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SPACE LAYOUT IN OCCUPANT BEHAVIOR SIMULATION

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ABSTRACT

Occupant behavior is widely regarded as one of the most significant sources of uncertainty in the prediction of building energy use. Preexisting simulation methods address this issue by automatically reproducing patterns of behavior found in historical occupant schedules. We extend these methods to incorporate spatial information. In our work, space layout influences the selection of individuals who participate in an activity, and the location where the activity occurs. Participants and locations are randomly selected based on probabilities derived from cost functions. One of these cost functions encourages participation between occupants of nearby workstations. Another discourages overcrowding. We apply the method to an existing office building to study how effectively an occupant model can be customized, and how accurately it can predict space utilization.

INTRODUCTION

Building occupants perform many difficult-to-predict and complex actions every day. These actions have a dramatic impact on indoor temperature, lighting conditions, and the state of a building control system. Thus a simulation which oversimplifies human behavior is unlikely to yield an accurate prediction of a building's energy requirements. Bourgeois et al. (2005) demonstrated the importance of modeling occupancy at a higher level of detail than is generally done in practice. Taking a typical energy model of an office building and adding individual simulated occupants, each with the ability to manipulate heating, cooling, and lighting controls, their energy use predictions changed by 62%. Hoes et al. (2009) showed that for a variety of office types, the use of a detailed occupant model can have a significant effect on both heating and cooling energy demand predictions, and both minimum and maximum indoor temperatures.

Our interest lies in the use of simulation to predict space utilization: which rooms or areas in a new building are likely to be occupied, and by how many people, at various times of the day. For an occupant-controlled indoor environment, this information is a prerequisite for simulating the manipulation of specific lighting controls, blinds, and thermostats. For a building with mostly automatic environmental controls, where occupants have less direct impact on energy use, their predicted whereabouts throughout the day can be used to determine when an adequate comfort level is needed in a particular room, and when it is unnecessary.

Several preexisting occupant behavior simulation methods generate realistic sequences of activities using probabilistic models trained on historical schedules of actual building occupants. We extend these schedule-calibrated methods such that each generated activity takes place at a specified location. In our method, occupant behavior depends in part on a *space layout*: a floor plan supplemented with certain occupancy-related parameters. Space layout influences the selection of individuals who participate in a shared activity, and the location where the activity occurs. The method is novel in that all activity participants and locations are randomly selected based on probabilities derived from cost functions. For example, if a simulated office worker initiates a meeting, a cost function is used to encourage participation among the occupants of nearby workstations. When selecting a location for the meeting, a similar cost function favors nearby meeting rooms, while another steers the occupants away from rooms that would otherwise become underutilized or overcrowded.

After reviewing related work and describing the contributed method, we present its application to an existing office building. The results are analyzed to assess how well the behavior of each type of simulated occupant matches the persona specified by the simulation user. We also study the model's validity by comparing the predicted utilization of several meeting rooms to their recorded bookings.

RELATED WORK

We are interested in simulation methods that aim to improve energy use predictions by generating fictional occupant schedules. An *occupant schedule* is a chronological sequence of activities for a single occupant for a single day. Table 1 illustrates the type of occupant schedule we pursue in this paper, where each activity includes the task performed, the number of participants, and the location where participants gather. The generated schedules should be interdependent; if the schedule in Table 1 is generated for one occupant, for example, then the schedules of seven other occupants should also exhibit a "Formal Meeting" in "Room 5018" starting around 2:58 pm.

Table 1: Example of an occupant schedule. The n_{po} is the number of participating occupants.

TIME	TASK	n_{po}	LOCATION
9:13	Desk Work	1	Cubicle 12
10:22	Informal Meeting	2	Office 19
10:42	Desk Work	1	Cubicle 12
12:17	Onsite Break	3	Kitchen
13:11	Desk Work	1	Cubicle 12
13:13	Washroom Break	1	Washroom A
13:14	Desk Work	1	Cubicle 12
14:58	Formal Meeting	8	Room 17
16:05	Desk Work	1	Cubicle 12
16:53	Washroom Break	1	Washroom A
16:56	Desk Work	1	Cubicle 12
17:52	Off	1	Offsite

Preexisting occupant behavior simulation methods represent activities at different levels of detail, and generate schedules based on different sets of input data. Though its primary purpose was to model the manual adjustment of electric lighting and blind systems, Lightswitch 2002 (Reinhart, 2004) includes a simple technique for generating occupant schedules in office environments. About a half-dozen parameters capture the expected times and durations of arrivals, morning/lunch/afternoon breaks, and departures. The transition times between these activities are randomly selected for each individual within an interval surrounding the expected times. Wang et al. (2005) proposed a similar method, except that between arrival and lunch and between lunch and departure, all periods of presence and absence are exponentially distributed. Zimmerman (2007) sampled uniform distributions for activity start and end times, and included shared activities involving groups of participants.

