A systematic development and validation approach to a novel agent-based modeling of occupant behaviors in commercial buildings

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Abstract

Occupant behaviors are one of the dominant factors that influence building energy use. Traditional building energy modeling programs use typical occupant schedules that often do not reflect actual situations. Robust occupant behavior modeling that seamlessly integrates with building energy models will not only improve simulation performance, but also provide a deeper understanding of occupant behaviors in buildings. This paper presents a development and validation approach to a novel occupant behavior model in commercial buildings. A robust agent-based modeling (ABM) tool, namely Performance Moderator Functions server (PMFserv), is used as the basis of the occupant behavior model. The ABM considers various occupant perceptions and interactions with window, door, and window-blinds based on the environmental conditions. An elaborate agent-based model that represents an office space in an existing building is developed. This is followed by a validation study of the ABM through the use of embedded sensors that capture the indoor ambient conditions and a survey to record actual occupant behaviors. By comparing the recorded behavior data with ABM output, this paper discusses the proposed ABM's prediction ability, limitations, and extensibility. Finally, the paper concludes with the potential of integrating the occupant behavior model with building energy simulation programs.

Keywords: Occupant behaviors; agent-based modeling; validation study; building energy; energy estimation

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1. Introduction

In the United States, buildings consume about 40% of the total energy use annually [1]. Therefore, abundant opportunities exist for energy savings associated with the building sector. In the life cycle of a building, six driving factors were identified by International Energy Agency (IEA) that will influence building energy consumption including climate, building envelope, building systems and equipment, building operation and maintenance, indoor environmental quality, and occupant behaviors [2]. From the past decades, research efforts have addressed some of the aspects for building energy efficiency [3-5]. However, among all the controllable factors above, building occupants are considered as a dominant factor that affects variability in energy use, while the studies pertaining to occupant behaviors in buildings for realizing energy-efficient buildings are still emerging. In addition, as one of the main functions of buildings is to provide comfortable context and services to the building occupants, research on the topic of occupant behavior modeling is helpful to develop a "smarter" built environment which is able to improve the occupant's comfort level and reduce building energy use at the same time [6].

Occupant behaviors influence building energy use in a various and stochastic manner [7-9]. As a consequence, occupant behavior information could serve as a crucial auxiliary element for improving building energy management in multiple aspects. On one hand, incorporating occupant behavior information into building simulation tools will potentially enhance energy simulation performance; on the other hand, occupant behavior information could be involved in managing building operations for system optimization and design of behavior interventions. Furthermore, occupant behavior is a key factor to evaluate building design and retrofit technologies [8, 10], as different occupant behavior patterns require corresponding technical solutions. A thorough understanding of how occupants interact with buildings and behave in buildings plays an important role in the building's life cycle energy performance.

A number of studies have shown that the uncertainty brought by occupant behaviors exerts significant fluctuation on building energy use [8-13]. However, existing building energy simulation programs use a relatively complete modeling system for physical and external design factors while oversimplifying the internal ones, particularly the interactions between occupants and building components. These programs have largely ignored occupant behaviors and instead treat occupants as "static" object. While an occupant interacts with the building depending upon the real world environmental conditions, these interactions are represented statically over time as opposed to their "dynamic" behaviors. This leads to large discrepancy between predicted and monitored energy use in most cases [14]. The error could be as much as 300% according to [15]. Turner and Frankel [16] compared the measured and predicted energy use for 62 LEED buildings and found obvious differences for all the buildings, and attributed part of the reasons to the fact that occupants act and interact with building dynamically in response to the changing ambient settings.

Building occupants are the “users” of the building, whose actions vary over external conditions and among different individuals. In the context of built environment, research focus is mainly on the direct interactions between occupants and building, which are usually referred as energy-related behaviors [17]. It typically includes the use of a building component (e.g. window opening/closing) and the control of building systems (e.g. HVAC, lighting, appliance). Particularly within commercial buildings, physical comfort is the priority of occupants to interact with the building.

Due to the complex mechanism of occupant behaviors, it is difficult to model every single possibility with one methodology. Hence, the modeling approach of occupant behaviors generally depends on the scope and purpose of the research, as well as the available technology and methodology support for the model. In fact, this topic has attracted numerous researchers’ attention in the past few years [18-20]. Among different occupant behavior modeling methods, agent-based modeling (ABM) was proposed by many researchers as one of the most effective methods. According to [21-23], ABM has the capability of addressing multiple behaviors together, and can represent both individual- and group-level interactions of autonomous agents. Particularly, an agent in ABM can simulate humans by incorporating characteristics of the surrounding environment and adaptation to changes in order to achieve a certain goal. In contrast with other modeling approaches, ABM begins and ends with the agent’s perspective. Agents have their own characteristics including sensations and behaviors, and they have the capability of interacting with their environment and other agents, which is governed by defined rules. The rules are the foundation to model agents’ relationships, interactions, and behaviors. A standard ABM is comprised of three elements [24]: 1) Agents, along with their attributes and behavior options; 2) Rules and topology, which defines how and with whom agents interact; and 3) Agents’ environment, which agents interact with in addition to other agents.

This paper proposes a novel ABM to model building occupants and their interactions with building components. Because occupant behaviors vary according to building types, occupant types, and accessible behavior options, it is impractical to integrate all potential scenarios in a generic model. Therefore, this research narrows down the scope to commercial buildings, and the occupants modeled are all full-time users without long-term absences. Direct interactions with building components are the targeted behaviors in this research. Personal activities such as reading, sitting, walking, writing, and other subtle activities are not studied.

The research follows a systematic sequence of development and validation for the occupant behavior model. First, a human behavior modeling tool based on performance moderator functions, PMFserv, is used to develop an ABM with a real-world educational building as test bed. This is the first time PMFserv has been used in the building simulation domain. Next, several rooms in the building were monitored to collect environmental data as ABM inputs, and actual behavior was recorded for comparison with ABM outputs for model testing and validation. Results showed the applicability of the model to be integrated with building energy algorithms for improved energy estimation.

The remainder of the paper is organized as follows: Section 2 reviews the previous research on occupant behavior modeling for building energy efficiency; Section 3 discusses the development of the ABM for the purpose of modeling occupant behaviors in commercial buildings; Section 4 presents a validation study of the developed ABM; and Section 5 offers a discussion on the limitations of the development and validation approach to the ABM, and concludes with recommendations for future improvements.

2. Literature Review

Because of the complexity of occupant behaviors, researchers have attempted to model occupant behaviors in building through various methodologies [19, 25]. For example, Papadopoulos and Azar [26] divided occupant behavior models into three parts: white-box (based on physical equations), grey-box (based on statistical and stochastic process), and black-box (based on machine learning algorithms); Hong et al. [17] classified the models as implicit and explicit, with the first addressing behavior-related physical systems, and the second one dealing with occupants directly. Based on a comprehensive survey [19], this paper proposes a classification in terms of whether the model is built on the basis of data, and thus classified general occupant behavior models into data-driven and simulation-based models. In short, data-driven modeling approaches require a large volume of data to develop statistical models of studied behaviors, whereas simulation-based models are based on pre-defined or empirical rules that regulate the behavior patterns.

A larger portion of earlier studies focused on data-driven methods. In [15], the researchers collected data during three seasons for four indoor and five outdoor environmental factors along with the window position from 15 buildings. The data was fitted using a multivariate logistic regression model to predict the probability of a window opening or closing event. Zhou et al. [27] studied window operating behaviors in an open-plan office occupied by multiple people. A combination of questionnaire and field measurements was conducted to acquire subjective and objective information about the studied behavior. That study discovered three patterns for window operation, and concluded that outdoor temperature, occupancy schedule, and on-off state of air conditioning are the main influencing factors. Ren et al. [28] focused on air-conditioning (AC) behavior only, and used a Weibull function to build statistical models for AC on-off events with the triggers being indoor temperature and house event, respectively. The research covered 34 families among eight different cities, and found the behavior patterns differ in these locations. Ahmadi-Karvigh et al. [29] proposed a framework of action detection, activity recognition, and associated energy waste estimation. They used plug meters to measure power usage of appliances and light sensors for lighting intensity, to detect occurred actions using clustering techniques. Then, semantic reasoning based on an ontology was applied to capture combination of different activities. According to the ground truth data collected for two weeks, the performance showed a high accuracy for real-time activity recognition.

In addition, researchers also studied occupancy status modeling using data-driven methods, which is less complicated than occupant behaviors. Dong and Lam [30] developed a Hidden Markov Model using a complex environmental sensor network in a workspace. Zhao et al. [31] used data mining techniques with electricity consumption data to train models of appliance use schedules that reflect passive occupant behaviors. Yang et al. [47, 48] modeled short-term and long-term occupancy status using classification and time series modeling methods respectively, with a set of sensor boxes consisted of multiple built environment variables. Similarly, [49] collected data using PIR sensor and reed switch for binary detection of occupancy in ten offices. More literatures can be referred to [50-52]. The modeling of occupancy can be considered as the prelude for occupant behavior modeling and, therefore, has been given more attention in the past.

