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Energy Technologies Area
September, 2017



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Simulation and visualization of energy-related occupant behavior in office buildings

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Abstract

In current building performance simulation programs, occupant presence and interactions with building systems are over-simplified and less indicative of real world scenarios, contributing to the discrepancies between simulated and actual energy use in buildings. Simulation results are normally presented using various types of charts. However, using those charts, it is difficult to visualize and communicate the importance of occupants' behavior to building energy performance. This study introduced a new approach to simulating and visualizing energy-related occupant behavior in office buildings. First, the Occupancy Simulator was used to simulate the occupant presence and movement and generate occupant schedules for each space as well as for each occupant. Then an occupant behavior functional mockup unit (obFMU) was used to model occupant behavior and analyze their impact on building energy use through co-simulation with EnergyPlus. Finally, an agent-based model built upon AnyLogic was applied to visualize the simulation results of the occupant movement and interactions with building systems, as well as the related energy performance. A case study using a small office building in Miami, FL was presented to demonstrate the process and application of the Occupancy Simulator, the obFMU and EnergyPlus, and the AnyLogic module in simulation and visualization

of energy-related occupant behaviors in office buildings. The presented approach provides a new detailed and visual way for policy makers, architects, engineers and building operators to better understand occupant energy behavior and their impact on energy use in buildings, which can improve the design and operation of low energy buildings.

Keywords: Occupant behavior, behavior modeling, building simulation, visualization, EnergyPlus, building performance

Introduction

Traditionally, in building performance simulation (BPS) programs, occupant behaviors are oversimplified and less indicative of real world scenarios, contributing to the discrepancies between the simulated and actual energy use in buildings. The International Energy Agency (IEA) Energy in the Buildings and Communities Program (EBC) Annex 53, Total Energy Use in Buildings: Analysis & Evaluation Methods, pointed out that occupants' activities and behavior are one of the six key factors directly influencing building energy use. Occupant behavior is now widely recognized as a major contributing factor to the uncertainty of building performance (Yan et al., 2015). The operational and space utilization characteristics of occupants are closely linked to energy use in buildings (Hoes, Hensen, Loomans, de Vries, & Bourgeois, 2009). According to the experiments on 248 dwellings, it was found that 71% of the energy demand variation was due to occupants' individual behavior and reaction to environmental conditions (Socolow, 1978). Furthermore, occupant behavior and lifestyle choices are also key factors contributing to building energy consumption (Pilkington, Roach, & Perkins, 2011). By investigating the impacts of various occupant interactions with building systems, such as the use of blinds, lighting system, windows and fan, simulation results reveal that energy use can be very different according to the occupant actions (Bonte, Thellier, & Lartigue, 2014). Consequently, it is suggested to mimic real-world occupant behaviors in a building energy simulation, considering the behavior

influence on both the thermal conditions and energy use in the building (Lee, 2014).

The occupant behaviors can be grouped into two categories: occupancy and occupants' interactions with building systems (C. Wang, Yan, & Jiang, 2011). Occupants have the freedom to enter or leave the building, and move within certain spaces in the building. The occupancy simulation determines the location of each occupant during each time period and is the foundation of occupant behavior modeling. It strongly impacts the simulation results of many technologies such as personalized ventilation system (Chen, Raphael, & Sekhar, 2012, 2016), occupancy sensors and occupant based controls (Hong, Taylor-Lange, D'Oca, Yan, & Corngati, 2015). Current BPS programs such as EnergyPlus (Crawley et al., 2001) and DeST (Yan et al., 2008) use deterministic and static weekly schedules to model occupancy. Specifically, spaces with similar functions typically use identical occupancy schedules. As a result, using these homogenous occupant schedule in energy modeling, each space will have same or very similar load profiles in the simulation outputs, and thus no diversity is represented. However, the real occupancy patterns in buildings may differ significantly from each other, considering 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). Therefore, realistic representation of occupant schedules used in building performance simulation has been brought to the forefront recently, and they tend to represent the stochastic nature of human behaviors. The most common way of generating stochastic occupant schedules in simulation tools is to reproduce occupancy pattern using selected occupant profiles and applying statistical model representing the occupant behavior processes (Virote & Neves-Silva, 2012). Page et al. proposed a probabilistic model to predict and

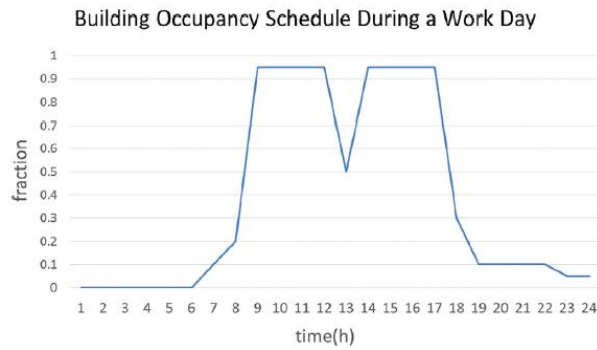
simulate occupancy in single-occupancy offices based on heterogeneous Markov chain model, which generalized stochastic occupancy schedules using weekly presence probability statistics and a mobility parameter regarding state change of presence and absence (Page, Robinson, Morel, & Scartezzini, 2008). Reinhart's (Reinhart, 2004) LIGHTSWITCH-2002 model determines the arrival, departure and temporary absence based on the cumulative 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 the 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 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 UK households based on surveyed time-use data, and the results provided time-series occupancy data and the number of active occupants in a house (Richardson, Thomson, & Infield, 2008). An approach for building occupancy simulation based on homogeneous Markov chain model was introduced to simulate the stochastic movement of occupants (C. Wang et al., 2011). The model was tested using MATLAB to generate the location for each occupant and the occupancy of each space of a building. Later on, it was updated and implemented in C++ (an object-oriented programming language) as a stand-alone application (Feng, Yan, & Hong, 2015). Recently, the Markov chain and LIGHTSWITCH-2002 models were integrated as the simulation engine of a web-based application with a user friendly graphical interface (GUI), named Occupancy

Simulator (Chen, Hong, & Luo, 2016; Chen, Luo, & Hong, 2016). The Occupancy Simulator simplified the data input by organizing occupants into occupant types and spaces into space types. Luo et al. (Luo, 2016; Luo, Lam, Chen, & Hong, 2016) used measured occupancy data from a real office building to evaluate and verify the performance of the Occupancy Simulator. The Occupancy Simulator was selected in the workflow to simulate the occupant presence and movement in this study.

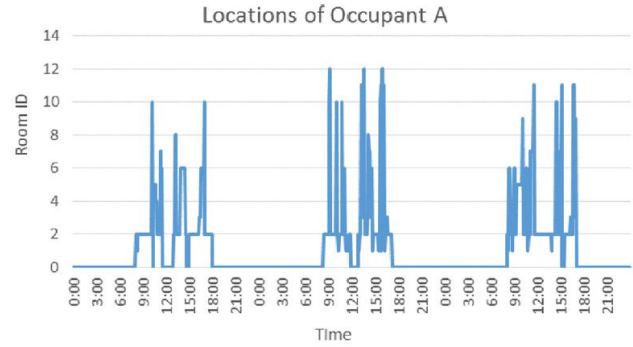
Occupants are not passive participants in buildings. Depending on the user-controllability of the systems in the building, occupants may be able to interact with building systems such as controlling lights, adjusting the thermostat, opening and closing windows and operating electrical equipment, all of which influence the energy consumption of buildings (O'Brien, Kapsis, & Athienitis, 2013; Sun, Yan, Hong, & Guo, 2014). There are three approaches to model occupant behaviors with current BPS programs: using built-in models, writing customized code (e.g. Energy Management System in EnergyPlus), or using co-simulation with existing BPS programs (e.g. co-simulation with EnergyPlus via BCVTB (Chen, Gu, & Zhang, 2015; Wetter, 2011) or FMI (Hong, Sun, Chen, Taylor-Lange, & Yan, 2015)). There are some built-in occupant behavior models available in BPS programs such as DeST and ESP-r. Currently, those models are limited and don't cover all the behavior models in this case study. Gunay et al. (Gunay, O'Brien, & Beausoleil-Morrison, 2015) implemented some of the behavior models from the literature for predicting occupancy and use of operable windows, blinds, lighting, and clothing for offices in EnergyPlus using the EMS code. Yet it still requires huge effort to extend the customized code to model more occupant behaviors, especially the occupant presence and movement models. An occupant behavior functional mockup unit (obFMU) was developed for simulating occupants' interactions with building physical systems (Hong, et al., 2015). It can

process the occupancy results generated by the Occupancy Simulator and perform co-simulation with BPS programs such as EnergyPlus. The EnergyPlus website (US DOE, 2016) provides testing and validation reports of EnergyPlus. The obFMU and EnergyPlus were selected to evaluate the impacts of the occupant behavior on energy performance in this study.