We refer to the Reinhart, Wang, and Zimmerman methods as *parameter-based*, as the input data that influences simulated behavior could be supplied as a set of parameters by a simulation user. In place of user-supplied behavioral parameters, a *schedule-calibrated* method inputs numerous schedules recorded by actual building occupants. It then applies a machine learning algorithm to automatically detect and reproduce statistically significant patterns of behavior. Both Page (2007) and Richardson et al. (2008) applied Markov chains for this purpose; the former to model the presence and absence of occupants in office spaces, and the latter to model the number of present and active household occupants. Goldstein et al. (2010b) proposed a technique for generating both numerical activity attributes (e.g. time of day, number of participants), and categorical attributes (e.g. task).

While schedule-calibrated methods seem more likely to produce realistic patterns of behavior, it would be easier for a building designer to customize a simulation given a parameter-based method. The hybrid approach described in Goldstein et al. (2010a) strives for both qualities by combining the information found in historical schedules with optional parameters supplied by the user in the form of *personas*. A simulated occupant assigned the persona in Table 2, for example, would arrive between 8:30 and 9:00 with some high probability (80% was used in the paper). None of the attributes refer to a lunch break, yet the simulation is likely to produce a relatively long break around noon in response to the historical schedule data. The method supports shared activities involving one *initiator* who "summons" additional participants.

Table 2: Example of a persona

PERSONA ATTRIBUTE	INPUT
Arrival	8:30–9:00
Departure	17:00–18:00
Informal Meeting Time	0:30–1:00
Formal Meeting Probability	20%
Onsite Break Occurrences	1–3
Offsite Break Probability	60%

Few preexisting energy-related occupant models track the locations of each simulated occupant, as would be needed to produce schedules like that in Table 1. A notable exception is User Simulation of Space Utilisation (USSU), described in Tabak (2008), which assigns locations to both individual and shared activities. When an occupant initiates a new activity, the simulation identifies all available locations that satisfy the activity's requirements. Of these candidate locations, the one selected is the one nearest the location of the occupant's previous activity.

USSU could be described as a parameter-based method requiring a relatively large number of input parameters. In addition to information about the timing and frequency of occupants' activities, the workflows of their organizations are supplied in the form of roles, organizational units, task groups, and other abstractions. Since both personal and organizational factors influence the way occupants interact with one another (e.g. the number of meeting participants), and because this interaction can affect space utilization (e.g. the selection of an appropriate meeting room), the complexity of the model can be justified. The drawback is the time and effort required for model preparation.

METHOD

Comparison with Related Work

The occupant schedules generated by the proposed method include all attributes shown in Table 1. The schedules are interdependent, and the selection of participants and locations requires a space layout.

To ease model preparation, we strive to minimize the number of required input parameters. Schedule-calibrated methods support this objective because, although historical datasets tend to be large and complex, they can be packaged with simulation software for reuse on different projects. Pre-packaged behavior