Data-driven approaches benefit from the variety of data collection and analysis methods. Among others, a statistical or machine learning model eliminated the effort to discern the causality between occupant behaviors and relevant stimuli, and provided an opportunity to discover results beyond a specific model. However, the approaches often suffer from the applicability issue, i.e., that the models may lose their prediction capability if applied to other buildings or populations [8]. In addition, a long-term and large-scale historical data collection is needed for model development, which can be intrusive to experiment objects. Last but not least, most studies using data-driven methods usually focused on one or a few behaviors, therefore, the developed models lack of ability to expand to other behaviors as a whole.

In contrary to the data-driven models which are normally based on actual buildings, simulation-based models are established within a virtual environment. Particularly, agent-based modeling has recently become popular as one of the most powerful simulation-based approaches for occupant behavior modeling in the built environment. Azar and Menassa [23] presented an ABM that explores the impact among occupants in an office. Three types of energy-consumers with respect to energy use patterns were defined. The study assumed that energy conservation occupant behaviors would be learned over time so that high energy users will eventually turn to lower energy users. As a result, total building energy use would decrease by more than 25% compared to traditional static occupancy information. Alfakara and Croxford [32] simulated occupant behaviors in residential buildings in response to summer overheating. A probability profile was created to illustrate the impact of ambient temperature change on window and air conditioning behaviors. By adjusting the profile threshold that represents different user modes, the behaviors were different under certain temperature ranges. Similarly, Kashif et al. [33] also focused on residential buildings, stated that usual time and environmental factors are the inputs that cause certain needs, which in turn lead to associated behaviors. The application example in the study described a fictional household situation. In the research of Lee and Malkawi [22], an ABM based on three beliefs was proposed. The researchers introduced a cost function that integrates the beliefs, and defined a goal-oriented system for agents to make behavior decisions. The ABM modeled five behaviors in an office area and analyzed the behavior impact to comfort level and energy use intensity.

One of the major limitations for most of the studies using an ABM is the lack of actual data involved in the model. Few researchers validated their models using data collected in-situ. Moreover, in most cases, the model is based on a sample or simplified prototype which may lead to doubts whether the simulated agent will perform the way actual occupants do, thereby, leading to deficiency in model reliability. Only a limited number of model validation studies were observed in the literature. In [21], a validation study was conducted to test the ABM which is based on Perceptual Control Theory. The model outputs were found to be comparable to the field measurements for individual and aggregated predictions. However, the model only considered thermally adaptive behaviors, and only selected behaviors were validated. Putra et al. [34] investigated the impact of load shedding on occupant comfort and behaviors. The ABM included heterogeneous agents and perception preferences and several simulation scenarios. Yet, only four of the simulation scenarios were examined with measured data and the test results failed to show an acceptable level of accuracy.

Table 1 summarized existing studies on building occupant behavior modeling using ABM. It is noted that validation studies of ABMs for occupant behavior modeling are not prevalent and the suitable testing method is not well developed. Furthermore, there is no consensus on the theoretical basis for ABM development. There is a need for further development of new ABM approaches that moves beyond existing occupant behavior models, and collection of actual occupant behavior data for model validation to support future application of the model (e.g. integration with building energy simulation).

Table 1. Research on occupant behavior modeling in buildings using ABM.

References	Building type	Modeled behaviors	Behavior drivers/stimulus	Key modeling rules	Platform	Is validation included?	ABM based on real building
[23]	Commercial buildings	Blinds, lighting and equipment, Hot water use	Energy conservation events; word of mouth influence	High energy consumers will turn to low energy consumers over time	AnyLogic	No	No
[33]	Residential buildings	Not specified, but a generic modeling	Usual time; environmental factor	Based on belief-desire-and-intention (BDI) architectures	Brahms	No	No
[21]	Commercial (office) buildings	Clothing adjustment; personal fans on/off; personal heaters on/off; thermostat up/middle/down; Windows open/closed	Thermal conditions (temperature, humidity, air velocity)	Perceptual Control Theory (PCT), with a complex customized modeling rules	MATLAB	Yes	Yes
[22]	Commercial (office) buildings	Blind use; clothing adjustment; door use; fan/heater use; window use	PMV value that is influenced by temperature, air speed, RH, etc.	OODA (observe, orient, decide, and act) Loop based on three beliefs	MATLAB	No	No
[34]	Commercial buildings	Adjust clothes; use local heater/fan; contact manager; adjust overhead light, task light, and blinds	Load shedding events; communication with manager	Building occupant, tenant representative, and building manager have different behavior options	NetLogo	Yes	One building for calibration, the other for verification
[32]	Residential buildings	Window and air conditioning (AC) use	Temperature	Probability profiles for the modeled behaviors based on temperature variation	Repast	No	Yes
[17]	Office buildings	Lighting control; window operation; HVAC control	Temperature; CO_2 concentration; daylight level	A drivers, needs, actions, and systems (DNAs) schema; Weibull functions to determine probability of behaviors	obFMU (customized with Functional mock-up unit)	No	Not specified

This paper	Commercial (office) buildings	Open and close of blinds, window, and door	External perceptions, value systems of human	See section 3 for details	PMFserv	Yes	Yes

2.1 Research aim and contributions

Based on the current research gaps, this research adopted a physiological- and psychological-based tool (PMFserv) that can be used for in-depth representation of human behaviors. The authors tested the feasibility of using PMFserv in two preliminary studies [35, 36]. A new and refined ABM using the platform for occupant behaviors in a built environment context that takes into consideration thermal and visual comforts as well as indoor air quality is discussed in this paper. The model differs from ABMs of other researchers in two aspects: first, the model adopts a human-oriented mechanism that considers the value systems of a person. In other words, the behavior output of agent is not solely based on the external factors such as built environment, but also involves how a person evaluates his/her needs based on the current external conditions. In this way, the model is more comprehensive and closer to the reality, and can be tuned based on different agent characteristics. Second, the model is developed in parallel with the subsequent validation study in terms of modeling units. The modeled built environment parameters and behavior options align with the data collection rooms, which is significantly different from most of the previous research that are usually based on a hypothetical situation.

The contributions of this paper to the building energy scientific community are two-fold: first, the development of the novel ABM demonstrated the feasibility of using a tool in the built environment area that was originally built for fields of social science and system engineering. The tool captures broader aspects of human behavior modeling paradigms, which may inspire ideas for future model development. More importantly, since most of the studies using ABM were based on synthetic data and scenarios, this research attempts to fill the gap by proposing a method for validation studies based on the developed ABM, in terms of data collection and model evaluation approaches. Table 1 also included this research in comparison with relevant literatures in the past, for the purpose of supporting the intellectual merits of the proposed work.

3. Development of ABM

The proposed ABM has three major parts. First, the agents in the model are building occupants. The model used in this research considers physical perceptions and mental cognition of individuals as the main features of agents. Meanwhile, emotion, stress, and physiology status are also included as useful factors for modeling.

Second, the environment which agents interact with in the model is within the thermal zone or room in the building. The ambient environment is the direct stimulus that influences the agent's behavioral decisions. Under the current model, other building properties such as room size, shape, location, etc., are excluded in the ABM as these have less impact on the occupant behaviors for the purpose of this research. This assumption is demonstrated to be valid and feasible in most of the cases [15, 17, 21].

Lastly, as the built environment and building component states are identified, it is expected that the agent will possibly accommodate accessible building components for their individual comfort level when values of environmental indicators exceed certain amount of the occupant's acceptable range. However, it should be noted that the ambient environment is not the only external factor that influences behavior in reality. For example, time, economic concerns, and other preferences of the agents can also affect the behavior patterns of building occupants [23, 33], especially in residential buildings. As this study focuses on commercial buildings, the dominant trigger for the agent is its thermal and visual comfort, and air quality level.

3.1 ABM platform and internal functioning modules

PMFserv is a server of many different Performance Moderator Functions (PMFs) that have been extracted from the social and human behavioral literature. PMFserv platform and its derivatives are built centered on multi-resolution agent-based approach [37], while the agents are generic in representing human under user-defined contexts [38]. The rationale for choosing PMFServ was to capture the realism in human behavior. The modeling platform has been successfully applied to simulation studies involving social systems [38] and healthcare [54]. Moreover, the value of PMFserv is not to just return a decision but explore the human behavior behind it, with multi-layer output panels available related to the agent, which can be extensively utilized for future studies. This research adopts the internal algorithms and modeling architecture within the platform, and customizes each module based on the modeling target, which is referred as a "grey-box" modeling method. Although not a fully-developed model using the tool, the occupant behavior model complies with the functions and rules as briefly described in the following.

Function 1: agent physiology, stress, and coping style

This module stores and maintains the agent's state of biological systems such as physical energy level in the format of tank flow, which eventually influence the agent stress status. The agent's behavior is bounded by the stress status. This function is the native property of an agent, which can be used for behavior constraint that leads to behavior failure with some probabilities. However, in this research, it is considered that no behavioral failures will occur under the modeling circumstances.

Function 2: agent emotions and value systems

The emotion and value systems function is the major determinant of the agent's cognitive appraisal of the environment, which can be measured by composite utility of the behavior options for the agent. The value system is characterized by a Goal, Standard, and Preference (GSP) tree based on utility norm and Bayesian theorem that defines the agent's short-term needs, behavior standard, and long-term preferences of the world.

