OCCUPANT BEHAVIOUR DIVERSITY MODELLING AND ITS APPLICATIONS

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ABSTRACT

It has been widely established that observed occupancy and occupant behaviour are diverse between individuals, whether it is a result of differences between people or subtle contextual differences. However, diversity is infrequently recognized in existing occupant models. As a result, corresponding uncertainty of building performance simulation predictions may be greatly underestimated. This limits one of the major benefits of stochastic occupant behaviour modelling: that probabilistic performance distributions can be estimated and exploited. This paper provides a comprehensive review of existing methods to represent occupant diversity in models. Following that, the diversity between occupants from an office building dataset is explored. The dataset includes occupancy from 16 private offices and equipment loads from 10 private offices. Finally, the paper concludes by providing general recommendations on the treatment of diversity for future researchers.

INTRODUCTION

Occupant behaviour has become widely understood to be a leading cause for uncertainty in building performance. Moreover, occupants have an increasingly significant effect on building performance as buildings become more efficient (Hoes, Hensen, Loomans, de Vries, & Bourgeois, 2009; Page, Robinson, Morel, & Scartezzini, 2008). Numerous field and simulation studies have found the difference between the highest and lowest energy consuming occupants in a similar or identical set of homes or offices to be at least a factor of two – and often much higher (Gram-Hanssen, 2010; Haldi & Robinson, 2011). This uncertainty comes at a considerable cost because in most cases, engineers will size equipment and renewable energy systems (in net-zero energy buildings) to cover the highest expected loads (Djunaedy, Van den Wymelenberg, Acker, & Thimmana, 2011). Furthermore, the predicted economic payback of various building upgrades – at design or for retrofit – can be significantly influenced by the assumptions made about occupants (Lee & Schiavon, 2014; Rasouli, Ge, Simonson, & Besant, 2013). The uncertainty of occupants can be mitigated through building design and through diversity of larger buildings or district energy systems, but greater knowledge of the complex and dynamic human-building, including quantification of uncertainty, is needed (O'Brien & Gunay, 2015).

On the contrary, diversity can also provide a smoothing effect on peak loads. For instance, if a model assumes that all occupants arrive simultaneously and turn on lights and computers and that meanwhile the controls are scheduled to activate heating or cooling simultaneously, peak building-level loads will be much higher than if arrivals are staggered.

The research community has been developing more advanced occupant models based on monitored data. It has been argued that occupants should be represented and modelled stochastically rather than deterministically (J. F. Nicol, 2001). That is, occupants are unlikely to respond in the same way to a given set of circumstances in a machine-like manner because there are many complexities to their decision making process. Thus, the recent modelling efforts have used stochastic models, with logistic regression being overwhelmingly favoured.

In the past several decades, a considerable body of research has focused on attempting to develop a model to describe the typical occupant for building simulation, rather than recognizing diversity between occupants with regards to their behaviour and presence. In essence, this results in a statistically representative occupant rather than a true representation of a population of occupants. While a degree of uncertainty is introduced by developing an agent-based stochastic model, another major source of uncertainty comes from differences between occupants, particularly when the population of occupants is not characterized.

Contrary to pure laboratory-based studies which control for contextual differences, such that personal characteristics and inter-personal traits can be quantified, there are additional layers of complexity from in-situ occupant monitoring campaigns. While, there is strong evidence to suggest that occupants have different sensitivities and preferences for comfort conditions (e.g., Boyce, 2014; F. Nicol, 2004), contextual factors further introduce considerations to observed behaviour (O'Brien & Gunay, 2014). The diversity in observed behaviours stems from multiple factors including sensitivity to environmental conditions, activity type, user interfaces, building controls schemes, job type and lifestyle, and many other contextual factors. Occupant preferences for indoor environmental conditions also depend on occupant metabolic rate, whether an occupant is reading, drawing or using a computer, and whether an occupant needs silence to concentrate. Furthermore, room and furniture layout could play a role on occupants' behaviour. For instance, an occupant who is seated at a small desk near a window would be more sensitive to daylight glare than an occupant who is seated far from a window at a large desk with flexible seating positions (Jakubiec & Reinhart, 2012). Anecdotally, some occupants may even alter their departure time from an office if conditions are uncomfortable. When occupant data are collected, they do not provide information on these factors individually, but the aggregate of all of them. Most occupant modelling studies have attempted to fit models to a limited number of environmental factors (Reinhart, 2004; Rijal et al., 2007) with the contextual factors accepted as random noise. A limited number of studies (Haldi & Robinson, 2010; Schweiker, Haldi, Shukuya, & Robinson, 2012; Sutter, Dumortier, & Fontoynont, 2006) have had the privilege of several controlled contextual factors such that their impact can be quantified.

