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Abstract

Occupancy has significant impacts on building performance. However, in current building performance simulation programs, occupancy inputs are static and lack diversity, contributing to discrepancies between the simulated and actual building performance. This paper presents an Occupancy Simulator that simulates the stochastic behavior of occupant presence and movement in buildings, capturing the spatial and temporal occupancy diversity. Each occupant and each space in the building are explicitly simulated as an agent with their profiles of stochastic behaviors. The occupancy behaviors are represented with three types of models: (1) the status transition events (e.g., first arrival in office) simulated with Reinhart's LIGHTSWITCH-2002 model, (2) the random moving events (e.g., from one office to another) simulated with Wang's homogeneous Markov chain model, and (3) the meeting events simulated with a new stochastic model. A hierarchical data model was developed for the Occupancy Simulator, which reduces the amount of data input by using the concepts of occupant types and space types. Finally, a case study of a small office building is presented to demonstrate the use of the Simulator to generate detailed annual sub-hourly occupant schedules for individual spaces and the whole building. The Simulator is a web application freely available to the public and capable of performing a detailed stochastic simulation of occupant presence and movement in buildings. Future work includes enhancements in the meeting event model, consideration of personal absent days,

verification and validation of the simulated occupancy results, and expansion for use with residential buildings.

Keywords: Occupant behavior; occupant presence and movement; agent-based modeling; occupancy model; stochastic model; meeting event model

1. Introduction

Traditionally, in building performance simulation (BPS) programs, occupancy inputs are static, deterministic, and less indicative of real world scenarios, contributing to discrepancies between the simulated and actual energy performance of buildings. The International Energy Agency's Energy in Buildings and Communities Program Annex 53 (Yoshino, 2013) pointed out that occupants' activities and behavior are one of the six key factors directly influencing building energy use. Occupant behavior is widely recognized as a major contributing factor to the uncertainty of building performance (Yan et al., 2015).

Occupant behaviors can be grouped into two categories: occupancy and occupants' interactions with building systems (Page, Robinson, Morel, & Scartezzini, 2008; Wang, Yan, & Jiang, 2011). The occupancy simulation determines the location of each occupant during each period and is the foundation of occupant behavior modeling. When occupants are located in a space, they may be able to control the building systems (such as lights, HVAC, and windows), and therefore influence energy consumption (Haldi, 2013). Some technologies such as personalized ventilation systems (Chen, Raphael, & Sekhar, 2012, 2016), occupancy sensors, and occupant-based controls (Hong, Taylor-Lange, D'Oca, Yan, & Corgnati, 2015) are strongly dependent on occupant presence and movement. Current BPS programs such as EnergyPlus (Crawley et al., 2001) and DeST (Yan et al., 2008) use deterministic and static weekly schedules to represent occupancy. This is because spaces with similar functions typically use identical occupancy schedules. As a result, using these homogenous occupant schedules in energy modeling, each space will have the same or very similar load profiles in simulation outputs—not accounting for diversity or occupant control. In reality, actual occupancy patterns in buildings may differ significantly from each other due to contextual factors such as building types, occupancy density, and occupancy types.

Consequently, the over-simplified occupant schedules always lead to an inaccurate estimate of the energy savings of energy conservation measures (ECM), especially those related to occupancy-based sensors and controls (Tahmasebi & Mahdavi, 2015). This study addresses the need for more realistic and flexible representation of occupant schedules used in building performance simulation, particularly the stochastic nature of human behaviors.

The most common way of generating stochastic occupant schedules in simulation tools is to reproduce occupancy patterns using selected occupant profiles and applying a statistical model representing the occupant behavior processes (Virote & Neves-Silva, 2012). Most agent-based occupancy simulations use the Markov chain model to determine the occupant's location based on their previous location (Yang, Santamouris, & Lee, 2016). Page, et al. proposed a probabilistic model to predict and simulate occupant arrival, departure, and long absence (short-term leaving) events in single-occupancy offices based on a heterogeneous Markov chain model using weekly presence probability statistics (Page et al., 2008). Wang, et al. (Wang et al., 2011) introduced a novel approach for building occupancy simulation based on a homogeneous Markov chain model, which simulates the stochastic movement of occupants and generates the location for each occupant at each simulation time step (Feng, Yan, & Hong, 2015). Reinhart's (Reinhart, 2004) LIGHTSWITCH-2002 model included an adapted version of Newsham's (Newsham, Mahdavi, & Beausoleil-Morrison, 1995) stochastic model to determine the arrival, departure, and temporary absence (short-term leaving) based on cumulated probability statistics. Stoppel, et al. also presented a stochastic approach for developing a probabilistic occupancy model focusing on occupants' long vacancy activities. The model identified long activity characterization of building occupant groups and generated occupancy profiles based on developed activity probability distribution profiles (Stoppel & Leite, 2014). Apart from these, non-probabilistic occupancy models based on occupancy-related data observation are also proposed in studies. A simulation model developed by Mahdavi, et al. was used to generate a daily binary occupancy profile based on aggregated past presence data, which resembled the statistical properties of the real observation of occupant behavior patterns (Mahdavi & Tahmasebi, 2015).

Richardson, et al. also presented a method for simulating occupancy schedules for United Kingdom households based on surveyed time-use data. The results provided time-series occupancy data and the number of active occupants in a house (Richardson, Thomson, & Infield, 2008).

Meeting events are an essential part of occupant activities in office buildings. However, few existing occupancy simulation models specifically consider the meeting events. Wang, et al. (Wang et al., 2011) used the Markov-chain model to determine meeting events, which led to the continuous distribution of the meeting start time and duration (e.g., a meeting can start at 9:10 am with a duration of 40 minutes or 10:20 am with a duration of 20 minutes). However, actual data gathered from meeting rooms shows that people tend to schedule meetings on the hour or 30 minutes past the hour with a duration of 30 minutes to two hours at increments of 30 minutes. For example, a meeting is scheduled at 10:00 am with a duration of 1 hour or at 1:30 pm with a duration of 1.5 hours. In this study, we develop a new stochastic model to simulate the meeting events based on the measured data of an actual conference room.

The existing occupancy simulation models typically focus on only one area of the occupancy simulation. Page, et al.'s (Page et al., 2008) and Reinhart's (Reinhart, 2004) occupancy models work for the status transition events, including occupant arrival, departure, and short-term leave (long absence); Wang, et al.'s (Wang et al., 2011) model emphasizes the random movement within the building; while Stoppel, et al.'s (Stoppel & Leite, 2014) model focuses on long vacancy activities. Each standalone model lacks a common representation method and thus cannot be easily reused by other users or applications. Moreover, these models need to be integrated to perform a full-scale occupancy simulation for the whole building. In addition, these existing occupancy simulation models lack a friendly user interface. Users are required to write their own scripts/codes or modify the existing scripts/codes to perform their occupancy simulation, which can be time-consuming and challenging for most engineers and researchers, and lead to issues of quality control and verification of the written codes. These drawbacks strongly affect the adoption of occupancy models in building performance simulation.

This study addresses these drawbacks by integrating several existing occupancy models, developing a data model to simplify user inputs, and creating a free, open-access, web-based application, the Occupancy Simulator (http://OccupancySimulator.lbl.gov). The Occupancy Simulator has a friendly graphical user interface and adopts the standard representation of occupant behavior using the obXML schema (Hong, D'Oca, Taylor-Lange, et al., 2015), which was built on the DNAS ontology describing occupant behavior in buildings (Hong, D'Oca, Turner, & Taylor-Lange, 2015). Luo (Luo, et al., 2017) used measured data to evaluate performance of various occupant presence and movement models, and chose and integrated the appropriate ones in the Occupancy Simulator. The Occupancy Simulator is freely available to the public and capable of performing a detailed stochastic simulation of occupant presence and movement in buildings.