Although various simulation models of occupant behavior have emerged in recent years, few of them paid attention to visualization of simulation results, which is critical to communicate occupant behavior simulation with building designers and engineers, building operators, and policy makers. Yan et al. (Yan et al., 2015) indicated that there are three major dimensions of occupant behavior models, (1) temporal (e.g., minutes, hours and days), (2) spatial (e.g., the whole building, individual zones and rooms), and (3) occupancy (e.g., statuses, count and behaviors). Nowadays, simulation results are normally presented using various types of charts, e.g., time-series charts, bar charts, and pie charts. Those charts play an important role in displaying the performance of the whole building as well as individual spaces. However, using those charts, it is difficult to visualize and communicate the importance of occupants' behavior to the building energy performance. The occupancy simulation results should present all these three dimensions synthetically. However, most previous studies only showed temporal and occupancy dimensions without the spatial information (Figure 1 (a)). It is appropriate to demonstrate results in one zone, whereas it is limited if occupants move among several zones. Figure 1 (b) showed another way to present temporal and spatial dimensions without occupancy information. Each figure is for one occupant. It is acceptable only for buildings with few occupants. Therefore, the problem is all the three dimensions have not been shown comprehensively in previous presentations of occupancy simulation results.



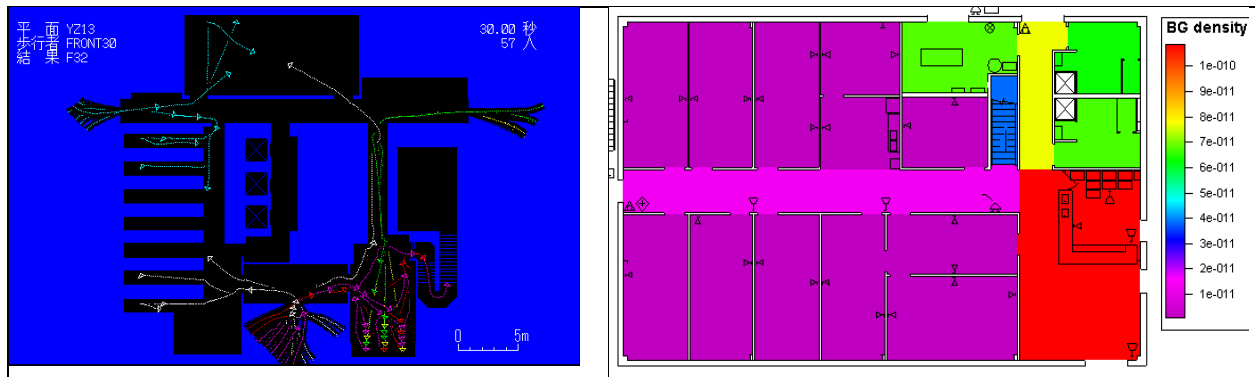
(a) Building occupancy schedule on a typical workday



(b) Schedule of individual occupant

Figure 1 Typical manner to show the occupancy simulation results (Feng et al., 2015)

There are existing tools from various fields (e.g., pedestrian movement simulation in evacuation, daylighting simulation, indoor thermal comfort simulation) providing spatial visualization of simulation data. Visualization of an evacuation process usually uses streamlines plotted on a space layout, where individual occupant is always represented as an agent by a vector (Figure 2 (a)) (Okazaki & Matsushita, 1993). Contaminant dispersal process simulation regarding indoor air quality tends to use color maps for visualizing the multi-zone building airflow and contaminant transport. Figure 2 (b) shows an example plotted by the CONTAM tool (Wang et al., 2010). For daylighting performance or indoor thermal comfort simulation, the simulation results are usually visualized with more detailed data in a single three-dimensional zone (Chiang, Wang, & Huang, 2012).



(a) Visualization for an evacuation process simulation (Okazaki & Matsushita, 1993)	(b) Visualization for a contaminant dispersal process simulation ¹
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Figure 2 Spatial visualization of simulation data in different fields

This study introduces a new approach to simulating and visualizing occupancy and occupant behaviors in office buildings using three tools: the Occupancy Simulator, the obFMU and EnergyPlus, and the AnyLogic model. The agent-based visualization module, built upon AnyLogic, presents all three dimensions of the occupant behavior simulation results with a user friendly graphical interface. The results can be visualized and animated, so that the end users can understand the simulation results easily. A case study is presented to demonstrate the process and application of these tools.

Methods

Four major tools as shown in Figure 3 with different colors were used to simulate and visualize the occupant behaviors and their impacts on building energy performance. First, the (2) Occupancy Simulator was used to simulate the stochastic occupant presence and movement. It generated an (3) occupant model based on the occupant behavior XML (obXML) schema (Hong, D'Oca, Taylor-Lange, et al., 2015; Hong, D'Oca, Turner, & Taylor-Lange, 2015) and the (5) occupancy movement results. Then, the (8) obFMU and (11) EnergyPlus co-simulation generated the (9) occupant based controls and the (12) building energy performance results. Finally, all the results are visualized in the (13) visualization model developed in AnyLogic.

¹ http://vsp.pnnl.gov/help/Vsample/Import_CONTAM_Data.html

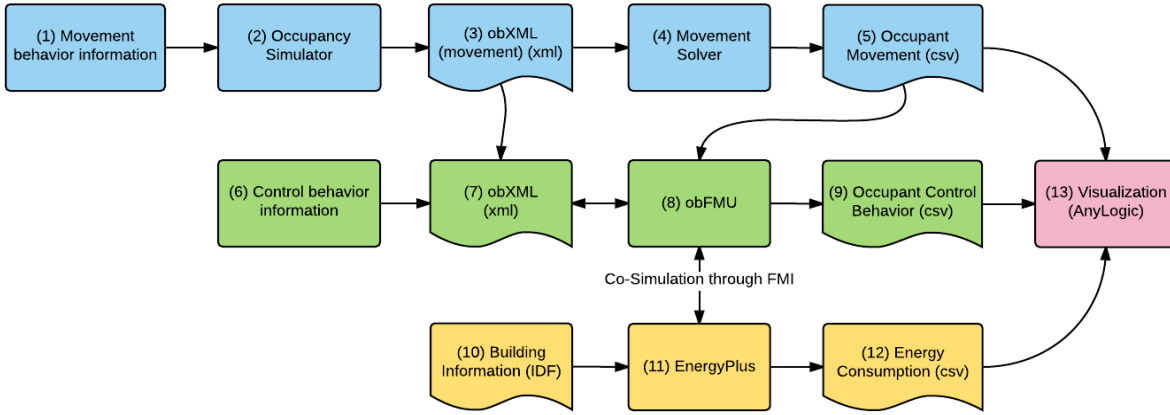


Figure 3 Workflow of the simulation and visualization of occupant behavior

Occupancy Simulator

Figure 4 shows the *Introduction* page of the Occupancy Simulator. The simulator includes a top bar, a tab bar, and the main content area. The top bar provides links to several related projects, and shows the unique session number for each simulation case. The session number can be used to retrieve all the information related to the simulation case, including inputs and results. The tab bar organizes data into multiple pages based on the data structure of the Simulator (Figure 5), including *Introduction*, *Start New*, *Spaces*, *Space Type*, *Occupant Type*, *Simulation*, and *Team*. Moreover, the main content area shows the detailed information of the selected page.

