling; nor are the attitudes of practitioners regarding occupant behaviour modelling well understood. In order to guide research and development efforts, researchers, policy makers, and software developers require a better understanding of current practice and acceptance of occupant modelling. This paper provides results, analysis, and discussion of the results of a 36-question international survey on current occupant modelling practice and attitudes in building performance simulation. In total, 274 valid responses were collected from BPS users (practitioners, educators, and researchers) from 37 countries. The results indicate that most assumptions made about occupants vary widely and are considerably simpler than what has been observed in reality. Most participants cited lack of time or understanding as their primary reason for not delving deeply into occupant modelling, but responded that they are receptive to further training.

Keywords: occupant modelling, design practice, modelling uncertainty, user survey

1 Introduction

It is widely recognized that occupants largely determine the energy and comfort performance of buildings. Their impact is increasingly important as building envelopes and equipment become more efficient (Hoes et al. 2009). Therefore, the question of how to appropriately model occupant behaviour in building performance simulation (BPS) software tools emerge. One could argue that the impact of occupants will decrease as building automation develops, but evidence suggests that even high performance buildings with advanced building automation systems (BAS) do not necessarily perform well or reduce the impact of energy-intensive behaviours (Clevenger and Haymaker 2006).

Despite the building performance uncertainty introduced by occupants, both presence and actions are usually modelled in very simplistic ways in simulation practice. Moreover, occupants are frequently modelled as passive recipients of indoor environmental conditions rather than active and adaptive agents (Brager and de Dear 1998; O'Brien and Gunay 2015). Common modelling approaches include basic schedules, typical power densities, and at most, simple rules about how occupants use equipment, lighting, and other energy systems of the building. An erroneous representation of occupant behaviour might lead to a series of problems due to unrealistic performance predictions (Gunay, O'Brien and Beausoleil-Morrison 2015). First of all, a building could fail to achieve the desired standards. Secondly, the lack of a common framework for occupant modelling may introduce bias: building designers and BPS users seeking to achieve a certain performance level may make optimistic assumptions about occupants; those doing equipment sizing may tend to make pessimistic assumptions to avoid liability and increase profits. Building designers could miss out on the opportunity of optimizing building design and control for occupancy. Other applications that could benefit from an appropriate representation of occupant behaviour include: aiding in risk assessment, improving controls and operations, and increasing comfort conditions by adding specificity to the occupants' needs.

Building energy codes and some design approaches imply that it does not matter if occupants are appropriately represented to improve absolute accuracy as long as the same assumptions are made for all investigated design cases. The advocates of this approach believe that BPS tools should be able to accurately predict the relative performance of building design variants compared with a base case (Soebarto and Williamson 2001). Accordingly, many building codes and standards reinforce this claim by requiring consistent occupant assumptions across the reference and design building models and for performance results to be presented relatively to the reference building. However, emerging research indicates that building design can influence occupant behaviour and that the optimal building design is itself affected by assumptions about occupants (O'Brien and Gunay 2015).

In recognition of the importance of improving occupant modelling approaches, research on this topic has surged in the past decade. A prevalent research approach to improve the reliability of occupant modelling is to develop statistical models that are based on observations of occupants in real buildings. A limited number of monitoring and data-driven modelling and design studies have been developed to obtain insights into real occupant behaviour (e.g., Reinhart and Voss 2003; Wang, Federspiel and Rubinstein 2005; Haldi and Robinson 2009; Andersen et al. 2013; Gilani et al. 2016). However, it remains unclear whether the results of these studies are suitable for simulation-aided design and code compliance in practice.

Numerous existing barriers prevent BPS users from appropriately integrating occupant behaviour in the modelling and simulation process. Standards or guidelines for appropriate occupant modelling assumptions are generally not established, except in simple ways in building energy standards, such as ANSI/ASHRAE/IES Standard 90.1 (2013). Few studies have successfully shown that observed occupant characteristics across different buildings, cultures, and climates are consistent. One rigorous example by Schweiker et al. (2012) showed that operable window operation in a Japanese building was significantly different than a Swiss building due to climatic, cultural, and technological differences. Moreover, most existing models are developed for a particular scale (e.g., zone or whole-building) and do not necessarily fit other scales. The limited existing occupant models tend to reside in scientific papers and do not lend themselves well to application by typical BPS users (Gunay, O'Brien et al. 2015). Meanwhile, most BPS tools are not equipped to model occupants in advanced ways. Identifying the most appropriate occupant modelling approach should be used for different BPS applications - fit-for-purpose modelling - is a current research topic (Gaetani, Hoes and Hensen 2016).

Because of the barriers mentioned above, improving the reliability of occupant modelling remains nearly exclusively an academic exercise. However, a sound understanding of the current perception of this issue from the point of view of practitioners is crucial to tune future research and development directions. In order to fill this knowledge gap, this paper presents the results of an extensive survey that aimed at understanding the attitudes and common practice regarding occupant modelling within the BPS users' community. The scope of the survey focused on BPS practice as a whole rather than specific tools.

This paper first briefly describes the survey (Section 2). Then, descriptive and inferential statistical techniques used to analyse and report the results of the survey are described in Section 3, with the aim of answering the following questions:

1) What are BPS users' attitudes about the significance of occupant modelling?
2) What assumptions do BPS users make about occupants in BPS models? How do these assumptions compare to reality? How confident are they about these assumptions?

3) Do BPS users feel that current software tools and standards are suitable for modelling occupants' behaviour appropriately?
4) How do BPS users feel about building performance uncertainty and communicating this to clients?
5) How do BPS users rate their current knowledge of occupant modelling? Are they willing to learn more?

Finally, the results of the survey and resulting analysis are discussed to fulfil the ultimate goal of this study: to inform researchers, software developers, and building standards developers about how to target their occupant modelling efforts.

2 The survey

Surveys have been extensively employed in the field of building performance simulation to improve both BPS tools and design practice (e.g., Pilgrim et al. 2003; Reinhart and Fitz 2006; Attia et al. 2012). The current survey design is greatly inspired by this previous body of work. However, no previous study has specifically addressed the issue of occupant modelling and simulation.

As part of the International Energy Agency's Energy in Buildings and Communities Programme (IEA EBC) Annex 66, 15 occupant modelling and simulation researchers (see authors and acknowledgements) developed a 36-question survey and posted it online using Google Forms. The online approach enabled the researchers to reach a population of approximately 5000 possible participants very efficiently. The 5000 figure is based on membership of the International Building Performance Simulation Association. Upon receiving ethics clearance from Carleton University, the survey was publicly opened on September 23, 2015.

Survey recruitment took place through BPS-related email lists and the IBPSA newsletter. Participants were incentivized to take part in the survey with about a dozen prizes (e.g., textbooks, smart light bulbs, and a journal subscription). The prizes were randomly awarded to those who provided their email addresses for this purpose.

The survey questions were separated into three categories: background information (e.g., profession, country, purpose for using BPS, and tools used), current practice (e.g., assumptions participants make about occupants), and attitudes and future practice. Given that occupant modelling can introduce considerable uncertainty in BPS predictions, several questions were focused on participants' and perceived clients' attitudes about declaring, describing, and quantifying uncertainty. Many of the questions were multiple-choice (i.e., select one or multiple, five-point Likert-type scale of *agree* to *disagree*, short answer, long answer). However, participants were allowed to add further information where they wished to share further insights (e.g., if none of the options applied). Participants were asked to provide their email address if they were willing to give clarifications, though none were contacted for this purpose. The full survey can be found in the appendix.

The survey was closed on October 30, 2015, when 274 valid responses from BPS users were obtained. This is similar or greater than other BPS user surveys found in the literature. As noted by previous BPS survey papers (e.g., Pilgrim, Bouchlaghem et al. 2003; Reinhart and Fitz 2006), sample size and sampling methodologies for such studies cannot be considered completely statistically representative. For instance, the sample is biased towards predominantly English-speaking regions since the survey was only written in English (slightly over half of the participants primarily work in Canada, the United States, the UK, New Zealand, and Australia). Furthermore, users of certain tools may be more likely to be members of the various user lists through which the survey was distributed (e.g., eQuest, EnergyPlus, IES VE, and DesignBuilder). Finally, the sample may be biased towards more diligent BPS users, with stronger-than-average opinions and who are actively seeking to improve their knowledge or influence current modelling practice. Additional biases may arise with regards to the survey design. Since the survey is explicit about occupant behaviour, participants might have been more inclined to ascribe relevance to it. Although the survey was anonymous, participants might have been reluctant to admit a low degree of confidence in their occupant modelling assumptions. Similarly, they may not wish to admit unfavourable views and practices (i.e., social desirability bias). Central tendency bias, whereby survey participants tend to answer Likert scale-based questions with near-median answers, may have influenced the data for the current survey. However, this bias was partially combatted by separating most Likert scale-based questions with other question forms.

3 Results and discussion

This section includes the survey results in the form of descriptive and inferential statistics. All survey results underwent quality assurance. Selected datasets were analysed using several statistical techniques implemented through the software package IBM® SPSS® Statistics Version 21 to distinguish patterns in the responses and extrapolate general findings. Several statistical techniques, as explained later, were used to explore relationships between groups of data and other compared groups in the dataset. Since all analysed variables were ordinal and categorical, Spearman's Rank Order Correlation was used for exploring the strength of correlation among variables, and non-parametric statistics were adopted. The Chi-square test for independency was used to explore the relationship between couples of categorical variables, and the Friedman test was used to explore the differences among groups, such as in the case of Likert-type variables. Due to the large amount of data collected, focus was placed on answering the primary research questions of this study. Note that italicized variable names and question numbers refer to those in the appendix.

