An Agent-Based Model Approach for Simulating Interactions between Occupants and Building Systems

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Abstract

Building occupants are one of the most dominant variable factors in building energy consumption. However, current building performance simulation engines incorporate occupant information as simple, static profiles, which lead to discrepancy in actual energy use as occupants interact with building systems in an active manner, i.e., occupant behavior over time is not captured by simulation algorithms. The need for modeling energy-related occupant behavior dynamically in energy simulation tools to increase prediction capability cannot be understated. This paper proposes a possible solution by discussing the use of a Performance Moderator Functions testbed (PMFserv) - a well-tested Agent-Based Modeling (ABM) tool, for occupant behavior modeling and its potential integration with energy simulation engine, EnergyPlus™. In order to extend PMFserv to buildings for improving energy estimation, a thermal zone in an educational building is tested and observed using sensing technologies. The study explores the interactions between occupants and building using cognitively detailed ABM, as well as the impact of occupant behavior on building energy use.

Introduction

Buildings account for more than 40% of the total energy use in the United States (Energy Information Administration, 2015). There is abundant potential for energy savings associated with buildings. Previous research has shown that building occupants are considered as the most dominant element that determines the energy use trend (Yan et al., 2015), as the function of buildings is to provide comfortable context and service for people in the building. Consequently, studies about modeling occupant behavior is beneficial to realize both building energy efficiency and occupants' comfort. Generally, occupant behavior information is rather necessary to incorporate in the building simulation models to enhance simulation performance. Besides, since people spend 80% of their lifetime in buildings (Yang and Wang, 2012), the information should also be involved in the actual building operations for systems optimization and interventions design.

Building occupants' actions vary over time. In the context of built environment, it is more effective and meaningful to understand how occupants interact with buildings, in other words, the energy-related behavior. These include the use of building systems (e.g. HVAC, lighting) and building components such as windows or doors. Additionally, occupant behavior includes the activities such as typing, writing, walking, appliance use, etc., which should also be studied, as they influence energy use indirectly.

Particularly in the building energy modeling domain, the uncertainty brought by such occupant behavior causes inaccuracy in building energy estimation. Currently, most building simulation tools treat occupant information as static profiles or single user patterns for input, which leads to discrepancy between simulated and actual energy use in most of the cases (Fabi et al., 2012). In fact, occupants dynamically interact with buildings, and different occupants may have different behavior preferences in response to ambient settings. The assumptions made by energy simulation tools about building occupants does not reflect actual situations, and it is difficult and unreliable to use a typical behavior pattern to represent various types of occupants. This limitation calls for a dynamic and interleaving simulation of occupant behavior and building energy use, where information exchange accompany with the whole building simulation process. Since, few of the existing energy simulation algorithms have a complete occupant behavior module to account for energy use attributable to the building users, this paper adopted a passive integration framework, which is based on a human behavior modeling platform and a robust building energy simulation engine, EnergyPlus™. The human behavior modeling framework, PMFserv, is a widely tested environment particularly in social science studies (Bharathy and Silverman, 2012). Owing to its robustness in modeling human behavior, we apply this platform to building occupants. To the best of the authors' knowledge, this is first time that PMFserv is applied to the area of built environment and integrated with a building simulation tool. This combination aims to explore the mutual impact of occupants and buildings thus to provide basis for accurate energy estimation and building design.

In this paper, ABM is implemented using a Performance Moderator Functions testbed (PMFserv) as the foundation for occupant behavior simulator. PMFserv is used to generate occupants' behavior according to indoor and outdoor environmental inputs that influence perceptions of building users. The behavior change at each time step is then obtained based on the perceptions and cognitions of the agent to create a schedule for EnergyPlus™ to calculate energy use and other internal conditions.

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Preliminary experiment show that this process has immense potential to model the interactions between building and its occupants dynamically. Study results demonstrate the fact that occupants' behavior influence building energy use in a different way rather than default mode. For this study, our focus is occupant interactions with building components, more specifically the window, blinds, door and heater.

