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EXPLORING THE VALIDITY OF OCCUPANT BEHAVIOR MODEL FOR IMPROVING OFFICE BUILDING ENERGY SIMULATION

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ABSTRACT

Building energy use is significantly influenced by building occupants or users. The integration of a robust occupant behavior model that captures energy-related behaviors and a building energy model will have the potential to improve energy simulation performance, as current virtual model of building lacks dynamic and practical occupant information input. Agent-based Modeling (ABM) has been successfully applied to model interactions between occupants and building components, but most of the models were developed on a simulation basis without actual data involvement. To address on this issue, this paper proposes an approach to modeling occupant behaviors in office buildings via the design of a novel ABM and relevant data collection for model testing and validation. A case study is conducted to investigate the performance of the model. The results show the applicability of the ABM and provide a feasible direction for tuning ABM for the purpose of building energy simulation improvement.

1 INTRODUCTION

Energy crisis and sustainability have become increasingly crucial topics among academia and industry. With the rising demand of energy use and future concern of scarce energy resources, the need for energy efficiency is growing steadily. According to US Department of Energy (USDOE 2014), there is a proportion of more than 40% of the total energy use that is attributed to buildings. This makes the building sector a promising target for energy saving and other indirect benefits such as CO_2 emissions reduction. The International Energy Agency (IEA) identified six factors that directly influence building energy use (Yan et al. 2015), among which the factor of occupant behavior has attracted the attention of many researchers. However, due to the stochastic nature of human behaviors, there are still gaps and limitations to effectively capture and model the interactions between building occupants and components. The obstacles lead to deviation of simulated and actual energy consumption of buildings and thereby affect building design and operation, since current building simulation model lacks the ability to reflect occupant behaviors precisely (Fabi et al. 2012; Hong et al. 2016b). Therefore, a valid occupant behavior model not only has the potential to add another dimension to building simulation model, but also assist in optimizing future control and operation of building equipment and systems towards a more comfortable while energy-efficient built environment.

Apparently, building occupants have generic patterns of their behaviors though individually there is uncertainty and variation under different circumstances. Generally, there are two types of behaviors for building occupants or users, in terms of the impact on energy consumption. On one hand, occupants interact actively with building components such as opening and closing windows or doors, operating window shades or blinds, controlling thermostat, and using electronic products (Hong et al. 2016a). On the other hand, behaviors such as walking, sitting, reading, clothing adjustment, and any other subtle actions also indirectly cause energy fluctuation. Currently, researchers focused more on the first set of behaviors, since those are significantly related to building energy use in general, which are therefore referred as energy-related occupant behaviors. Energy-related behavior is defined by the IEA, Annex 53 as "observable actions of a person to adapt to ambient environmental conditions such as temperature, indoor air quality or sunlight" (IEA Annex 53). In addition, for different building types, occupants behave differently with respect to behavior drivers and internal needs of individuals. For example, in office buildings, people tend to adjust building components based on their physical comfort level, which is directly influenced by ambient environment. While in residential buildings, it might be more complicated owing to many other elements including time, economic concern, and personal habits, etc. Hence, the modeling methodologies differ with various concentrations. Yet, studies (Ahmadi-Karvigh et al. 2018; Kashif et al. 2013) have demonstrated the possibility to track behaviors or activities of people in residential buildings.

From the summary of the authors (Jia et al. 2017a), occupant behavior models can be developed using different methodologies according to particular research perspectives and purposes. These models can be further categorized into simulation-based and data-driven models. While different approaches have their own advantages, Agent-based Modeling (ABM), as one of the simulation-based approaches, is proved to be a useful and promising modeling method. ABM starts from the occupant's vision, and is able to predict behaviors at both the individual and group levels (Langevin et al. 2015). Plus, it could model all aspects of an agent that satisfy the modeler's interests, and has a high capability to integrate with building simulation models. However, most of the researchers that applied ABM for building occupant behavior modeling devoted effort on frame and rules development for the model, yet failed to involve any verification or validation steps. In other words, few researchers used real-world data to test the performance of the ABM beyond a pure simulation stage (Langevin et al. 2015; Putra et al. 2017). Moreover, there is no collective agreement on the modeling principles and algorithms of ABM for occupant behaviors in buildings, which still needs exploration for a more advanced system development.