2. Methods

The Occupancy Simulator simulates presence and movement of each occupant by three types of events using three stochastic models: (1) the status transition events (e.g., first arrival in office) with Reinhart's LIGHTSWITCH-2002 model, (2) the random moving events (e.g., from one office to another) with Wang's homogeneous Markov chain model, and (3) the meeting events with a new stochastic model. To simplify the user input process, occupants with similar movement behaviors are grouped into an occupant type, and spaces with similar use patterns are grouped into a space use type. Furthermore, building templates can be developed that provide default assumptions of occupant density, occupant profiles (number and types), and space profiles (number and use types). In this way, even a large or complex building can be defined quickly. The simulated results represent three levels of occupancy schedules meeting most application needs: (1) the whole building level (number of occupants), (2) the individual space level (the number of occupants and the occupied status), and (3) the individual occupant level (where, and in which space, a particular occupant is).

2.1. Software Architecture

Figure 1 presents the software architecture of the Occupancy Simulator. The agent-based web application was built upon Ruby on Rails (rubyonrails.org), an open-source web framework with model-view-controller (MVC) software architecture. The (1) *viewer* generates the user interface to collect inputs as well as to show results. The (2) *controller* handles the commands from users and performs necessary calculations. The (3) *data model* defines the data structure, which is introduced in the following section. The (4) *database* stores users' inputs as well as the results. One control command named *Simulate* triggers the movement simulation. For this command, the (2) *controller* generates an (7) *occupant model in XML format* based on the (5) *occupant behavior (OB) XML Schema* (Hong, D'Oca, Taylor-Lange, et al., 2015), which is developed on top of the (6) *OB DNAS (drives, needs, actions, and systems) framework* (Hong, D'Oca, Turner, & Taylor-Lange, 2015). The (7) *occupant model in obXML file* is used as input by the (8) *movement solver* to generate the (9) *occupancy results in CSV and EnergyPlus IDF file formats*. The results are stored in the (4) *database*, and displayed in the (1) *viewer*. BPS programs can further use the generated occupant schedules at the space level to simulate the energy performance of buildings.

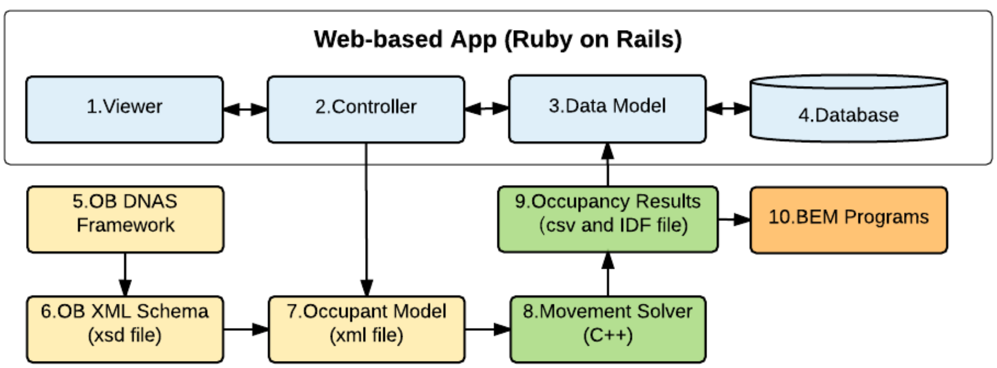


Figure 1. Software architecture of the Occupancy Simulator

2.2. A Hierarchical Data Model to Simplify the Input Process

To reduce the amount of data inputs, the Occupancy Simulator adopts a hierarchical data model that allows users to group occupants with similar occupancy behaviors as an *OccupantType*, and spaces with similar functions as a *SpaceType*. Figure 2 shows the data structure of the Occupancy Simulator. The Occupancy Simulator creates a *Building* instance for each simulation case, which includes a session number and multiple instances of *Spaces*. Each *Space* has an area, a multiplier, and a *SpaceType*. The multiplier determines the number of similar spaces in the building. The *SpaceType* defines the occupancy density, the *Meeting* events for meeting room, and the percentage of each of the *Occupants*. The parameters for each *Meeting* event include the probability distribution of meeting duration, the minimum and maximum number of occupants per meeting, and the minimum and maximum number of meetings per day. Each *Occupant* has an *OccupantType*, which is defined by the *MovementBehavior* of the occupants. The *MovementBehavior* represents the spaces occupancy and the events for arrival, departure, and short-term leave (e.g., coffee break or lunch time). The spaces occupancy includes the percentages of time and the average durations for the cases when the occupant stays in their own office, another office, any auxiliary rooms, meeting rooms, and outdoors. For arrival and departure events, Occupancy Simulator defines the typical time when the event occurs and the variation of occurrence time. For short-term leave events, the model also requires the typical duration of the event, the variation, and the event occurrence time. Based on the input information, the Occupant Simulator calculates the location of each occupant at each time step based on the movement simulation engine introduced below.

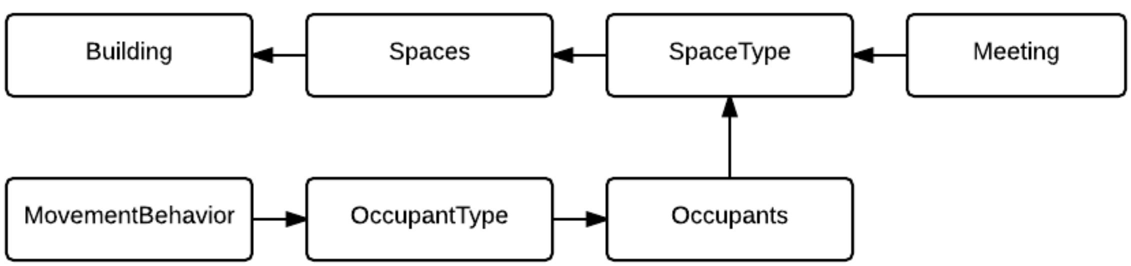
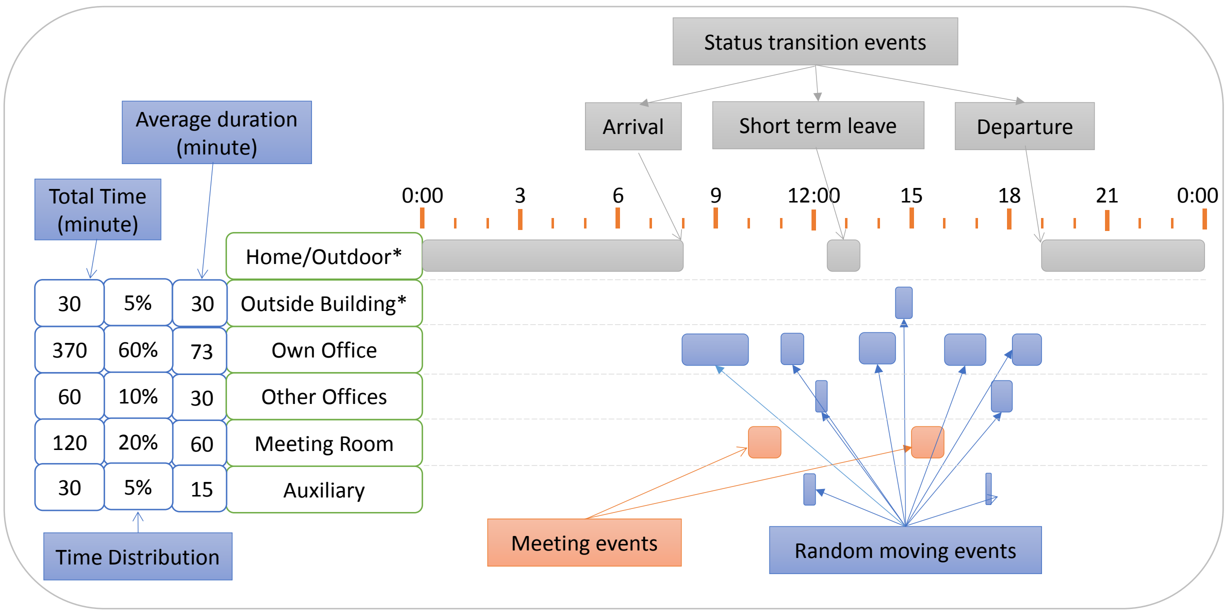