An example result of a lighting use study is shown in Figure 1. It shows the regression of data from 10 individual observed occupants. Notably, the illuminance at which there is a 50% probability that each occupant will turn on the light at arrival varies by a factor of approximately 15 (20 lux to 300 lux). Not only is this parameter diverse, but the slope of each curve shows considerable diversity. The slope parameter indicates the predictability that occupants will act, where a perfectly vertical line would be deterministic and a gentler slope indicates a high degree of variability of light-switching actions for a single occupant. But many practical and theoretical questions arise for in-situ occupant monitoring campaigns, including:

- Are the differences between occupants caused by inter-occupant physiological differences or contextual factors (e.g., occupant orientation, occupant activity, indoor surface reflectance and specularity)?
- Does the measurement methodology affect models? For instance, were the sensors located in the exact same position, relative to the occupant or the space?
- How should such data-driven models be converted and generalized for use in building simulation?
- Based on the curves for individual occupants, can conclusions be drawn about adequate sample size?

In spite of the aforementioned benefits of modelling diversity within occupant populations, this matter has been treated in relatively simple ways that leave many research questions, and in some cases could lead to significant error. This paper provides a literature review of occupant diversity modelling approaches and then provides an in-depth examination of several occupant datasets. Finally, the implications of diversity and diversity modelling are examined.

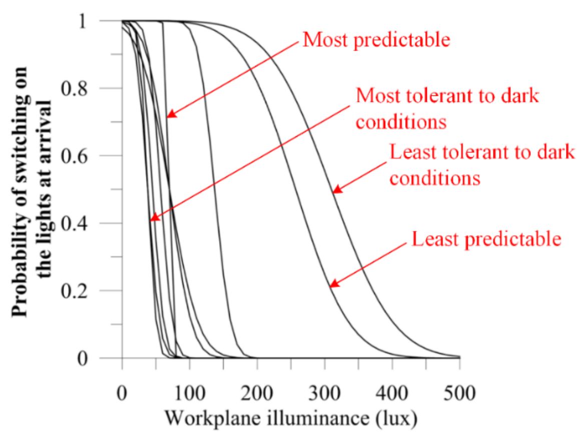

Figure 1 Example of occupant diversity from Reinhart and Voss (2003); each line represents a regression of data from a single occupant.

LITERATURE REVIEW

Where occupant diversity modelling for BPS applications is acknowledged in the literature, it is normally comprised of four possible approaches: 1) use of real measured occupant data in simulation, 2) clustering of occupant types (e.g., active and passive), 3) developing models with reported errors from aggregate data from all monitored occupants, and 4) developing models for each occupant and then developing metamodels that define the model coefficient distributions (Haldi, 2013). The following sections briefly summarize the methods and merits of each approach.

Mapping real data to simulation

Perhaps the simplest way to represent occupant behaviour realistic inside BPS is to directly map observed behaviours into building models (e.g., using schedule objects) (e.g., O'Brien, Kapsis, Athienitis, & Kesik, 2010). Assuming the sample size is adequate, this would incorporate diversity. However, the limitation of this approach is that it does not generalize results such that they can be applied to other buildings (e.g., unbuilt buildings) in the way that other modelling approaches can. But it would be suitable for estimating energy savings from building retrofits or control modifications. This method is not pursued in the current paper, as it has limited applicability.