To reduce the amount of data inputs, the Simulator allows users to group occupants with similar behaviors as an *OccupantType*, and spaces with similar functions as a *SpaceType*. Figure 5 shows the data structure of the Occupancy Simulator. The Simulator creates a *Building* instance for each simulation case, which includes a session number and multiple instances of *Spaces*. Each *Spaces* has a floor 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 type of *Occupants*. The parameters for each *Meeting* event include the minimum and maximum number of meetings per day, the minimum and maximum number of people per meeting, and the probability distribution of

meeting durations. Each *Occupants* has an *OccupantType*, which defines the *MovementBehavior* of the occupants. The *MovementBehavior* defines the spaces occupancy, the arrival and departure events, and the short term leave events (e.g., lunch, coffee break). The spaces occupancy includes the percentages of time and the average durations for the cases when the occupant stays in Own Office, Other Office, Auxiliary Rooms, and Outdoor. For each event, it defines the typical time when the event occurs and the variation of the time. For the short term leave events, it also requires the typical event duration and its variation. Additionally, users can specify the simulation period, time step, and holidays in the *Simulate* page. Based on the information, the Occupant Simulator simulates the location of each occupant at each time step based on the first-order homogeneous Markov chain model and the LIGHTSWITCH-2002 model. Users can download the results of the simulated occupant schedules in CSV and EnergyPlus IDF files, and further use them in building performance simulation.

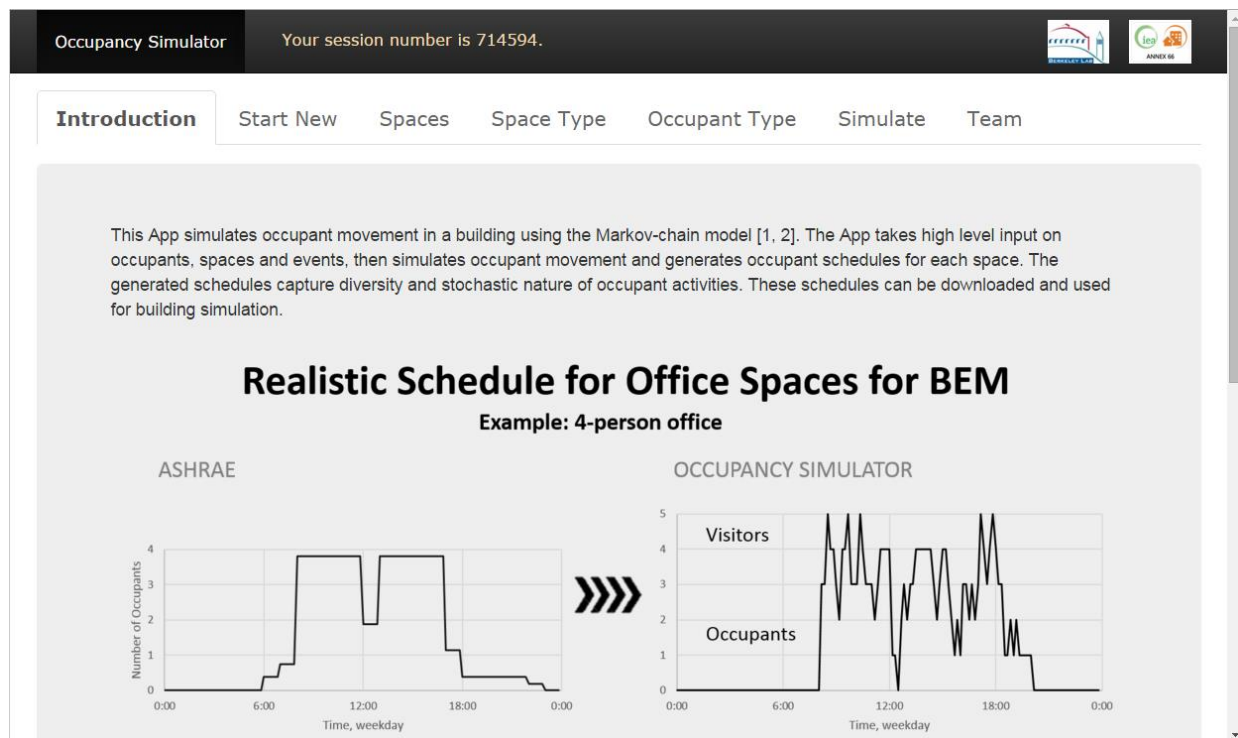


Figure 4 The introduction page of the Occupancy Simulator

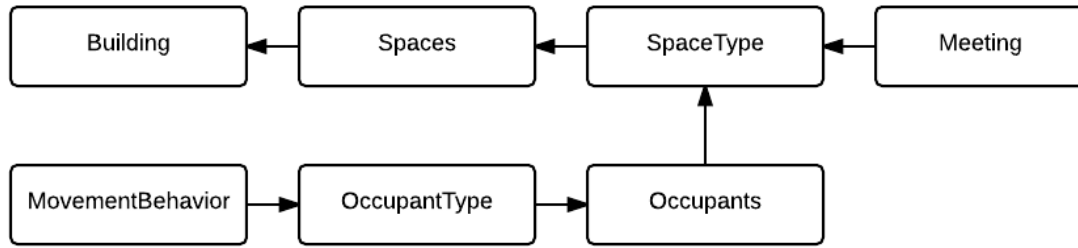


Figure 5 Data structure of the Occupancy Simulator

EnergyPlus and obFMU co-simulation

EnergyPlus V8.4 and obFMU V1.2 were adopted via co-simulation to analyze the impacts of occupant behavior on building energy performance. EnergyPlus is a powerful simulation tool to model the heating, cooling, lighting, and ventilation systems, while obFMU (Hong, et al., 2016) provides the capability to model occupant-based control strategies. Figure 6 shows the data exchange between EnergyPlus and obFMU during each time step. EnergyPlus exports the zone air temperature, zone CO₂ concentration, zone daylighting illumination level (at the daylight sensor position), outdoor air temperature, and outdoor rain indicator to obFMU. The obFMU reads the parameters from EnergyPlus and the occupancy results from the Occupancy Simulator, and performs time-step calculation to determine the operation schedule for HVAC, windows, shade/blind, lighting, and plug load, as well as the thermostat setpoint. The occupancy, operational, and thermostat setpoint schedules are then used by EnergyPlus to analyze the energy performance of the building.