Based on the facts above, this paper studies three specific energy-related behaviors in an office building, using the approach of ABM. The ABM is implemented with a unique human behavior modeling platform that is originally built for social science and system engineering (Bharathy and Silverman 2013). A previous study was conducted on the model development process for application in the built environment domain (Jia et al. 2017b). In this paper, relevant environmental data is collected using a smart sensor board and public weather station, in order to serve as the ABM inputs, and a paper-based survey is conducted to record actual occupant behaviors in the same rooms to compare with simulated outputs. The initial study results show a good fit of actual and simulated behavior outputs within certain built environment.

The rest of the paper is organized as follows: Section 2 introduces previous studies on occupant behavior modeling for building energy efficiency; Section 3 briefly describes the modeling rules and execution procedure of the ABM in this paper; Section 4 discusses the data collection approaches and scale, and presents ABM validation approach; Section 5 presents the validation results and provides a discussion on the uses and limitations of the ABM; and Section 6 summarizes and concludes the paper.

2 PREVIOUS STUDIES AND RESEARCH MOTIVATION

As stated in the section before, building occupant behavior modeling is usually falling into two categories, namely simulation-based models and data-driven models. In the literature, more research lean on the data-driven approaches, which establish mathematical trend or relationship on the basis of collected data in the experiment. For example, Feng et al. (2016) distributed a large scale questionnaire survey to find the influencing factors for occupant behaviors such as operating window, air-conditioning, and lighting, etc. Then a quantitative relation model between air-conditioning behavior and triggers of environment and event was developed to define a particular behavioral pattern. Based on the energy consumption with different behavior patterns, the researchers presented five typical occupant types for the study objects. Another research used Markov Chain to forecast behaviors as time series data. Dong and Lam (2011) built a Hidden

Markov Model based on Gaussian Mixture Model to estimate occupancy status in an office room. But this method is more suitable for long-term occupancy modeling, which only addressed the occupied condition of one room. Additionally, some researchers monitored variables of energy use or environment parameters that associated with certain occupant behaviors. Zhao et al. (2014) measured power usage of common appliances in an office to learn the occupant "passive" behaviors. Several data mining algorithms were trained and tested to predict individual and group level appliance use schedules. Similarly, Yang et al. (2012) collected eight different indoor environmental parameters and associated them with ground truth data – occupancy count status. The data was then processed using a neural network algorithm to derive the mathematical relations between them. The two studies above only focused on occupancy schedules, which is less detailed than behaviors. One of the benefits of data-driven approaches is that it is not necessary to explore the causality of human and his/her behaviors. However, the models cannot be simply transplanted to other test beds without losing much of the statistical credence (Yan et al. 2015). Moreover, these modeling methods need a long-term data collection period and thus are not applicable to any future buildings.

Simulation-based models are often based on a virtual environment, which operate in a rule-dependent mode. Agent-based Modeling is one of the most popular methods in this category. In the research of (Kashif et al. 2013), the researchers proposed a causal model of occupant behaviors in home buildings with Brahms modeling language. Usual time and environmental factors were the main triggers of behaviors. The model also considered the communication between two inhabitants, while coupling the behavior simulator with a physical simulator that provided simulated environmental data. Azar and Menassa (2011) used ABM to simulate interactions between agents instead of building systems, and achieved a 25% difference in the final predicted energy consumption. Three occupant classes were defined in terms of energy-consuming rate, and it was assumed that during the simulation process, energy conservation event would happen at certain time period, so that high energy consumers were turning into low energy consumers gradually. Therefore at the end of the simulation, the case study building lowered down its power use in a 3-year cycle. The two studies modeled occupant behaviors in different building types with different perspectives, however, they both failed to validate the models. As a result, it is not convincing enough that people would react the same way as they were assumed, which makes the ABM less practical for further application. The study by Langevin et al. (2015) is a rare case that tested the ABM with actual data. The researchers presented a model through the theoretical framework of Perceptual Control Theory (PCT), and treated thermal sensation as the perception under control. The proposed model generated comparable results to the field measurements for both individual and aggregate predictions. However, the model only considered behavior options relevant to thermal comfort, and validated selected part of the modeling behaviors merely.