Clustering

Numerous modelling efforts have attempted to sort occupants into discrete typologies such that a small number of simulations can be run to infer a possible range of building performance levels. Among the primary approaches on this matter is to divide populations into passive and active users (e.g., Parys, Saelens, & Hens, 2011; Reinhart, 2004; Rijal et al., 2007). In these papers, active users consistently adapt to environmental inputs while passive occupants never or rarely take actions. This approach is formed on the basis that several typologies of occupant have emerged from monitoring studies. The approach has been used by others; for instance, Meerbeek et al. (2014) clustered all monitored occupants into groups with regards to their blind adjustment activity levels. However, it is not evident from the results whether the occupants naturally cluster; the results resemble a continuous distribution.

The clustering approach has appeal due to its simplicity. There has been a human tendency to attempt to categorize people (e.g., personality types). However, several challenges have emerged. First, using occupant typologies require estimates of population size for each cluster (Bourgeois, Reinhart, & Macdonald, 2006). Secondly, it is not evident from the data that discrete clusters occur. The few researchers who have provided individual characteristics suggest much the opposite: that the data more closely resemble a continuum (Haldi & Robinson, 2010; Meerbeek et al., 2014; Reinhart & Voss, 2003; Yun, Steemers, & Baker, 2008). Finally, it is unclear whether an active user of one system is also an active user of the others. One can imagine that if multiple adaptive actions are modelled, the number of distinct occupant types would quickly become unmanageable. For instance, if there are five possible actions of interest (e.g., light switching and window opening) and two user types for each, there would be 32 (2^5 different occupant types). Among other challenges, this would require on the order of hundreds of monitored occupants for models to be developed.

Models with reported coefficient errors

A prominent modelling approach in the past decade has been to develop models by aggregating monitored occupant data (e.g., window opening events and presence) and attempting to fit the data against one or more statistically significant input variables (Haldi & Robinson, 2009). Given that the equations that define the decision-making process (e.g., logistic regression curves) are unlikely to perfectly fit the data, some researchers have reported coefficient error. The error distribution can then be used to select model coefficients at the beginning of each simulation period (nominally a year). In essence, this is selecting an occupant with a different characteristic to be run for the entire simulation period. There are, however, several limitations to this approach. Most notably, depending on how the data from multiple occupants are combined, the models (in the case of agent-based models) are biased towards those occupants that are most active. For instance, if one occupant turns on lights ten times more than another the net effect of combining data from the two occupants will lead to a model that has the average occupant. Furthermore, there is a tendency to reduce the variance by fitting a single equation to multiple occupants.

Metamodels with reported coefficient distributions

To address the bias mentioned in the above method, Haldi (2013) suggested that a model be developed for each monitored occupant and then a probabilistic distribution for the model coefficients, from each occupant model, can be developed. In this way, the characteristics of each occupant are not biased through aggregation.

Next, the paper shall discuss these methods in the context of several datasets. The ultimate goal of this work, beyond the scope of the paper, is to compare the modelling approaches' ability to reproduce the diversity of occupants.

METHODOLOGY

Two datasets were explored and simple models were created to examine diversity between occupants. The data sets include occupancy in 16 offices for durations between one and four years and plug loads (computer, printer, other small office equipment) in 10 offices for between two and eight months. The offices are located in a modern academic building in Ottawa (Figure 2).

Occupancy

Occupancy is important both because of the implications on heating, cooling and ventilation, but also because of the adaptive actions. Previous research has shown that predicting arrival and departure events and timing is important because it significantly affects how occupants use lights, blinds, and other adaptive comfort building systems (Haldi & Robinson, 2010). Occupancy in 16 academic offices was collected for between one and four years using built in passive infrared sensors that were part of the thermostats in each space. The results should be taken into the context that occupants are all engineering professors, have relatively flexible hours, and are frequently absent for teaching, meetings, and travel. The control system logs every time that a movement is detected. This approach is unable to determine the number of occupants, though only a single occupant is expected in the private offices for the majority of the time. The data were obtained using an application program interface (API) of a building automation system (BAS) data archiving system.