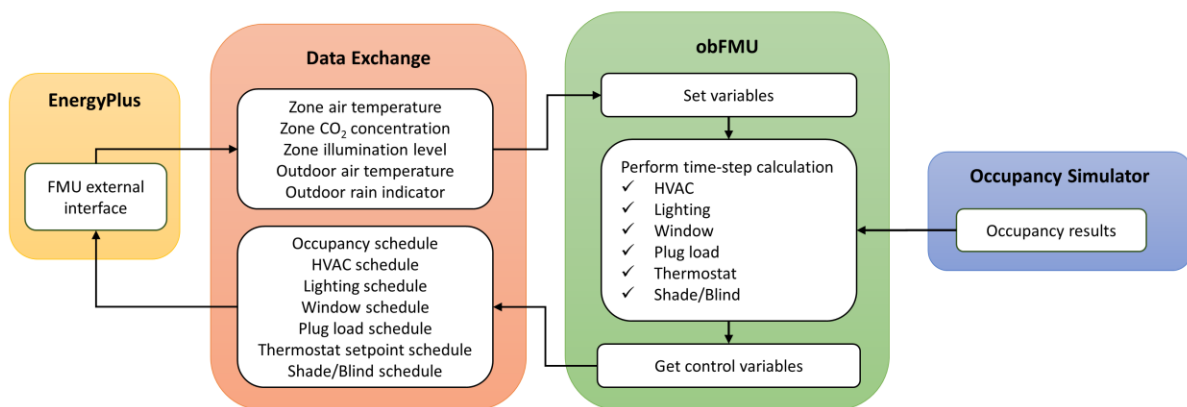


Figure 6 Data exchange between EnergyPlus and obFMU

Figure 7 shows the types of occupant behavior models currently implemented in the obXML and obFMU. To create an occupant behavior model, users can select one *Interaction Type*, one *System Type*, one, multiple or none *Event Types*, one or none *Other Constraints*, and one *Probability Models*. There are three *Interaction Types*, including Turn On (Open), which set the schedule to 1; Turn Off (Close), which set the schedule to 0; or Proportional Control, which set the schedule to any given control value. There are six Systems, including the Windows, Lights, HVAC, Thermostat, Shade/Blind, and Plug loads. The occupant behavior modeling architecture provides flexibility and allows users to design and create their own models. The modeling architecture was recently applied to create a library of 52 OB models based on literature review (Belafi, Hong, & Reith, 2016).

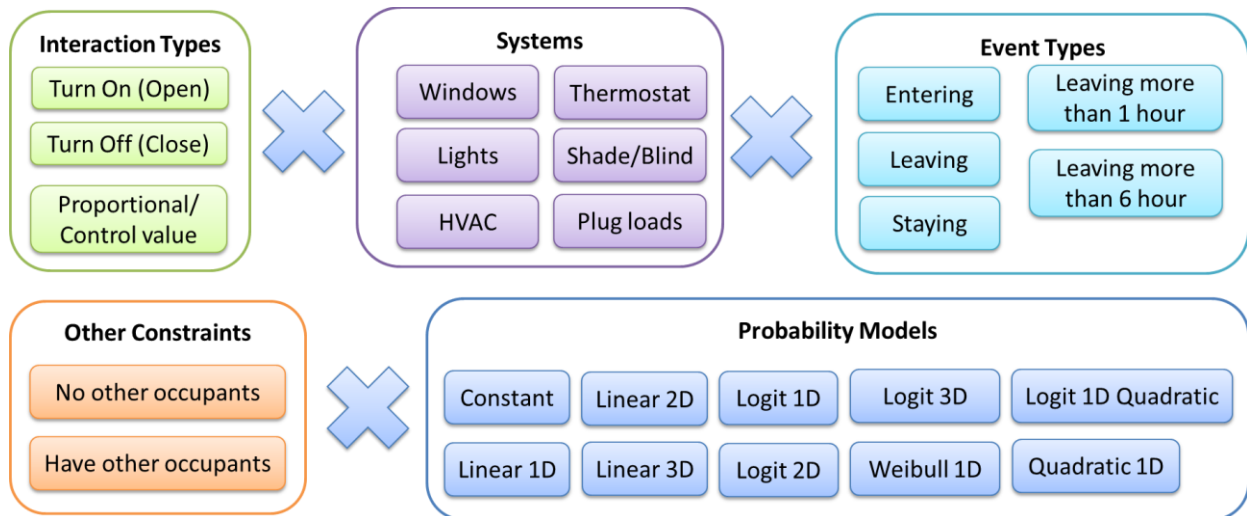


Figure 7 Types of occupant behavior models implemented in obXML and obFMU

AnyLogic for Results Visualization

The results visualization module is developed using AnyLogic Version 7.2. AnyLogic is a widely used simulation tool for agent-based modeling. Meanwhile, it also supports other two simulation methodologies: system dynamic and discrete event. Agent-based modeling defines humans and objects as agents, who can make decisions by their autonomous, cooperation and

learning attributes. It enables the user to capture the complexity and heterogeneity of problems to any desired level of details. For example, in occupant behavior simulation, the agent-based model can define agent in different levels (i.e. a group of occupants, an individual occupant or a specific behavior). AnyLogic is powerful in 2D/3D visualization with internal 2D/3D module and interface with other software (i.e., AutoCAD and SketchUp). AnyLogic has been widely used in modeling for diverse areas such as manufacturing and logistics, business processes, human resources, consumer and occupant behavior. AnyLogic provides a free personal learning edition and fee-based academic and commercial licenses.

The architecture of the result visualization module is illustrated in Figure 8. From top to bottom is the system level to the physical level. The bottom layer is the data layer for data interaction, store and processing. It reads data flow of occupant movement, occupant behavior and energy use from the interface with Occupancy Simulator, obFMU and EnergyPlus respectively. The second layer from bottom up is the agent layer, which defines the types and attributes of agents. Different agents can map various objects in reality, including occupant, building, system and appliance. In this study, four kinds of agents are defined, representing occupant, light, HVAC system and window. The details of agent attributes are introduced in the Case Study Section. The third layer is configuration layer, which configures the system parameters and initial status. There are four parts of configuration information needed: (1) spatial information (i.e., scale of the space, layout and room function); (2) temporal information (i.e., time step, start and end time); (3) occupancy information (i.e., number of occupants, movement speed and roles); (4) appliance information (i.e. number of appliance, position and initial status). The top layer is the visualization layer, which demonstrates the simulation results. The movement results can be showed in 2D/3D windows, and the energy result can be showed in statistical and diagram

windows. The architecture is based on independent layers, which are loosely coupled and easy to reconfigure and extend for various problems in future studies.