In the authors' previous research, a novel ABM was developed to simulate interactions between an occupant and building components (Jia et al. 2017b). That work demonstrated that the occupant performs differently with the change to the ambient environment. Following our previous work, this paper scientifically tests the performance of the occupant behavior model by conducting relevant data collection and validation study. To better illustrate the validation work as a whole, a brief introduction of the ABM is provided in the next section.

3 AGENT-BASED MODEL OF BUILDING OCCUPANT BEHAVIOR

3.1 Model Units

The development of the occupant behavior model complies with the critical elements of a typical ABM. First, as shown in Figure 1, the agent refers to building occupant. For this agent, the two major drivers are the agent's (occupant's) physical perceptions and cognition awareness. Besides, the agent is equipped with miscellaneous characteristics such as emotion, stress, and physiology conditions which also contribute to the decision-making process of the agent, but these are not the emphasis of the research context and purpose of this paper. Second, the simulation environment represents an actual educational building. The agent, in a single-occupied office in this educational building, has control access to window, door, and window blinds at will. Unlike models from other researchers, the behavior options excluded some common objects such as heater, lighting, or air-conditioning control, as in reality, the occupant does not possess a heater, lighting is automatically operated, and air-conditioning is controlled via central unit. Third, the fundamental rules that govern how agent interacts with the building components are mainly associated with indoor/outdoor environment. It is assumed that ambient environment is the major stimulus that affects individual's comfort level and hence his/her behavior decisions. Although other factors such as time, event, or room size and orientation might interfere the agent's activity decisions, they are not involved in the model at the current research stage. However, the feasibility of this setting was proved by other researchers (Hong et al. 2016a; Gaetani et al. 2016).

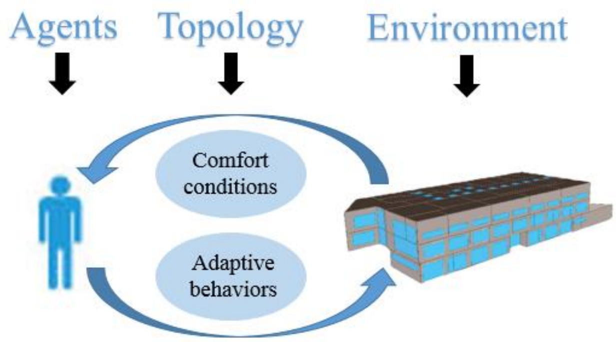

Figure 1: Projection of ABM structure to the context of built environment.

This research adopted a platform for complex human behavior modeling named PMFserv. In the modeling platform, there are five units that must be modeled. The creation of an agent, and his/her mental awareness are the inherent units. However, though the settings of the agents' attached features (e.g. gender, age) could be modified, this paper will not expand on the details (refer to Jia et al. (2018) for more information). Instead, the two distinguished units are highlighted in this section.

First, the "object" module which the agent can directly perceive is created. As stated before, "Built Environment" is the only item in this case. Under this item, all the related environmental parameters as well as building components status are included. For environmental parameters, temperature and humidity, indoor CO_2 concentration and illumination levels are the main ingredients. Supporting parameters (ranges) such as maximum and minimum indoor comfort temperature, comfortable indoor illumination ranges, etc., are also included as inputs for model flexibility. Physical status of window, door, and window blinds are represented as Boolean variables (i.e., true or false) and initialized prior to simulation. All of the above discussed are model inputs for the ABM. The second model unit relates to the agent perceptions. The model considers three primary perceptual types, namely thermal comfort, visual comfort, and indoor air quality comfort, with each linked to the corresponding parameters in the "Built Environment" object. Besides, custom rules are programmed for the activation of any perceptions of agent, whenever the values of environmental parameters are updated in every time-step. So far, the triggering mechanism i.e., opening or closing of door, window, and window blind, is set according to environmental thresholds and component state. For example, if the current situation is "window_closed" and the CO_2 level is higher than a percentage of the maximum comfort level, the perception of "window_close_fresh_air_needed" is activated.