3.1 About the participants (survey questions 1, 2, 3, 4, and 5)

The majority of the 274 participants were engineers (59%), followed by 25% researchers/educators, and 8% architects. Twenty participants identified themselves as belonging to other professions, such as consultant, energy modeller, energy facilitator, software developer, building scientist/physicist, and lighting designer. Participants were asked about their years of experience in using BPS tools. The vast majority of participants (89%) had at least two years of experience using BPS tools. The participants worked in 37 different countries, with 27% and 15% working in the United States and Canada, respectively; 8% in the United Kingdom, and 4 to 5% in each of the Netherlands, Portugal, Belgium, and Switzerland. Participants responded that EnergyPlus, IES VE, and DesignBuilder were the most used BPS tools. The participants used BPS tools mostly during early design stage, while building code compliance, environmental assessment, detailed design, and post-occupancy evaluation are the other frequently-cited purposes (Figure 1).

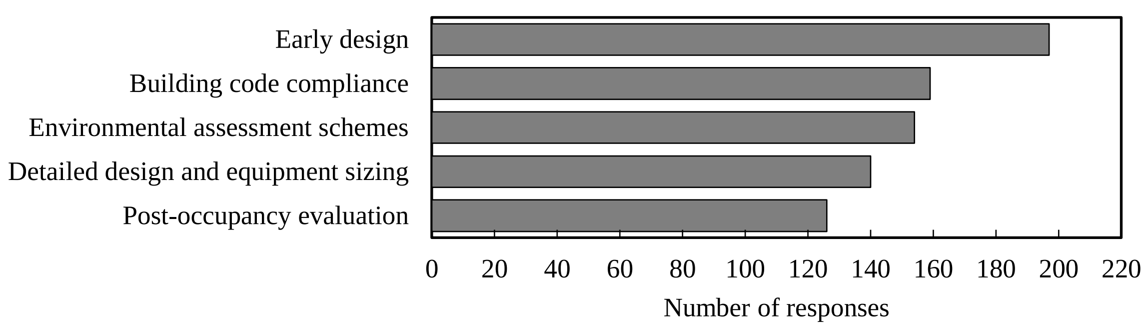


Figure 1. Participants' purpose for using BPS tools

3.2 What are BPS users' attitudes about the significance of occupant modelling? (questions 6, 26, and 28)

A slight majority (56%) of participants agreed or somewhat agreed that, based on their experience, occupants use more energy in reality than what they normally assume in BPS tools. Figure 2 shows that occupant behaviour is perceived to be the leading source of discrepancy between BPS predictions and measurements by the majority of participants (though the authors acknowledge possible bias from the overall survey theme).

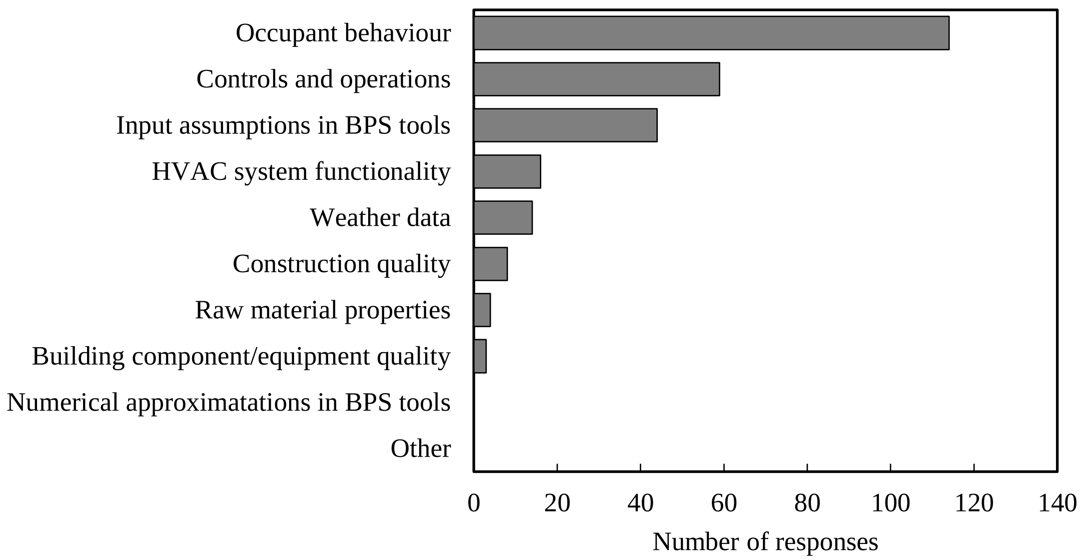


Figure 2. Participants' attitude about leading source of discrepancy between BPS predictions and measurements

The same results were compared for different professions. The original two variables *Profession* and *SourceDiscrepancy* were transformed into two new variables: *Academics_Nonacademics* and *MainSourceDiscrepancy*. *Academics_Nonacademics* is a categorical variable that takes two values: *Academics* (including researchers and/or educators) and *NonAcademics* (including architects, engineers, and others). *MainSourceDiscrepancy* is a categorical variable that takes two values: *occupant behaviour* and *other* sources of discrepancy. Figure 3 shows the number of times that occupant behaviour was or was not considered the main cause of the performance gap among the academics and non-academics.

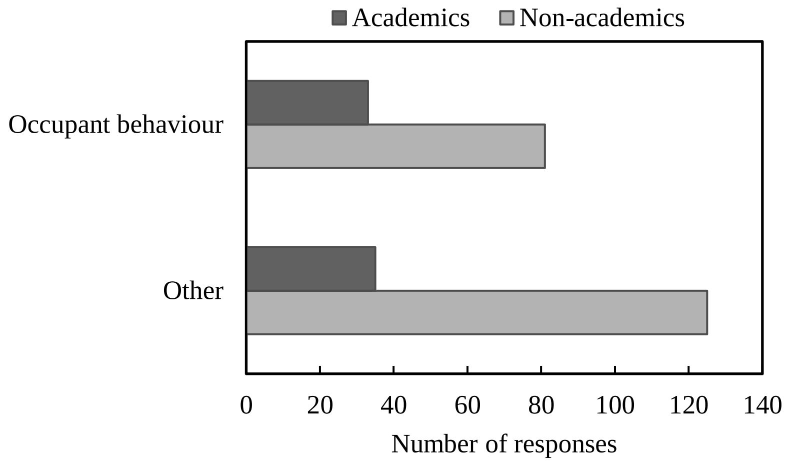


Figure 3: Leading source of discrepancy between predictions and measurements for academics and non-academics.

The relationship between such two modified variables was explored with a Chi-square test for independence. In order to use this test, the assumption concerning the 'minimum expected cell frequency' that is the number of items falling in at least 80% of the bins must be higher than 5, must not be violated. In this analysis, all the expected cell sizes are greater than 5 (>29.28), hence the 'minimum expected cell frequency' assumption is not violated. Since the designed question generates a 2 by 2 table, Yate's Correction for Continuity was used to explore the relationship between the two variables to compensate for the overestimate of the Chi-square value. $\chi^2(1, n = 274)$ is 1.42, with an associated significance level of 0.23, which is larger than the alpha value of .05. Regarding the effect size, the *phi* coefficient is .08, which is considered a very small effect (<0.10) based on Cohen's criteria (Cohen 1988). Hence, from a statistical point of view, there is no significant difference between academics and non-academics in perceiving occupant behaviour as the leading source of discrepancy between predictions and measurements. Though proportionately, more academics cited the significance of occupant behaviour.

Next, the effect of years of BPS experience was evaluated with respect to whether users believe occupants are the primary cause of the discrepancy between predictions and measurements. The original two variables *ExperienceBPS* (ordinal variable that takes the five values: *Fewer than 2 years*, *2 to 5 years*, *5 to 10 years*, *Over 10 years*) and *SourceDiscrepancy* (categorical variable that can take 12 values) are transformed into two new variables *Experts_NonExperts* and *MainSourceDiscrepancy*. *Experts_NonExperts* is a categorical variable that takes two values: *Experts* (*5 to 10 years*, *Over 10 years*) and *Non-experts* (*Fewer than 2 years*, *2 to 5 years*). *MainSourceDiscrepancy* is a categorical variable that takes two values: *occupant behaviour* and *other* sources of discrepancy (Figure 4).The relationship between such two modified variables was explored with the Chi-square test for independency. A preliminary verification of the 'minimum expected cell frequency' show that, in this analysis, all the expected cell sizes are greater than 5 (>35.87), hence such assumption is not violated. The Chi-square test for independency, with Yate's Continuity Correction, was resulted in $\chi^2(1, n = 274) = 0.07$, $p = 0.933$, *phi* = -0.012. Moreover, the *phi* coefficient (-0.012) shows that the effect size can be considered very small (< 0.10) according to the Cohen's criteria (Cohen 1988). Hence, from a statistical point of view, there is no significant association between the belonging to the experienced group and the belief that occupant behaviour is the main cause of the performance gap.

Figure 4. Leading source of discrepancy between predictions and measurements according to the BPS users' experience.

When asked about the purpose of appropriately modelling occupants, 46% of participants responded that the primary objective is to fill the gap between predicted and actual building performance. Other important reasons to appropriately represent occupant behaviour in BPS tools are: to improve building design (19% of responses), and to improve occupants' comfort (16%) (Figure 5). The same outcome can be extrapolated by disaggregating the responses by profession. Then, engineers and researchers and/or educators rank *to improve general building design quality* in second position, whereas architects and other stakeholders and consultants chose *to improve occupants' thermal and visual comfort* (Figure 6).