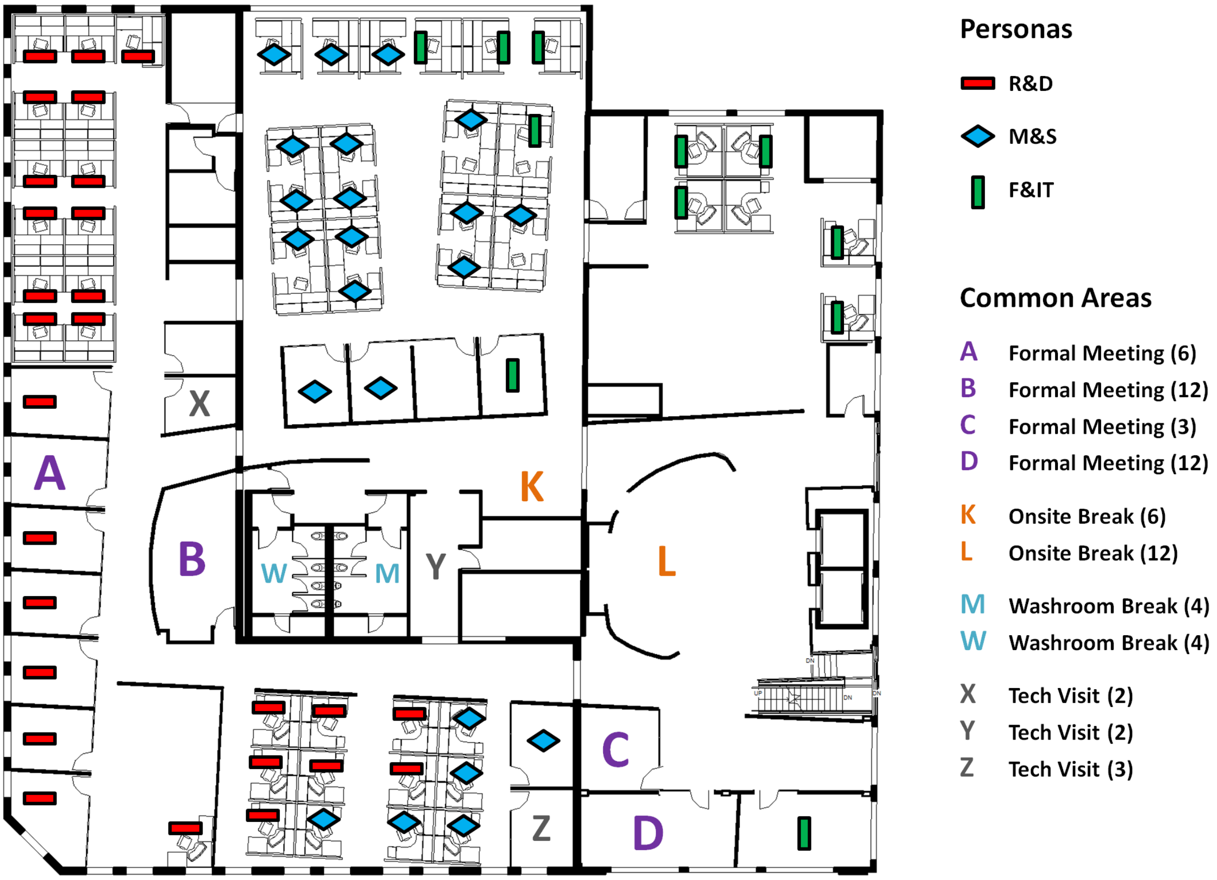


Figure 1: The space layout of an office with 60 occupants and several common areas

on its own may not suit a specific project, so we adopt personas to support customization.

The proposed method is similar to USSU in that participants of shared activities are randomly selected. However, USSU uses organizational parameters to derive the probabilities that occupants are selected as participants. Our input data includes relatively little organizational information, so we derive these probabilities from the space layout.

A key difference between USSU and the proposed method is that in the latter, when an activity has more than one candidate location, the selection is random. A location far from the initiator may be selected, as may a room that is already overcrowded, albeit with a low probability. Another difference is that distances are measured from the initiator's *base location*, their workstation in an office or their bedroom in a household, instead of the location of their previous activity.

Space Layout

With historical schedules pre-packaged, the input data supplied by the simulation user consists of the following: one persona for each type of simulated occupant; a distance parameter D that influences occupants' preference for nearby locations; and a space layout. For our purposes, the space layout must supply the base location of each occupant, the locations where each "Randomized" task can be performed (see Table 3), and the capacity of each location. It must also be possible to derive some measure of distance between any two locations. Our vision is that future building designers will supply simulation-ready space layouts by taking the floor plans that exist today, and adding a modest amount of additional information.

An example of a space layout is shown in Figure 1. The base locations of 60 occupants, their cubicles and personal offices, are each marked with one of three personas: Research & Development (R&D), Marketing & Sales (M&S), or Facilities & Information Technology (F&IT). There are also several common areas: four meeting rooms (A, B, C, D), a kitchen and lunch room (K, L), two washrooms (M, W), and three locations housing printers, photocopiers, and other devices (X, Y, Z). The task and capacity associated with each location is given on the right. Meeting Room A is used for formal meetings, for example, and has a capacity of 6. The capacity is a subjective estimate of the maximum number of people that can simultaneously occupy a location without feeling overcrowded.