Related work

Previous studies (Jia and Srinivasan, 2015; Jia et al., 2017) have shown that the methodology of occupant behavior modeling and simulation can be divided into different categories, based on their characteristics and the purpose of research. For example, Andersen et al. (2013) measured indoor and outdoor environment factors in a 10-minute interval, and record the window position during the same time period. Multivariate logistic regression was applied to infer the probability of window opening/closing event for four groups of buildings. However, the study did not apply the models for building simulation improvement. Zhao et al. (2014) monitored electricity data of regular appliances in office, and captured ground truth data of six experiment occupants with pedometers. Three data mining algorithms were trained and tested to predict schedule of appliance use behavior, which were pre-defined in the study. Another popular method for occupant behavior modeling is stochastic modeling using Markov Chain. For example, Dong and Lam (2011) developed a Hidden Markov Model based on Gaussian Mixture Model to estimate occupant numbers in a room. This method is more suitable for long-term occupancy modeling, which only address the occupied status of a room.

Compared to the methods above, ABM is relatively new and more specialized in simulation, which has shown great potential to mimic occupant behavior, and to further integrate with energy simulation tools for improving simulation performance. Research has been done expanding this method in the built environment area. Kashif et al. (2013) proposed a human behavior simulation module for residential buildings, which is connected to a physical simulator. These researchers claimed that occupants' comfort needs are what lead to an activity, and the needs are associated with certain time periods and environmental factors. Brahms modeling language was used for implementation of the theory and idea. Lee and Malkawi (2014) introduced a complex Agent-based model for occupant behavior simulation which is based on Fanger's Predicted Mean Vote (PMV) model that behavior is controlled by three types of beliefs. The researchers used MATLAB for modeling with assumed parameters, and further studied the impact of different behavior on energy use with EnergyPlus™. Similarly, Langevin et al. (2014) presented a model which represented office occupant as a simulated agent that acts adaptively based on Perceptual Control Theory (PCT), where agent's thermal sensation and acceptability range are modeled probabilistically, and the behavior happens when the corresponding thermal sensation is out of the acceptable range.

In summary, the application of ABM for occupant behavior modeling is well suited for improving building energy simulation performance. In an ABM, an individual occupant is represented as autonomous agent with unique attributes such as needs, sensations, and behavior options. The agent is able to perceive its surrounding environment and "react" like a real human being, so that the agent could interact with the environment or other agents in the same context to achieve a certain goal under constraints. Moreover, among all the current methods of modeling occupant behavior, ABM has the best capability to directly associate with energy simulation tools. However, currently there is no agreement on how to use this method for occupant behavior simulation. Using a simulation integration approach linking occupant behavior modeling and EnergyPlus™, our study is the first-of-its-kind ABM platform that has been applied to the area of built environment.

Simulation method

In this research, a unique Agent-based Modeling platform, which is particularly built for human behavior modeling is tested for the built environment area. The platform is transforming corresponding information to Energyplus™, to explore the influence brought by typical occupants' behavior.

Introduction of PMFserv

The platform selected for occupant behavior modeling in the research named PMFserv is originally built for social science and systems engineering. Silverman et al. (2007) have built the PMFserv framework and its derivatives centered on a multi-resolution Agent-based approach. While some of these models are specialized in conflict scenarios, the agents themselves are generic in representing human behavior under different contexts.

PMFserv modeling framework and the software were developed over the past ten years at the University of Pennsylvania as an architecture to synthesize many best-of-breed models and best practice theories of human behavior modeling. This environment also facilitates the codification of alternative theories of factional interaction and the evaluation of policy alternatives. More information on PMFserv can be found in (Bharathy & Silverman, 2012; Silverman et al., 2007).

Development of the occupant behavior model

According to Macal and North (2014), a typical Agent-based Model has three elements:

- Agents, along with their attributes
- Rules or topology, which governs how agents react
- Environment, where agents conduct behavior

Therefore, the general implementation of the occupant behavior model follows the descriptions above. In this model, agents correspond to building occupants, whose