Function 3: agent perception and object affordance

The perception function in PMFserv defines how an agent perceives the objects and other agents surrounded in the virtual world and thus searches the environment for a potential action to take that affords the agent in terms of needs satisfaction. In this research, the rules that govern the perceptual types are the focus of the occupant behavior model, as the application of PMFserv to the built environment area. Customized rules are described in section 3.3 as case study examples to elaborate the specific implementation of this module.

Other Functions

Besides the major functions above, PMFserv provides sociology module that is able to model socially aware agents and groups. For example, this module characterizes relationships between different agents in the environment and how they influence each other's emotions and decisions.

3.2 Model execution principle

In general, the agent is equipped with three elements: 1) the perception system, determined by the surrounding environment (object) that provides context information; 2) the value system, which stands for the agent's cognition mindset that is represented by the GSP tree; and 3) personal properties, which includes stress, and physiology, that will be swayed by behaviors. The behavior decision is made based on a factor that measures the importance of each behavior option – the Decision Utility. This factor is directly associated with value system and personal properties, and indirectly associated with perception system, and varies at each time step.

The developed model executes the simulation process on a time-step basis. There are no particular time restrictions. At each time step, the model outputs one behavior that the agent gives priority. From the beginning of each step, context that consists of the input and other supporting parameters defined by authors provides the micro-context values which deal with different dimensions of the context (in this case, ambient condition and state of building components) to the agent. Thus, the agent evaluates the perceived state of the environment based on the context and determines the current behavior options that are activated under the condition. The activated behavior options, in turn, arouse the related weighted values of the value system and personal properties, and make the agent appraise these behaviors by summing up the weight numbers as the Utility for final decision. Following this algorithm, the behavior option of the highest calculated Utility is decided by the agent (occupant) as the output behavior at each time step [38].

The decision-making process for the ABM platform is illustrated in Figure 1, which combines the agent's mental cognition (represented by the value system) and the physical perception of the environment (represented by the perception system and influenced by the Object). In the model development formation, the authors focused on the latter part for accommodation in the application area of built environment. Specifically, by updating input environmental variables' values at each time step, three types of perceptions (refer to section 3.3.1 for details) will possibly be triggered. Meanwhile, the status of the associated building components are in combination with corresponding built environment indicators to reflect the current overall situation so that the agent will take an action to improve the situation or stay put if satisfied.

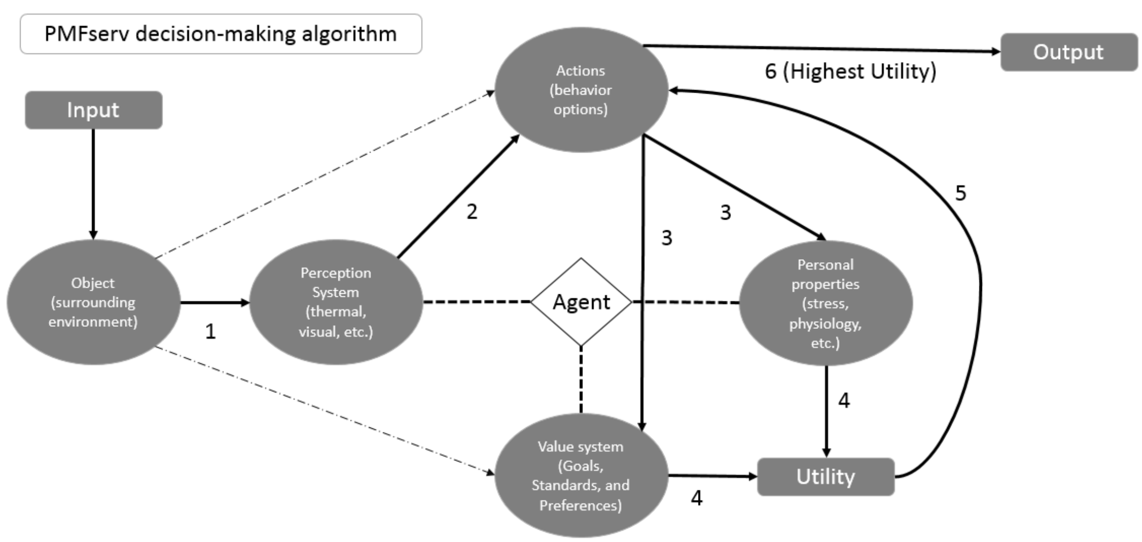

Figure 1. Decision making process of the agent

3.3 Model development based on a case study building

The ABM platform provides generic functional modeling modules and relevant calculation algorithms for agent decision-making. For the purposes of this research, a new instance of the ABM was created such that it represented an actual office space in an educational building situated in the University of Florida (UF) campus. This requires identification of model components (e.g., indoor ambient environment, building components that the agent interacts with), modeling rules (e.g., agent comfort levels), etc. It is to be noted that no generic model of a typical office building exists in the PMFserv platform and, hence, the ABM was developed from scratch.

The case study building is a three-story building on the UF campus. The third story is primarily faculty offices on the west side, offices for the administrative staff in the north side, research centers along the east side, and graduate student offices in the core of the building. This building is served by a centralized Heating, Ventilation, and Air Conditioning (HVAC) system. Conditioned air is supplied to thermal zones via Variable Air Volume (VAV) units, typically, three adjoining faculty offices constitute one thermal zone, i.e., supplied by one VAV unit.

Office occupants have control to open and close windows, doors, and window blinds. However, these occupants do not have access to thermostat controls. The lighting systems are fitted with occupancy sensors, yet can be turned off manually when necessary. A few occupants have personal devices such as heaters or desk lamps that are used for their individual thermal comfort purposes.

3.3.1 Main functioning modules of the developed ABM

The next step in ABM development is populating data to the main functioning modules to represent the occupant; this occurs in five sub-steps namely defining (a) occupant characteristics (agent's emotion, physiology, and stress levels), (b) object that can be perceived by occupant, in this case, the ambient environment and building components' states, (c) occupant goals, standards, and preferences (agent's mental awareness and cognitive levels), (d) occupant perceptual types (agent's level of thermal and visual comfort, and indoor air quality), and (e) occupant actions.

Occupant characteristics: The occupant is a faculty occupying the office space. For this purpose, an agent prototype referred to as "Professor" was created in the library that has native properties such as emotion, physiology, and stress levels. Default values were used for the initial condition, assuming that agent simulation process always commences at the beginning of the day under study. The emotion, physiology, and stress levels are personal to the agent, essentially, their individual internal status. These are subject to change owing to agent's personal properties.

Object perceived by the occupant: Agent directly perceives and interacts with the environment modeled. It is considered that the indoor ambient environment is the major driver that affects the agent's comfort level and, hence, its behavior decisions. As a result, the object of "Built Environment" was created. This object consists of what the agent perceives, i.e., the indoor ambient conditions and what the agent interacts with, i.e., the building components and their status (Table 2). Besides, the variable occupancy (room occupied status) was also created for the ABM rules definition, as the model will only be activated when the occupant is staying in the room. The values of all the parameters were initialized in the model, among which occupancy, building component status and the six environmental factors (Table 2) were served as model inputs during the simulation process, and the rest were fixed numbers during the model simulation process. These fixed numbered parameters that provide comfortable ranges of the agent are also used as arguments for the rules definition, and the values of human comfort level are referred from [39], i.e. maximum level of CO_2 is approximately 1,000 ppm. Table 3 listed the standard comfortable range of different environmental parameters used in the model.

Table 2. Model parameters related to the agent's perception of the environment, interaction with building components and other items.

Items in Object module	Parameters in the model
Agent's perception of the environment	Outdoor environment: temperature, relative humidity;
	Indoor environment: ambient temperature, relative humidity, CO_2 concentration, illumination level.
Agent's interaction component	Building components: door, window, window blinds
	Status: open, close
Other auxiliary items	Occupancy: whether the room is occupied or not
	Temperature: assumed maximum and minimum indoor and outdoor temperature that can be reached (used for perceptual rules definition)

Table 3. Standard comfortable range of indoor environmental parameters

Parameters	Unit	Value
Temperature (High)	Celsius Degree (°C)	26
Temperature (Low)	Celsius Degree (°C)	18
Relative Humidity (High)	Percentage (%)	60
Relative Humidity (Low)	Percentage (%)	25
Carbon Dioxide Concentration (Max)	Parts per million (ppm)	1000
Illumination (High)	Lux (lx)	600
Illumination (Low)	Lux (lx)	50
Illumination (Ideal)	Lux (lx)	250

Occupant Goals, Standards, and Preferences Tree (GSP Tree): The GSP Tree determines the agent's mental awareness and cognition. It describes the short-term and long-term goals and value systems of the agent. For example, safety, economic, and health concerns are some of the typical items in the tree structure. All the items are following a hierarchical architecture and are given a weight value to reflect the significance of that item. These items are activated when a behavior is conducted in the simulation process, so that the values of the related items will be used for the "Utility" calculation for decision-making at the next time-step. In this model, a default structure of GSP Tree of a generic human's mindset, as well as the weight values for each tree item were used in the model after consulting with the platform developers. Refer to Appendix A1 for more details.