Base locations and location-specific parameters could be added to a floor plan like that in Figure 1 in a few hours or less. The user must also supply persona attributes (see Table 4), but the total model preparation time should remain reasonable.

Participant Selection

As in Goldstein et al. (2010b), whenever a simulated occupant's activity is complete, a new activity is randomly generated. The task is selected first, followed by the number of participating occupants (n_{po}), followed by the activity's duration. If $n_{po} > 1$, then an additional $n_{po} - 1$ occupants are summoned to join the initiator. In Goldstein et al. (2010a), all occupants of the same persona were assigned the same probability of being summoned to participate in a shared activity. Here the persona is ignored, and the probability that a particular occupant will be summoned depends on the space layout.

When a shared activity is generated for a specific initiator, each other building occupant i is assigned a cost value C_i. One occupant is then selected at random, where the probability P_i of selecting occupant i is determined from the cost values according to (1). The selected occupant becomes a participant of the shared activity. Similar random selections are made from among the remaining occupants until all $n_{po} - 1$ additional participants have been chosen.

$$P_i \propto 2^{-C_i} \tag{1}$$

For participant selection, the cost C_i associated with occupant i is obtained by evaluating the distance cost function ϕ.

$$C_i = \phi(d_i)$$

The distance cost is a function of d_i the distance between the base location of occupant i and the base location of the initiator. Deriving the cost vs. distance relationship from empirical data is important future work. For the time being we propose the cost function in (2), which is based on two assumptions. For occupants in close proximity, we assume that distance has relatively little effect on which occupants interact. As travel times increase, we assume a linear relationship between distance and cost.

$$\phi(d_i) = \frac{\delta^3}{\delta^2 + 4} \quad \text{where} \quad \delta = \frac{d_i}{D} \tag{2}$$

Note that ϕ depends on the model parameter D. Roughly speaking, two occupants within a distance of D are likely to interact with one another, whereas two occupants separated by a distance appreciably greater than D are likely to avoid each other. As shown in Figure 2, if an occupant's base location is at a distance of D from the initiator's, the distance cost is 0.2. The occupant will then have a relatively high probability of being selected as a participant. An occupant located at twice that distance has a cost of 1 and a noticeably smaller chance of being selected. For large and increasing distances d_i, the cost function rises linearly with a slope of $1/D$, and the probability P_i approaches zero.

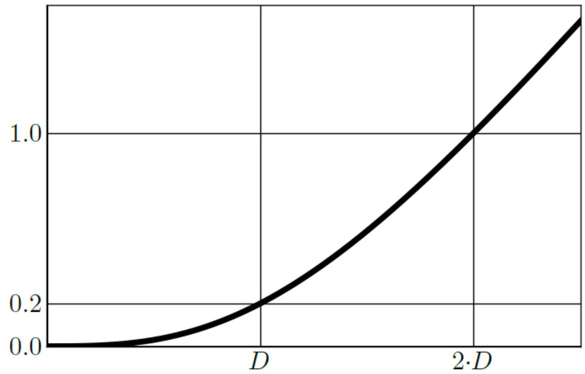


Figure 2: Distance Cost $\phi(d_i)$

Location Selection

When any activity, shared or solo, is generated for a specific initiator, the location where the activity takes place must be selected. The first step is to choose one of three *location selection methods* based on the task performed. The mapping between tasks and location selection methods depends on the type of building; we propose the mapping in Table 3 for office buildings.

Table 3: Office tasks and location selection methods

TASK	**LOCATION SELECTION METHOD**
Off	Offsite Only
Desk Work	Base Only
Informal Meeting	Base Only
Formal Meeting	Randomized
Tech Visit	Randomized
Washroom Break	Randomized
Onsite Break	Randomized
Offsite Break	Offsite Only

An activity with an *Offsite Only* task occurs outside of the building. A *Base Only* task is performed at the activity initiator's base location, their cubicle for instance. For a *Randomized* task, all locations designated for that task in the space layout are possibilities, and one is chosen at random. The probability of selecting a location is given by (1), the same formula used for participant selection. In this case P_i is the probability of selecting location i.