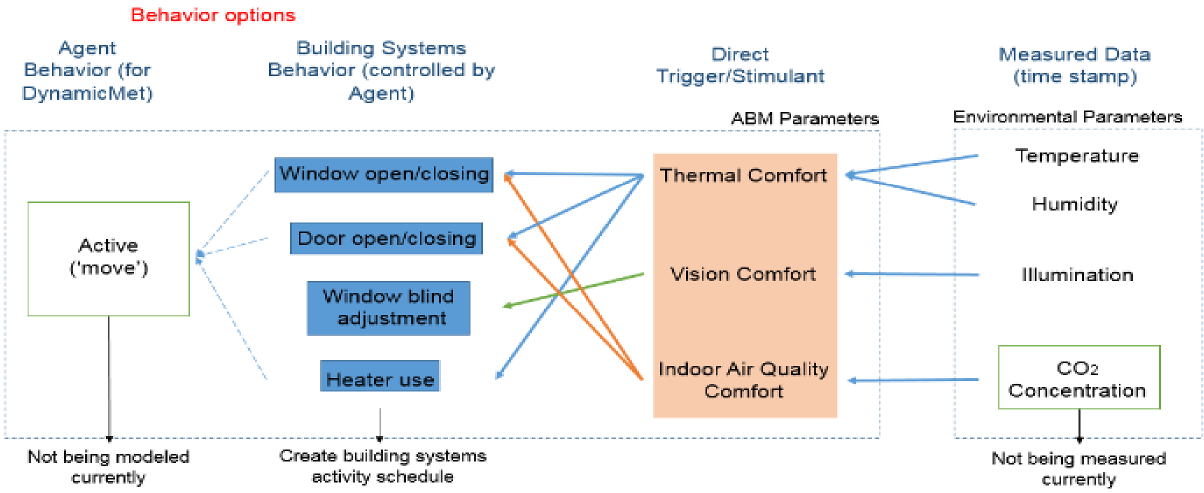

Figure 1: Corresponding relationships among the ABM

attributes consists of perceptual types and cognitive awareness, as well as common behavior options that are both energy and comfort related. Other auxiliary characteristics such as physiology and stress level, which subtly influence occupant behavior decisions, are also attached to the agent. The fundamental rules that dictate the system are based on the comfort needs of building users, where the influencing external factors are environmental conditions. In the context of the built environment, especially for office or commercial buildings, people usually care about their physical comfort level rather than other issues such as energy expense. Therefore, the direct stimulus of behavior decisions in the model are considered as three classes in terms of human comfort types. In the current stage, the model adopted a simplified rule that if any ambient environment condition exceeds the comfortable range of the agent, the corresponding perception will be triggered and then used for later calculation. Last but not least, the environment of the ABM is an office type building, where occupants have several options to adapt to ambient environmental conditions. In the simulation case studies, four behavior options are included. The causal relationship among environmental parameters, occupant perceptual types, and behavior options are illustrated in Figure 1, as the foundation of the model.

The system is capable of simulating various behavior in one model based on a decision-making algorithm. As a result, at each simulation time step when certain variables are input in the model, there will be a utility calculation process that would finally output a pre-defined behavior option.

Decision making algorithm based on the model

According to the designing mechanism of the model, agents behaviors are determined by two aspects under certain environment. On one hand, the agents in this framework are cognitively deep and come equipped with values (short-term goals, long terms preferences, standards of behavior including cultural and ethical values, and personality). On the other hand, the surrounding environment provides contexts, which carry and make decisions available for consideration. These agents make decisions based on a minimum of two set of factors, (i.e. Decision Utility as a function of):

- Values: The system of values that an agent employs to evaluate the decision choices, and
- Contexts: The contexts that are associated with choices.

The values guide decision choices, and in our case, have been arranged hierarchically or as a network. The contexts sway the agent decisions by providing additional and context specific utility to the decisions evaluated. The contexts are broken up into micro-contexts. Each micro-context just deals with one dimension of the contexts (for example, relationship between the perceiver and target and so on). With a given set of values, an agent (or person) evaluates the perceived state of the environment and the choices it offers under a number of micro-contexts, and appraises which of its weighted importance values are satisfied or violated. This in turn activates emotional arousals, which are finally summed up as utility for behavior decisions. At each step, the decision of the highest utility calculated is considered as the behavior that will be taken by the agent (occupant).