Figure 2. The hierarchical data model of the Occupancy Simulator

2.3. Occupant Presence and Movement Models

There are three types of occupant presence and movement models integrated into the Occupancy Simulator, as shown in Figure 3. The first model relates to the status transition events, which represent occupants getting to the building or leveling the building, such as first arrival, last departure, and going out for lunch. The second model relates to the random movement events, which represent occupants moving around inside the building, such as going to restrooms, visiting other office spaces or auxiliary spaces. The last model relates to the meeting events, which represent several occupants having a meeting for a certain period. These events can be customized, added or removed based on the three models. For example, users can customize the first arrival time, add a meeting event, or remove the lunch event. However, users cannot create new models directly through the Occupancy Simulator graphical user interface (GUI).



Note*: The "Home/Outdoor" is used for the status transition events, while the "Outside Building" is used for random moving.

Figure 3. Schematic diagram for the occupancy simulation engine

2.3.1. Status transition event models

The Occupancy Simulator integrated Wang, et al.'s (Wang et al., 2011) Markov chain model and Reinhart's LIGHTSWITCH-2002 model to simulate the status transition events including the arrival, departure, and short-term leave events. The LIGHTSWITCH-2002 model was used in the case study and introduced as follows.

For arrival and departure events, users need to provide the cumulative probability of the event occurrence time (Figure 4 (b)), which can also be transformed from the probability of the event occurrence time (Figure 4 (a)). A single real random number with a uniform distribution between 0 and 1 is first generated, and then the corresponding event occurrence time is obtained based on the cumulative probability curve. In the Figure 4 (b) example, the random number generated is 0.55, which corresponds to an arrival time of 8:10 am.

The short-term leave event is separated into two parts: event occurrence times and the event duration. The event occurrence time is handled in the same way as arrival and departure events. The same method is used to determine the duration using the cumulative probability of the duration.

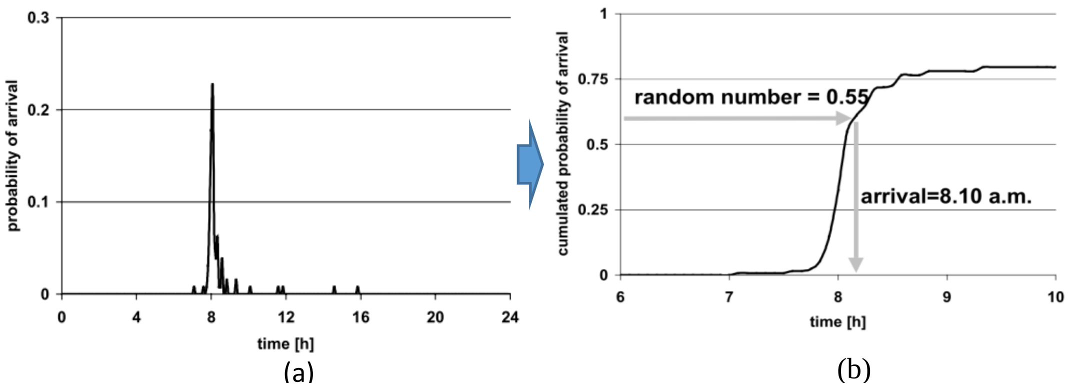


Figure 4. Cumulative probability function of arrival time (Reinhart, 2001)

2.3.2. Random moving event model

For the random movement events, Wang, et al.'s (Wang et al., 2011) homogeneous Markov chain model was adopted and used in the case study. The most important procedure of the Markov chain model is to generate the transition probability matrix (P) as shown in Figure 5. Each element in the transition probability matrix (P_{ij}) represents the probability of moving from space i at previous time step to space j at current time step. The size of the matrix is $N \times N$ when there are N spaces in the model. Wang, et al.'s model used each occupant's percentage of time and average duration in each space as inputs to generate the transition probability matrix for each occupant. A set of $2 \times N$ parameters was used to generate the $N \times N$ matrix by solving an optimization problem with $3 \times N$ equations (one equation for each row, one equation for each column, and one equation for each diagonal), which greatly simplified the model input. However, solving the optimization problem becomes a big burden when the number of spaces increases. To overcome this challenge, the spaces are organized into different space categories as shown Figure 5 in this study. For office buildings, spaces are categorized into Outside Building (Outdoor), Own Office, Other Offices, Meeting Room, and Auxiliary rooms. Three additional assumptions are made. Figure 5 shows an example applying the assumptions for the case study with 13 spaces. The elements with the same values based on the assumptions are filled in with the same color. First, the probabilities of moving from one space in category A to any space in category B are the same. For example, the probabilities of a researcher moving from his Own Office (Researcher Office) to any other Office are the same: $P_{2,3} = P_{2,4} = \cdots = P_{2,9} = X_{2,3}$ (Figure 5). Secondly, the probabilities of staying in any space in the same category are the same. For example, the probabilities of a researcher staying in any Auxiliary space are the same: $P_{11,11} = P_{12,12} = P_{13,13} = X_{5,5}$ (Figure 5). Lastly, the probabilities of moving from one space to another space in the same category are the same. For example, the probabilities of a researcher moving from one Other Office to another Other Office are the same: $P_{3,4} = P_{3,5} = P_{3,6} = P_{4,6} = \cdots = P_{8,9} = Y_{3,3}$ (Figure 5).The number of variables is reduced from 169 to 27. The number of equations is reduced from 39 to 15, including the five equations for the rows highlighted with arrows, five equations for the columns highlighted with arrows, and five equations for each variable on the diagonal from the top left to the bottom right. . The new model significantly reduces the number of variables and equations for the optimization problem, which also significantly reduces the simulation time. The new model can be used for models with any number of spaces as long as the spaces are categories into the given space categories.