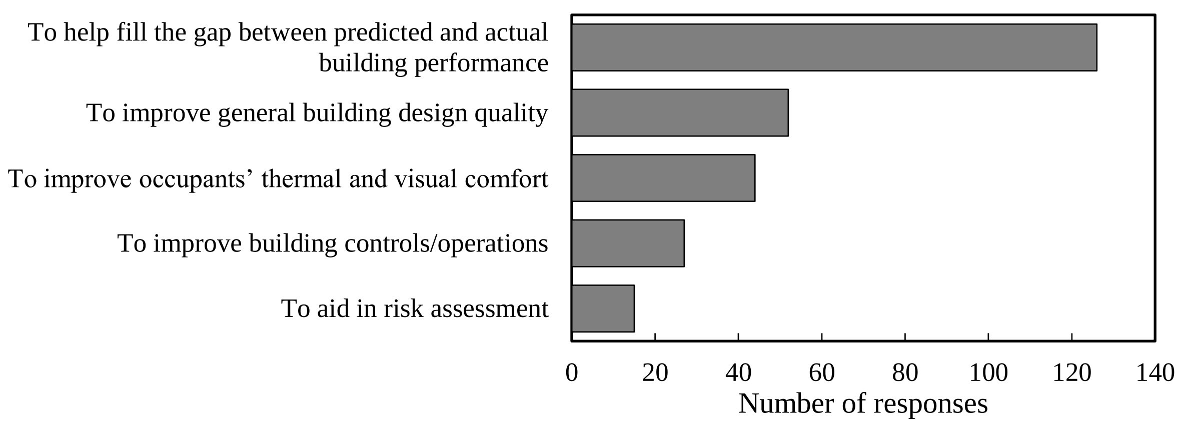


Figure 5. Participants' reasons for the importance of appropriately representing occupant behaviour in BPS tools

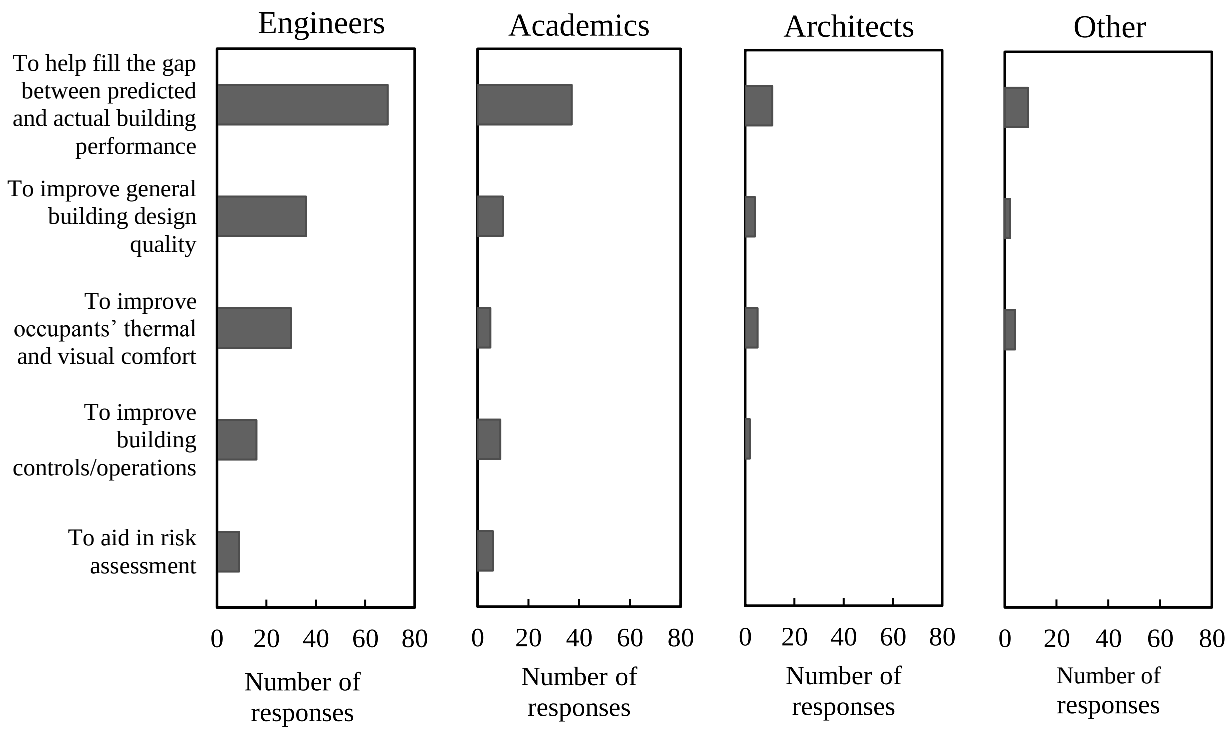


Figure 6: Perceived reasons to appropriately model occupant behaviour in BPS disaggregated by professions.

To investigate whether there is a different perception on the objective of occupant modelling among academics and non-academics, the transformed variable *Academics_Nonacademics* (as previously defined) and the variable *PurposeAccurOB*, which is a categorical variable that can take five values, were analysed with a Chi-square test for independency. A preliminary verification of the 'minimum expected cell frequency' shows that, in this analysis, 83.3% of cells have a frequency of 5 or more, therefore the assumption of Chi-square concerning the 'minimum expected cell frequency' is not violated. Due to the number of categories of the two variables, the Pearson Chi-square was used to explore the relationship between the two variables. $\chi^2(1, n = 274)$ is 10.10, with an associated significance level of 0.072, that is larger than the alpha value of .05. Regarding the effect size, the *Cramer's V* coefficient is 0.192, that can be considered a medium effect (< 0.30) using Gravetter and Wallnau's criteria (Gravetter and Wallnau 2004). Hence, from a statistical point of view, the purpose of appropriately modelling occupant behaviour in BPS does not significantly differ between academics and non-academics.

3.3 What assumptions do BPS users make about occupants in BPS models? How do these assumptions compare to reality? How confident are they about these assumptions? (Questions 7-24)

When the survey participants were asked about their most frequent assumptions about occupant modelling, a common response was that occupant modelling assumptions depend on the purpose of the model. For instance, several participants stated that they will use simple occupant modelling approaches for code compliance simulation runs, while using overly conservative assumptions for equipment sizing and highly detailed observation-based approaches for post-occupancy measurement and verification. Thus, the analysis that follows is limited to qualitative comparison and discussion. While definitive conclusions about modelling assumptions and real behaviour cannot be made due to limited information from participants, it would appear that current assumptions are generally simplistic and either overly optimistic or conservative depending on the application.

The scope of analysis includes modelling of occupancy (presence), plug loads, lights, blinds, operable windows, and thermostats. When participants were asked for other occupant-related domains that the survey did not explicitly cover, the responses were: activity level/metabolic rate (25 participants), infiltration and ventilation (19), manual control of fans (15), clothing level (13), and domestic water use (11).

In an optional open question in the survey, the participants were asked to recall episodes, if any, when occupant behaviour proved to be significantly different from their assumptions made within the BPS tool. Where relevant, these comments are also discussed in this section, as they provide insights into the discrepancy between assumptions and reality.

3.3.1 Occupancy

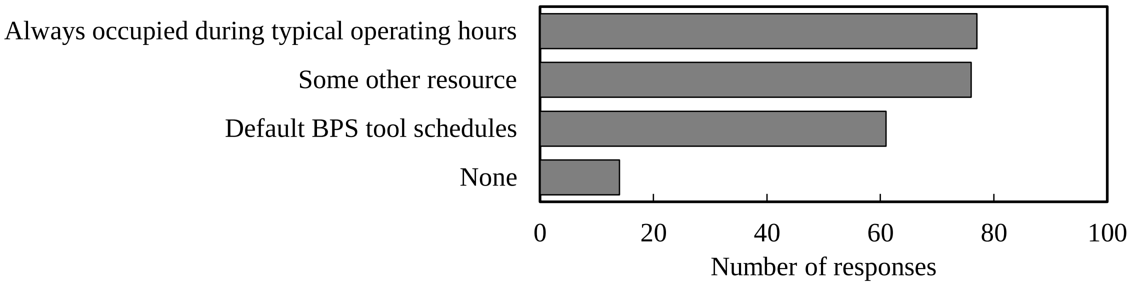
Nearly all participants reported three assumed occupancy schedules with approximately equal frequency: *Always occupied during typical operating hours (e.g., 9AM - 5PM for offices)*; *I use some other resource; and I use default BPS tool schedules for the building/space type* (Figure 7a). Meanwhile, two-thirds of participants reported that they assume partial occupancy relative to full capacity and another 19% assume full capacity (Figure 7b). Several participants reported that they explore the impact of several different occupancy assumptions to better understand the risk associated with their assumptions.

Contemporary societal and technological trends are having a considerable impact on office occupancy and significantly contrast traditional occupancy schedules and default BPS tool schedules. While the US Department of Energy Reference Buildings (Deru et al. 2011) suggests assuming 95% occupancy in offices during regular business hours, Gunay et al. (2016) reported that several studies have found that peak occupancy rarely exceeds 50%. Meanwhile, flexible hours, overtime and longer working hours, teleworking, and lean office/hoteling office management are becoming increasingly prevalent (GSA Office of Governmentwide Policy 2012; US Department of Labor 2014). This trend was noted by the participants; for instance, some comments indicated much longer-than-predicted occupancy durations for educational buildings. Some participants also noted that occupancy in some building types (e.g., exhibition halls) proved to be much less predictable than in others.