Occupant perceptual types: Agent's perception towards the surrounding objects, in this case, the office space, is a critical component of the model development. Previous studies [40] have shown that in the context of built environment, there are three primary types of physical perceptions namely, thermal and visual comforts and indoor air quality. Therefore, different combinations including a perception type and the state of related building components were created in this module. For example, the perceptual type of "FreshAirNeeded_Window_Close" refers to the scenario wherein the window is "closed" and the CO_2 level "exceeds a fraction of the comfort level". Meanwhile, these perceptual types are bounded by self-defined perception rules that are programmed with parameters defined in the object "Built Environment" as input arguments. Appendix A2 shows sample code that defined the custom perception rules for visual comfort perception. Once the current situation (building component states and environmental factors) satisfies the threshold of certain rules, corresponding perceptual types are activated so that the agent will have the possibility to conduct relevant behaviors. Therefore, each perceptual type is correlated to at least one behavior option, which is the last piece of the modeling units.

Occupant actions: The behavior options are the agent's degrees of freedom relative to the components above. After a short interview and observation of the targeted occupants/rooms, the most common behaviors are operation of window, door, and window blinds. Therefore, to build a model that is close to reality, the ABM incorporates six behavior options which consist of open and closed states for each building component. Moreover, as stated before, some occupants may have access to other miscellaneous devices (e.g. lamps, heaters) for environment control. However, behaviors related to ancillary devices were ignored since their use is not prevalent and the goal was to create a generic behavior model. With the behavior options being modeled, each behavior causes a result and returns the outcome to update values in the "Built Environment" object. In addition, a connection between each behavior and corresponding perceptual types was established, and the behavior influence on the designated items in the GSP Tree was defined, which are referred as affordances of the behavior. The significance of this property is to map environmental factors (model inputs) to behavior options (model outputs), while the decision-making algorithms calculate the Utility for each behavior during the simulation process of the ABM.

3.4 Model Execution and Discussion

The ABM was developed as a library that comprises the functioning modules above. To execute the model, a simulation scenario must be created. The first two modules, namely agents and objects, can be considered as class which is analogous to a class in Object-oriented Programming (OOP). These two classes must be instantiated in the simulation scenario for model execution. Thus, one or more instances could be added to the scenario, which increase the flexibility of the model. One of the benefits of this setting is that the model (library) can be extended to multi-occupancy rooms. Moreover, it allows for a combination of various agents and objects from one library. For example, if needed, additional occupants such as student, staff and building manager can be created; objects including time, and room properties can also be added to the library. Hence, the model can be applied to any rooms at the building level, which increases the versatility of the model.

When executing the model, the values of the input environmental parameters in the "Built Environment" object are updated at each time step in the created scenario. If certain perceptions are triggered at the moment, the model outputs one behavior that the agent prioritizes; otherwise, the agent will not conduct any behavior on the building components. The item status of corresponding component in the object will be automatically updated based on the output of that time step. The model execution repeats the process and progresses beyond the former step until simulation ends. The simulation executed in the scenario does not influence values of the modules in the original library. Final behavior outcomes can be exported for further uses such as validation study or simulation integration.

4. Validation Study of the Developed ABM

Since ABM is a simulation-based modeling approach, a validation study is necessary to enhance the reliability and robustness of the model. This requires a time interval record of environmental parameters and occupant behaviors. The analysis of ABM output using real-world ambient environmental data and actual behavior can be used to assess performance and also tune the settings and rules of the ABM. The validation study investigates how specific occupants react to the changing environment and evaluates the ABM through results comparison. It also aims to facilitate the integration of the ABM with building energy simulation engine as future research.

4.1 Environmental and Occupant Behavior Data Collection

4.1.1 Data collection approaches

The data collection for this research includes two parts, namely environmental data sensing and occupant behavior data recording. Related indoor environmental data was measured with a customized sensor node. The sensor node is comprised of an embedded single-board microcontroller computer, and three separate sensors that record indoor temperature (Celsius degree) and relative humidity (%), illumination (lux), and CO_2 concentration (ppm), respectively. A programming script was written and uploaded to the sensor board to configure the assembling device and log the environmental data along with a time stamp. The time interval for data collection was five minutes. All data were stored on a Micro-SD card. One of the advantages of the customized sensor node is its flexibility, which allows more sensors to be added to the sensor node if necessary. The data file was uploaded to a cloud drive every two hours via the Wi-Fi connection. Figure 2 shows the configurations of the sensor node.

Figure 2. Customized smart sensor node

Since the ABM requires outdoor ambient temperature and relative humidity as model inputs, these data were acquired from a local weather report website [41]. The website provides historical weather data collected by different weather stations that are spread in the locations of interest. For this study, a weather station located near the building was selected as data source. The temperature and relative humidity data with time information were extracted for the studied time period at a time interval of 30 minutes to one hour.

For behavioral data, a daily survey with behavior options and corresponding time intervals was used. To balance the data precision and to avoid disturbing occupants, the time interval was set to 15 minutes from 8:00 AM to 5:00 PM. Additional time intervals could be added according to the occupant's actual schedule. The survey sheet is attached as Appendix B. The monitored occupants were asked to initialize the starting status of the targeted building components every day, and then manually make a check mark at a box corresponding to a certain time whenever a behavior occurs. The survey was approved by Institutional Review Board (IRB) at UF to protect the privacy of the persons in the experiment. Meanwhile, a commercial off-the-shelf system consisting of a central hub and a set of magnetic sensors was installed on the door and window in one of the rooms, to log their open/close status through an Ethernet connection. This sensor system was used only for validating the daily survey sheet for several days.

4.1.2 Data collection scale and preprocessing

The data collection area was limited to the third floor of the test bed building, containing a row of single-occupancy faculty offices located on the west side of the building. Although random sampling was not used, based on the actual situation in the building and references from literature [21], five offices were selected with occupants of different genders and age ranges in order to avoid skewing the data. Five sets of sensor nodes and daily survey sheets were distributed to the offices with overlapping data collection time periods. Figure 3 shows the floor plan and targeted rooms of the building. The targeted occupants were given multiple daily survey sheets and were requested to complete the survey voluntarily, preferably on consecutive days. Embedded sensor boards were placed on the desk close to the occupants, and were never powered off during the data collection period.

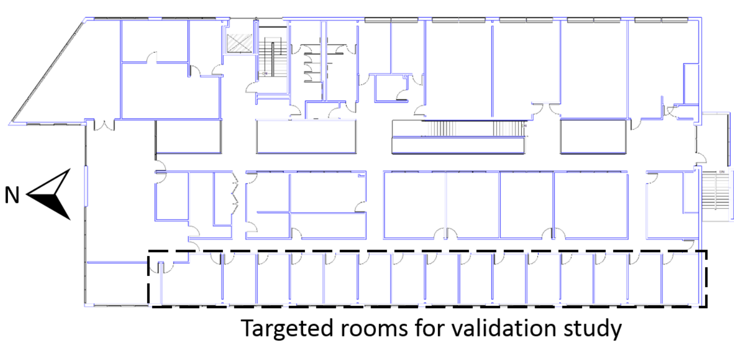

Figure 3. Selected sample rooms for validation study

The data collection period was in the spring season, during which the temperature and relative humidity variations between day and night are conducive to opening windows and the sun is low in the western sky during working hours.

Four-week volumes of survey sheets were provided to the occupants and two to four weeks of data was returned depending on each occupant's availability. The data collection needs to be expanded with respect to both the number of spaces and the time period in order to improve the reliability of the validation result for the ABM. However, the current study is considered sufficient to evaluate the general performance of the model and draw preliminary conclusions based on the observed results. On average, there are 25 to 35 behavior records per person per day.

The raw behavioral data for each occupant over the validation period was preprocessed by converting the status of the door, window, and blinds into numerical values of "0" for closed or "1" for open. Therefore, at each time interval, a vector was used to record the current status of the door, window, and blinds. For example, [1, 0, 1] means the door is open, the window is closed, and the blinds are open at the moment. Also, at each time step, the ABM inputs were extracted from the environmental data collected by sensors, and a mapping of the ABM outputs onto the preprocessed behavior data at the same time interval was obtained for performance metric calculation.

4.2 Performance test of the developed ABM

Since the purpose of the ABM is to estimate how occupants interact with building components under specific environmental conditions, the simulated output from the ABM is compared to the recorded behavior using visualization and quantified performance metrics.

4.2.1 Evaluation metrics and methods

This research used a black-box validation method, i.e., the validation focuses on the final results as compared to white-box validation method that focuses on the internal mechanism and structure. The reasons are two-fold: First, Bharathy and Silverman [42] conducted white-box validation of the human behavior modeling platform. Several documents discussing the technical details of PMFserv are available [37, 38]. Therefore, for this research, it is not necessary to test the internal behavioral algorithms. Second, since the research goal is to enhance building energy modeling by adding the human dimension, a black-box validation is sufficient to demonstrate the validity for future application of the model. Therefore, the validation can focus on whether the output of the occupant behavior model reflects reality, so that incorporating the information to building energy model would potentially improve the modeling capability.