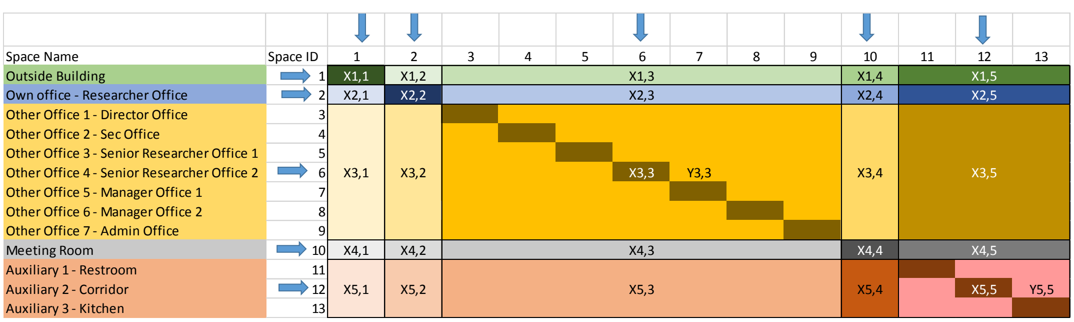


Figure 5. Schematic diagram of the random movement algorithm with simplification

2.3.3. Meeting event model

For status transition and random movement events, decisions are controlled by the individual occupant agent. However, meeting events usually involve multiple occupants in each meeting. Therefore, it is reasonable to generate meeting events by the meeting room agents rather than the occupant agents. For each meeting event, the most important information is the meeting start time, meeting duration, and the number of people in the meeting. To support the development of the meeting event model, meeting events from a real meeting room were collected. The meeting room, which can host up to 12 people, was managed using Google Calendar, where employees can view existing meetings as well as schedule new meetings. The meeting event data from Jan 1, 2015, to July 2, 2015, was collected, which included meeting start and end times and the number of invited people for each meeting. Table 1 shows the distribution of meeting duration for the meeting room. The majority (72%) of the meetings had a duration of 1 hour. Figure 6 shows the percentile and the average number of meetings per weekday. The meeting room was used more frequently on Tuesday, Wednesday, and Thursday with an average of 4.2 meetings per day compared to Monday and Friday with an average of 2.6 meetings per day. Figure 7 shows the number of people invited per meeting. The percentage of meetings with two or three people is significantly higher than meetings with other numbers of people. There are also many meetings with only one person. The person may use it for conference calls or other participants are not added to the Google Calendar. Figure 8 shows the distribution of meeting start times. About half (47%) of the meetings started at 11am, 1pm, 2pm or 3pm. Almost all the meetings are started on the hour or 30 minutes past the hour.

Table 1. Distribution of meeting durations

Meeting Duration (hour)	Number of times	Percentage
0.5	62	12%
1	387	72%
1.5	67	13%
>=2	19	3%

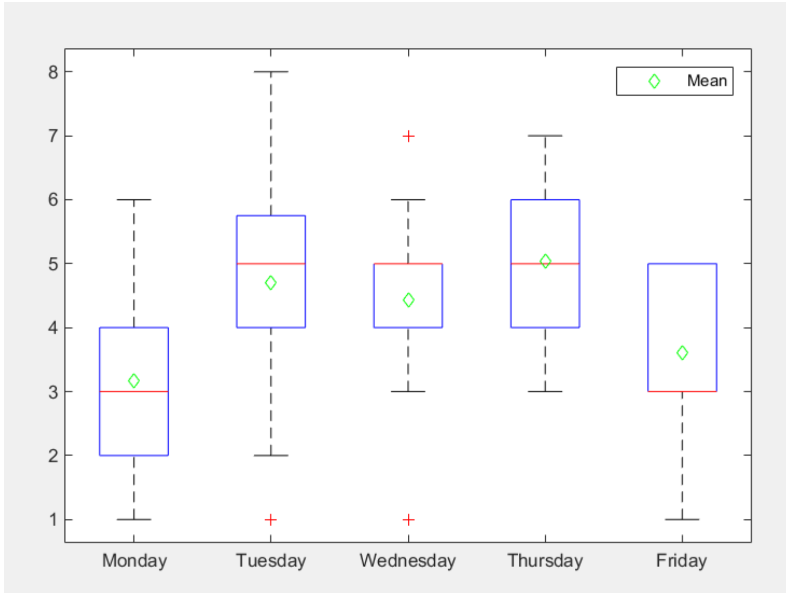


Figure 6. Percentile and the average number of meetings per weekday

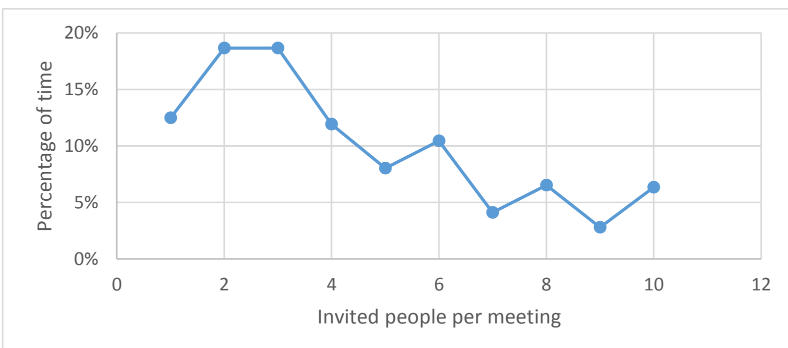


Figure 7. Number of invited people per meeting

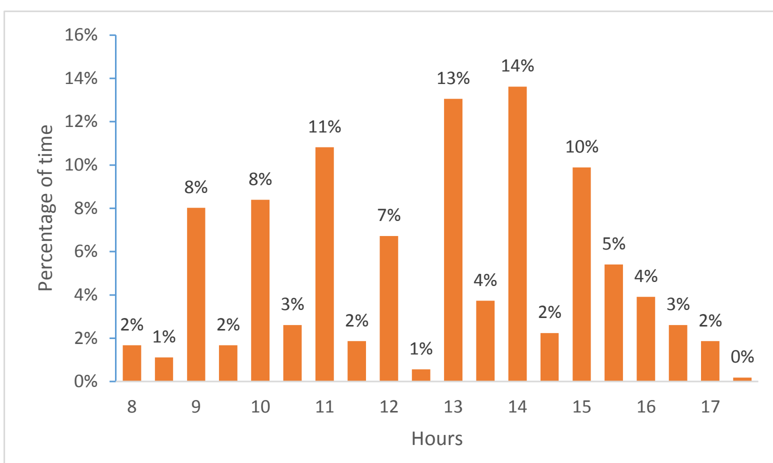


Figure 8. Probability distribution of meeting start time

Figure 9 shows the schematic diagram of the meeting event model developed in this study. For each day, each meeting room agent first randomizes the number of meetings. For each meeting, it also randomizes the meeting duration and the number of people in the meeting. It then searches through each period started on the hour or 30 minutes past the hour. If there are enough people who can attend the meeting during the time period, the period is then added to the list of available time periods. In the end, the system randomly picks one time period and associated occupants for the meeting. Actual participants of a meeting are randomly but limited to their availability to attend meetings; i.e., their total meeting time does not exceed the quota (derived from user inputs of occupant profiles). This model requires users to provide the meeting duration distribution similar to Table 1. The model also requires the minimum and maximum number of meetings per weekday type, and assumes the number of meetings per weekday type has uniform distribution based on Figure 6. Currently, the model only requires the minimum and maximum number of people per meeting, and it assumes that the number of participants per meeting has a uniform distribution. However, a user-customized distribution can be adopted in the future if such distribution function can be provided by users. Further research of meeting events can also provide more realistic distribution function.