For residential buildings, British and American time use surveys suggest that traditional schedules (e.g., US DOE Reference Buildings) about time spent at home and sleeping, household activities, and leisure are reasonable (Lader, Short and Gershuny 2006; US Department of Labor 2014). However, changes in retirement age, life expectancy, and the aforementioned trend for teleworking can all be expected to reduce the suitability of traditional residential occupancy assumptions.

Accurately predicting occupancy in all building types is arguably the most critical of all other domains that follow because occupancy is a strong predictor for modelling states and actions of plug loads, lighting, window blinds, operable windows, and thermostat adjustments. Moreover, many automated mechanical and electrical systems are controlled by occupancy sensors. In contrast, some participants noted that current modelling approaches neglect the relationship between occupancy and occupant actions. But clearly, occupants need to be present in order to take actions and moreover, evidence suggests that the likelihood of actions highly depends on occupancy-related events; for example arrival (Haldi and Robinson 2010).

(a)



(b)

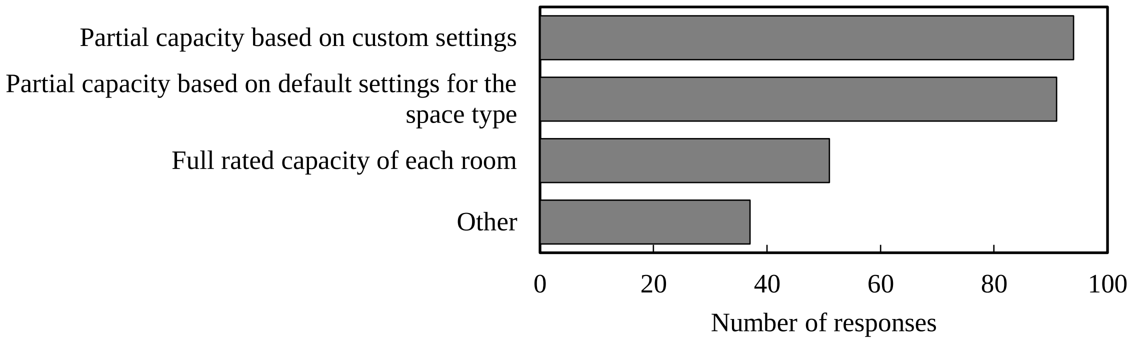


Figure 7. Participants' assumptions about occupancy (occupant presence): (a) schedule and (b) number of occupants

3.3.2 Plug loads and equipment

Most of participants (70%) reported that they typically model plug and equipment loads from a top-down approach using power density, while 20% use a bottom-up approach of adding the power from individual pieces of equipment (Figure 8a). More than for other domains, many participants stated that the equipment modelling approach is very dependent on the building model purpose; they may use typical or standard values for code compliance runs, while relying on detailed measurements if the building is already operating or the client is able to provide more detail.

With respect to changing technology and societal patterns, a bottom-up approach can yield better accuracy because it requires customization and better characterization of the equipment and macroeconomic indicators (Swan and Ugursal 2009). Nevertheless, for early stage design such information may not be available in sufficient detail. The survey participants primarily reported using standard schedules for equipment from building standards or simulation tools (42%) and equipment schedules based directly on occupancy (30%) (Figure 8b). In reality, office plug-in equipment loads are correlated with occupancy but they remain quite high after occupant departure (approximately 40% of the power level compared to during occupancy), regardless of duration of vacancy (Webber et al. 2006; Gunay, O’Brien et al. 2016). Prevalence of servers and other machinery may further increase power user during unoccupied periods. Thus, independently of the selected approach, it is important to acknowledge that loads do not drop to zero during vacancy. Many trends – prevalence of operating system sleep software, regulations on phantom loads, remote access of computers, and attitudes about the time required for computers to load up and damaging equipment through frequent powering up and down – require careful consideration of plug load monitoring (Pixley et al. 2014).

Type of equipment is also another factor that influences how occupants use plug load equipment. For instance, through a survey of North American office workers, Gunay, O'Brien et al. (2016) discovered that office workers tend to leave desktop computers on more than laptops. Similarly, trends in residential appliances and other plug loads are significant. For instance, Natural Resources Canada (NRCan) (2011) reported that most household appliances doubled in energy efficiency in the past 20 years, but that the increase in the number of small household appliances more than offsets these energy savings. Thus, the prevalence of the current survey's participants to use top-down equipment modelling approaches (i.e., existing schedules and power densities) is quite risky because of their tendency to become obsolete over time. While bottom-up approaches may be speculative, they force the BPS user to give significantly more thought and attention than is normally devoted.

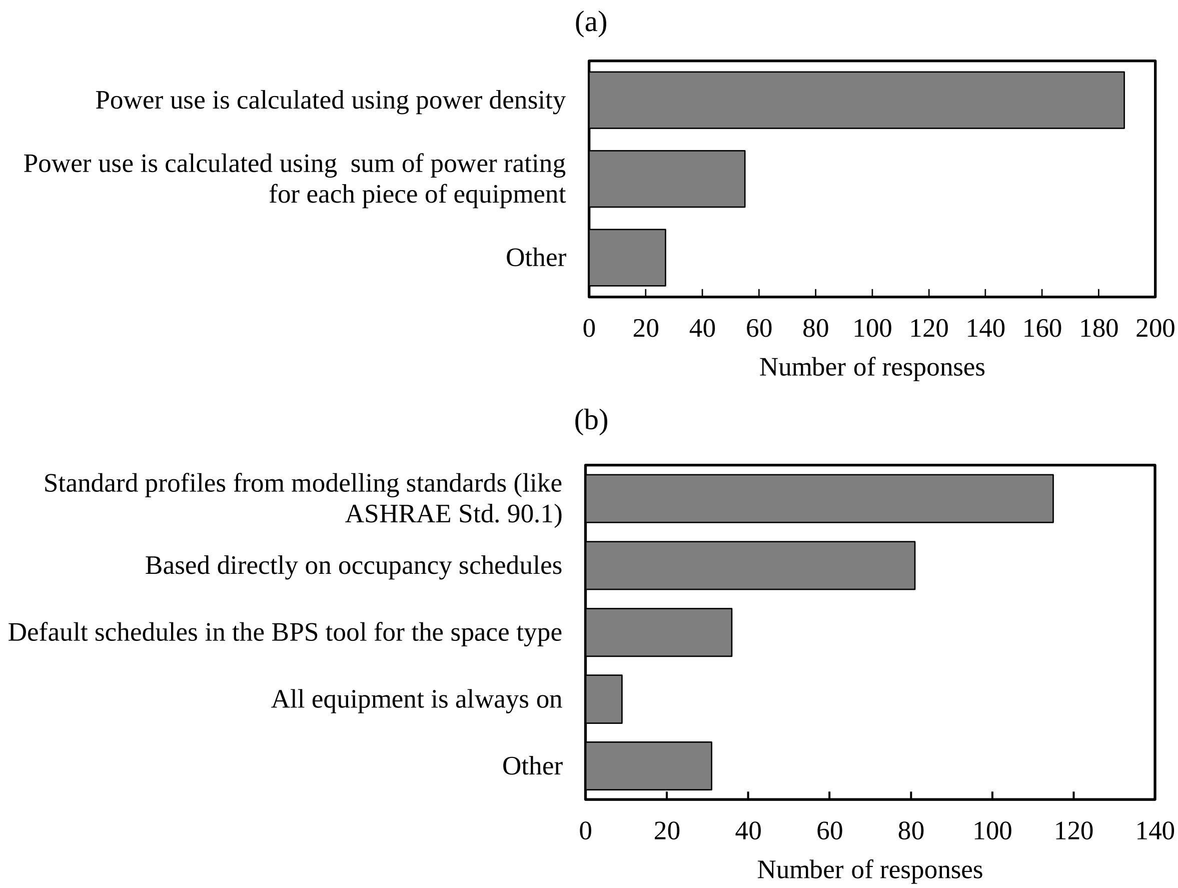


Figure 8. Participants' assumptions about plug loads: (a) power use, (b) schedules.

3.3.3 Light use

The survey participants indicated three common assumptions about manual light switching: *always on during occupancy* (37%); *on during occupancy only if daylight levels are inadequate* (36%); and *dimming to supplement daylight levels* (19%) (Figure 9). The literature generally indicates that daylight availability is a good indicator for light switching behaviour. If daylight is available – and it may be well below the standard recommended illuminance values – the fraction of lamps that are on is typically much less than the fraction of spaces occupied for private offices (Reinhart and Voss 2003; Gunay, O'Brien and Beausoleil-Morrison 2016). Contrary to the common assumption that lights are dimmed to complement daylight illuminance, several studies have found that occupants manually dim lights at a frequency much less than daily (Maniccia et al. 1999; Moore, Carter and Slater 2003; Boyce et al. 2006). Similarly, occupants rarely turn off lights mid-day if illuminance levels become adequate and instead usually turn them off at departure at the end of the day (Hunt 1979). Moreover, the tendency for cleaning staff in commercial buildings to turn on and leave on lights at night is often overlooked (e.g., Deru et al. 2005). In shared office spaces, the common assumption that lights are always on during occupancy is reasonable. Occupants often fear conflict over light preferences (Galasiu and Veitch 2006) and thus lights remain on more than expected in shared spaces (Hunt 1979).

Compared to office buildings, the literature on occupants' use of lights in residential buildings is significantly less mature and the topic is much more complex. Occupant demographics and lifestyle, lamp characteristics, and dwelling characteristics all play a role in predicting light state and power use (Gifford et al. 2012). Contrary to in offices, occupancy in residential buildings is a poor indicator of light state unless activity (e.g., sleeping, working, cooking, and watching television) is known. In summary, manual light switching is highly dependent on the building type, space, activity, and control systems; however, the literature strongly suggests that the survey-reported assumptions about daylight displacing electric lighting are optimistic.