In this study, the ABM platform focuses on a decision making process which combines agent's cognition (represented by Values) and perception of the environment (represented by Contexts) (Figure 2). In this paper, the latter part is emphasized as an application to the area of building energy simulation. The ABM model accounts for three types of comfort including thermal comfort, vision comfort and air quality comfort for perceptual types, and correspondingly, indoor/outdoor temperature and humidity, illumination, and concentration of CO_2 are taken as environmental inputs for behavior decisions. Specifically, hearing comfort is ignored in the model, in that it is not recognized in related research as a significant factor as the other comfort types. As stated in the previous section, once the surrounding environment is out of the agent's comfortable range, particular perception calculation is then initiated for final utility ranking. Nevertheless, a more comprehensive model is needed later, to adjust rules between environmental conditions and comfort range that could best reflect reality. The communication and influence among occupants themselves should also be studied.

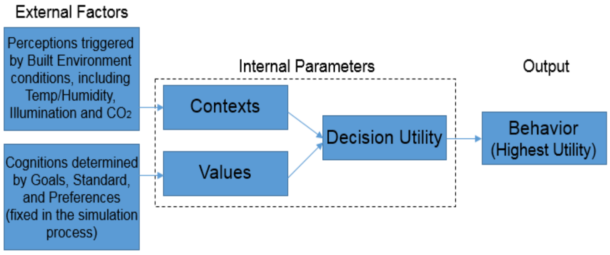

Figure 2: Decision making algorithm

Simulation integration approach

The proposed simulation integration approach is a combination of the ABM described earlier with a building energy simulation engine. The idea of this integration originates from the idea that occupants in office buildings may adjust windows, blinds, doors and heaters to improve their working environment in a form to satisfy their comfort requirements. Thus, the building simulation engine should be able to capture these behavior changes to better estimate energy use. EnergyPlus™ is selected as the engine, based on its wide applicability and the capabilities of representing certain behavior changes in its internal settings.

The simulation approach is basically an information transmission process within the simulation period (Figure 3). At the start of the simulation, related environment data is entered as input for the ABM (PMFserv), then the agent will perceive the level of comfort and make a decision on which action to take according to the ranking of "utility". The decision outcome generated in the zone is then stored and will be used as input to EnergyPlus™, where corresponding settings are adjusted to reflect the particular behavior. Similarly, at each time step, the environment factors and status of building components are updated to run the ABM. At the end of the simulation, a list of behavior decisions is created for the simulation run period. The list is assimilated as a behavior schedule to be used in EnergyPlus™. The entire process is currently conducted manually on an hourly basis, with the total simulation time set to a short time period, i.e. one regular week (as used in this experiment). This process can also be seamlessly run automatically through a bridge program in the future research stage in order to carry out simulation for a more sub-divided time step (minute-based) for a longer time period as well, i.e. 8760 hours.

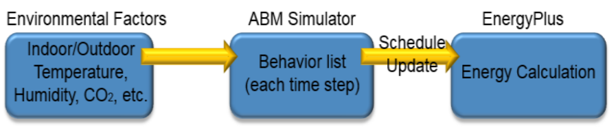

Figure 3: Dataflow of the integrated simulation

The outcomes of the ABM simulator are defined based on a realistic office in this paper, which consist of window opening/closing, door opening/closing, blind turning on/off, and heater switching on/off. These behavioral adaptations can be represented in EnergyPlus™ as listed in Table 1. It should be noted that these parameters are not the only representative variables for these types of behavior and more options are available. Plus, the settings could be completely implemented through Energy Management System (EMS) applications as the research progress.

Table 1: Variables in EnergyPlus™ for behavior change

Objects	Status	Settings in EnergyPlus™
Window	Open/Close	ZoneInfiltration: EffectiveLeakageArea
Door	Open/Close	ZoneRefrigerationDoorMixing
Blinds	On/Off	WindowProperty:ShadingControl
Heater	On/Off	ElectricEquipment

Case study

Simulation settings

To test the performance of the proposed occupant behavior model and the simulation integration framework, a case study is conducted for a single thermal zone in an office building located in Gainesville, Florida. This building has three stories with approximately 4,543 m^2 of total gross floor area. Most of the permanent occupants located in the third floor could control windows, doors and blinds in their private office, while not having access to a personal heater. However in this study, it is assumed that the agent has the behavior option. The aim for this assumption is to further investigate the influences brought by different behaviors and the potential energy savings if the behavior is intervened. In the simulation, one of the offices in the third floor with only one permanent occupant is taken as simulation testbed for results comparison and presentation, shown in Figure 4. In this study total simulation period in one test case is four weeks (624 hours), restricted by manual operation of the models.