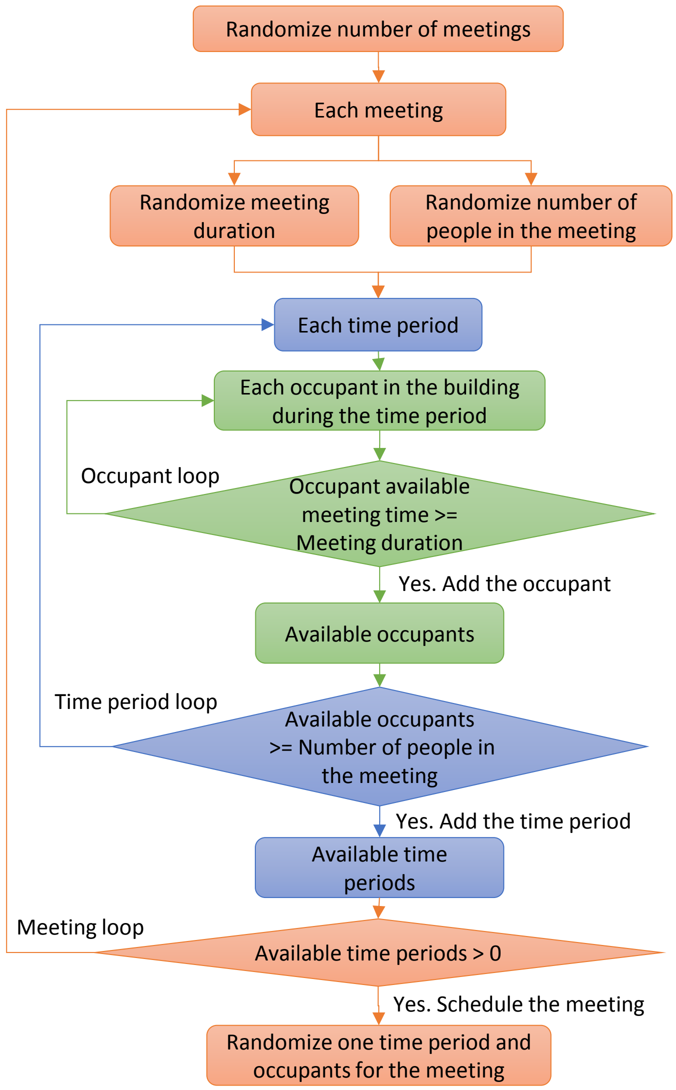


Figure 9. Schematic diagram of the meeting event model

3. Case Study

A case study is presented to demonstrate the use of the Occupancy Simulator. It shows the required data inputs to and the results from the Occupancy Simulator. A small, one-story office building with 44 m (144.4 ft) (L) × 20 m (65.6 ft) (W) × 3.5 m (114.8 ft) (H) is selected for the case study. The building has a total of 16 occupants, eight offices (four private offices and four shared offices), a corridor, a kitchen, a restroom, and a meeting room. Figure 10 shows the plan view of the office building, including the number of occupants in their own offices.

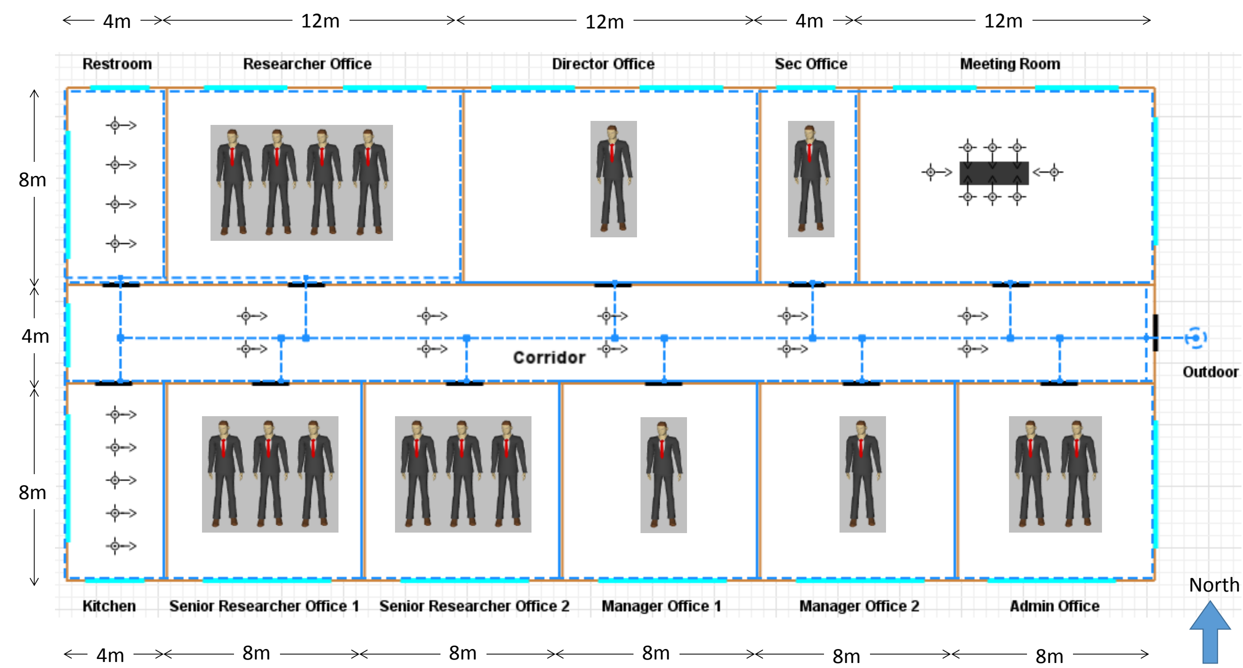


Figure 10. Schematic of the office building

3.1. Space layout setting

To start a new analysis, we need to provide the building type and floor area, which are *Office – Small* and 880 m^2 (9472 ft^2) in this case. Figure 11 shows the snapshot of the *Spaces* page, which provides the space type, area, and multiplier of each space. Users need to provide the occupant density and the occupant types for each office space type (Figure 12). The building template, in this case ***Office – Small***, provides default settings for the number and size of various types of spaces in the building, as well as occupant density and occupant type for each space type based on the DEER (Database for Energy Efficiency Resources) building prototypes (Itron, 2005). DEER leveraged the California Residential Appliance Saturation Survey (RASS) (California Energy Commission, 2016b) and the California Commercial End Use Survey (CEUS) (California Energy Commission, 2016a) to determine the space types and their size and occupant densities for each building type. Users can overwrite these defaults once the model is created.