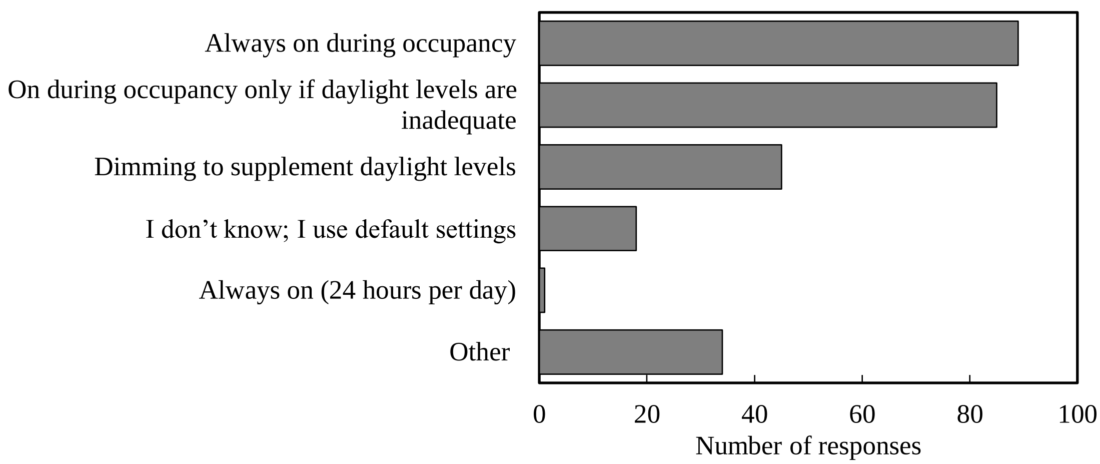


Figure 9. Participants' assumptions about light switching.

3.3.4 Window blinds and shades

The top four responses about blind use were: *closed for high solar gains and/or high indoor/outdoor temperatures* (28%); *Always open or no blinds/shades at all* (26%); *Partial closing to reduce glare but maintain some daylight and views* (14%); and *I don't know (I use default settings)* (13%) (Figure 10). Given that the default blind control setting in BPS tools is normally to have the blinds in open position or non-existent, approximately 39% of surveyed modellers assume blinds are open. This is in stark contrast to the blind studies in the literature, which report that most blinds are partially or fully closed (O'Brien, Kapsis and Athienitis 2013). The possible survey question responses do not necessarily capture all assumptions, but the result that about 49% of participants indicate that blinds are closed in response to thermal and/or visual stimuli is consistent with the literature. However, the literature also suggests that many occupants leave blinds in their closed state for a long period ranging from the rest of the weeks to months (Van Den Wymelenberg 2012). To corroborate these findings, one of the survey participants modelled a school that relied on daylighting, only to discover that the blinds were always shut – presumably to increase the visibility of the projector screen. Simple rule-based blind operation is unlikely to capture the residual effect of visual and thermal discomfort. The primary driver of blind closing in most offices is visual comfort based

(O'Brien, Kapsis et al. 2013), unless they are not air conditioned (Inkarojrit 2008). Like for nearly all occupant behaviour domains, many contextual factors (e.g., privacy and quality of view) play a poorly understood role in occupants' blind use decision-making processes that have yet to be integrated into even research-oriented modelling efforts (O'Brien and Gunay 2014).

Blind use in homes is not as well correlated to visual or thermal comfort and depends greatly on lifestyle, time of day, and space uses (Bennet, O'Brien and Gunay 2014). In summary, the modellers' reported assumptions about blinds being generally open and only being closed during periods of visual or thermal discomfort greatly underestimate observed blind occlusion levels and the corresponding solar gains, and overestimate daylighting potential and corresponding energy savings, and views to the outside. However, current assumptions may be appropriate for cooling equipment sizing.

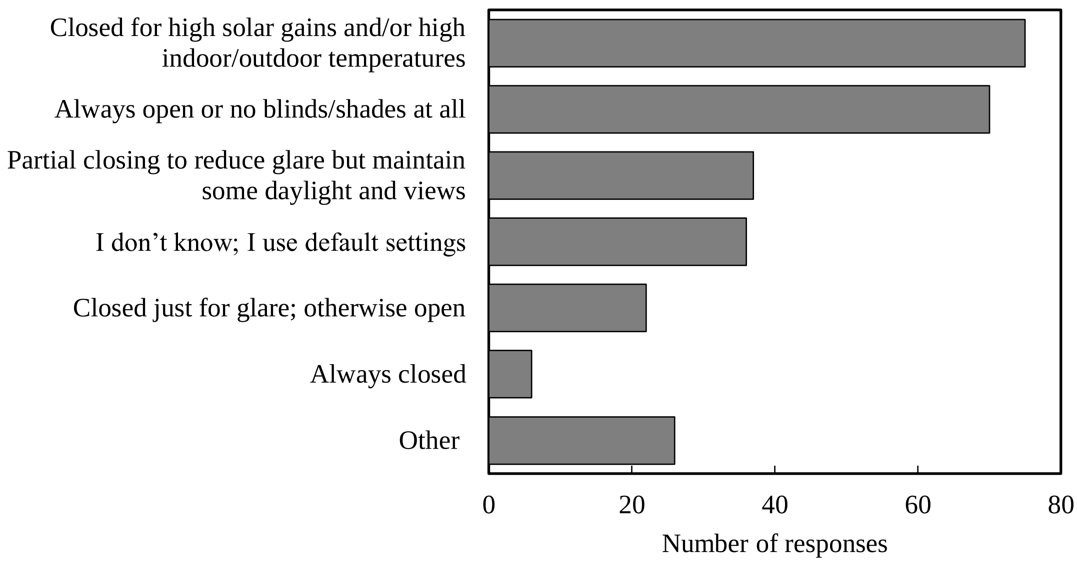


Figure 10. Participants' assumptions about window shades position

3.3.5 Operable windows

The prevalent responses about operable window use behaviour were: *Windows open/closed based on inside and/or outside temperatures* (37%), *The buildings I model typically don't have operable windows* (23%), and *Always closed* (19%) (Figure 11). The assumption of a temperature-driven operation of windows was largely unmentioned when the respondents reported occupants behaving differently than expected. In particular, the modellers lamented people for opening windows when the outdoor air temperature is cold and for filing discomfort complaints despite not opening windows to prevent overheating. Extensive studies of operable window use in offices have indicated a multitude of good predictors for window opening actions and position, including indoor and outdoor temperature, wind speed, indoor air quality, time of day (e.g., arrival time and departure time) and social constraints (single office versus shared office) (Fabi et al. 2012). For homes, the literature indicates that outdoor air temperature is a prevalent predictor of window opening state or action; however, there are many other predictors including activity type (e.g., cooking and smoking), room type, and occupant age (Fabi, Andersen et al. 2012). None of the survey participants mentioned that they use customized window operation logic, thus indicating that current operable window use modelling practice is significantly simplified relative to reality. The appropriateness of current operable window modelling approaches depends greatly on the purpose of the building model (e.g., code compliance).

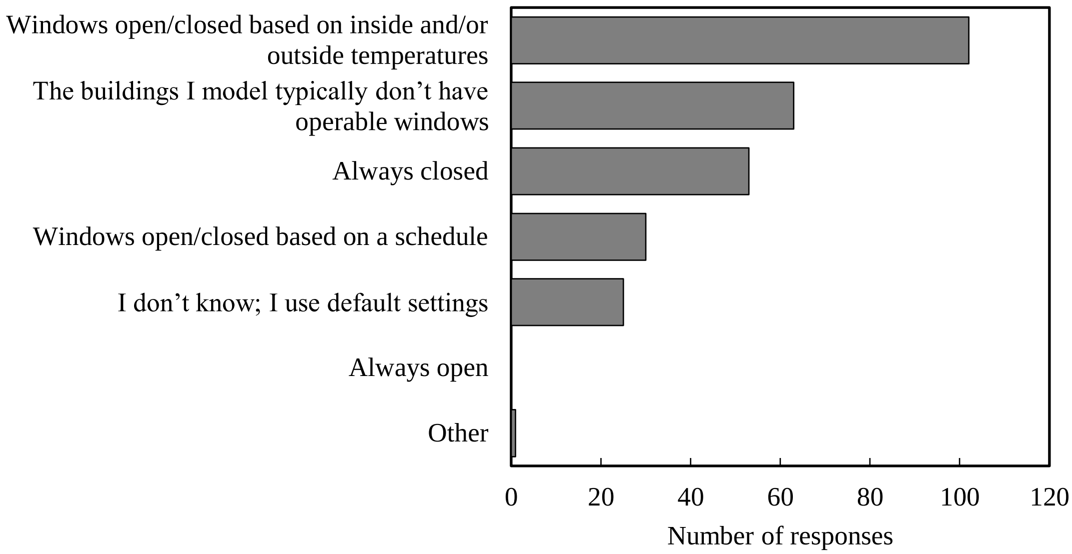


Figure 11. Participants' assumptions about operable window position

3.3.6 Thermostats

The vast majority (66%) of participants indicated that they model thermostats as having a daily schedules, while another 16% indicated a constant schedule all year (Figure 12). None of the other responses explicitly acknowledged occupant interaction with thermostats. The US Department of Energy Reference Buildings (Deru, Field et al. 2011) suggests modelling setpoint setbacks in office buildings, but constant setpoints in residential buildings. Setpoints in large office buildings are often centrally controlled by operators, who often constrain temperature deviations for individual thermostats. Thus, setpoints are largely at the mercy of operators; not occupants (the scope of the current paper). In a large Finnish survey, over 80% of participants in homes and offices reported adjusting thermostats on a monthly or less frequently (Karjalainen 2009). In a study of 40 apartments in the heating season, Gunay et al. (2014) found that heating setpoint selection is diverse between occupants and that both temperature settings and diurnal fluctuations (i.e., inferred setbacks) are highly dependent on whether occupants pay for their heating energy use. Moreover, Meier et al. (2012) found that between 70 and 89% of programmable thermostats have not been programmed and are manually adjusted, if at all. In brief, the current thermostat setpoint assumptions made by modellers may be reasonable, but the literature suggests that manual thermostat adjustments are often much less frequent than daily.