For location selection, the cost C_i associated with location i is the sum of a distance cost $\phi(d_i)$ and a utilization cost $\psi(n_i + n_{po})$.

$$C_i = \phi(d_i) + \psi(n_i + n_{po})$$

The distance cost is obtained from (2) as done for participant selection, except that d_i is now the distance between location i and the base location of the activity's initiator. Thus nearby locations are favored.

The utilization cost is a function of $n_i + n_{po}$, the projected number of occupants at location i should that location be selected. Here n_i is the current number of occupants at location i. Again the cost function should be derived from empirical data, but in the meantime we propose a formula based on several assumptions. One assumption is that people strive to fill spaces to just under their capacities, leaving some extra space for greater comfort or the possibility of additional participants. We also assume that there is a slight aversion to underutilization. It seems plausible, for example, that a pair of office workers would deliberately meet in a 3-person room in order to leave a large conference room empty for the benefit of their colleagues. However, we assume people to be far more concerned about overcrowding a space than using it inefficiently, so the cost defined below rises dramatically after the capacity N_i of location i is exceeded.

$$\psi(n_i + n_{po}) = 1 + \frac{27}{4} \cdot \left(\eta^3 - \eta^2\right)$$

$$\text{where} \quad \eta = \frac{n_i + n_{po}}{N_i}$$

Our proposed utilization cost function is plotted in Figure 3. As indicated, an ideal location in terms of size would become two thirds full if selected. The cost of having too few occupants in a space is bounded by 1, the same as the cost of filling it to capacity. The capacity is not a hard limit, as spaces can become overcrowded. However, as shown, the utilization cost increases rapidly with overcrowding.

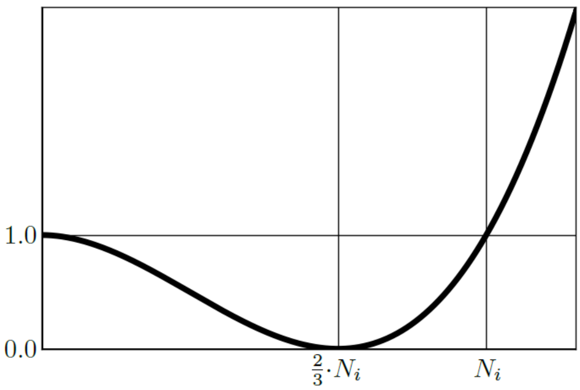


Figure 3: Utilization Cost $\psi(n_i + n_{po})$

EXPERIMENT

Objectives and Model Preparation

The space layout shown as an example in Figure 1 is the actual layout of a floor of an existing office building. We applied the proposed method to this office space to gain insight into how effectively an occupant model can be customized, and how accurately it can be expected to predict space utilization.

The idea behind customization is that, ideally, the personas inferred from the generated schedules should match the personas invented by the modeler. But due to participation in shared activities, the behavior of an occupant of one persona may be altered by the influence of occupants of other personas. We ran simulations with and without spatial information to study how the distance-based participant selection technique affects persona attributes.

The other objective of the experiment was to study the validity of the location selection technique. By aggregating information found in thousands of generated schedules, one can estimate the likelihood that any location is occupied at any given time of day. The difficulty lies in testing these space utilization predictions, as real-world occupancy data is required. In the office environment used for our experiment, it is common practice to reserve meeting rooms ahead of time using an electronic booking system. We aggregated six months of these bookings and compared the results with those obtained via simulation.

For the machine learning component of the model, we supplied 207 historical schedules recorded by several actual occupants of the building we modeled. With our choice of personas, these occupants would all be classified as R&D. Recall that in practice these schedules are to be packaged with simulation software. Ideally there would be thousands of schedules, recorded by more diverse sets of individuals.

To customize behavior, we distributed a ten-question survey to all occupants on the floor. Responses to eight questions were used to populate the input persona attributes shown in Table 4. The occupants were also asked how many days they worked from home or out of town. Based on their answers, simulated R&D occupants were assigned a 90% chance of showing up at all on any given day, M&S occupants were assigned a 40% chance, and F&IT occupants were assigned 80%. The last question was used to group each respondent into one of the three personas. Roughly half of the occupants responded: 16 of the R&D persona, 7 from M&S, and 5 from F&IT. In practice we would not expect a modeler to conduct a survey to populate the personas. But to study the validity of our location selection technique, it was important to minimize inaccuracies in the requested behavior.