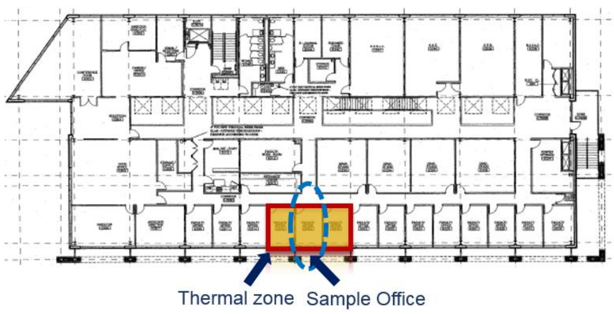

Figure 4: Building, zone and office used for simulation

To simplify the modeling workload in EnergyPlus™, the behavior schedules created for the single office occupant, are applied to the thermal zone in which the office is situated. Environmental data input was obtained from a wireless sensor network installed in the office, and a local weather station website ("Weather Underground"). The sensor network includes several multipurpose sensors that also collect window and door status information. Details of the embedded devices and data collection coverage scope will be introduced in the next section.

For the purpose of comparing how the results from the default EnergyPlus™ settings differ from those that apply the Agent-based model, two scenarios are tested in this study. The first scenario is the baseline model that keeps all the original settings: schedules are unchanged; and the second scenario applied the occupant behavior schedules obtained from the ABM. As a result, all the settings were altered for the studied zone, while the simulation was run throughout the whole building. In addition, for the weekends during the simulation period, all settings remain the same in both cases. A simulation settings summary is shown as follows:

1. Testbed Building: Educational building (behavior change only in Zone VAVX 48).
2. Time Period: 4 weeks (11.14-12.9).
3. Weather File: USA_FL_Gainesville.Rgnl.AP.722146_TMY3.
4. Scenarios: Baseline, ABM schedule.
5. Number of Agents: Single Agent
6. Environmental Inputs Source: Embedded sensors (Dry Bulb Temp, RH, Illuminance), Weather station (Outdoor Temp, RH).

Relevant data collection

Aside from the simulation platform design, relevant data collection is necessary for two reasons. First, actual data input, such as temperature, humidity and illumination is more likely to construct realistic ambient environment of occupant, so that the model output is more reliable and will have the potential to outperform simulated environmental data. Second, when data collection contains several behavior measurements, it could be used to build models with different data-driven methods for results comparison and validation. Another possible usage of the data could be real-time monitoring of variation caused by building occupants that could be used to develop an energy optimization policy.

In the initial set up for data collection process, indoor environmental measurements record indoor temperatures, relative humidity, and indoor illumination (lux) at the same time stamp at 5-minute interval. These parameters are measured and logged through a customized embedded sensor network, which composed of a smart motherboard, corresponding raw sensors, and some peripherals. The data measured by the raw sensors are logged in a Micro-SD card (Secure Digital), which is plugged into the mother board. After the test phase, more sensors will be added to this sensor node to measure additional environmental parameters such as CO_2 and sound level (dB). Plus, when data volume become bigger, an online database may be needed for data storage. Figure 5 shows a sample of the customized sensor node. Finally, the outdoor environmental parameters acquired from the weather report website provides hourly temperature and humidity data.

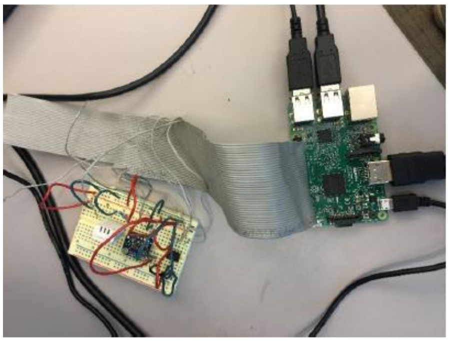

Figure 5: Sample picture of collecting device

Behavior measurements currently utilize a commercial sensor network consists of a hub that is connected to the local internet, and two magnetic sensors that are attached to the door and window to record their on/off status. The information could reflect the actual occupant behaviors of opening window/doors. After the test phase, other common behavior data need to be detected with corresponding sensors or meters. The behavioral data are used for improving the ABM through validation and calibration process.