3.2 Model Execution Procedure

At each time step, the model outputs one behavior as decided by the agent based on environmental parameters and physical status of building components. The agent is attached with personal goals (represented by "value"), and makes decisions based on the Utility which is a function of values and contexts. Under the virtual conditions (indicated by parameters input), the agent perceives the state of his/her surrounded environment (contexts) and may possibly have more than one perceptions being triggered. Meanwhile, the agents evaluates the perceptions and its affordances (namely behavior options) and appraises the weighted importance values of each option. The option of the highest Utility will be generated as the decision of behavior at this step. As an application to the built environment domain, the most significant module is the "contexts". In Figure 2, the logical sequence of model execution with respect to impact of physical environment is depicted, which is the core of the ABM.

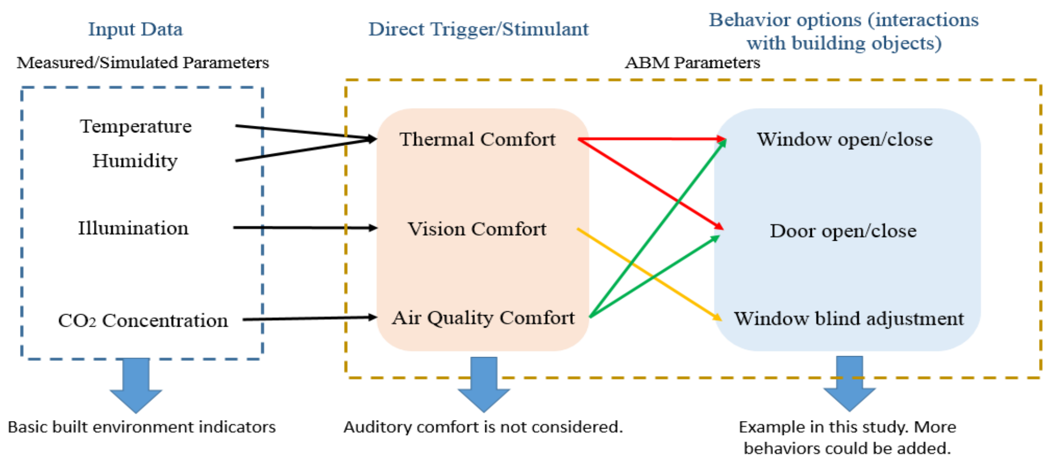

Figure 2: Model execution logic on the perception unit perspective.

The ABM executes simulation in this order: at the start of the simulation, all the values in the "Built Environment" object are initialized. Then, the model runs to output the behavior which the agent gives priority based on the Utility. If no perception is triggered, the agent will stay without making any physical status change to window, door, and window blind, i.e., with no output at this time step. If there is an output of behavior to a building component, the status of this component will be updated automatically in the corresponding parameter of the "Built Environment" object. Following this procedure, at the beginning of each time step, the values of environmental parameters are updated with measured data, and the model repeats the calculation process above until the simulation ends. A list of behavior outcomes can be exported in a Microsoft Excel™ file, which can be translated into any format that is used for simulation integration or validation study.

4 MODEL TESTING AND VALIDATION METHOD

With the development of the ABM, it is important to test whether the model generates reasonable and acceptable results, in contrast to the reality. The idea of the validation work is to construct a virtual environment that mimics the actual environmental conditions in the test room, and compare the simulated output with recorded behavior information at the same condition on a time step basis.

4.1 Data Collection Approaches and Scale

Two types of data are collected in this research: environmental measurements and behavior record. For indoor environmental data, a smart sensor board was customized and placed near the occupant in the testing room. The sensor board mainly comprises a micro-computer board with plug-in interface, and three separate raw sensors that measures temperature, humidity, illumination, and concentration of CO_2. A program was written to configure the assembling device, and read the values of four indoor environmental parameters to a Comma Separated Value (CSV) file every five minutes with time stamp information. The data was stored in a Micro-SD card which is inserted to the smart board. Another program was running at the same time to upload the data file to an online storage drive every two hours via Wi-Fi connection. As the ABM requires outdoor temperature and humidity data, actual outdoor data is obtained from a public weather report website (Weather Underground) which provides hourly weather data.