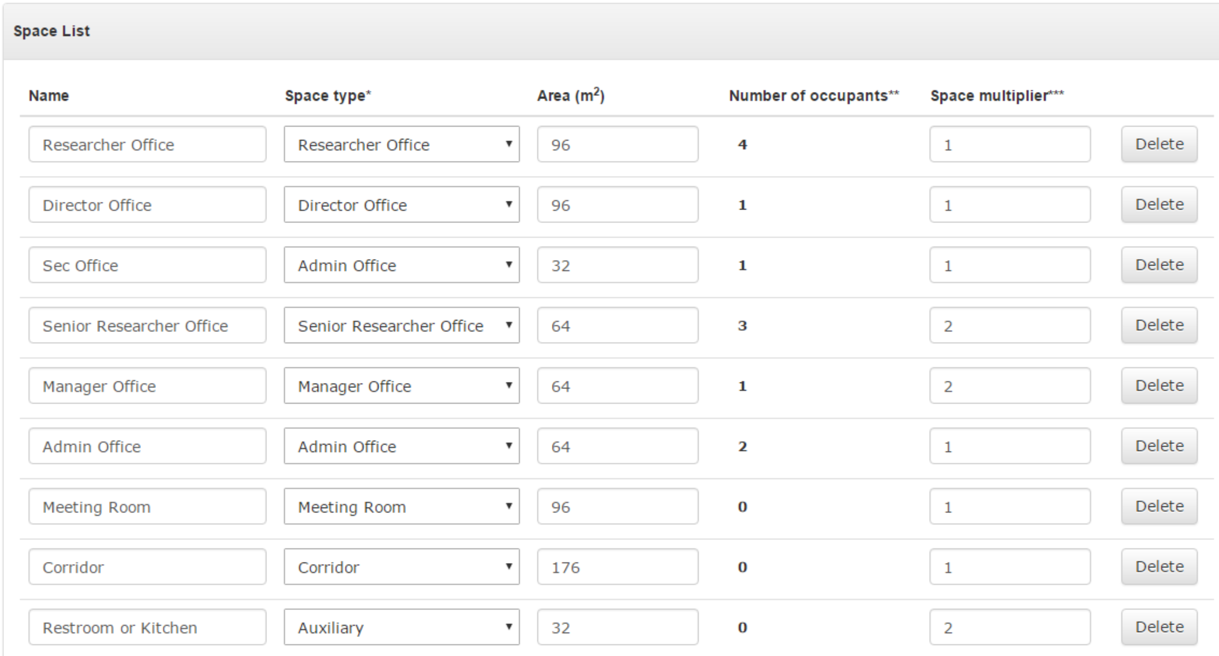


Figure 11. Snapshot of the Spaces page

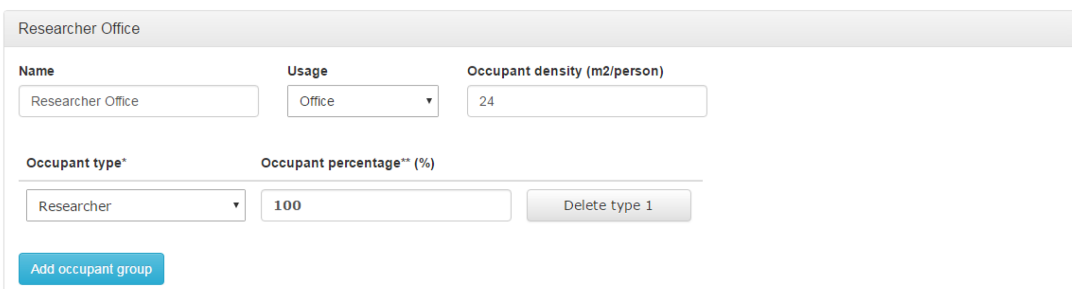


Figure 12. Example of Office in the Space Type page

3.2. Meeting events setting

The *Meeting room* space type requires the description of meeting events with the number of meetings per day, the number of people per meeting, and the meeting duration distribution. Figure 13 shows the meeting events for the case study. There are one to five meetings per day on Mondays and Fridays, and three to six meetings per day on Tuesdays, Wednesdays, and Thursdays. It has two to eight people per meeting. The meetings have a 72% chance to last for one hour.

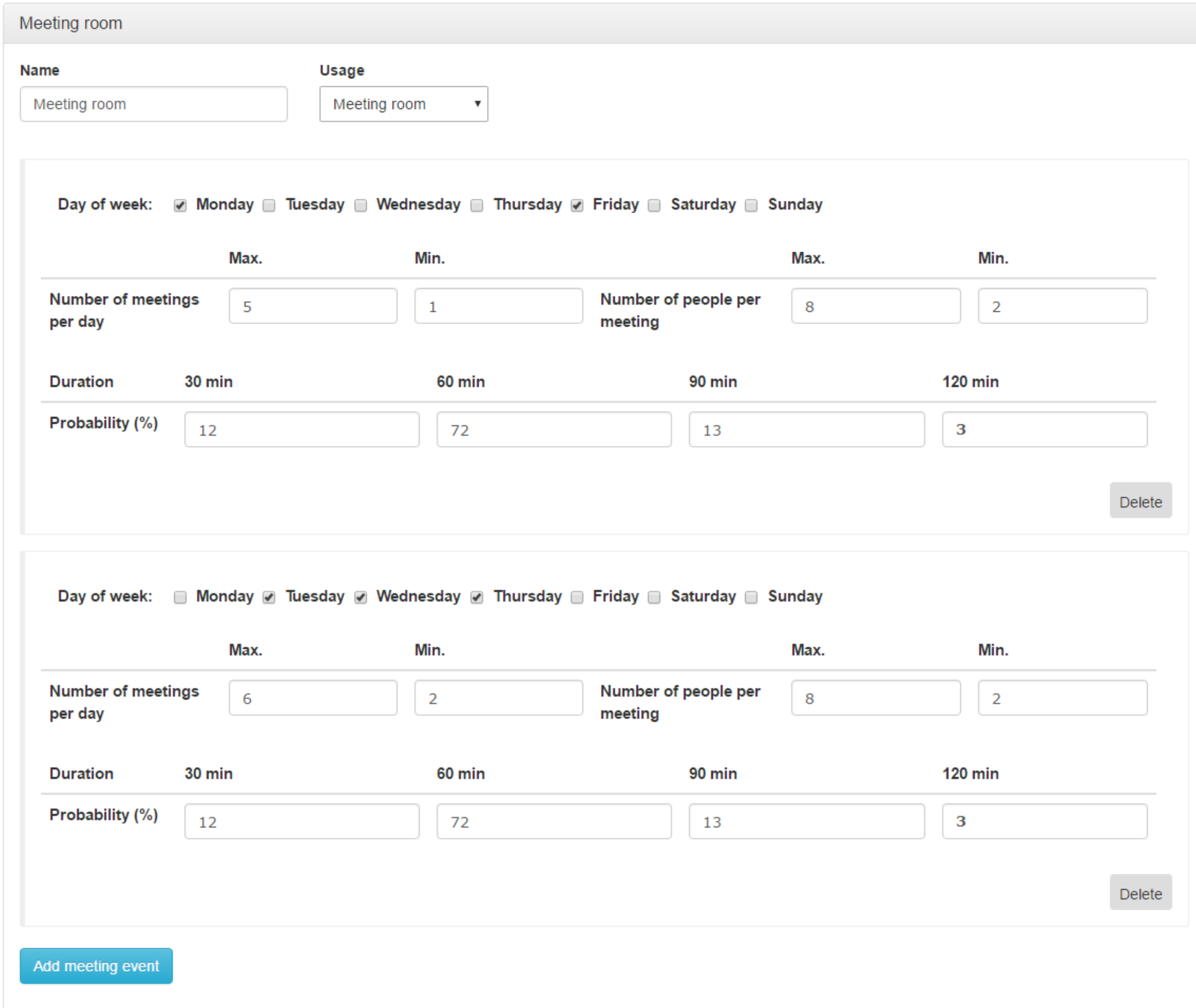


Figure 13. Example input of a *Meeting Room* in the Space Type page

3.3. Occupant status transition events and space occupancy settings

Figure 14 shows the example of the *Researcher* occupant type, which requires the typical time and variation of the first arrival and last departure events, and the space occupancy information. It also allows users to define short-term leave events such as lunch and coffee break with information about event occurrence time and duration. Figure 15 shows the measured data from a field case study of a university office building—the percentage of time that occupants are in their own offices (Luo, 2016). It shows that professors spent about 74% of their time in their own offices; values are 79% and 83%, respectively, for researchers and administrators. Measured data are used in this case study to determine the occupant's percentage of time in their own offices, and it is assumed that occupants spend the same amount of time in other offices, auxiliary rooms, and outdoors.