Four evaluation metrics are used in the paper to compare ABM simulated and actual behavior data for validation, namely recall, precision, accuracy, and F1 score. The value span for the four metrics are from 0 to 1. The definitions of these metrics are easily interpreted using the data in this study. It is assumed that the status of "open" for all targeted building components are positive samples, and "close" are negative samples. Thus, each simulation output of a building component is classified as: a True Positive sample (TP), a False Positive sample (FP), a True Negative sample (TN), or a False Negative sample (FN). For example, for the window, TP indicates the number of time steps when the ABM predicts the window is open when it is open actually and FN is the number of time steps when the ABM predicts the window is closed while it is open. Similarly, TN indicates the number of time steps when the ABM predicts the window is closed when it is closed, and FP means the ABM predicts window is open while it is actually closed in reality. Based on this classification, the calculation for the evaluation metrics is as follows:

$$\text{Recall} = TP/(TP + FN)$$

$$\text{Precision} = TP/(TP + FP)$$

$$\text{Accuracy} = (TP + TN)/(TP + FP + FN + TN)$$

$$\text{F1 score} = 2TP/(2TP + FP + FN)$$

To conduct the comparison for ABM validation, first, the personal and environmental characteristics of the real occupants were fed to the agent and surrounding environment variables in the ABM. These include the same behavior options, comfort ranges, daily occupancy, and local environmental conditions. Then, the ABM was executed under the same conditions as the actual world, to obtain the simulated behavior results. In other words, as input parameters for the ABM, collected environmental data served as the virtual environment that represents the same conditions the occupant experiences in the real world. The process repeated at each time step to generate a list of vectors representing the status of the building components. Meanwhile, the actual behavior from the daily surveys were overlaid on the simulated results from the ABM for the same time period. Essentially, a direct mapping of simulated and actual data was obtained for analysis. Finally, for each behavior, the four standard metrics were calculated to measure the simulation performance of the ABM. This process was also used to calibrate the ABM from the validation results.

4.3 Results and Analysis

4.3.1 Individual-level evaluation

The five occupants in the experiment are referred to as A through E. The actual behavioral data from the daily surveys were compared with the ABM outputs, and plotted for analysis. Although the developed occupant behavior model aims to capture a generic behavior of faculty members, the behavioral differences between these individuals cannot be ignored. As shown in Figure 4 to 6, two out of the five sample occupants that show a distinct discrepancy in behavior patterns are discussed.

For occupant A, the simulation result and actual record of behavior for window blinds operation on a selected day are shown in Figure 4 (left), as well as the sole influencing environmental factor - indoor illumination. The actual status of blinds was open from the beginning through the majority of the day, which indicates the lighting intensity during the time frame satisfied or was slightly below the occupant's visual comfort range. Towards the end of working hours on the day, sunlight from the west-facing windows increased the interior illumination level significantly. The interior illumination level apparently exceeded the comfort level, which drove the occupant's decision to close the blinds. It is observed that the overall trend of the simulation result accords with the actual record. However, the simulated blind closing behavior occurred immediately when the illumination value started to increase, while the actual results reported a lagging after the parameter reached the maximum value. This delaying phenomenon was observed and studied in other research [43], which could be attributed to different reasons. Finally, the gap in the simulation result reflects a short time when the occupant was not in the office and no environmental inputs were used for those particular time steps.

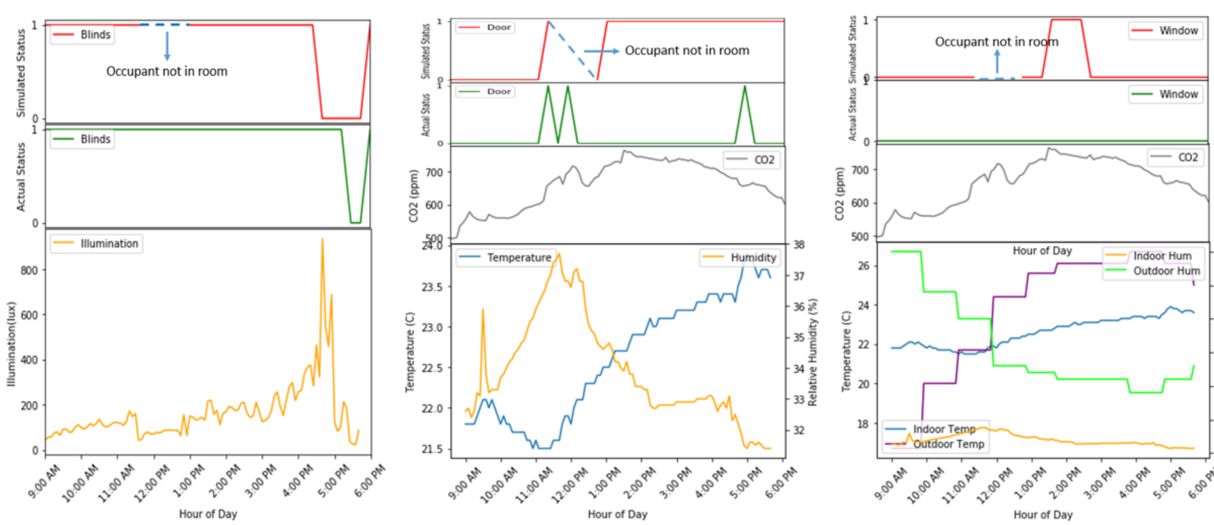

Figure 4. ABM simulation results and survey record for occupant A for blinds, door and window operation on a selected day, with the respective relevant environmental parameters.

Figure 4 (middle) shows the simulation result and actual record of door operation behavior on the same day. Three environmental parameters were considered influential to door operation, including indoor temperature, relative humidity, and CO_2 concentration. The actual record indicated an initial status of door closed at the beginning of the day, and some alternative changes occurred during the daytime. However, the simulated result only predicted two behavior alternations, and nearly one third of the time periods were not matching reality for the day. One of the main reasons of this observation is that door operation behavior is related to many other non-environmental factors. Examples could be a random visit of other building occupants, or some personal events such as going to class or restroom. The ABM can hardly capture these stochastic events under the current settings. However, the ABM indirectly considered associated factors such as privacy and security which somehow affected the simulation result. Generally, it is argued that the ABM is more reliable if the occupant's door operation behavior is mainly driven by environmental conditions.

For window operation behavior, two additional environmental variables including outdoor temperature and relative humidity were involved. For instance, if it is cold or humid, i.e. rainy, outside of the room, the occupant may still keep the window close even though the indoor environment is slightly uncomfortable. In addition, if the occupant perceives that the indoor air quality is uncomfortable (indicated by a higher CO_2 level) [53], he/she would normally open the window for fresh air intake. Similar to blinds operation behavior, the control of window is also influenced mainly by environmental factors. Particularly, in the test bed building, the window is the only building component for the occupant to adjust the room thermal conditions, given that the thermostat is not accessible in the room. Figure 4 (right) shows the window operation behavior for occupant A. It is observed that the occupant did not operate on the window on the day, while the ABM predicted a small portion of time for window opening behavior. There could be multiple reasons other than environmental factors that caused the actual state, yet the prediction performance generally conforms to the reality.

Figure 5 showed a same set of results of occupant A from another day. The observed outcomes for blinds and door are similar to Figure 4, where the explanations also apply to this particular day. However, it is noticed that the actual window status alternated on the day, which was probably influenced by outdoor environment and indoor air quality. The central HVAC maintained stable indoor temperature and relative humidity, while the outdoor environment had significant change during the day. But since the outdoor temperature was low, the ABM assumed that occupant would close the window for thermal comfort over air quality comfort at the beginning of the day.

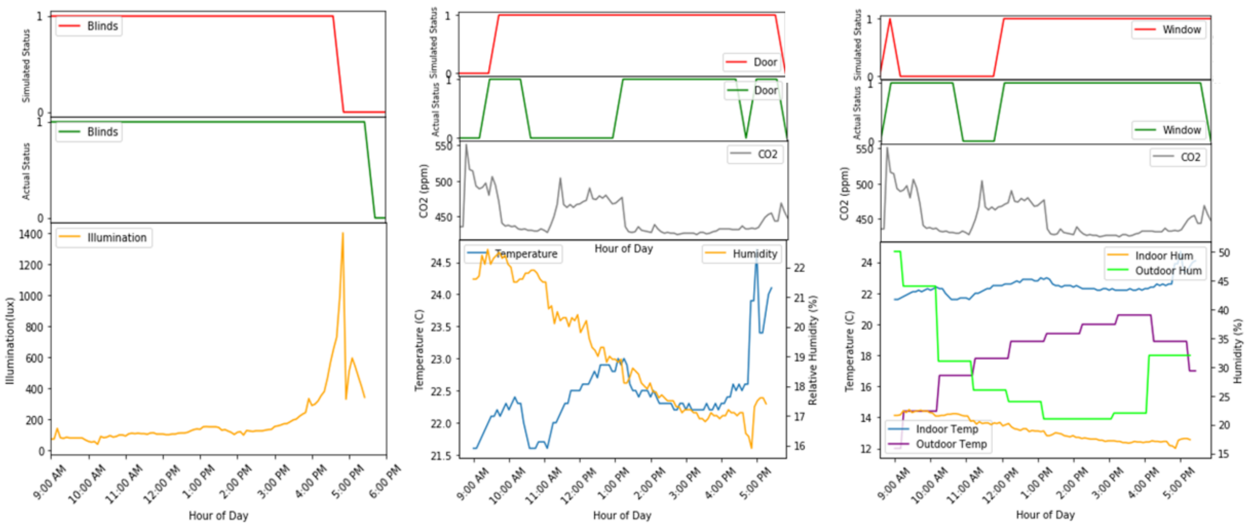

Figure 5. ABM simulation results and survey record for occupant A on another day, with the respective relevant environmental parameters.