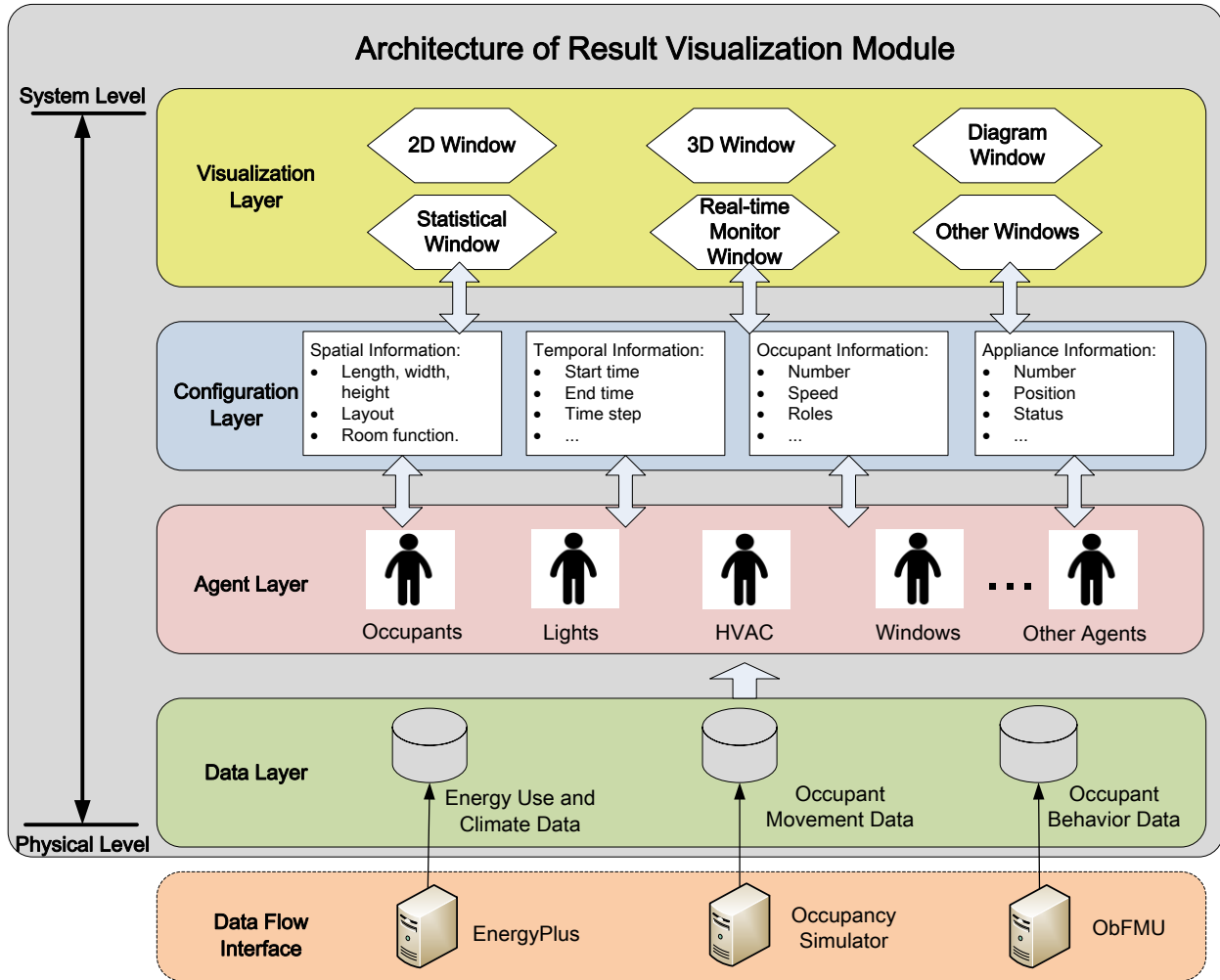


Figure 8 Architecture of the result visualization model

The workflow of the result visualization is illustrated in Figure 9. The first step is to define agents, including their types and attributes. The second step is environment initialization, which describes the special information. In this step, the space layout is shown in both 2D and 3D windows. The third step is time coupling, which matches the time step of simulation results from different models, including Occupancy Simulator, obFMU and EnergyPlus, with Anylogic. It is essential to make timeline consistent. Otherwise the results are disordered. The fourth step is 2D/3D visualization. The movement and behavior of occupants can be shown in 2D/3D space.

The next step is statistical results and real-time monitor, which visualizes the status of appliances, energy use and other environment data. The last step is validation. The results can be compared to theoretical studies and other simulation methods. If it needs improvement, it will repeat the process from the first step. If not, the process will be finished.

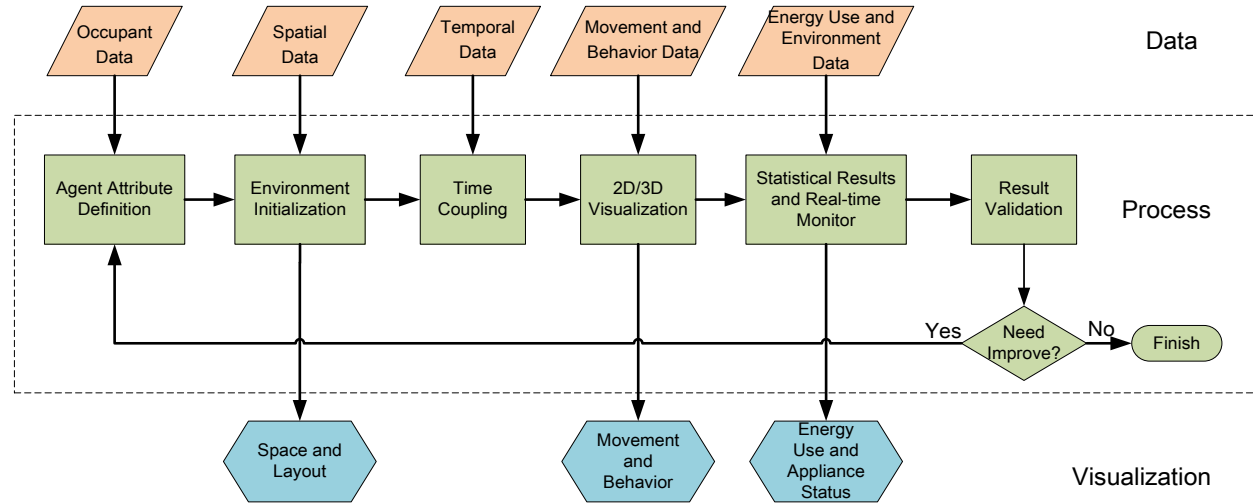


Figure 9 Workflow of the result visualization model

Case Study

A 44 m (L) \times 20 m (W) \times 3.5 m (H) one-story office building located in Miami, FL, USA, was used for the case study. Miami has a hot and humid climate (ASHRAE Climate Zone 1A) with daily average dry bulb temperature of 19.4°C for January and 28.1°C for July. Figure 10 shows the plan view of the office building, including the number of occupants in each room. The occupant movement models, EnergyPlus model, occupant behavior models, and the Anylogic visualization model are introduced as follows.

Occupant movement models using Occupancy Simulator

To analyze the impacts of occupancy on the building energy performance, two types of movement behaviors are studied as shown in Table 1. Both movement models have the same arrival, lunch, and departure events. The workers typically arrive at 8:30AM and depart at

6:30PM with a 30-minute variation. They typically go to lunch at 12:15 with a 15-minute variation, and the lunch duration is typically one hour with a 15-minute variation. The space occupancy defines the percentage of times that the workers spend in each different category of spaces during the office hours except meeting time. For type M_A, the workers spend about 70% in their own offices, 20% in other offices, and both 5% in outdoor and auxiliary spaces. For type M_B, the workers spend about 85% in their own office, 5% in other offices, and both 5% in outdoor and auxiliary spaces. For the conference room, there are two to six meetings per day with two to eight people per meeting for the weekdays, and there are no meetings during the weekends. 72% of the meetings have a duration of one hour.

Table 1 Movement models

Movement Type		M_A	M_B
Events	Arrival	8:30 AM \pm 30 minutes	
	Departure	6:30 PM \pm 30 minutes	
	Short term leave for lunch	12:15 PM \pm 15 minutes Duration: 1 hour \pm 15 minutes	
Space Occupancy	Own office	70%	85%
	Other office	20%	5%
	Outdoor	5%	5%
	Auxiliary	5%	5%
Meeting events during weekdays	Number of meetings per day	2 to 6	
	Number of people per meeting	2 to 8	
	Meeting duration probability distribution	0.5 hour: 12% 1 hour: 72% 1.5 hours: 12% 2 hours: 4%	

Energy model using EnergyPlus

The EnergyPlus simulation model is developed based on the minimum requirement of ASHRAE 90.1-2013 (ASHRAE, 2013b) for small offices. The window-to-wall ratios are 0.23 for East and 0.29 for other three orientations. Packaged single zone heat pump systems are used with a cooling seasonal energy efficiency ratio (SEER) of 13.0 (an equivalent COP of 3.65), and a

heating seasonal performance factor (HSPF) of 7.7 (an equivalent COP of 3.74). The cooling setpoint is 23.89°C while the heating setpoint is 21.11°C for all the spaces. The ventilation rates are set to the sum of 2.5 L/s/person and 0.3 L/s/m² based on ASHRAE Standard 62.1-2013 (ASHRAE, 2013a). The infiltration rate is 0.56896 L/s/m² of above grade exterior wall surface area. The lighting power density is 10.76 W/m² and the plug-load is 6.78 W/m².