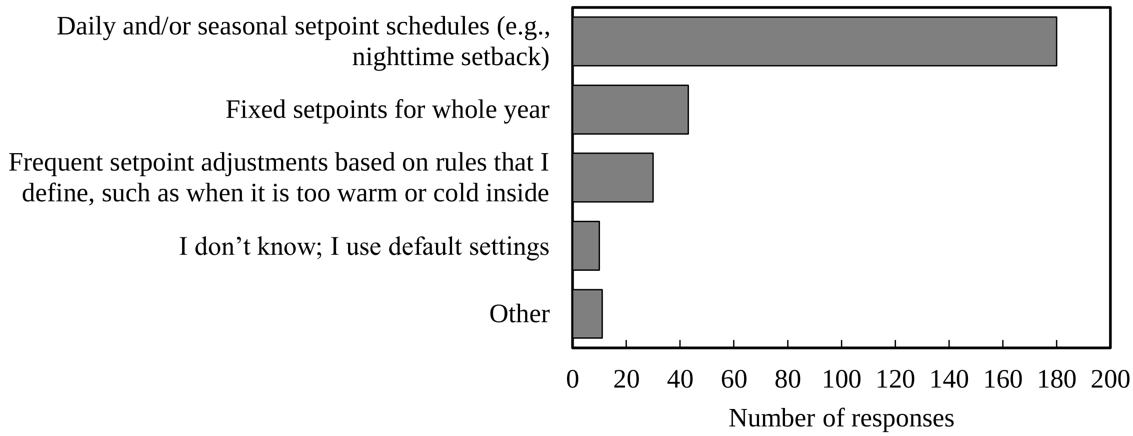


Figure 12. Participants' assumptions about thermostat setting

3.3.7 Participants' confidence in their assumption about occupant modelling

Figure 13 represents the confidence of modellers in their assumptions about occupant modelling in practice. The degree of confidence changes substantially according to the aspect of occupant behaviour which is being modelled. In particular, most respondents tend to be confident in their assumptions for occupancy, plug loads, lights, operable windows, and thermostats. Since the answers to the modelling confidence questions are in the form of a five-value Likert scale, parametric techniques cannot be used to identify whether the level of confidence in the modelling assumptions changes according to the aspect of occupant behaviour. Therefore, the non-parametric Friedman test was used to investigate the same respondents on five different contexts. The results of the test, χ^2 (5, n = 273) = 82.93, $p < 0.005$, indicate that there is a statistically significant difference in the users' confidence in their assumption about occupant modelling. Inspection of the mean values of the variables data (where 1 is confident) shows a descending level of confidence starting from thermostat setting (2.34), to occupancy (2.44), plug loads (2.53), lighting switching/dimming (2.56), operable window use (2.57), and shade/blind control (2.95). Arguably, the domains in which participants expressed the greatest confidence are those which are more common BPS inputs. Thus, BPS users may have become more acquainted and confident with these inputs (e.g., thermostat setting and occupancy) than operable window and shade/blind control.

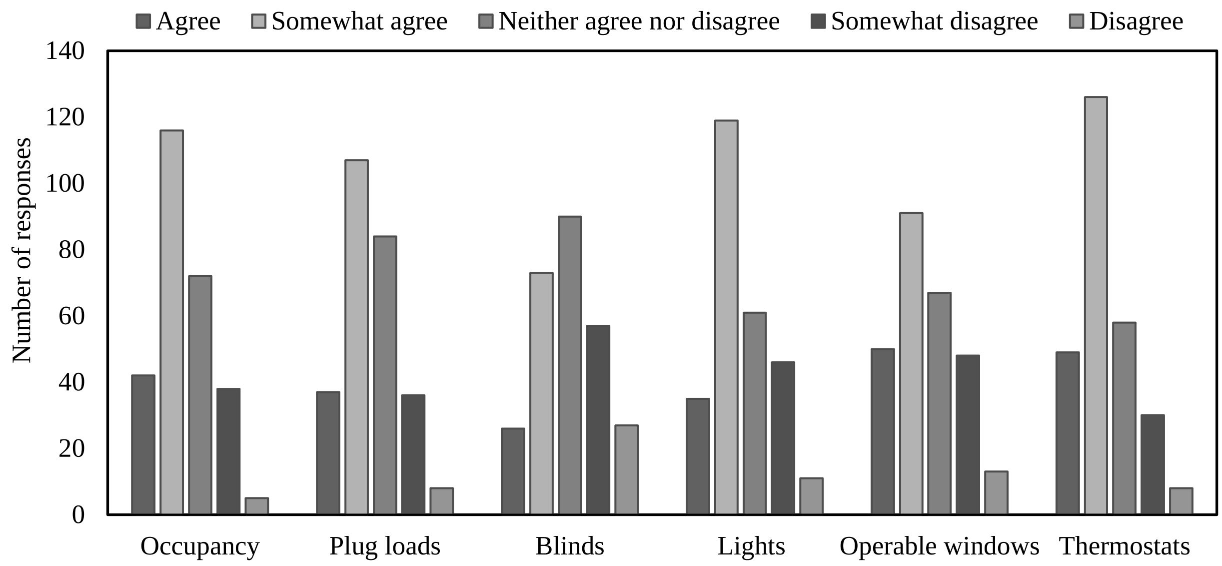


Figure 13. Participants' confidence in their assumption about occupant modelling.

Generally, the participants who are confident about their assumptions reported that they believe the assumptions are appropriate for the specific aim of their simulation or they represent widely accepted standards. However, they also note that such standards often encourage unrealistic simplifications, such as implying that appropriate modelling is not essential for comparative analysis. Where automatic control strategies are present, modellers are confident about their occupant behaviour assumptions, for example blinds operation to increase daylighting. Moreover, they note that at early stages of the design process, the available information is so limited that conservative assumptions are required. Modelling occupant behaviour is not perceived as 'safe' as it cannot be guaranteed. A slight majority (52%) of participants agree or somewhat agree that relying on occupants to behave appropriately to improve their comfort rather than purely electrical and mechanical approaches is risky (Question 25). When they are not confident about their assumptions, the main comment from the participants is that there are no better available modelling options.

3.4 Do BPS users feel that current software tools and standards are suitable for modelling occupants appropriately? (Questions 9 and 30)

The survey showed that the majority (75%) of participants agreed or somewhat agreed that BPS tools should have more occupant modelling features to improve accuracy, even if this requires substantially more user inputs and effort (Figure 14). A slight majority (65%) of participants were neutral or disagreed that BPS tools are effective at communicating occupant modelling assumptions (Figure 15), thus indicating significant room for improvement.

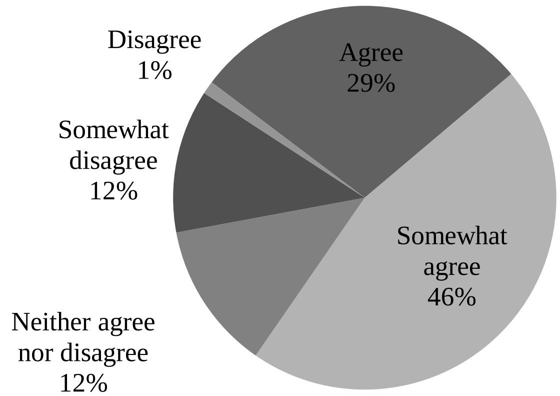


Figure 14. Participants' attitudes towards improving occupant modelling features in BPS tools.

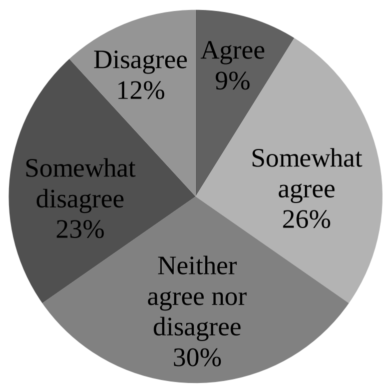


Figure 15. Participants' attitudes that BPS are effective at communicating assumptions about occupants

The more common and interesting occupant modelling features and needs suggested by participants included:

- A feature to show the relative importance of occupant-related characteristics,
- Uncertainty reports, like in other engineering domains such as structural engineering and the frequency of natural disasters,
- Use of high-resolution occupant modelling to improve furniture layout, and luminaire and diffuser placement,
- A feature to better predict savings from occupancy controls and daylight sensors based on real behaviour,
- More accurate or easy-to-use methods to model indoor environmental quality, including daylight glare,
- Much better characterization of occupants across different building types,

- Better documentation on how to model occupants and exploit the results.

3.5 How do BPS users feel about building performance uncertainty and communicating this to clients? (Questions 33-36)

One of the appeals, but also challenges, of stochastic occupant modelling is that it explicitly introduces uncertainty into BPS predictions. A surprising number of survey participants suggested that they could tolerate the extra computational burden of quantifying this uncertainty. When asked if they would be willing to wait for 50 to 100 simulations to run (in order to obtain probabilistic performance predictions from BPS tools), 58% of survey participants agreed or somewhat agreed.