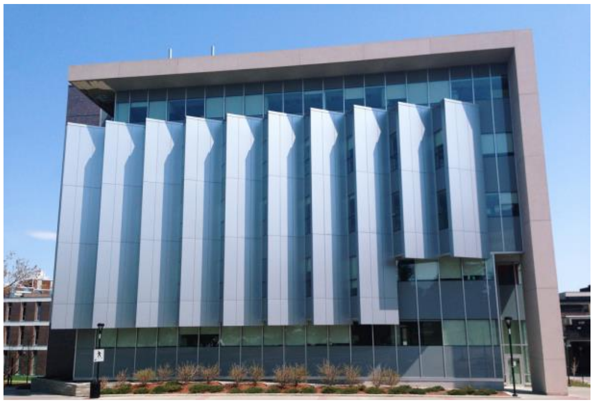

Figure 2 Office building where monitoring occurred.

The data of each office were pre-processed using custom Matlab code to remove anomalies and expected errors. First, the data was arranged into 5-minute timesteps such that if the occupant was present for any part of a 5-minute timestep, the entire timestep was assumed to be occupied. This leads to a small error and reduces the ability to study very short absences (e.g., washroom break), but it is much more convenient for modelling purposes. Five minutes was selected to balance accuracy and practicality. Simulation tools typically use between 5 and 15 minute timesteps for zone and building level phenomena. Next, occupancy events that consisted of a presence duration of 5 minutes or less and surrounded by an absence of 10 minutes or more, before and after, were removed. These are deemed to be janitor cleaning visits or quick drop-off or pick-up events. Such events are unlikely to be associated with significant heat gains or adaptive actions (e.g., light switch events). Prior to this filtering, numerous overnight visits were observed in the data. Anecdotally, the author, who is included in the dataset was not in his office between midnight and 7AM, yet numerous brief occupancy periods were detected.

Next, the data were rearranged in an array such that each column represented the occupancy for a day. For the current paper, weekends were removed for simplicity. Weekend occupancy for most of the occupants was exceptionally rare. The Page et al. (2008) model was implemented, as it is become a commonly used algorithm due to its contributions in modelling likelihood of state changes and modelling the frequency and duration of long absences. It also provides some useful occupancy characteristics, including some of those examined in the current paper, as follows.

- Mean occupancy: fraction of weekday timesteps when an occupant was detected (e.g., a 40-hour work week would be 40/120 or 0.333).
- Arrival time: the distribution (mean, standard deviation) of first arrival times for days when occupied time is greater than 0.
- Departure time: the distribution (mean, standard deviation) of last departure times for days when occupied time is greater than 0.
- μ: ratio of timestep transitions when occupancy state changes to timestep transitions when occupancy remains the same (Page et al., 2008)
- Likelihood of long absence: fraction of monitored weekdays that the occupant embarks on a long absence of one day or longer (excluding weekends).
- Distribution of long absences: the coefficients (shape parameter *a* and scale parameter *b*) of the Weibull function that is fit to the distribution of the duration of long absences (in days).

Plug load modelling

Ten office occupants and their total office electrical loads for plug-in equipment were monitored for between 1200 and 6000 hours each. The offices are the same as those from which the occupancy was monitored. The results should be interpreted with the context that the occupants purchased their own computer (i.e., not centrally purchased), and do not have nearby access to network printers (i.e., they are likely to have their own desktop printer), and are not responsible for paying energy bills. Hourly power use was sent wirelessly to a remote computer and recorded using two different devices (Belkin Wemo and Plugwise). The temporal resolution is a limitation of the monitoring equipment, but is not expected to impact simulation predictions for the current or other typical applications. Occupancy was detected and the data was post-processed assuming that if the PIR sensor in each office did not detect occupancy for 10 minutes that the occupant was absent. The occupant/equipment traits of interest include:

- Mean and variance occupied and unoccupied plug load power (W)
- Mean and variance occupied, unoccupied, and total monthly plug load energy (kWh)
- Likelihood of turning equipment on at arrival
- Likelihood of turning equipment off at departure

It should be noted that in some instances, occupant behaviour and equipment traits are undistinguishable. For instance, if equipment loads rapidly decrease upon occupant departure, the monitoring equipment is too poor a temporal resolution to distinguish between the occupant turning it off and the computer or printer going into sleep mode.