In contrast to occupant A, the simulated behavior patterns of occupant B differ more significantly from actual behavior. Figure 6 (left) shows the window blinds operation on a selected day for occupant B. The overall lighting intensity in the room was much lower than the recommended light level for an office work environment. However, according to the survey record, occupant B did not operate the window blinds the entire day. The reason could be due to a different personal light intensity preference or because the occupant was using other sources of lighting for visual comfort, i.e. a desk lamp that was out of the sensor's range. Because the illumination level was low, the occupant behavior model predicted an open blind behavior. An interesting phenomenon is that around 2:00 pm, although the light level dropped to a very low level, the ABM did not output another open blind behavior. This is because at this time step, the model output another behavior according to the Utility function results, which indicates that there were multiple uncomfortable perceptions felt by the agent at that time period.

For the door operation behavior, the simulation results for occupant B captures a similar trend as the actual the survey record (Figure 6 middle), while some behaviors at certain time steps are missed. The reason for this observation is similar to the explanation of door behavior for occupant A. Occupant B left the door open most of the time, probably due to personal habit. The door closing behavior periods were comparatively short, which caused the simulation model to miss some behaviors. This could occur for many reasons other than environmental conditions, such as a short meeting, which are not included in the behavior model. However, the raw survey sheets show that the missing data records are infrequent and sporadic and thus do not affect the overall simulation results.

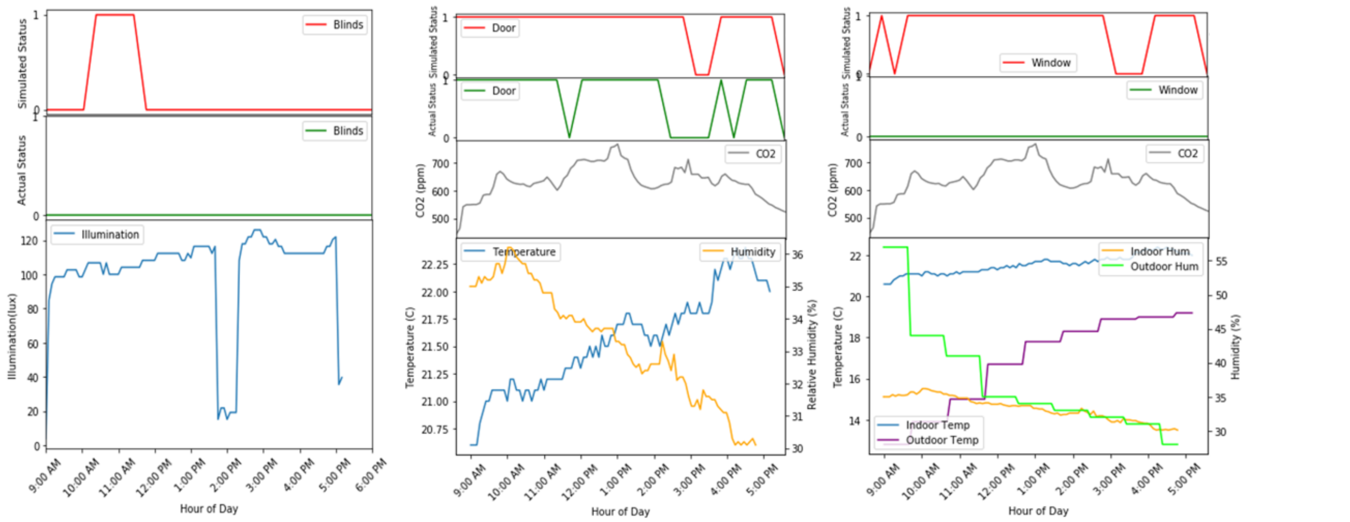

Figure 6. ABM simulation results and survey record for occupant B for blinds, door and window operation on one day, with the relevant environmental parameters

The actual record of window operation behavior for occupant B shows that the occupant never open the window no matter how the ambient conditions changed during the day (Figure 6 right). According to the on-site observations and interview with the occupant, opening and closing the window is not a normal behavior, unless an extreme situation occurs. However, since the ABM only focused on the influence of environmental conditions on behavior decisions, the simulation results show the window opening and closing during the day, mainly based on the level of CO_2 in this case. One of the reasons is that both the indoor and outdoor thermal conditions were within the comfort range for most of the day, which is typical in the spring season at the building location. As such, the ABM can serve as an advisor and suggest behaviors such as opening and closing windows that would improve indoor environmental conditions for the occupant.

4.3.2 Overall evaluation

Due to the complexity of occupant behaviors, the behavior pattern of each occupant is likely to be different. The survey results also indicate variations for the same occupant on different days given similar environmental conditions. Therefore, the virtual model does not aim to track exactly how people in the built environment will react to certain ambient conditions. On the contrary, the model is considered to be applicable if the overall performance reaches an acceptable level, in terms of the evaluation metrics. Table 4 summarizes the model performance. Note the overall results are not simply the average of all five occupants, since the five occupants occupied their offices at different times due to their schedules. Instead, the results are obtained by calculating the performance measures from behavior records of all occupants for each building component. This measure reflects the general performance of the ABM, as the model aims to represent a generic "faculty" behavior pattern.

Table 4. Agent-based model performance measure summary for the sample occupants

Occupant	Building system	Recall	Precision	F1 Score	Accuracy
A	Blinds	0.98	1.00	0.99	0.98
	Door	0.88	0.53	0.66	0.70
	Window	0.78	0.83	0.80	0.80
B	Blinds	N/A	0.00	0.00	0.39
	Door	0.93	0.81	0.87	0.79
	Window	N/A	0.00	0.00	0.67
C	Blinds	1.00	1.00	1.00	1.00
	Door	0.89	0.38	0.53	0.55
	Window	N/A	0.00	0.00	0.73
D	Blinds	1.00	1.00	1.00	1.00
	Door	0.98	0.84	0.90	0.85
	Window	N/A	0.00	0.00	0.84
E	Blinds	0.50	1.00	0.67	0.50
	Door	1.00	1.00	1.00	1.00
	Window	N/A	0.00	0.00	0.79
Overall	Blinds	0.82	0.84	0.83	0.74
	Door	0.96	0.79	0.87	0.81
	Window	0.78	0.35	0.49	0.77

It can be seen that for each individual, the model simulation performance differs for the three building components. For example, for occupant A, blinds and window operation have a higher accuracy, while the prediction accuracy for door operation is relatively low. Besides the explanation above, another possible cause is that the frequency of door control can be very high that repeated alternation of open and close happens during the 15-minute time interval. This in turn influenced the occupant's actual record for door operation, and eventually decreased the prediction performance for door behavior of the ABM. However, the recall value for door operation obtained satisfactory result, as well as the other two components. In other words, the ABM predicted the behavior of "opening" fairly well for occupant A. A low precision of 0.53 indicates the ABM falsely predicted opening the door while in reality it was closed for a portion of time steps. It is inferred that either the occupant has a wider comfortable range or there are other factors that influence the behavior even though the indoor environment is out of the comfort level.

Taking occupant B as another example, the simulation results deviate more significantly from the survey records. Although the door operation behavior has an acceptable performance, both window and blinds have lower accuracy. Recall is not applicable in this case, and the precision value is 0 for this occupant. The reason is that this occupant never reported opening the window or blinds. Therefore, since "opening" behavior is defined as the positive outcome, there are no positive samples for this occupant. As a result, true positive and false negative numbers are both 0, which makes the value of precision 0 and the calculation of recall not applicable. Similarly, the value of "N/A" and "0" appear in other occupants' results as well for the same reason.

In the summary statistics, referred to as "overall," behaviors on all three building systems achieve a relatively high accuracy, i.e., approximately 80%. From the perspective of black-box validation, the ABM can be applied for further use, i.e. simulation coupling. However, there are additional information to note. Specifically, for blinds use, most of the occupants kept the component open for better vision from natural light. This increased the positive sample numbers that leads to higher recall and precision; for door use, although all the parameters show a satisfactory value, the ABM performs much differently among individuals, with some of the reasons mentioned above. For window use, since most of the sample occupants did not open their windows, the positive outcomes are largely from occupant A. Lastly, the fact that the sample time steps for each individual are slightly different needs to be taken into consideration when applying the model for other research purposes.