The vast majority of participants (76%) agreed or somewhat agreed that BPS users should do a better job of communicating to clients that building performance predictions are uncertain. A noteworthy fraction of participants (37%) believed that their clients would lose confidence in BPS if they informed them of the underlying uncertainties in the BPS predictions. For representing uncertainty, the participants felt that box and whisker plots were best (47%), followed by a probability distribution (26%) and cumulative probability distribution plot (10%) (Figure 16) (see Appendix, Question 36 for the example graphs that were shown in the survey).

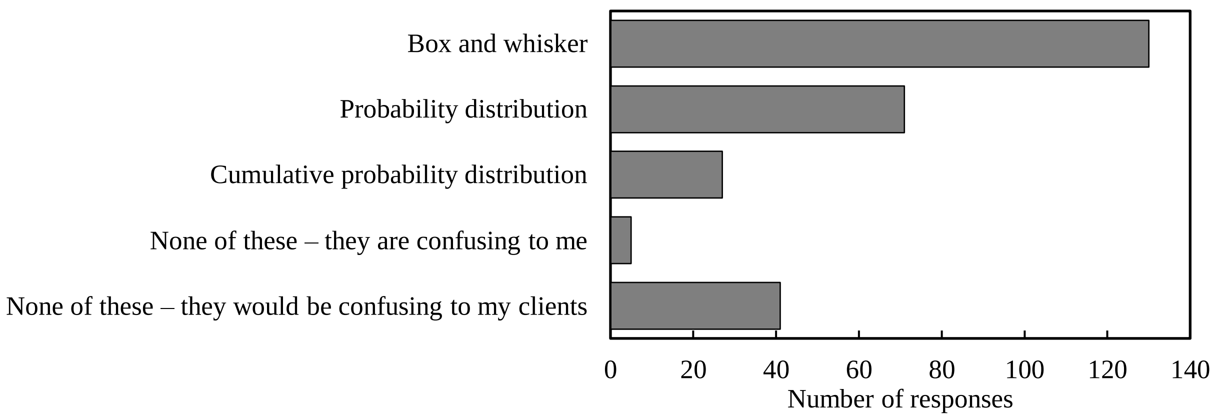


Figure 16. Participants' attitudes about the most effective uncertainty visualization techniques for communicating uncertainty to clients

3.6 How do BPS users rate their current knowledge of occupant modelling? Are they willing to learn more? (Questions 27, 31, and 32)

Participants were asked about how familiar they are with occupant modelling. About half of the participants (47%) identified themselves in the moderate level of knowledge, about 27 and 23% at the basic and advanced level, respectively, and 1-2% at the level of non-existent and leading authority. "Time and effort" (33%) and "lack of understanding/education" (19%) were the biggest barriers to more appropriate occupant modelling. Among the participants, 44% agreed and 36% somewhat agreed that they would be willing to read comprehensive document or attend an all-day workshop on occupant modelling, if available. This result indicates a strong desire for continuing education on occupant modelling in BPS.

To evaluate the relationship between knowledge of occupant modelling and BPS user experience, the two original variables *ExperienceBPS* and *KnowledgeOM* were analysed using the Spearman Rank Order Correlation. The analysis shows that there is a small, positive statistically significant correlation between the two ordinal variables, $r = 0.29$, $n = 274$, $p < 0.001$. This indicates that higher levels of knowledge of occupant modelling correlates with higher levels of experience in BPS.

To find the relationship between participants' experience/knowledge and their willingness to learn more on this topic, Spearman Rank Order Correlation was used to correlate these variables (i.e., *ExperienceBPS*, *KnowledgeOM*, and *WillFurthEducation*). This analysis did not show statistically significant relationships between these variables (Table 1). Therefore, according to the data, the participants' willingness for further education in occupant modelling is independent from their experience with BPS and knowledge of occupancy modelling.

Table 1: Outcome of a Spearman Rank Order Correlation between participants' willingness for further education in occupant modelling, and both their experience with BPS and knowledge of occupant modelling.

		ExperienceBPS	***KnowledgeOM***
WillFurthEducation	Spearman's rho	0.01	-0.04
	Sig. (2-tailed)	0.39	0.50
	n	274	274

The Spearman Rank Order Correlation was also used to analyse how participants' willingness to obtain further education correlates with their attitude towards imposing more occupant modelling approaches in building codes (i.e., *StandardMandateAccurateOM*) and providing more features in BPS tools for occupant modelling purposes (i.e., *MoreOMFeatureBPS*). The results show that the desire for further education (i.e., *WillFurthEducation*) is correlated in a positive and statistically significant manner with *StandardMandateAccurateOM* ($r = 0.44$, $n = 274$, $p < 0.001$) and *MoreOMFeatureBPS* ($r = 0.33$, $n = 274$, $p < 0.001$). This suggests that those participants who are more willing to learn more about occupant modelling are also willing to have more occupant models integrated into BPS tools and more accurate occupant modelling approaches to be mandated in standards.

4 Conclusions

This paper summarized and analysed the 274 valid responses of a 36-question survey that was deployed to provide a better understanding of occupant modelling practice in building simulation. The results indicate that, while current occupant modelling practice in BPS is quite simplistic, there is a strong awareness of its importance from BPS users. Fify-six per cent of participants agreed or somewhat agreed that real occupants use more energy than assumed in models. Contrary to the notion that BPS tools should be used only to assess relative building performance for building code compliance, 58% of survey participants responded that it is not acceptable to merely represent occupants consistently, if the methods are not realistic. The majority of participants (74%) agreed or somewhat agreed that modelling standards should increase occupant modelling requirements.

The most commonly cited reason to improve occupant modelling is to reduce the gap in performance predictions. When offered nine commonly-cited sources of discrepancy between BPS predictions and measured building performance, 44% of participants named occupant behaviour as the most significant. The participants' profession (i.e., researchers and practitioners) and the level of experience in using BPS tools (i.e., more/less than five years) do not influence participants' perception of occupant behaviour as the leading source of discrepancy between predictions and measurements.

The survey indicates that current assumptions that modellers make about occupants are much simpler than what has been observed about occupants in reality. In many cases the current assumptions are overly optimistic and could lead to over-predicting building performance. Conversely, some of the assumptions made will lead to greatly oversized mechanical equipment. Many of the participants showed impressive insight in that they customize occupant modelling assumptions to the purpose (e.g., code compliance vs. early design). To the authors' surprise, BPS users generally reported that they were quite confident about their occupant modelling assumptions. BPS users' confidence in using occupant-dependent features already integrated in BPS tools differs in a statistically significant manner with respect to domain. In addition to the occupant-related domains explored in the survey, numerous survey participants expressed a need for greater modelling capabilities in BPS tools and more research on occupant clothing and activity level and domestic water use. The vast majority (75%) of participants agreed or somewhat agreed that BPS tools should have more occupant modelling features.

When asked whether BPS tools should better address uncertainty, 76% of survey participants agreed. However, 37% stated that clients would lose confidence in BPS if uncertainty were explicitly expressed. Perhaps energy codes and other authoritative sources should mandate uncertainty reporting such that individual BPS users are not penalized for communicating it. Among the different proposed uncertainty visualization techniques for communicating uncertainty to clients (i.e., probability distribution, cumulative probability distribution, and box and whisker), the majority of the participants (47%) identified the box and whisker graph as the most effective, followed by the probability distribution plot (26%).

When participants were asked about the biggest barriers to more appropriate occupant modelling, 33% of participants responded *time and effort*, while 19% responded *lack of understanding/education*. Therefore, this study demonstrates a need to educate practitioners on occupant modelling. A strong majority (81%) of participants agreed or somewhat agreed that they are interested in learning more through courses or written guidelines. The participants who are more willing to learn about occupant modelling are also willing to have more occupant models integrated in BPS tools and believe that modelling standards should mandate more accurate occupant modelling approaches.

This survey revealed considerable necessary future work on research and education, model and software development and evaluation, and policy making regarding occupant modelling in the simulation-based design process.

Many participants mentioned that the rigour with which they model occupants is highly dependent on the application at hand, for example code compliance vs. detailed measurement and verification studies. The participants indicated that this is a manual process and a judgment call on their parts; but more formalized and automated control over occupant modelling resolution would greatly benefit BPS users. Similarly, occupant modelling approaches are dependent on building scale. Standard occupancy profiles are likely adequate for large office buildings where an averaging effect whereby the total number of occupants in a building follows a fairly repeatable pattern. But agent-based models that describe individuals are more targeted at smaller scales such as office façade studies, in order to develop a comprehensive understanding of the occupant-building relationship is characterized. Further discussion on the appropriateness of different occupant modelling approaches for various BPS applications is a necessary research topic Gaetani, Hoes et al. (2016). Meanwhile, BPS users are seeking training on best practices for occupant behaviour modelling.

More robust and validated occupant models need to be developed and implemented into BPS tools. The few existing studies in the literature that compare occupant behaviour across climates or even buildings suggest that we are many years away from characterizing occupants to the same degree of accuracy as physical phenomena, such as heat transfer through envelopes. However, there remains an opportunity for tools to have built-in what-if analyses pertaining to occupants. For instance, a single click operation could enable the simulation and output of three different occupant scenarios for example energy conserving occupants, average occupants, and energy-wasting occupants. Some survey participants mentioned that for existing buildings, they manually include some of the observed occupant behaviours (e.g., tendency to not turn off lights regardless of daylight levels) into detailed building models that are used for post-occupancy evaluations. Future BPS tool features could better facilitate the process of incorporating occupant observations into models, such as EnergyPlus' feature that reads in schedules from files. Guidance on not only the mechanics of occupant modelling but also the strategies to evaluate and design for uncertainty should be developed with the BPS user community in mind. The corresponding documentation and transparency of BPS tools regarding occupant modelling and representing results with uncertainty expressed also requires significant improvement.