For this study, the test building selected is a typical educational building situated in the University of Florida campus, State of Florida, USA. The three-story building has multi-functioning rooms at all levels. Most of the faculty offices are located on the third floor, which are all single occupancy rooms. All the rooms are serviced with Heating, Ventilation, and Air Conditioning (HVAC) system that are centrally controlled. For the research scale of this paper, a corridor of offices oriented to the west satisfied the requirement as the data collection sample rooms. To avoid skewness of the sampling data, five faculty offices were further selected randomly with occupants in different genders and age ranges. Five sets of sensor boards and survey sheets were assigned to the rooms, with overlapped data collection time period. Figure 3 shows the third floor plan of the test bed building and selected rooms for data collection.

For occupant behavior information, a paper-based survey sheet was designed and distributed to the experiment occupants. The survey sheet which was approved by the University's Internal Review Board (IRB) includes consecutive 15-minute time intervals from 8:00 AM to 5:00 PM each day at each row, and the open/close status for window, door, and blinds respectively at each column. The occupants, University faculty, were asked to complete the survey sheet manually with date information if they stay in the room for a long duration i.e., more than 15 minutes. Additionally, they only need to make an "x" mark at the correct box whenever he/she conducts a behavior at a certain time. In one of the test rooms, a commercially available sensor system consisting of a hub and two magnetic sensors was installed. This system logged window and door status. The device was used for random check of survey sheet record and other research objectives that are out of this paper's scope.

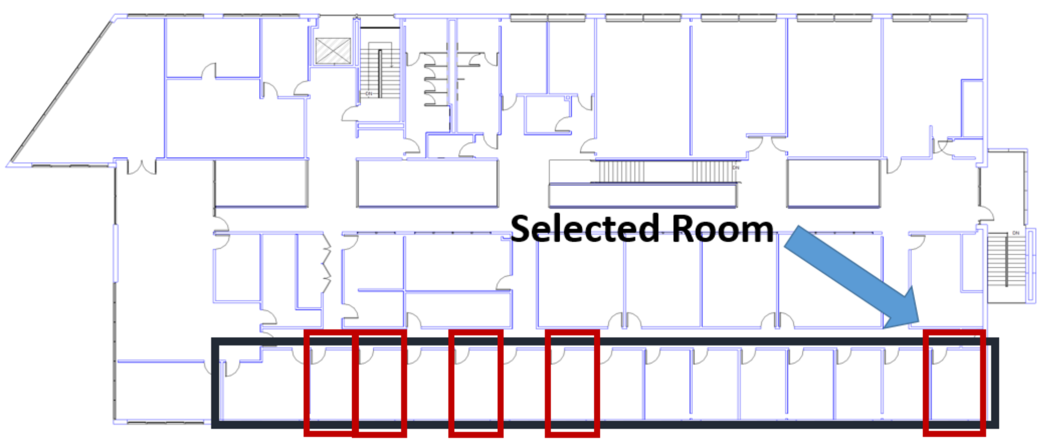

Figure 3: Zones and rooms on the third floor of the case study building (red color indicates the data collection rooms, the selected room at the corner is for result presentation).

The data was collected in the Spring season where the day/night temperature and humidity variations are obvious. The data collection process lasted for two to four weeks depending on the availability of occupants. Considering the average duration which the occupants stayed in the offices, there are approximately 25 to 35 time steps of behavior records per person each day.

4.2 Data Preprocessing

Because the ABM outputs and survey results have different format, data transformation strategies were first applied to the raw datasets. In this study, two states of building component were defined: open and close. As a result, the original data was reflected as Boolean values of true (open) and false (close). For comparison purpose, the information was then transformed to numerical values, where true (open) corresponds to “1”, and false (close) corresponds to “0”.

Since the raw survey results included check marks penned by occupants, these results were simply transformed in the same format of the survey sheet, with time intervals listed in rows, and the status of window, door, and blinds in columns. The only difference is that the status information became “1” or “0” instead of the text of open or close.