To present the model testing results from a more comprehensive view, Figure 7A illustrates the status change percentages occurring in each of the three building components for each occupant during their self-reported time period. Different behavior patterns can be observed clearly from the figure. Notice that window opening status is not common for the five occupants, and blinds operation is also a rare behavior. A clue to this phenomenon may be because of the data collection season, which is spring with occasional rain during daytime. Also, these occupants have rather distinguished visual comfort needs. Specifically, for occupant C, a personal heater is presented in the office so that window is not the first option for indoor environment adjustment.

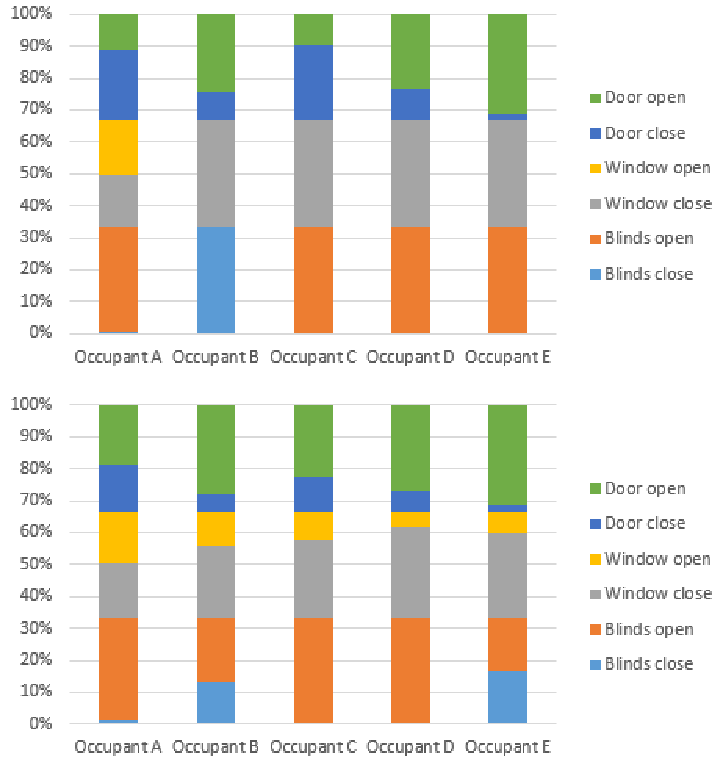

Figure 7. Actual (top, 7A) and simulated (bottom, 7B) building component status changes as a percentage of total events for three building components and five occupants during the survey period

Figure 7B shows the modeled status change percentages as a comparison to Figure 7A. Although the model is applied to all occupants, the simulated behavior patterns still present differences, owing to different inputs (ambient conditions) for the five offices. In addition, the simulated results show a similar proportion of behaviors to the measured results, demonstrating a good performance of the occupant behavior model for all five occupants. However, the simulated results have a rather symmetrical distribution in behavior outputs, especially for the window opening behavior. The blinds operation behavior is also slightly over-estimated by the model, but the error rate is much lower. One reason is that the ABM places thermal comfort and air quality comfort over visual comfort, which prioritizes the behavior options related to the first two perceptions.

4.4 Summary and Discussion

The observations of individual's behavior selected two representative samples (occupant A and B) to evaluate the model performance. As occupants have distinct characteristics, such as thermal and visual comfort ranges, different behavior decisions under similar external conditions were evident. This is reflected in Table 4, where the ABM performs well for some occupants but achieves lower accuracy for others, e.g., blinds operation for occupant B. Ideally, each individual should have an independent model tailored to reflect their own patterns, however, it may be impractical to customize separate models for each person occupying the spaces. One approach to navigate effort (i.e., multiple ABMs of individual occupants in the space) versus accuracy is to identify major occupant typologies by their function; an example in the case of educational building is faculty, administrative staff, and students. Each of these occupant types can be modeled which may lead to improved performance.

The survey records from the occupants show insights into occupants' perception and their interactions with building components. For example, some occupants have a rather stable pattern of behaviors in terms of the operation on the three building components, regardless of the variation of the ambient environment. The possible reasons may be summarized as follows: 1) they are always satisfied with the ambient environment (broader comfortable threshold); 2) other options exist such as desk lamp, personal heater, etc., which influence the use of the modeled building components indirectly. More research may be needed to understand the causality of driving factors and behavior decisions at both individual and group levels.

Finally, in terms of the generalizability of the validation results, though the ABM is developed to represent occupants in all of the faculty offices on the third floor, the actual spaces used in this study only accounts for one third of the targeted spaces. The individual-level results presented in this paper, owing to page limits, focused on one to two days with two out of five rooms as sample, which may not be generalized to cover the entire situation. These limitations are further discussed in the next section and will be addressed in the future improvement of the model. As a result, this validation study aims to provide domain researchers a feasible verification process rather than claiming an accurate validation result.

Although the ABM exhibited acceptable performance in the overall evaluation metrics results, the validation study could be expanded further to improve the robustness of the model, from perspectives of simulation and actual behavior comparison, and model architecture. This may include additional sample data over extended time periods, increased occupant numbers and types, and building types and spaces with varied orientations. Moreover, it is argued that the validation approaches should be designed based on the future application of the model. For instance, a time-step-based validation was conducted in this study, as the authors plan to implement a simulation coupling with EnergyPlus™ which is executing in a time-step mode.

5. Conclusions

Occupant behaviors are identified as an important influential factor of building energy use. A deeper understanding in the way occupants interact with building components not only provides valuable data to develop systems and controls to optimize energy use during the life cycle of the building, but also helps improve occupants' comfort. This research proposed a systematic approach that combines the development and validation of an ABM-based occupant behavior model for the purpose of gaining insights of how occupant behaviors change and differ individually, given a set of environmental parameter values. A case study that implemented the methods in a realistic commercial building was conducted to illustrate the validity and feasibility of the approach.

First, an ABM was developed in the context of the built environment that virtually predicts occupant's behavior. This model was built under the assumption that occupants may adapt to the surrounding environment through accessible building components for comfort. Subsequently, the occupant behavior model was tested with a black-box validation method, using the data collected by sensor nodes and a paper-based survey. The results on both individual and group levels indicated an acceptable fit on a time-step basis, which showed the validity of using the model for further studies such as integrating with building energy models. However, a few limitations still exist that should be addressed in the future.

Limitation 1: Barriers to Occupant Behavior Modeling using ABM

The occupant behavior model was developed with the assumption that environment is the only stimulant for occupant behaviors. However, many other factors also affect people's behaviors. For example, external factors such as occupant routine, schedule, room size or location, and internal factors such as personal background, e.g. comfort range, age, and gender, psychological state, and privacy all contribute to behaviors. The completeness of the model can be advanced by incorporating more relevant factors as behavior drivers. Nevertheless, from the perspective of an engineering study, it may be unnecessary or redundant to consider every aspect that may influence human behaviors, since this research does not intend to implement an accurate virtual reality environment, but focuses more on capturing the range of behavior and providing supplementary information for building energy modeling. In addition, as stated in [44], it is impossible to completely model occupant behavior, as individuals are too complex and random.

With respect to the randomness of people, the ABM only investigated the deterministic relationship between the behaviors and drivers. Stochastic influences should be studied to eliminate a definitive simulation result as opposed to the “random” nature of occupant behaviors. Moreover, some subtle behaviors that are not directly energy-related were excluded from the model. These behaviors may lead to effects which should not be ignored.

Limitation 2: Case Study Limitations

The case study is an example of the research methodology. The model has not been tested in different types of conditions and building types, such as shared and open offices, residential buildings or buildings with more complex functions. In fact, occupant behavior will vary significantly in different buildings due to the accessibility of occupant alterable building components and related factors. Despite the fact that this research is defined in the scope of commercial buildings, the generality of the model is limited to the current conditions.

Furthermore, the data collection period is four weeks in the spring, which does not cover the climate in a full year. However, people may have different preferences and habits during different seasons, leading to different behaviors under similar environmental conditions. In addition, only five occupants were selected as research samples, which can be expanded to a larger scale. The offices are all single-occupancy rooms, which means no interactions between multiple occupants were considered. This condition, however, has been studied by other researchers as separate research and can be modeled in the modeling platform if needed.

Last, but not the least, the paper-based survey not only caused certain disturbance and pressure for the occupants, but might also lead to data collection errors. Manual report is error-prone for a longer duration of data collection. This can be improved by installing smart sensing devices on targeted building components that can automatically log object status data with more detailed time granularity.

5.1 Recommendations for Future Study

This research systematically established an occupant behavior model for improving commercial building energy efficiency, which lays the foundation for future studies. The proposed research workflow aims to help various stakeholders including building designers, engineers, and managers optimize and control building systems and facilities based on the behavior patterns of building users. The research also aims to facilitate the development of building energy simulation programs and energy management solutions, as well as designing behavior intervention policies. Further studies will be conducted to realize the goals.