To interpret distance, we used $D = 10$ metres and assigned Euclidean distances to d_i. With our single-floor model, the distance between an initiator's location $[\hat{x}, \hat{y}]$ and a candidate location $[x_i, y_i]$ was approximated using $d_i = \sqrt{(x_i - \hat{x})^2 + (y_i - \hat{y})^2}$. If a space layout were to include several floors, one could use $d_i = \sqrt{(x_i - \hat{x})^2 + (y_i - \hat{y})^2 + \gamma \cdot (z_i - \hat{z})^2}$ where $\gamma > 1$. The effect of the parameter γ would be to discourage travel between floors. It is worth noting that USSU employs a more accurate technique for calculating distances. A graph traversal algorithm is used to find the actual route an occupant would travel between locations, avoiding walls and other obstacles. This technique could be used to obtain the distances d_i supplied as arguments to our cost functions. The difficulty lies in automatically constructing a graph of possible paths from the space layout.

Table 4: Comparison of input personas and personas inferred from simulation-generated schedules

PERSONA	ATTRIBUTE	INPUT	SOLO	NON-SPATIAL	SPATIAL
R&D	Arrival	9:30–11:00	9:23–11:04	9:23–11:04	9:23–11:04
	Departure	17:15–20:00	17:23–20:26	17:19–20:14	17:21–20:15
	Informal Meeting Time	1:00–2:00	0:13–2:57	0:47–3:37	0:36–3:19
	Formal Meeting Probability	50%	39%	48.4%	48.1%
	Onsite Break Occurrences	1–5	0.1–3.7	0.3–5.5	0.2–5.2
	Offsite Break Probability	40%	49.8%	65.2%	62.9%
M&S	Arrival	8:00–9:30	7:59–9:30	7:59–9:30	7:59–9:30
	Departure	16:30–19:15	16:38–19:40	16:41–19:34	16:41–19:37
	Informal Meeting Time	1:00–3:00	0:38–3:41	0:50–3:45	0:56–3:50
	Formal Meeting Probability	**10%**	12%	28.7%	**42.9%**
	Onsite Break Occurrences	0–4	0–3.8	0–4.5	0.2–4.8
	Offsite Break Probability	30%	29%	41.3%	47.9%
F&IT	Arrival	8:15–9:00	8:14–9:00	8:14–9:00	8:14–9:00
	Departure	16:30–18:15	16:26–18:49	16:41–18:25	16:40–18:33
	Informal Meeting Time	1:00–5:00	0:09–4:38	0:14–3:33	0:48–3:47
	Formal Meeting Probability	50%	48.2%	66.5%	52.6%
	Onsite Break Occurrences	1–4	0.2–4.3	0.5–4.8	0.6–5.0
	Offsite Break Probability	50%	53.2%	63.1%	61%