To conform to the processed survey results, the ABM results were aggregated to a vector form. For instance, a sample output of ABM is shown in Table 1. With the initial status of the three components set to “close”, after step 1, the transformed data format became [0, 0, 1], which stands for window close, door close, and window blinds open. Following this strategy, after each step, a vector was obtained. Also, at each step, the inputs of the ABM were extracted from the sensor data, and with time information in the datasets, the environmental data at the same time interval with survey results were used to generate the simulated output in order to have a one-to-one mapping for further analysis.

Table 1: Example of raw outputs for one agent in the ABM (only showing 5 time steps).

Target	Action
Blinds	Open
Blinds	Close
Window	Open
Window	Open
Window	Close
Door	Open

4.3 Testing Metrics

To evaluate the ABM simulation performance, several standard metrics were computed for operations on window, door, and window blinds separately. These includes:

1. Sensitivity or true positive rate = TP/(TP + FN);
2. Specificity or true negative rate = TN/(TN + FP);
3. False positive rate = 1 – Specificity = FP/(TN + FP);
4. Accuracy = (TP + TN)/(TP + FP + FN + TN).

Among these parameters, each outcome of 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 each occupant, there are around 500 time steps in total, considering the involved number of days and average time steps for each day.

5 RESULTS AND DISCUSSION

In this paper, only one occupant out of the experiment targets was selected for result presentation. As shown in Figure 3, the room at the corner of the corridor is the representative room, as the occupant of this room has a relatively consistent and stayed for a long time in the office.

In Figure 4, the simulation result and actual record of behavior for window blinds operation of a random day are shown, as well as the sole influencing environmental factor fluctuation, namely indoor illumination. The results indicate that the initial status of blinds is open at the beginning of the day for the occupant, and during the most portion of the day, the lighting intensity is either satisfied with the occupant’s visual comfort level, or slightly lower than that. Therefore, the occupant kept the blinds open for the most time of the day. Towards the end of the day when the occupant resided in the office, the illumination level increased significantly, due to the outside sunlight from the west in the afternoon. The illumination level exceeded the normal comfortable range intensely, therefore, the occupant chose to close the blinds to block the direct exposure to the sunlight. It could be seen from the actual status, that the blinds closing behavior was slightly later than the maximum value state of illumination, while the simulation results assumed the behavior happened immediately in this situation. This delaying phenomenon is an interesting finding, and is observed and studied by other researchers. There are many reasons that may cause this condition, however, the general trend of the simulation result is considered to agree with the actual record. Last, but not the least, it should be noted that there is a small period in the day that the occupant was out of the office. The gap in the simulation result reflected this vacancy since no environmental inputs were used for those particular time steps.

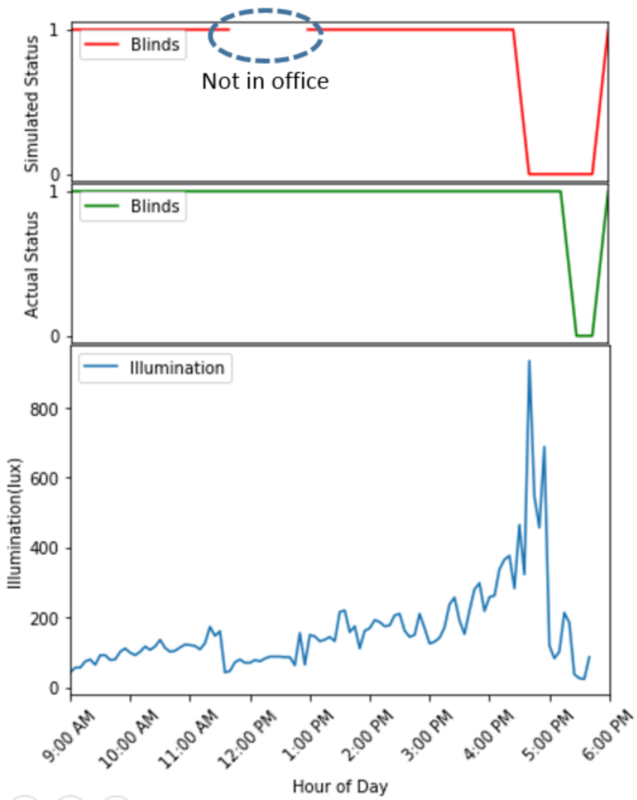

Figure 4: Simulation results and survey record for window blinds operation in a random day, with illumination level showing underneath.