The instrumental devices are the basis of future validation and calibration work for the ABM. A validation study will be conducted in the next research step to assess the applicability of the ABM.

Results and discussions

The raw outcome of the ABM consists of a behavior list taken by the agent at each time stamp. It is assumed that the occupant works in the office 8 hours per working day, during which he/she performs an action at each hour. At each decision-making step, the behavior is allowed to be repeated, even if it has been taken before. For example, the agent opened the window for some reason, however at the next time step the environment is still making him/her uncomfortable. Therefore he kept the window opened without doing anything else, according to the Utility calculation.

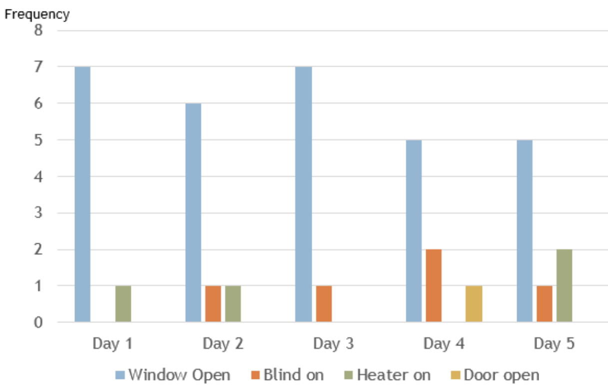

Figure 6: Raw output of ABM

Figure 6 shows the count for the behavior taken over 5 days. For instance, it can be seen that the window opening behavior is the most common behavior and occurred differently for each day, but usually lasted for the whole day, as there is no window closing behavior taken by the agent. The other behaviors happened in a slightly different mode from the ABM. However, it should be mentioned that the occurrence of each behavior only provides an insight of the agent's preference, while the order or the time step, when one behavior is taken, matters for coupling to EnergyPlus™.

Specifically, the raw output of the ABM needs to be translated into effective schedule that could be implemented in EnergyPlus™. The translation process is based on the output behaviors and orders they are executed. For example, in day 1, heater use is generated as the first execution behavior, and since no turning off heater behavior is generated, we consider the heater use behavior lasts for the whole day. Following this principle, the 5-day sample of typical behavior schedules is developed as shown in Figure 7. Two points are noticeable from the results. First, each behavior has a different schedule for each day; Second, for each day, the behavior patterns vary in a subtle manner, which conforms to the idea that occupants' behaviors change over time. Lastly, we assume that each building component in the model only has two conditions: open (on) and closed (off). So, the schedule only shows 0 or 1 whenever it changes. The schedule could be adjusted to percentage values as needed to reflect a more accurate condition of building systems and components.

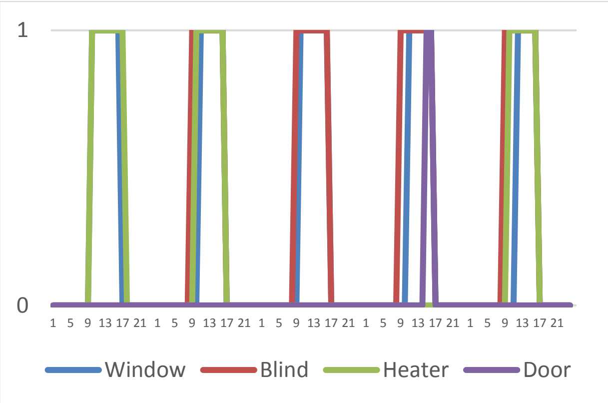

Figure 7: Schedules obtained from raw results

After taking into account the occupant behavior influence to the thermal zone, the 4-week energy simulation results are shown (Figure 8). The simulation adjustment for Scenario 2 occurs in one zone (VAVX 48) of the building, and energy use of the whole building is increasing as behavior schedules were modified based on the ABM occupant behavior schedule. The results show that energy use difference in one year could be significant. This demonstrates the necessity of incorporating occupant behavior information in building simulation. To better illustrate the importance of this research, historical measured energy use data will be involved in the next research step to compare with the simulated results. Ideally, the ABM-based model tends to generate closer output to actual data in terms of total energy use within the same timeframe.