RESULTS

This section presents a summary of the results obtained from the dataset. The objective of presenting the data it to discuss diversity in the context of modelling approaches.

Occupancy

Figure 3 shows the distribution of fraction of 24-hour weekday hours present during their entire monitoring period. The distribution is relatively continuous with a single outlier. The two occupants who spent less than about 1 hour per week in their office are likely on sabbatical or long-term leave.

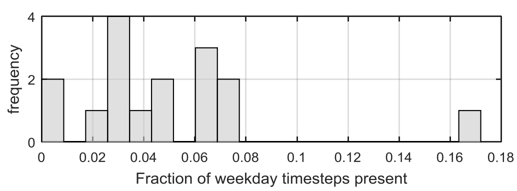

Figure 3 Distribution of the fraction of weekday hours that each occupant is present (e.g., the outlying occupant spent about 17% of weekday hours or about 4 hours per weekday)

Focussing on just the days when the occupant arrived in their office, Figure 4 shows the mean and standard deviation for arrival and departure for each occupant (though the distribution is not necessarily symmetrical about the mean). It also shows the mean duration of occupants. The graph shows the occupants sorted by average presence duration. Note that in this case, the occupants were weighted equally to obtain population statistics. This is the fundamental difference between the third and fourth modelling approaches that were discussed in the literature review (Haldi, 2013). The alternative approach would be to weight occupant and occupancy traits by hours or days present such that occupants who make rare appearances in their office are do not affect the model significantly.

Next, the mean daytime mobility parameter μ was explored for each occupant. The mobility parameter is indicative of the restlessness of the occupant and indicates the ratio of the timesteps that the occupant leaves or arrives relative to the timesteps occupant remains present or absent. As for the previous parameters, the distribution is relatively distributed and continuous (Figure 5). The occupant who has a mobility parameter of about 0.3 indicates that only about 23% of 5-minute timesteps involve a transition (arrival or departure).

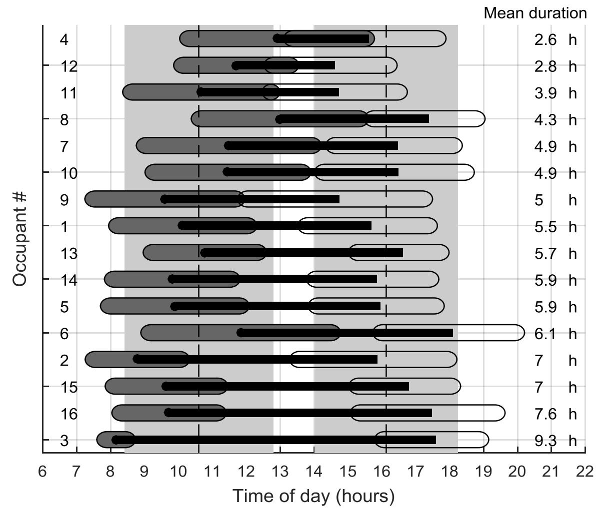

Figure 4 First arrival, last departure, and presence duration statistics for the individual occupants and as a population. The vertical dotted lines represent the median first arrival and last departure times, while the two gray bands represent the mean first arrival and last departure times plus or minus one standard deviation.

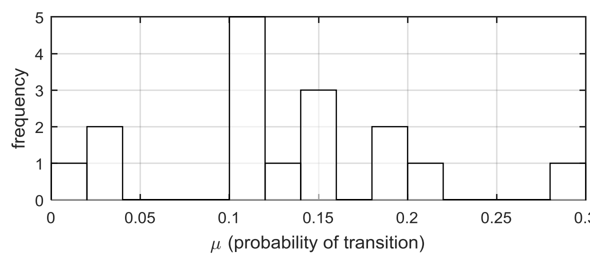

Figure 5 Distribution of μ during normal working hours.