First, it is worthwhile to compare data-driven methods to the ABM in terms of prediction accuracy. It should be noted that the ABM is not mutually exclusive with data-driven models, in that an agent's behavior can range from simplistic and reactive rules to complex behaviors regulated by artificial intelligence techniques [45]. Specifically, if proved to be practical, ABM rules can be defined based on statistical inference or data mining-based models as part of the system that manages the behaviors of autonomous agents. [26] and [46] are examples that combine these approaches with an ABM which potentially utilizes the benefits of both methods. In this way, the need to delve into the internal relationship between behaviors and influencing factors is reduced, and the stochastic feature of occupant behaviors can be involved by adding probability to the modeling rules.

Since the occupant behavior model was defined in single-occupied offices, further research could be extended to multi-occupant rooms. Under this circumstance, the behavior mechanism becomes more complicated as communications between different occupants influences how they operate building components. Fortunately, the ABM platform allows the modeling of multiple agents as well as their mutual effects, which enables behavior modeling from individual to the group level. Meanwhile, more behavior options such as those pertaining to plug loads can be added and studied as can other typical behaviors in buildings. Additional properties including occupant physiological and psychological conditions that can be modeled in PMFserv should also be specifically designed, which is one of the major considerations of using the platform.

The research methods and results can be used for simulation coupling with traditional building energy models to quantify the impact of different behavior patterns. A comparison on the fluctuation of energy use in different simulation settings can assess building performance in a more comprehensive way. Additionally, the ABM can be fed with real-time data to manage building operation for an existing building. As behaviors mostly result from uncomfortable indoor environmental conditions, the building systems can start to adjust schedules and operation in advance to achieve a better balance between building energy efficiency and occupant comfort.

Acknowledgement

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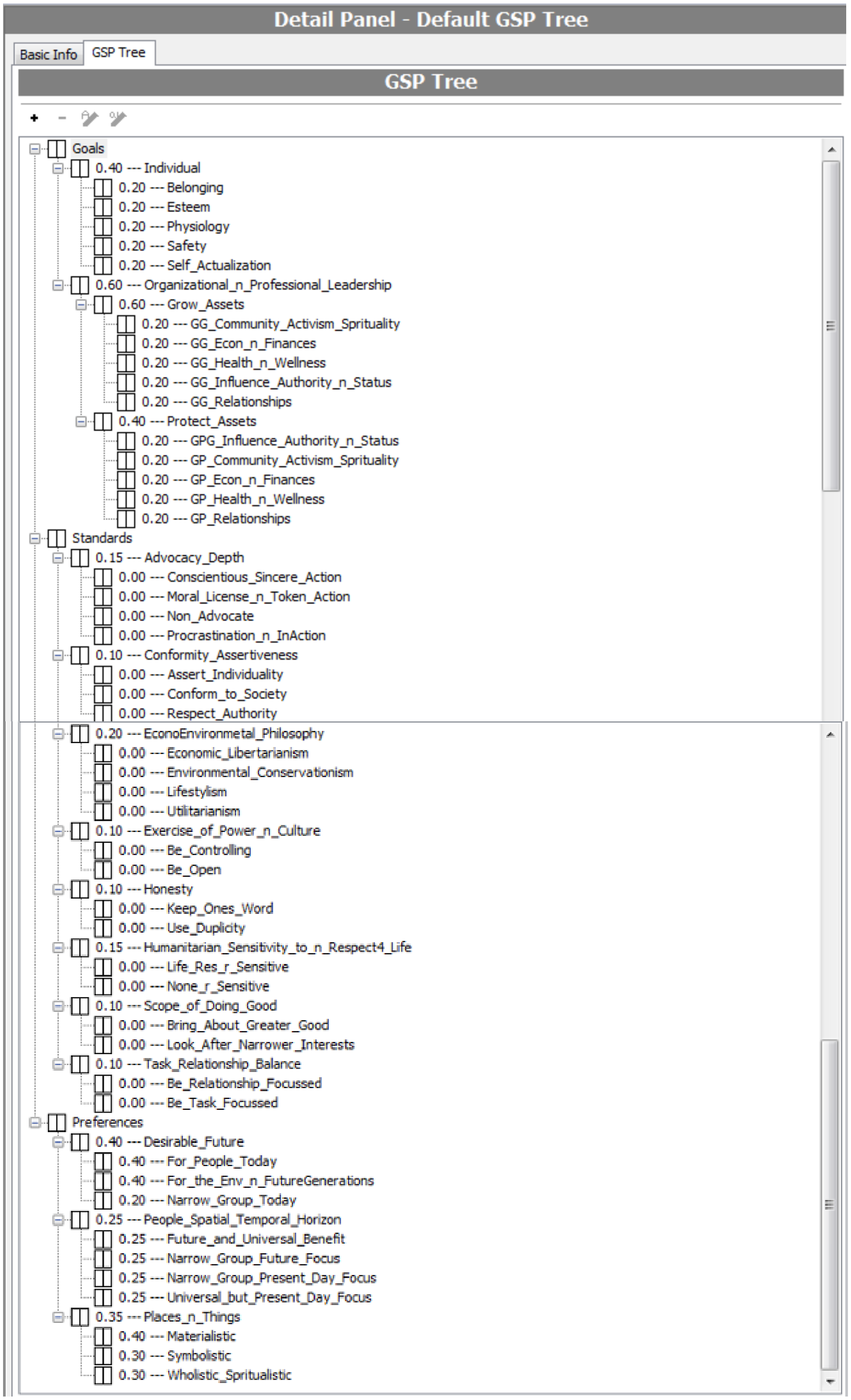
Appendix

A1.



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0.40 --- Materialistic
0.30 --- Symbolistic
0.30 --- Wholistic_Spritualistic

Figure A1. GSP tree created in the ABM.

A2.

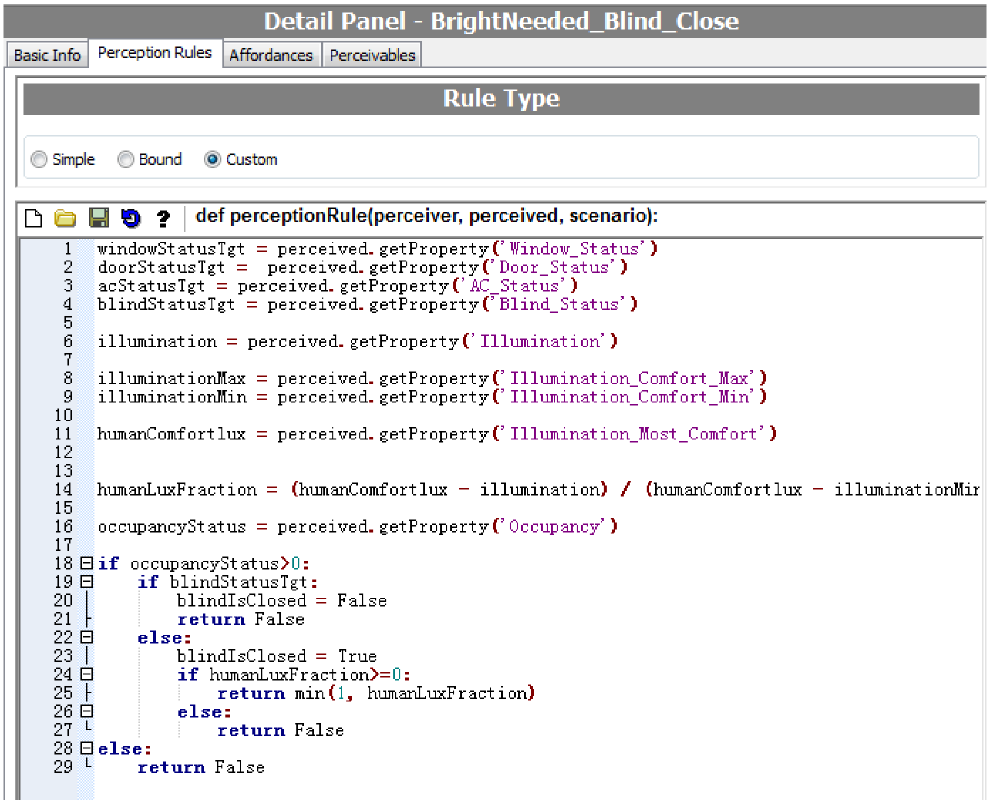

Figure A2. Custom rules for blind open due to visual perception.

B.

Room

Date

	Door		Window		Blinds	
	Open	Close	Open	Close	Open	Close
8:00 - 8:15 AM						
8:15 - 8:30 AM						
8:30 - 8:45 AM						
8:45 -9:00 AM						
9:00 - 9:15 AM						
9:15 -9:30 AM						
9:30 - 9:45 AM						
9:45 -10:00 AM						
10:00 - 10:15 AM						
10:15 -10:30 AM						
10:30 - 10:45 AM						
10:45 -11:00 AM						
11:00 - 11:15 AM						
11:15 -11:30 AM						
11:30 - 11:45 AM						
11:45 -12:00 PM						
12:00 - 12:15 PM						
12:15 - 12:30 PM						

Figure B1. Survey sheet for behavior data record. (Note: this figure cut part of the rows in the survey sheet, while the complete survey time period is from 8:00 am to 5:00 pm.)

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