Occupant behavior model using obFMU

For the occupant's interaction with building systems, two sets (B_A and B_B) of occupant behavior models are introduced as shown in Table 2 and Table 3. The behavior models cover lighting on/off control, plug-load proportional control, window open/close control, thermostat setpoint, and HVAC on/off control.

Table 2 Type B_A behavior model for occupant's interaction with building systems

System	Interaction type	Event type	Other constraints	Probability model
Lights	Turn on	Entering a space		Constant model with 95% probability
				Weibull 1D model based on daylighting illuminance
	Turn off	Leaving a space more than 6 hours	No other occupants	Constant model with 95% probability
Plug loads	Proportional control with value of 100%	Entering a space		
Thermostat	Proportional control with value of 22.5°C			
HVAC	Turn on	Entering a space		Constant model with 95% probability
				Weibull 1D model based on room air temperature
	Turn off			Weibull 1D model based on room air temperature
		Leaving a space more than 6 hours	No other occupants	Constant model with 95% probability
Window	Open	Entering a		Constant model with 50%

		space		probability
				Weibull 1D model based on room CO ₂ concentration
	Close	Leaving a space more than 6 hours	No other occupants	Constant model with 95% probability

Table 3 Type B_B Behavior models for occupant's interaction with building systems

System type	Interaction type	Event type	Other constraints	Probability model
Lighting	Turn on			Weibull 1D model based on daylighting illuminance
	Turn off	Leaving a space more than 6 hours	No other occupants	Constant model with 98% probability
				Weibull 1D model based on daylighting illuminance
Plug loads	Proportional control to 100%	Entering a space		Constant model with 100% probability
	Proportional control to 30%	Leaving a space more than 6 hours	No other occupants	Constant model with 95% probability
Thermostat	Proportional control to 21.11°C	Entering a space	For winter	
	Proportional control to 22.5°C	Entering a space	For spring and fall	
	Proportional control to 23.89°C	Entering a space	For summer	
HVAC	Turn on			Weibull 1D model based on room air temperature
	Turn off			Weibull 1D model on room air temperature
		Leaving a space more than 1 hour	No other occupants	Constant model with 95% probability
Windows	Open			Weibull 1D model on room CO ₂ concentration
	Close	Leaving a space more than 6 hours	No other occupants	Constant model with 95% probability

Occupancy and behavior models for each space

To analyze the impacts of different movement models and different behavior models on the energy performance, similar spaces are assigned with either different movement model or different behavior model. Table 4 shows the occupancy and behavior models for each space.

Table 4 Occupancy and behavior models of the office spaces

	Movement Type	Behavior Type
Sec Office	M_A	B_A
Admin Office	M_B	B_A
Researcher Office	M_A	B_A
Director Office	M_A	B_B
Senior Researcher Office 1	M_B	B_A
Senior Researcher Office 2	M_B	B_B
Manager office 1	M_A	B_B
Manager office 2	M_B	B_B

Visualization Models using Anylogic

Geometry Setup

The schematic of aforementioned one story office building is implemented in Anylogic Version 7.2, both in 2D and 3D. The 2D geometry is shown in Figure 10, while the corresponding 3D geometry is shown in Figure 11. In Figure 10, the dark yellow lines represent the walls, which partition the physical spaces. The blue dashed lines represent the logic spaces and the routes of occupant moving. The windows and doors are represented by the solid blue and black lines, which are likewise in proportion to the real size.

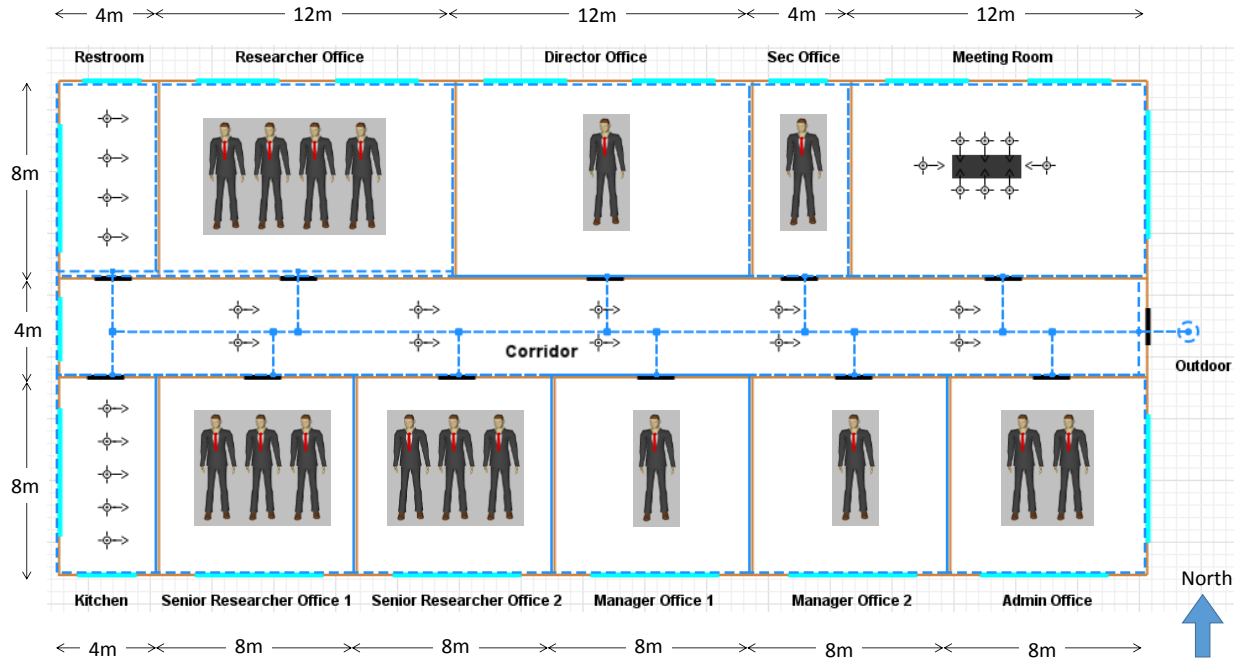












Figure 10. 2D geometry of the office building

Definition of Agents

In this case study, four kinds of agents (i.e., occupant, light, window, and HVAC system) are defined to visualize occupancy and energy simulation results. The attributes of each agent are illustrated in Table 5.

Table 5. Agents and their attributes in AnyLogic

Agent	Figure	Number	Position	Status Visualization
Occupant		16	Dynamic, defined by occupant movement result	Moving: Movement in space Stay: Position in space
Light		11	Statistic, defined by geometry	On:  Off: 
HVAC System		11	Static, defined by geometry	On:  Rotary fan* Off:  Static fan

Window		10**	Static, defined by geometry	Closed: 
				Open: 

* The rotation speed of the fan indicates the real-time power of the air conditioner.

** The window of the Restroom is not controlled by occupants.

Occupant: There are 16 occupants in this case study, and their corresponding rooms are shown in Figure 10. They have two statuses, namely moving and stay, which are shown by the position of occupants in the geometry.

Light: There are 11 lights in this case study, which means each room has its own lighting control. Two statuses are defined for lights, namely on and off. The “on” is represented by the figure with bright yellow color, while the “off” is represent by the figure with gray color, shown in Table 5.

HVAC system: The same as lights, each room has a dedicated air conditioning system and control, so there are 11 HVAC systems. The static figure with a gray circle in the center represents the “off” status of HVAC system, and the rotary fan with a yellow circle in the center represents the “on” condition. Since the power of HVAC system is variable, the rotation speed of the fan indicates the real-time power of the HVAC system.