For the population at hand, multi-day absences are not unusual since work hours are quite flexible and some occupants may travel for conferences or vacation. Figure 6 shows the distribution of probabilities that the occupants embark on an absence of one day or longer, excluding weekends, which were stripped from the dataset. Meanwhile the distribution of absence durations is shown in Figure 7. For this case, Weibull distributions were fit to the data for ease of displaying the data. The corresponding Weibull distribution parameters are shown in

Table 1. The results indicate that six occupants have two-day absences as the most common, whereas the rest are most frequently absent for a day when they embark on long-term absences. Beyond two days, all occupants are less likely to take longer absences. But as for the other occupancy traits, the distribution is

relatively continuous and certainly not multi-modal such that clustering would be appropriate.

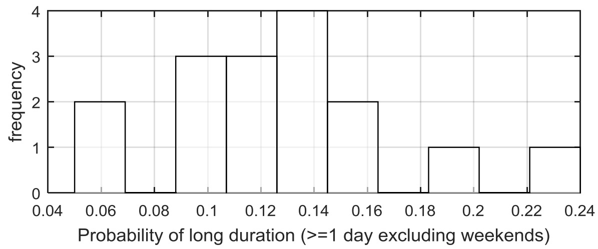

Figure 6 Distribution of the probability of each occupant not arriving one day and being gone for at least one day.

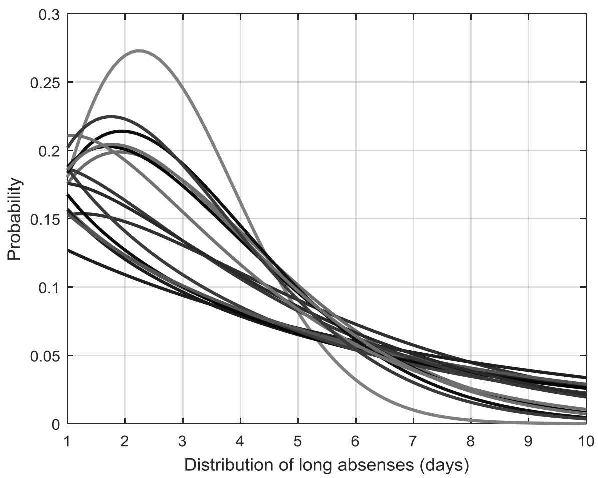

Figure 7 Distribution of absence durations for each occupant

Plug loads

Next, the plug load traits were explored using custom Matlab code. Figure 8 shows the mean occupied and unoccupied power consumption of each office, where occupied periods were defined as hours during which occupancy was 30 minutes or greater. The results show that eight out of the ten occupants use 50 W or less during absence, with two notable outliers. Meanwhile, the occupied power consumption is relatively evenly distributed between about 13 W and 270 W. The figure shows the pairs such that the slope of the lines indicates the difference between mean occupied and unoccupied power consumption for each occupant. The offices floor area is approximately 15 m^2. For context, the Department of Energy reference buildings use the assumption of 10.76 W/m^2 for office equipment or 161 W for these offices. But only three of the offices averaged higher than this and the mean of the mean occupied loads was 114 W.

Assuming equal weighting among the ten offices, the mean of the occupied and unoccupied mean loads are 48 and 114 W, respectively. Meanwhile, the variance of the occupied and unoccupied mean loads are 56 and 86 W, respectively.

Table 1 Weibull distribution parameters for duration of

Occupant number	Scale parameter, *a*	Shape parameter, *b*
1	3.157	2.013
2	4.852	1.231
3	3.773	1.534
4	6.847	0.991
5	5.436	0.919
6	5.511	0.888
7	4.986	0.894
8	4.242	0.931
9	5.542	0.947
10	4.083	1.154
11	3.659	1.475
12	4.316	1.182
13	3.562	1.605
14	3.651	1.506
15	3.494	1.286
16	3.362	1.566

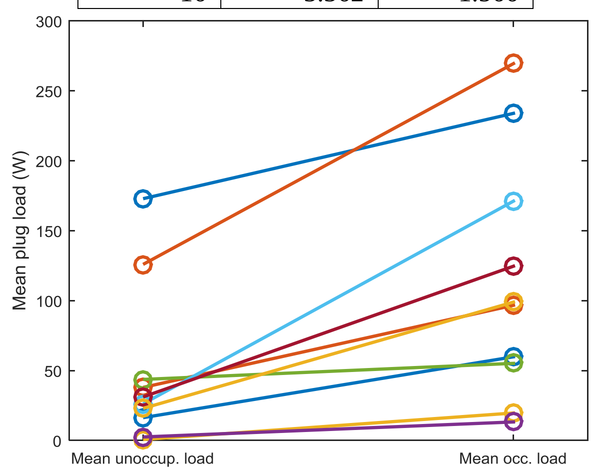

Figure 8 Unoccupied and occupied mean power consumption for each of the ten monitored offices.