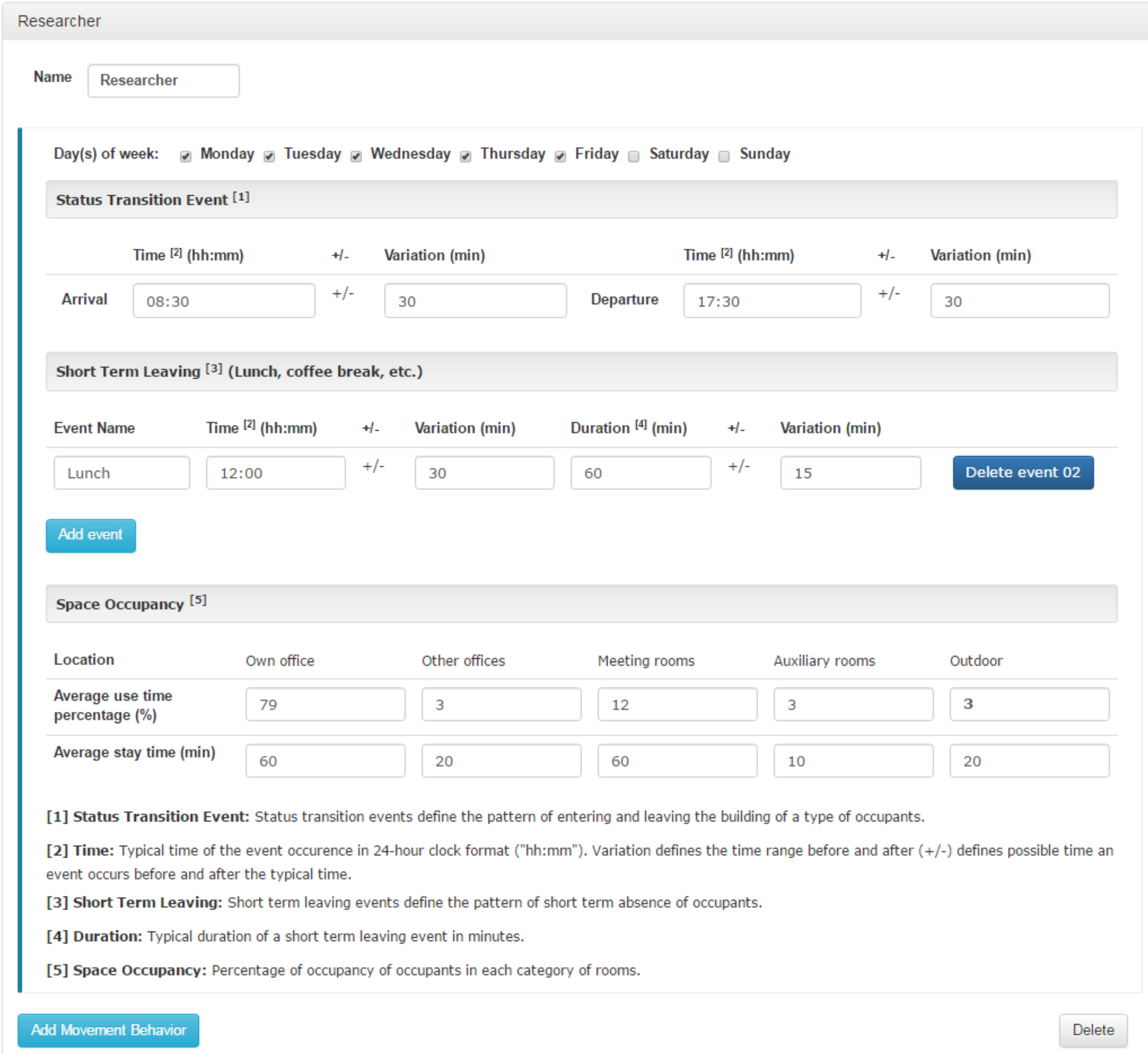


Figure 14. Example input of a Researcher in the Occupant Type page

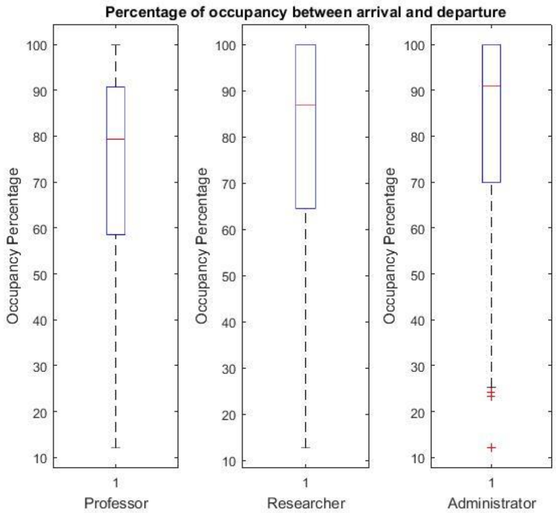


Figure 15. Measured percentage of time that occupants are in their own offices (Luo, 2016)

3.4. Simulation results

After all the input information is collected, users can specify the simulation period, time step, and holidays in the *Simulate* page (Figure 16). Holidays can default to the United States. Public holidays, which are provided automatically, or can be customized by entering the individual dates of holidays observed by the occupants of the buildings. It takes about one minute to run an annual simulation for this case. The results can be viewed in the *Simulate* page, with the customization of results period and room/whole building (Figure 17). Users can also download the results of occupant schedules in CSV and EnergyPlus IDF files formats, and further use them in building performance simulation.