In Figure 5, the simulation result and actual record of behavior for door operation of a random day are shown. Unlike window blinds operation, there are three influencing environmental factors for door operation, namely indoor temperature, humidity, and CO_2 concentration. Figure 5 shows the temperature and CO_2 fluctuation only, as the humidity variation is relatively stable (around 32%) and has a very similar trend with temperature change. The results indicate that the initial status of doors is closed at the beginning of the day for the occupant, and during the daytime, the occupant opened and closed the door alternatively. However, door operation behavior may be related to many other non-environmental factors, for example, if the occupant needed to go to a class or meeting, or some visitors came to the office. For the simulation settings, it is difficult to capture these stochastic events. In the ABM, the door operation behavior is only influenced by indoor environment. However, the ABM considers the "goals" of agent, while one of the goals is privacy and security. This factor was modeled in the ABM and eventually affected the door simulation result. Therefore, it can be claimed that the ABM is more reliable if the occupant is in the room and no sudden events happen. Finally, in terms of comparison, simulated result agrees with actual record 70% of the time (shown in Table 2), which is sufficient to make the ABM applicable for future use.

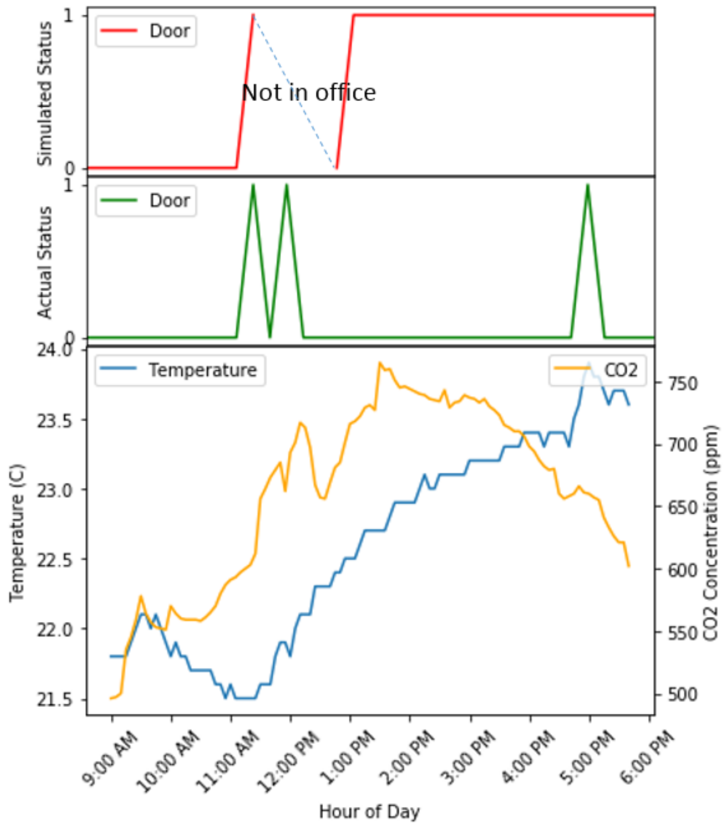

Figure 5: Simulation results and survey record for door operation in a random day, with indoor temperature and CO_2 concentration showing underneath.

The window opening behavior is influenced by more variables, including outdoor temperature and humidity. For example, if it is cold and raining sometime in the day, even if the indoor environment is uncomfortable in some aspects, the occupant may not choose to open the window. However, in comparison with door operation behavior, window operation behavior depends more on the environmental factors. In fact, in the test building, window is the only building component for the occupant to adapt to the indoor environment, with the HVAC control not accessible in the room. In this paper, the sample results from ABM and survey are not shown. Instead, in Table 2, the overall performance of the ABM is summarized.