While Figure 8 shows considerable diversity within the population, the variation for each occupant is also very wide in some instances. Figure 9 shows the occupied and unoccupied office power consumption for each occupant. Anecdotally, from the author's office, the variation is caused by periods of heavy printer use and coffee making. Meanwhile, bimodal distributions occur in some instances because it appears that computers can be inconsistent as to whether they go into sleep mode during absence. For instance, occasionally, they will restart for automatic updates and remain powered on.

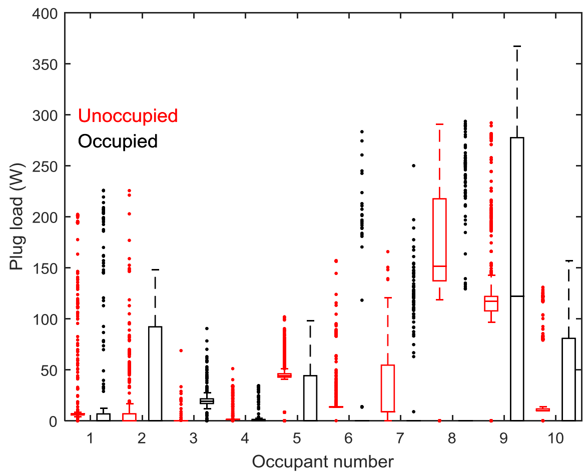

Figure 9 Distribution of unoccupied and occupant power use for each occupant. The boxes extend to the 25th and 75th percentiles, while the points represent outliers.

Variation between mean monthly energy is also wide, as demonstrated in Figure 10. Moreover, the vast majority of energy, except for occupant 3, is used during unoccupied periods. However, except for occupant 3, the ratio of energy consumed during vacancy is between 26 and 90% of the total energy use.

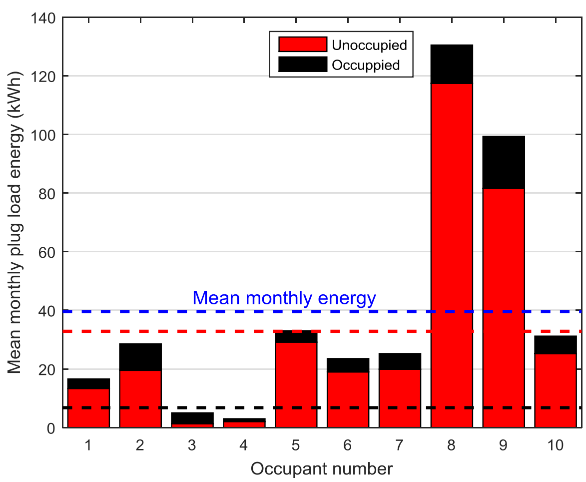

Figure 10 Mean monthly plug load energy use, divided into occupied and unoccupied periods, for each occupant. The population means for energy use during occupied, unoccupied, and the total time are shown as dotted lines.

DISCUSSION

The objective of this paper was to provide an introductory investigation of occupant diversity modelling. While, the dataset is limited to two occupant domains and a relatively small sample size, the results provide evidence for the appropriateness of the diversity modelling approaches.

First, none of the occupant traits that describe occupancy or plug-in equipment use behaviour indicate that clustering the occupants into typologies is an effective approach. On the contrary, the traits tend to from continuous distributions with some outliers. Similar conclusions for window opening and blind adjusting behaviours were drawn by Haldi (2013). These preliminary results point to the third and fourth reviewed modelling approaches being more suitable to represent diversity.