In terms of the thermal zone that is modulated and simulated, three factors were chosen to present the influences that are caused by occupant behaviors. Table 2 summarized the value differences between the two scenarios.

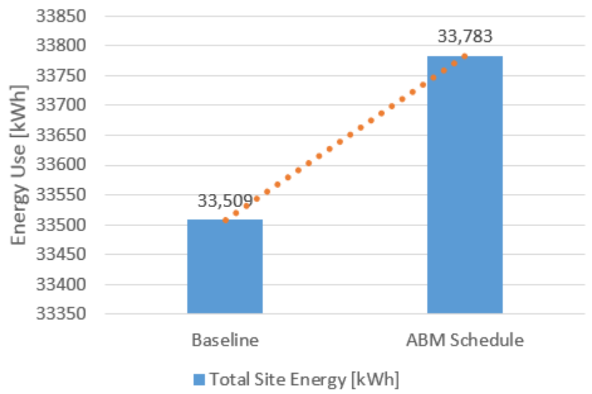

Figure 8: Energy use comparison of the baseline and ABM modified simulation for 4 weeks

The first factor is a direct reflection of occupant comfort level during the simulation period, which is represented by time that the set point does not meet the requirement. In ABM scenario, it is obvious that there are less hours that the setpoint does not meet pre-settings because of the occupant behavior; the second factor is from the heat gain summary report, where infiltration heat addition is significantly different in the two scenarios. The two results showed that behaviors such as opening the window and heater adjustment, raised the amount of heat from outside that brought burden to the HVAC system. Therefore, total energy consumption will potentially be increased; finally, the third factor influences HVAC energy use and occupant comfort as well. It is clear that the behaviors taken are increasing the sensible heat, which means more energy will be consumed to maintain a stable indoor environment. It can also indicate the occupant prioritizes comfort before energy use in an office building.

Table 2: Selected parameters for results comparison

Scenarios	**During Occupied Heating [hr]**	**Infiltration Heat Addition [GJ]**	**Equipment Sensible Heat Addition [GJ]**
Baseline	163.5	0.035	0.335
ABM Schedule	92.5	0.066	0.565

In general, results demonstrate that occupants' behavior are indeed affecting building energy use, and default settings of building simulation engine underestimate this impact. As observed from this study, at the outset, we primarily focus on structuring and integrating the necessary models to conceptualize the problem adequately.

Future directions

This research experiment is an initial trial of the ABM platform and integration with building energy simulation tools, such as EnergyPlus™. However, limitations exist for future exploration. First, the simulation coupling process was done manually for this experiment, which is not feasible for a longer period or smaller time granularity. This needs to be improved by creating bridging programs for automatic simulation execution. Second, the experiment is designed on a simulation-based framework with no validation. In other words, no actual behavioral data is involved in the simulation study. However, as mentioned before, relevant data is being collected for future use. Third, the ABM model itself needs to be modified to reflect a more realistic situation of simulated environment, including agent characteristics description, behavior options, and rule revision.

Conclusion

In response to the limitation of current building simulation engines that simplify occupant behavior, this paper introduced the use of an ABM based on perception and cognition of an agent and an energy simulation model in EnergyPlus™. This integration is able to specify the interactions between building and occupant in a dynamic form and implement the effect for improving building energy simulation as a whole. The results showed quantitative impact of common behaviors to energy use and other built environment factors, which helps develop more accurate simulation and designing behavior intervention. Future research will improve the ABM, which will include more perception types and behavior options, and to validate the output of the simulator. Moreover, the co-simulation framework should be connected by a bridging program to realize automatic data exchange instead of manual operation. Lastly, the estimated energy use should compare to actual building energy use over a longer simulation period for model calibration and validation.

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