According to the table, the simulation accuracy is over 70% for all three building component operations, which obtains an average of 83% for simulation results. Among them, blinds operation has the highest accuracy, because of the fact that the behavior is highly related to environment and not influenced by other external elements. On the other aspect, door operation has a relatively low accuracy, while the reasons were explained before in the analysis of Figure 5. Moreover, door is the most frequently operated building component that can even be open and closed repeatedly during a 15-minute time interval. This decreases the probability of door to be accurately tracked in an ABM model. For sensitivity, or true positive rate, all the three components obtain satisfactory values. In other words, in terms of opening behavior, the ABM can predict fairly well for the occupant. On the contrary, specificity measures the closing behavior for the occupant. For door closing behavior, the number is 60%, which is lower than its sensitivity. This means that there are more time steps when the door is actually closed but the ABM assumes the agent would open the door. It can be concluded that sometimes the occupant kept the door close even though the indoor environment is out of his comfortable range, or the occupant has a wider threshold for environmental comfort level.

Table 2: Performance summary of ABM.

Metrics	Window	Door	Blinds
Sensitivity	0.78	0.88	0.98
Specificity	0.82	0.60	1.00
False positive Rate	0.18	0.40	0.00
Accuracy	0.80	0.70	0.97

In summary, it could be concluded that the ABM is able to capture typical occupant behaviors in the built environment in brief. This occupant behavior model can thus be further used in different areas. For example, the model can be integrated with a building energy model (BEM) to account for energy impact brought by building users, and assist building designers or building managers to regulate building systems load design and elaborate energy use policies. Moreover, a co-simulation can be implemented with the ABM and any BEM to potentially improve building energy use estimation in a holistic way. Nevertheless, limitations still exist for this study.

The development of the model emphasized the impact of ambient environment on occupant behavior. In other words, the model only investigated the deterministic relations between the behaviors and relevant drivers. Although considered as a valid idea, more possible factors should be involved in the ABM. Information such as occupancy schedule, daily routine, and personal background (e.g. comfort range) can be a practical supplementary to the model. Plus, stochastic influences should be studied and engaged in the future model, as people in reality will not act exactly like the programmable “agents” in most of the cases. Furthermore, the ABM only dealt with three common behaviors in office building, while in reality, occupants may have other activities when feeling uncomfortable. For example, one of the experiment occupants has a personal heater in the office, therefore the heater is often turned on if the room is too cold for this person. This in turn influences her decisions on operating other building components. Lastly, the paper-based survey may cause unexpected error in this study. Especially as the time interval was set to 15 minutes for the survey sheet, it is possible that the occupants conduct multiple behaviors during this time interval. This problem could be solved by installing smart sensors on the experiment objects, so that the status can be logged accurately with any time granularity as needed.

6 CONCLUSIONS

To address the issue that current building energy simulation model usually lacks dynamic occupant behavior information, this paper examined the overall performance of an Agent-based Model that simulates occupant behaviors in office buildings. The ABM was developed with a human behavior modeling platform that applied to the built environment area for the first time. Three common behaviors were studied in this paper including operations on window, door, and blinds. The ABM is based on the assumption that occupants will interact with building components to adapt to uncomfortable indoor environment. A data collection process using smart sensor board and paper-based survey was conducted to acquire real-world environment data and behavior record. Actual behavior data of one occupant was then compared with simulated behavior results under the same environment conditions on a time step basis. It was demonstrated that the simulation model captures the generic nature of occupant’s activity with the fluctuation of ambient environment. In addition, the simulation results coincide with the actual behavior trend as indicated by comparison of a random day. The average simulation accuracy of the ABM reached 83% for the targeted objects, which represented a positive capability to apply for further research purposes. In the future work, the ABM must be optimized with more parameters and information included, and a larger scale of data will be collected to test and validate the ABM in order to promote its robustness and reliability. The ABM proposed by this paper is planned to be integrated with the building energy model of the case study building, to quantify the occupants impact on building energy use and realize a co-simulation framework for more comprehensive building performance simulation.

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