Simulated vs. Requested Persona Attributes

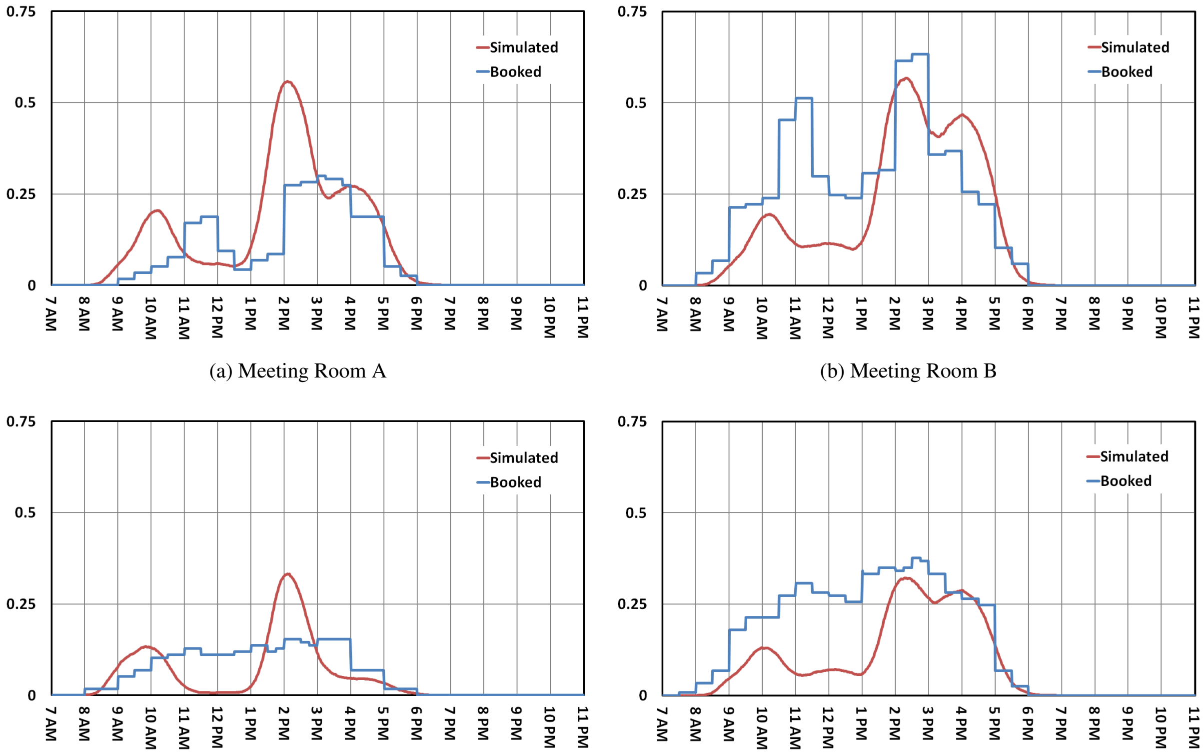
Table 4 compares the persona attributes supplied as input data to those inferred from simulation results. For each of the three personas in our model, the attributes in the “SOLO” column were inferred from 10,000 independently generated occupant schedules. In this case, even if a shared activity was generated (e.g. a meeting), the initiator remained the lone participant. The behavior reflected in these independent schedules differs somewhat from the input personas because it was also influenced by the 207 historical schedules. The largest discrepancies are associated with the *Informal Meeting Time* attribute, the total time per day spent in impromptu conservations taking place at occupants’ workstations. But for the most part the input and solo attributes are similar, indicating effective customization of behavior.

The non-spatial and spatial personas were inferred from interdependent schedules. In both cases, the schedules for all 60 occupants on the floor were generated simultaneously for each of 10,000 simulated days at the office. These simulations included occupant interaction; the initiator of a shared activity would summon the $n_{po} - 1$ other participants, influencing their schedules. The influence of one occupant on another increases the discrepancy between requested and simulated behavior, particularly if their personas differ. The non-spatial simulation used the preexisting method of Goldstein et al. (2010a) on its own, whereas the spatial simulation used the extended method described in this paper.

The purpose of this analysis is to assess the impact of the proposed treatment of space on behavior customization. We therefore focus on comparing the input attributes to those inferred from the spatial simulation. On the whole the requested behavior is clearly reflected in the simulation results, though for certain attributes there are noticeable discrepancies. For example, the *Offsite Break Probability* is the probability that an occupant takes at least one temporary break outside the office building on any given day. For the M&S persona a probability of 30% was requested, but the spatial simulation yielded a probability of 47.9%. In this case the simulated Offsite Break Probability exceeded the requested value for all three personas in both the spatial and non-spatial results, so it is difficult to say whether the discrepancy is a result of our new treatment of space or the preexisting approach to occupant interaction.

The *Formal Meeting Probability* is the chance that an occupant has at least one planned meeting in a meeting room on any given day. For the M&S persona the requested value was 10%, the preexisting approach yielded 28.7%, and the spatial simulation produced an even greater probability of 42.9%. In this case there is reason to suspect that our treatment of space contributed to the discrepancy. As seen in Figure 1, many M&S occupants are located in close proximity to either an R&D occupant or an F&IT occupant. With a requested probability of 10% compared with 50% for the other two personas, an M&S occupant is unlikely to initiate a formal meeting. However, when an R&D or F&IT occupant initiates a meeting, they may well summon a nearby M&S occupant to participate. Consequently, the behavior of the M&S occupants changed by a considerable degree.

To summarize, the new distance-based participant selection technique still allows for the customization of behavior using persona attributes. But in some cases, when compared with the preexisting non-spatial alternative, the new approach is more likely to “blend” the behaviors of occupants of different personas.