Window: There are ten windows in this case study, since the window of the Restroom is not controlled by occupants. Two statuses (i.e., open and closed) are defined for windows, and the different shapes of windows represent different statuses, shown in Table 5.

Environment Configuration

Simulation time: The simulation duration is from January 1st to December 31st 2015, and the time step is 10 minutes. The model time unit is 1 minute, and its default value of proportional scale to real time is 1:10. That means one model time unit stands for 10 minutes, or the simulation time is tenfold speeded up. This speed can be reset during execution.

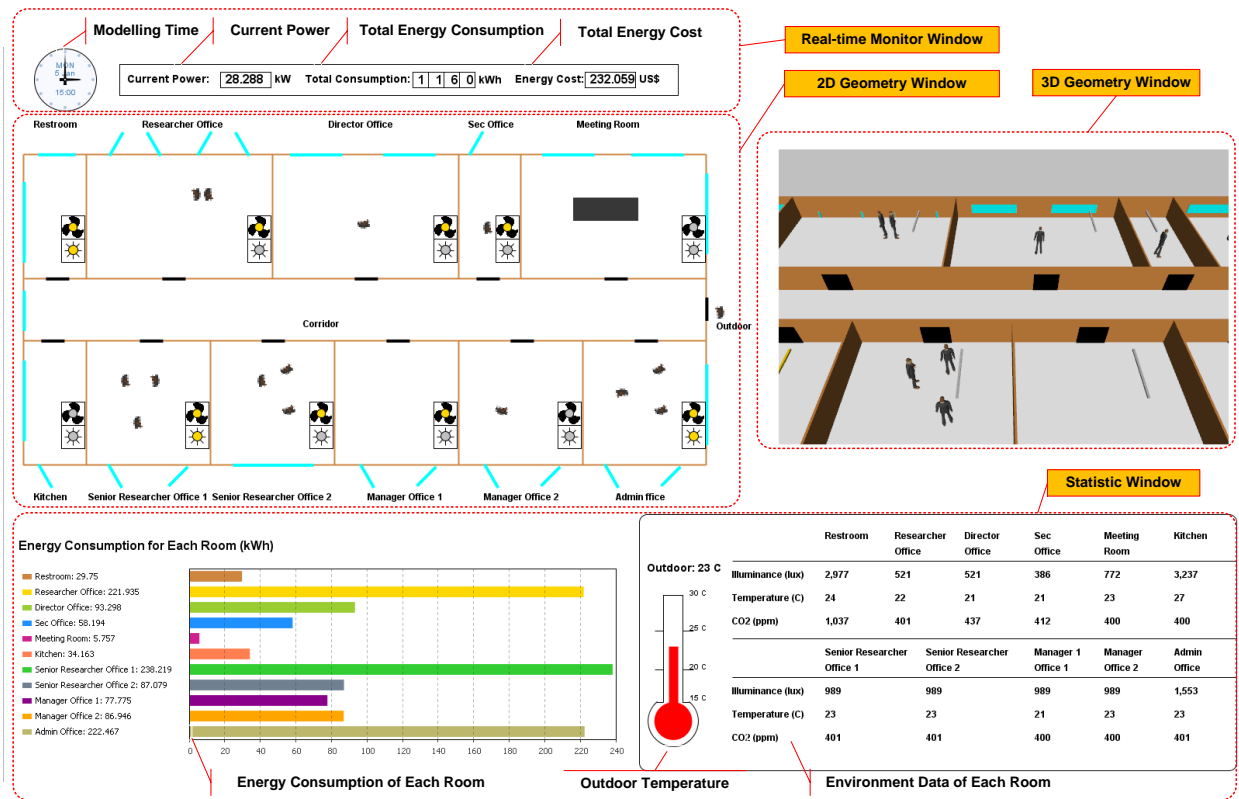
Visualization window: The visualization window is 1600 by 1000 pixel. There are four function blocks of the window (i.e., 2D window, 3D window, statistical figure and real-time monitor).

Input data: There are three categories of input data (i.e., energy and environment data, occupant movement data and occupant behavior data), which are from EnergyPlus, the Occupancy Simulator and obFMU respectively. The model reads the data flows from these three platforms, and then transforms them to visualized results.

Results

Visualization Interface

The interface of visualization model is shown in Figure 11, which includes four windows: (1) real-time monitor window; (2) 2D geometry window; (3) 3D geometry window and (4) statistic window. The real-time monitor window shows the general information of simulation, including simulation time, current power, total energy consumption and total cost of energy. The 2D geometry window shows the 2D layout of the building and the figures of four agents (i.e., occupant, light, window and air condition), which is introduced in Section of Agent Definition. The 3D geometry window shows the same information as 2D geometry window, but in 3D space. The statistic window shows more details of simulation results, including energy consumption, temperature, CO₂ concentration and illumination of each room. The energy consumption of each room is shown in the bar chart changing with time, which can obviously reveal the energy consumption of each room in real time. The outdoor temperature is shown by the figure of the thermometer. The height of red bar in thermometer indicates the outdoor temperature. The details of environment data of each room are on the lower right table, which shows the real-time simulation results.



* Note: the lighting illuminance is only for the daylighting and doesn't include the artificial lights.

Figure 11. The interface of the visualization model in AnyLogic

Visualization of Occupant Movement

Occupants move continuously within 13 zones (i.e., 11 rooms, corridor and outdoor). Instead of using simple zone number to indicate occupant movement, this study can demonstrate occupant movement in 2D and 3D geometry with real building layout, shown in Figure 12 and Figure 13. This study considers the real routes of occupant movement. For example, if an occupant moves from the conference room to the restroom, he/she should go through the corridor. Furthermore, rather than transferring from one room to another instantaneously, this study considers the speed of occupant movement, which is one meter per second in this simulation. With the 2D/3D geometry, real movement route and the movement speed, the results of occupant movement can be modeled and visualized close to reality.