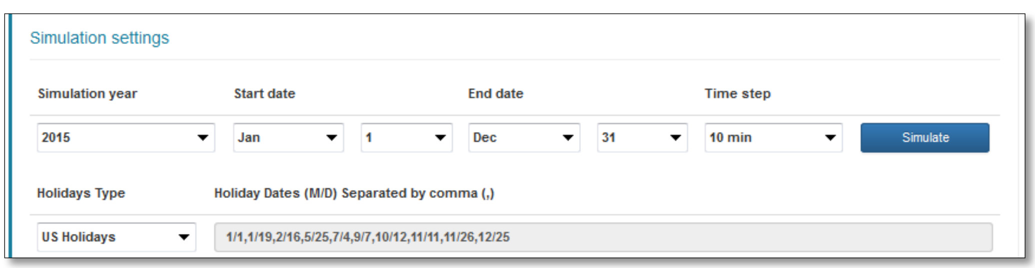


Figure 16. Simulation settings in the Simulate page

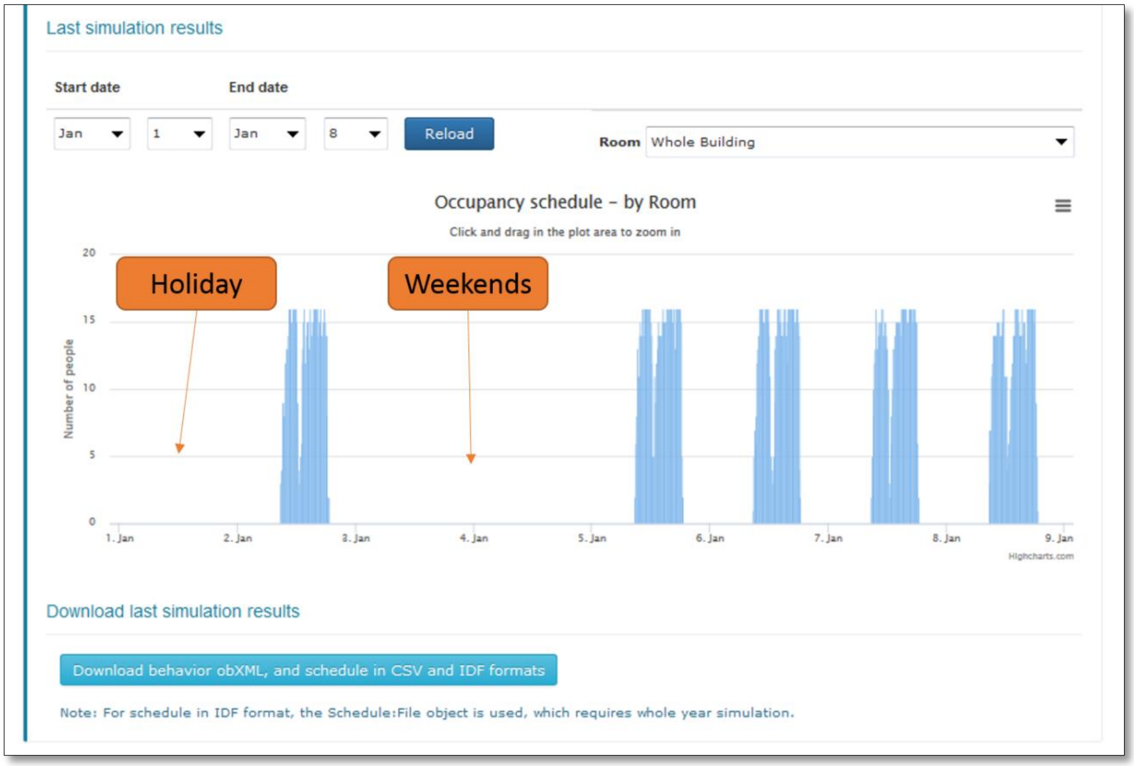


Figure 17. The occupancy simulation results view in the Simulate page

To produce occupant schedules in EnergyPlus IDF files, an annual simulation is required. Users can specify a time step of 5, 10, 15, and 20 minutes. The graphic view of the schedule can be zoomed in and out, and the view can be exported as an image in PNG, JPEG, PDF or SVG format. The user inputs are also saved into a behavior obXML file which complies with the obXML XML schema (Hong, D'Oca, Taylor-Lange, et al., 2015; Hong, D'Oca, Turner, et al., 2015). The obXML file can be used to model occupant behavior using the obFMU through co-simulation with EnergyPlus (Hong, Sun, Chen, Taylor-Lange, & Yan, 2016) or other BPS programs adopting functional mockup interface.

4. Discussion

The Occupancy Simulator aims to capture the spatial and temporary diversity of occupancy in buildings by explicitly simulating each occupant and each space in the building as agents. Therefore, the simulated occupant results represent three levels of occupancy: the whole building level (number of occupants), the space level (occupied status and the number of occupants) and the occupant level (where and in which space he/she is at a particular time). The Occupancy Simulator is a free and web-based detailed occupancy simulation tool. It is designed to generate stochastic occupant schedules replacing the simplified and static schedules for building performance simulation, but it can be used for other purposes in the building design stage—for example, to study space usage, and carpet use and maintenance (depending on occupant traffic). As a web-based application, it is easy to maintain as no software installation is needed on the client side, and it is available for all operation systems and devices (even for mobile phones). Recently, Sun and Hong (Sun & Hong, 2016) used the occupancy simulator to support the analysis of energy saving potential of occupant behavior measures. Chen et al. (Chen, Liang, Hong, & Luo, 2017) applied the occupancy simulator to support the simulation and visualization of energy-related occupant behavior in office buildings. In the future, the Occupancy Simulator may be used to generate schedules supporting assessment of new measures for the development of building energy code and standards.

There are several limitations of the current implementation of the Occupancy Simulator. First, it uses the Markov chain model to simulate occupant movement behavior, which does not consider occupants' walking time or path from one space to another. It handles holidays at the building level; however, it does not consider personal absent workdays (e.g., sick leaves, vacations, work from home days, or business trips). Future versions of the model will likely include a category of the personal absent workdays in the Occupant Type definition. Another limitation is that occupants' presence and movement are assumed to be independent of indoor space environmental conditions (i.e., not influenced by space temperature, humidity, or indoor air quality). To expand its use from current commercial buildings focus to residential buildings, additional events will need to be added, such as sleeping, cooking, dining, and watching TV.

Another area to improve is the new stochastic model of meeting events, which is based on the google-calendar schedule data of one typical meeting room. This leads to the uncertainty of the collected occupancy data, which may deviate from the actual number of persons attending the meetings in reality. We extracted several key input parameters for the meeting events model, including the minimum and maximum number of meetings per day, the minimum and maximum number of people per meeting, and the probability of meeting durations. However, the model might not be valid for other types of meetings, e.g., short (less than 30 minutes) meetings or meetings with participants join late or leave early. We also allow users to create different meeting events for different days of the week. It should be pointed out that users can customize those parameters to create their own meeting room events based on their available data. Other meeting rooms may have different use patterns, especially when technologies other than Google Calendar are used to manage the meeting events. More meeting events data from multiple meeting rooms are needed to further validate or improve the new model.

Another point to consider is that the Occupancy Simulator performs stochastic simulation, implying that generated occupant schedules will be different for each simulation run. Users may need to repeat the simulation procedures multiple times to fully understand the dynamic and stochastic feature of the results. Feng, et al. (Feng, Yan, & Wang, 2016) studied the simulation repetition and temporal discretization of stochastic occupant behavior models in building performance simulation. The study showed that repeating a simulation 10 times gives a favorable estimation of the mean value of the distribution, and the time intervals of 5, 10, and 15 minutes achieve close results.

Besides its use as a web application, the algorithm and solver of the Occupancy Simulator are implemented in obFMU (Hong et al., 2016), a functional mockup unit (FMU) for occupant behavior modeling. Therefore, the Occupancy Simulator is available as an FMU for co-simulation with BPS programs, such as EnergyPlus and ESP-r.

Other future work includes interoperability with current BPS programs and building information modeling; For example, importing user inputs from EnergyPlus IDF files, BIM (IFC or gbXML) files, and OpenStudio OSM files. In the current occupant behavior research, data is limited. The occupancy sensor normally provides 0 or 1 status rather than the number of occupants. Users may only have occupancy data at the whole building level, e.g., through the gate access systems. Another effort is to develop a comprehensive library of occupant types, meeting room types, and space use types for commercial buildings through a large-scale survey and the monitoring of more buildings. The library can be used in the design stage when no actual occupancy data is available yet. The evaluation and verification of the Occupancy Simulator is an important work and presented in Luo (Luo, 2016; Luo, Lam, Chen, & Hong, 2017).

5. Conclusions

The Occupancy Simulator is an agent-based web application that simulates occupant presence and movement in buildings considering detailed spatial and tempora1 diversity. It can be used to generate stochastic occupancy schedules for building performance simulation as well as other use cases related to space use. The contribution of the paper includes: (1) developing a new stochastic model to simulate meeting events based on actual meetings data, (2) enhancing the mathematical algorithms to solve Wang's homogenous Markov chain model for random movement, which improves the computing performance significantly and enables the occupancy simulation for any number of spaces and occupants in a building, (3) integrating individual occupancy models into a single tool that enables the simulation of all occupants and all spaces in a building, (4) developing a hierarchical data model to organize user input, which significantly simplifies the input process while keeping the flexibility for full detailed input, and (5) making the tool a web-based application that is easy to use (no installation of client software and runs on all operating systems and devices) and freely available. We welcome the use of the Occupancy Simulator, and hope users to provide feedbacks and suggestions, so we can continue to improve the Simulator for the building energy modeling community.

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