(a) Meeting Room A

(b) Meeting Room B

(c) Meeting Room C

(d) Meeting Room D

Figure 4: Meeting Room Utilization

Simulated vs. Booked Space Utilization

Figure 4 shows the predicted and measured probabilities that various meeting rooms are occupied at any given time of day. For each of the four meeting rooms in the space layout, the predicted space utilization profile was created by aggregating the 10,000 days worth of interdependent schedules generated by the proposed simulation method. The measured profiles were derived from six months worth of bookings made by real occupants to reserve the actual meeting rooms. The booking data serves as ground truth for the experiment. It reflects the real occupants' meeting time and location preferences, but was not used to calibrate the model. An obvious weakness in this analysis is that occupants sometimes use meeting rooms without booking them, or book them without using them.

As shown in the space layout of Figure 1, Meeting Rooms A and B have capacities of 6 and 12 respectively, and are located near one another. The model predicts, with a reasonable error, the overall demand for both of these rooms combined. However, it seems to underestimate the occupants' preference for the larger and somewhat more central Room B. Looking at timing, the double-peaked shape of the booked profiles is reflected in the simulation. For Room A the simulated morning and afternoon peaks occur an hour too early. For Room B the morning peak is predicted an hour early, but the afternoon peak is quite accurate.

The low overall simulated demand for Meeting Room C, with a capacity of 3, seems consistent with the relatively scarce bookings. However, the simulation inaccurately concentrates the demand around 10 am and 2 pm. Located nearby, Room D has a capacity of 12. It was booked far more often prior to 2 pm than predicted by the simulation, but after 2 pm the two profiles are in close agreement. Both of these rooms were frequently reserved for day-long activities, neglecting breaks. It is therefore possible that the dips predicted around noon are more accurate than they appear.

A key objective of the proposed method is to predict space utilization with minimal input data, and in this context the agreement between predicted and measured results is reasonable. The profiles would likely have been closer had the 207 historical schedules been recorded not only by R&D occupants, but by M&S and F&IT occupants as well. However, if historical schedules are to be packaged with simulation software and used on multiple projects, this type of error is practically unavoidable. We note that in this experiment, one effect of the distance cost function was to predict greater use of the central Room B than the peripheral Room D with the same capacity. At the same time, the utilization cost function gave Room D a higher overall demand than the nearby but smaller Room C. The bookings validate both of these predicted trends.

DISCUSSION

In the preexisting USSU system, a modeler supplies detailed organizational information to control which types of occupants interact. Our participant selection technique avoids much of this input data, simplifying model preparation. However, occupants of one persona may summon nearby occupants of other personas, which in some cases leads to discrepancies between requested and simulated behavior.

What could be done to adhere to requested behavior while still allowing occupants of different personas to interact? One possibility is to optimize behavioral parameters by running numerous multi-occupant simulations. This pursuit may benefit from *genetic algorithms*, as applied to occupancy prediction in Yu (2010), as well as *functional crowds* (Pelechano et al., 2008). Another question is whether one should deliberately allow simulated behavior to differ from requested behavior. Theoretically, designers could run simulations to see how space layout affects persona attributes. Could such predictions be trustworthy?

Our location selection technique successfully predicted the more popular of two equally sized meeting rooms at different locations, and the more popular of two nearby meeting rooms of different sizes. Yet to improve the cost functions and rigorously validate the method, a vast amount of empirical data is needed. It may be necessary to monitor and record the coordinates of thousands of real occupants over time. To overcome the effect of site-specific rules and conventions on space utilization, numerous buildings would have to be included in the study.

Two possible enhancements to the method deserve mention. In the presented experiment, all simulated occupants were assigned workstations on the floor. In reality, parts of the floor may be occupied temporarily by workers from other parts of the building, or visitors from outside the building. These *temporary occupants* could be modeled using "Offsite" base locations. Another modest enhancement is the calculation of occupant densities for each space over time.

To go from predicting space utilization to energy use, the proposed method must be integrated with energy models as previously done with USSU (Hoes et al., 2009). Our method would provide the number of occupants at various locations at any given time. Action-oriented behavioral models would then predict the manual manipulation of building controls at these locations (Mahdavi and Pröglhöf, 2009).

CONCLUSION

We have introduced novel probabilistic techniques for selecting activity participants and locations in the context of occupant behavior simulation. These techniques were incorporated into a broader method that uses historical schedules to automatically inform simulated behavior, personas to customize that behavior on a per-project basis, and a space layout to provide site-specific occupancy information. By limiting the amount of required input data, we hope to encourage the preparation of simulation-ready spatial occupant models at the building design stage, improving all subsequent energy use predictions.

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