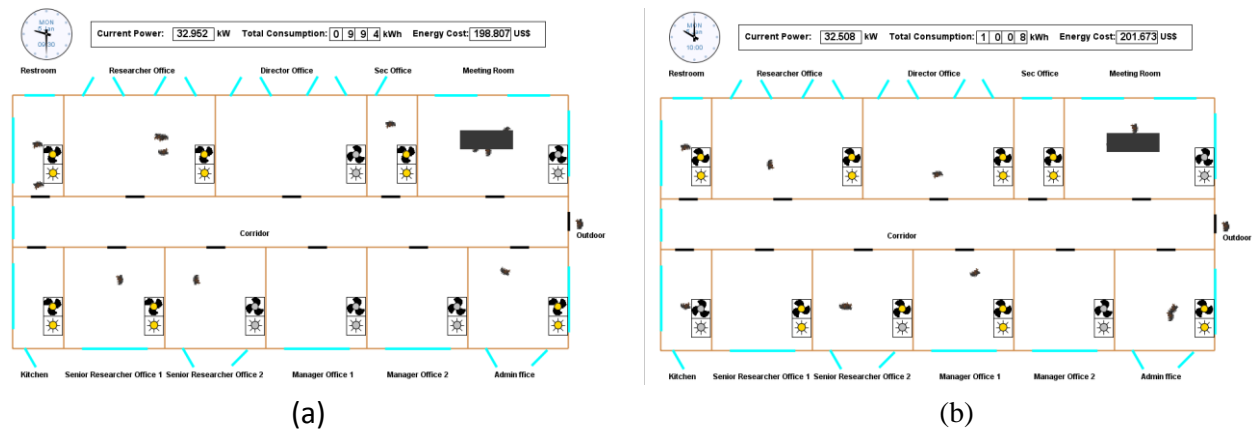


Figure 12 Occupant movement and behavior in 2D geometry

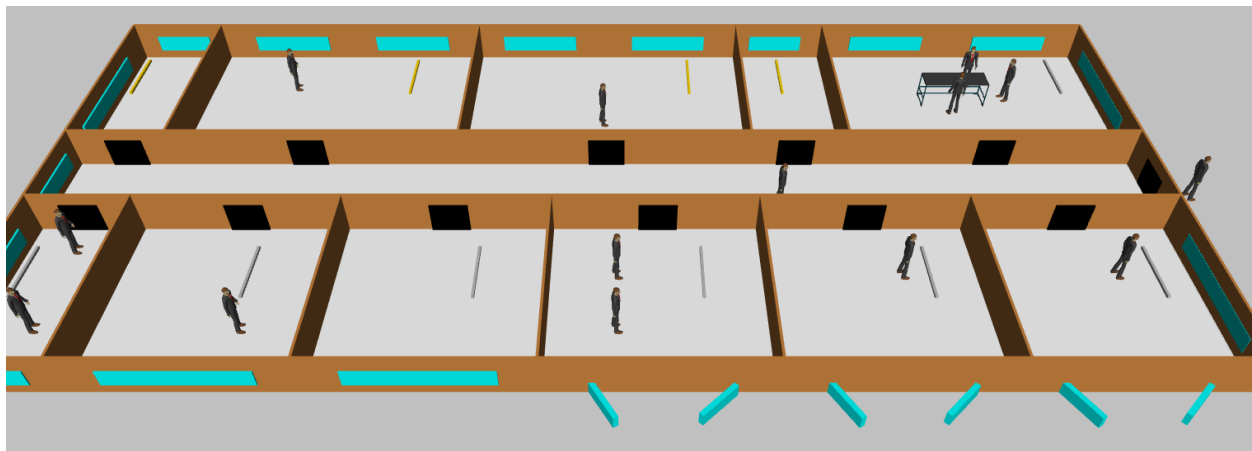


Figure 13 Occupant movement and behavior in 3D geometry

Visualization of Occupant Behavior

This case study focuses on three occupant behavior, namely light control, window control and HVAC system control. The statuses of related appliances are used to reveal these behaviors. For example, the on or off status of lights indicates the turn on or turn off light behaviors of occupants. The simulation interface shows the dynamic statuses of lights, windows and air conditioners, which demonstrate occupant behaviors. To illustrate how status changes during simulation, Figure 12 (a) and (b) are compared. In Figure 12 (a), the lights and HVAC systems of the Restroom, Researcher Office, Sec Office, Kitchen, Senior Researcher Office 1 and Admin Office are on, while others are off. The windows of the Researcher Office, Director Office, Sec Office, Kitchen, Senior Researcher Office 2 and Admin Office are open, while others are closed.

Figure 12 (b) is 30 minutes after Figure 12 (a). It shows that an occupant came into the Director Office, turned on the light due to the low daylighting illuminance of 473 lux, and turned on the HVAC system for cooling due to a high indoor air temperature of 26°C. Some other lights and HVAC systems are also changed by occupants during the 30 minutes period (e.g., the light and HVAC system of the Kitchen and the HVAC system of the Senior Researcher Office 2).

Visualization of Energy Performance

The accumulated energy consumption of each room is shown at the bottom left of Figure 11. The Senior Researcher Office 1 and 2 have similar settings (same occupant movement model, the number of occupants, orientation, size, lights, windows, and HVAC systems) except the occupant interaction behavior models. The results show the Senior Researcher Office 1 consumes much more energy than the Senior Research Office 2 due to the different interaction behaviors. The animation shows the lights and HVAC system of the Senior Researcher Office 1 operates longer than those of the Senior Researcher Office 2.

Discussion

The four tools used in the case study are available to the public: the Occupancy Simulator is freely available at occupancysimulator.lbl.gov; the obFMU is freely available at behavior.lbl.gov; EnergyPlus is freely available at energyplus.net; and AnyLogic provides a free personal learning edition and fee-based academic and commercial licenses.

Advantages

There are mainly three advantages of the presented occupant behavior simulation and visualization approach. First, it can synthetically demonstrate the temporal, spatial and occupancy information, which are the three most important dimensions of occupancy simulation. Previous studies overlooked the geometry and layout of the building, which caused the simulation results deviated from reality. In the proposed visualization model, the geometry of the

building is scaled down with a specific proportion. The occupants move in the space along real routes with appropriate walking speed. Compared to the method of previous studies, shown in Figure 1, the proposed visualization model is much closer to the reality and user-friendly.

Second, besides the geometry information, the proposed visualization model can demonstrate various occupant behaviors comprehensively with dynamic figures and colors. It can likewise show the interrelations among occupant behaviors, occupant movement, appliances/equipment, geometry and time. Therefore, this model integrates multi-dimensional information in a single view.

Finally, the proposed visualization model is easy for simulation result verification and real project application. Based on the second advantage, the occupancy simulation results can be shown comprehensively, and the interrelations among results can be revealed. It can help verify the simulation results. For example, if there is no occupant movement in one zone, but the light status is changed, it indicates the results are incorrect. Also, the visualized and animated figures help users understand the results in the real projects.

Expansibility and Applications

Since the visualization model is in loosely coupled structure using AnyLogic, mentioned in the Section of Methods, it can be modified and expanded easily. System parameters can be configured flexibly, and new functions can be implemented in further research (e.g., water use behavior, gas use behavior, and plug load behavior). Based on this model, various applications can be developed. For example, the comparison of different energy consumption between occupant control and sensor control, the different scenarios or modes of occupant behavior and the test of new systems (e.g. smart building control systems).

Limitations

The agent-based AnyLogic model provides the value of visualizing spatial phenomena. However, with the addition of special information, we lose the convenience to visualize temporal information. The animations are only good for visualizing results of short-term periods, such as one day or one week. It is not a good way to present results for an entire year. It should be pointed out that the AnyLogic model is intent to provide an additional way to visualize the occupant behavior simulation results rather than replacing the traditional methods using charts. Users can use charts to show the annual results and use the AnyLogic model to better understand the details of occupant behavior and their impacts on building energy performance.

In the simulation and visualization workflow, the occupancy simulation and the occupants' interaction with building physical systems are simulated separately. The current workflow does not capture the behavior such as leaving a space due to issues of thermal comfort or indoor air quality. Currently, we need to manually build the AnyLogic model. It is a big challenge to develop a module to automatically generate the AnyLogic model from the EnergyPlus and obFMU input and result files.

Future work

Future work is recommended to validate the model by comparing simulated results with detailed measured interval data (including occupancy and their interactions with building systems) from real buildings. The results visualization module was presented to stakeholders of policy makers, architects, and engineers, and received their positive feedback. However, a comprehensive feasibility and usability study is needed to evaluate the performance of the presented simulation and visualization approach.

Acknowledgment

This study is supported by the Assistant Secretary for Energy Efficiency and Renewable Energy of the United States Department of Energy under Contract No. DE-AC02-05CH11231 through

the U.S.-China joint program of Clean Energy Research Center on Building Energy Efficiency. This work is also part of the research activities of IEA EBC Annex 66, definition and simulation of occupant behavior in buildings.

Conclusions

The presented occupant behavior simulation and visualization approach provides a new detailed and visual way to show occupant energy behavior and their impact on energy use in buildings. The simulation workflow successfully demonstrated the integration of the Occupancy Simulator, obFMU, and EnergyPlus to evaluate the energy-related occupant behaviors. It provides a way to estimate the mutual effect of occupant presence, occupants' interactions with building systems and the energy performance of building systems. The AnyLogic results visualization module was newly developed to provide an additional way to visualize and communicate the importance of occupant behaviors with stakeholders of policy makers, architects, engineers and building operators.

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