Finally, code and standards developers should begin to increase the rigour of occupant modelling requirements to better reflect observed occupant behaviour. Case studies demonstrating the importance and capabilities of occupant modelling have the potential to greatly improve BPS user and building designer awareness.

5 Acknowledgements

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6 Appendix: The survey

Questions	Possible answers	Name of variables used in the statistical analysis
Background		
1. How would you best describe your profession?	Engineer; Architect; Policy maker; Researcher and/or educator; other:________	*Profession*
2. For how many years have you been using building performance simulation (BPS) (also known as building energy modelling)?	Fewer than 2 years; 2 to 5 years; 5 to 10 years; Over 10 years; I do not use BPS *(jump to end of survey)*	*ExperienceBPS*
3. In which country is the majority of your work?	(dropdown list)	
4. For which of the following purposes do you use BPS? (check all that apply)	Building code compliance; Environmental assessment schemes (e.g., LEED, BREEAM, DNGB, etc.); Early design; Detailed design and equipment sizing; Post-occupancy evaluation of performance, controls optimization, or retrofit analysis; Life cycle cost assessment (LCAA); Other(s): ____	
5. Which whole-building simulation tool(s) do you use? (select all that apply)	AECOsim Energy Simulator; DesignBuilder; DeST; DOE-2.1x; Ecotect (Autodesk); EnergyPlus; eQuest; ESP-r; Green Building Studio (Autodesk); HAP (Carrier); Hevacomp; HOT2000/3000; IDA ICE; IES VE; Modelica; OpenStudio; RETScreen; Safeira; SIMBIAN; Simergy; Tas; Trace (Trane); TRNSYS; Other(s):______	
6. From my experience, the leading source of discrepancy between BPS predictions and measurements is inadequate model representation of ______	Weather data; Raw material properties; Building component/equipment quality; Construction quality; Occupant behaviour; Controls and operations; HVAC system functionality; Numerical approximations in BPS tools; Input assumptions in BPS tools; None: there are minimal discrepancies between BPS predictions and measurements; Other(s)_____	*SourceDiscrepancy*

Questions	Possible answers	Name of variables used in the statistical analysis
Current modelling practice		
7. Which of the following best represents your overall assumptions about occupants in BPS?	I use default values and do not check assumptions; I use values derived from standards (e.g., ASHRAE 90.1); In each project, I modify the default settings based on my prior experience and judgment; I assume occupants will act to minimize energy use (e.g., optimally control lights, blinds, windows, equipment, etc.); Other (please elaborate): _________________	
8. It does not matter if assumptions about occupants' in BPS tools fully represent real occupants as long as occupants are represented the same way in all design variants.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
9. The BPS tool(s) that I use are effective at communicating assumptions and default settings about occupants.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
10. What modelling assumption do you most frequently make about occupancy (occupant presence) schedules?	Always occupied during typical operating hours (e.g., 9:00-17:00/5PM for offices); I use default BPS tool schedules for the building/space type; I use some other resource. Please specify______; None of the above	
11. What modelling assumption do you most frequently make about the number of occupants in a space?	Full rated capacity of each room; Partial capacity based on default settings for the space type; Partial capacity based on custom settings Other__________	
12. Regarding the above answer about occupancy, I feel confident that this representation is appropriate for the aim of my simulation.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	

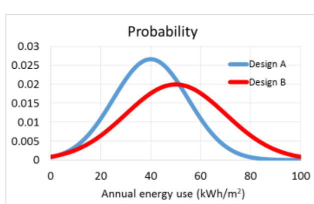
Questions	Possible answers	Name of variables used in the statistical analysis
13. What modelling assumption do you most frequently make about appliances and plug loads power use?	By summing the power rating of each piece of equipment; By using power density (e.g., W/m^2 or $BTU/hr{\cdot}ft^2$); Other___________	
14. What modelling assumption do you most frequently make about appliances and plug loads schedules?	All equipment is always on; Default schedules in the BPS tool for the space type; Standard profiles from modelling standards (like ASHRAE Std. 90.1); Based directly on occupancy schedules Other___________	
15. Regarding the above answers about appliances and plug loads, I feel confident that this representation is appropriate for the aim of my simulation.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
16. What modelling assumptions do you most frequently make about manual movement and positioning of window blinds/shades?	Always open or no blinds/shades at all; Always closed; Closed just for glare - otherwise open; Closed for high solar gains and/or high indoor/outdoor temperatures; Partial closing to reduce glare but maintain some daylight and views; I don't know - I use default settings; Other ________________	
17. Regarding the above answer about manually-controlled window blinds/shades, I feel confident that this representation is appropriate for the aim of my simulation.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
18. What modelling assumptions do you most frequently make about manual light switching/dimming?	Always on (24 hours per day); Always on during occupancy; On during occupancy only if daylight levels are inadequate; Dimming to supplement daylight levels; I don't know - I use default settings Other __________	

Questions	Possible answers	Name of variables used in the statistical analysis
19. Regarding the above answer about light switching/dimming, I feel confident that this representation is appropriate for the aim of my simulation.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
20. What modelling assumptions do you most frequently make about manual movement and positioning of operable windows?	The buildings I model typically don’t have operable windows; Always open; Always closed; Windows open/closed based on a schedule; Windows open/closed based on inside and outside temperatures; I don’t know - I use default settings; Other:________	
21. Regarding the above answer about operable windows, I feel confident that this representation is appropriate for the aim of my simulation.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
22. What modelling assumptions do you most frequently make about thermostat settings?	Fixed annual setpoints; Daily and/or seasonal setpoint schedules (e.g., nighttime setback); Hourly or sub-hourly set point adjustments based on rules that I define, such as when it is too warm or cold inside; I don’t know - I use default settings; Other:____	
23. Regarding the above answer about thermostat settings, I feel confident that this representation is appropriate for the aim of my simulation.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
24. What other occupant-related model inputs do you typically specify in your models?	(Please list all.)	

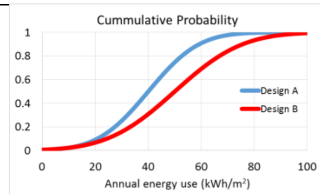
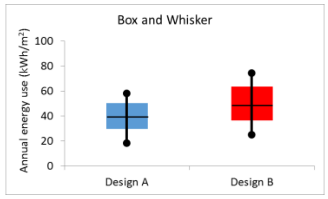
Questions	Possible answers	Name of variables used in the statistical analysis
Attitudes and future practice		
25. Designing buildings that rely on occupants to adapt to discomfort (e.g., open windows if overheating occurs) could save energy but is risky due to potential liability (e.g., chronic occupant discomfort) or increased costs.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
26. In my experience, real occupants use more energy through their actions and habits than I assume in BPS tools.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	
27. How do you rate your current knowledge of occupant behaviour modelling?	Non-existent; Basic; Moderate; Advanced; World-leading authority	*KnowledgeOM*
28. The most important reason to appropriately represent occupant behaviour in BPS is...	To help fill the gap between predicted and actual building performance; To aid in risk assessment; To improve building controls/operations; To improve general building design quality; To improve occupants' comfort; Other(s)__________	*PurposeAccurOB*
29. Modelling standards should mandate more accurate occupant modelling approaches.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	*StandardMandateAccurateOM*
30. Simulation tools should have more occupant modelling features to improve accuracy, even if it requires substantially more user inputs and effort.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	*MoreOMFeatureBPS*
31. I would read a comprehensive document or attend an all-day workshop about occupant modelling if it were available.	Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree	*WillFurthEducation*

<table>
<tr><th>Questions</th><th>Possible answers</th><th>Name of variables used in the statistical analysis</th></tr>
<tr><td colspan="2">Barriers to using advanced occupant behaviour models in BPS</td><td></td></tr>
<tr><td>32. What is the biggest current barrier to using more detailed occupant behaviour modelling approaches?</td><td>Time and effort; Understanding/education; Client interest; Codes and modelling standards; BPS tool limitations;

Other(s)___ ______</td><td></td></tr>
<tr><td colspan="2">Researchers are developing stochastic occupant models that are based on probabilities and data from monitored occupants. For example, instead of assuming occupants will turn on lights below a specific daylight level, the models assume there is a certain likelihood that occupants turn on lights associated with each daylight level. But as a result, each time a simulation is run, it may yield different results. As a result, it may be necessary to run 50 to 100 simulations in order to obtain a proper characterization of occupants.</td><td></td></tr>
<tr><td>33. Running simulations 50 to 100 times to obtain probabilistic results would be an acceptable practice if it were done automatically by the software tool.</td><td>Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree</td><td></td></tr>
<tr><td>34. If I told my clients that BPS predictions are uncertain, they would lose confidence in me and/or simulation.</td><td>Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree</td><td></td></tr>
<tr><td>35. BPS users should do a better job of communicating to clients that building performance predictions are uncertain.</td><td>Agree; Somewhat agree; Neither agree nor disagree; Somewhat disagree; Disagree</td><td></td></tr>
<tr><td>36. Which of the following uncertainty visualization techniques would be most effective for communicating uncertainty to clients?</td><td>None of these – they are confusing to me;
None of these – they would be confusing to my clients



Probability distribution</td><td></td></tr>
</table>

Questions	Possible answers	Name of variables used in the statistical analysis
	 Cumulative probability distribution  Box and whisker	

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