Second, the bias introduced by the weighting method between occupants becomes apparent. For instance, Figure 3 shows that the occupants were present between 1 and 17% of weekday hours, on average. Weighting the occupants equally may undermine the influence that the most present occupant has on energy use (plug loads, heating and cooling, lighting, etc.). On the contrary, if adaptive actions are being modelled (e.g., lights or blinds), the greater presence of one occupant may lead to model bias towards their tendencies; whereas, we desire an unbiased model. Future work is planned to develop detailed models from the current datasets to test the modelling approaches' ability to reproduce occupant diversity.

One of the objectives of this research was to use the knowledge of diversity between occupants to estimate the required sample size of monitored occupants required to properly represent a population. Occupant monitoring campaigns come at a significant cost. There is also significant effort required to recruit participants, install and maintain sensors and logging systems, and to process and analyze the data. Thus, there is tremendous value to researchers in minimizing the sample size while ensuring adequate representation.

Drawing from statistics theory, we can estimate the required sample size (National Institute of Standards and Technology (NIST), 2016). Assuming that the data (e.g., the mean plug loads during occupied periods for each occupant) resemble a normal distribution, the sample size required is approximately:

$$n \approx \left(\frac{z_{\alpha}^2}{\delta^2}\right)\left(\frac{\sigma^2}{\mu^2}\right)_{population}$$

Where n is sample size, z_{α}^2 is the z-score corresponding to the significance level α, δ is required precision of the estimate (relative to μ), σ^2 is the population variance, and μ is the population mean. In the current case, the mean and variance of the population are unknown, thus they are approximated as being equal to the sample properties. Several illustrative examples are explored to demonstrate the method and provide some preliminary guidance on required sample size.

Suppose we explore the distribution of the mean occupied plug loads and wish to ensure that there is a 95% probability that we have achieved an error of the mean estimate of no more than 10W. From the sample size of 10, we estimate that the population mean and standard deviation are 114 W and 86 W, respectively. It follows than δ is 10W/114W and z_α is 1.96. Therefore, we require a minimum sample size of approximately 284.

Following a similar procedure, we may estimate the required sample size to model the fraction of occupied weekday timesteps that occupants are present. Approximating the population standard deviation and mean from the sample of 16, we get $\mu = 0.129$ and $\sigma = 0.073$. Using the same parameters as the previous example and $\delta = 10\%$ (acceptable error relative to population mean), the required sample size is 123 or greater.

The above illustrative examples suggest that sample sizes on the order of hundreds are required to represent the total occupant population. This is typically an order of magnitude greater than what is used in the state of the art monitoring campaigns: 10 to 15. However, further research is required to explore acceptable model error in various applications (e.g., early building design and controls applications).

CONCLUSION

This paper set out to explore a seldom-discussed issue in the field of occupant behaviour modelling for building simulation applications: diversity between occupants. Prior modelling efforts have typically focused on attempting to fit data to one or a small number of occupant archetypes without attempting to characterize the diversity of occupants and their behaviour. This paper used several illustrative datasets to quantify diversity between occupants.

It was shown that the coefficients of variation are quite large, indicating that the spread in occupant characteristics is broad. For instance, the most present occupant was in his or her office about 24 times longer than the least present occupant out of the sample of 16. Meanwhile, the highest consumer of electricity for office equipment used 43 times more than the lowest consumer, on a monthly basis, out of 10 occupants.

Contrary to numerous previous studies' attempt to cluster occupants into user types (e.g., active and passive), the examples explored here indicate a continuous distribution in occupant properties with few hints that they lend themselves to discrete divisions. In the future, weighting methods (e.g., by occupant vs. by actions) deserves considerable thought.

Finally, this paper draws from statistics theory to provide a method to estimate the minimum sample size. The results using the current datasets suggest that sample sizes should be several hundred, though this is highly dependent on acceptable error. However, most current monitoring campaigns upon which occupant models are based involved 10s of occupants; not hundreds. Ultimately there is a massive cost associated with monitoring a large number of occupants, but future papers should explore the relationship between occupant diversity and their sample size.

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