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SIMULATING HUMAN BEHAVIOR: AN AGENT-BASED MODELING APPROACH

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ABSTRACT

A new methology using agent-based modeling for human behavior simulation is presented. This approach aims to address the limitations and/or challenges of dealing with behavioral components in existing building simulation programs. Also, it tries to improve behavior decision process by mimicking actual occupants in buildings. In a simulation experiment, a window use behavior was tested with agent-based modeling and demonstrated its ability to account for dynamic changes of the behavior, in real-time, and the behavior impact on both the microclimate and energy uses in a space.

INTRODUCTION

Human behavior in buildings has commonly been cited as the favorable attribute that explains the gap between the simulated and actual energy consumption data. Nevertheless, due to the uncertainties in behaviors, most current simulation research neglects to fully account for realistic occupant behaviors (Zimmermann, 2006).

The objective of this paper is to uncover limitations in current practices for human behavior simulations, and to introduce agent-based modeling as a new methodology to address the limitations, so that real-life behaviors can be modeled.

In a previous paper, authors have outlined the challenges of behavior simulation in buildings and explained how manipulating the simulation schedules (occupancy, lighting, equipment, and HVAC) can control the load changes due to occupant behavior (Lee et al., 2011). In addition, our ongoing efforts to address the behavior simulation in research identify the following limitations: First, a clear causality between behaviors and environmental stimulus is not fully defined and/or reflected in simulation programs. Typically, occupant behaviors such as window use or electric light use are either ON during operating hours, and OFF otherwise, without being responsive to the dynamic changes of the stimuli. Second, a single behavior decision is made for the entire space (or zone) based on an averaged environmental stimulus (e.g., temperature). For example, ASHRAE Adaptive Comfort Model prescribes the upper and lower temperature limits for the use of operable windows in a naturally ventilated space. The simulation takes the zone temperature average to determine one window use behavior for the entire zone. The limitations hardly allow us to apply realistic behaviors of an actual building, hence, they open up opportunities for increased accuracy in simulation results.

To mitigate the shortcomings of current behavior simulation, an agent-based modeling approach is presented in the paper. Agent-based modeling is defined as 'modeling agents – or building occupants – individually to account for effects of the diversity among agents in their behaviors, in the pursuit of understanding the whole system' (Macal et al., 2010). The strength of agent-based modeling, particularly in human behavior research, is summarized below:

- All behavioral aspects of agents can be modeled (Azar et al., 2010).
- Allow for different agents to communicate with each other for joint-decision making in a given environment (Luck et al., 2003).
- Addresses the uncertainties of the real world by using techniques from statistics, computer science, etc. (Ramos et al, 2008).

In the following section, a simple simulation experiment is presented to highlight the potentials of agent-based modeling, and it discusses how agent-based modeling can be integrated into an existing building simulation program.

METHODOLOGY

Agent-based modeling is normally a simulation tool, programming language, or prediction models used for simulating agent behaviors and agent interactions, which is consisted of three core elements: (1) a set of agents, their attributes, and behaviors, (2) a set of agent relationship and methods of interaction, and (3) agents' environment (Macal et al., 2010; Luck et al., 2003). The scope and complexity of agent-based modeling depends on the specifics of the above three elements. Nevertheless, even the simplest agent-based modeling, which consists of agents and their relationship, could unveil valuable findings about the system as a whole (Bonabeau, 2002).

Agent-based modeling presented in the paper is programmed in Matlab, with a goal of mimicking a

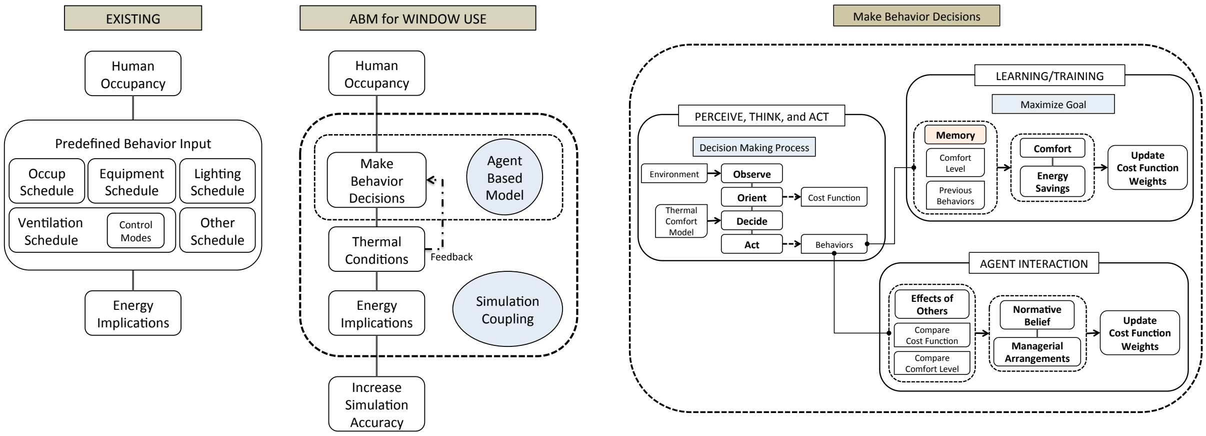


Figure 1 Comparison between existing and proposed simulation process

mimic building occupants by understanding the given environment (spatial and thermal), thinking about various behavior decisions in response to the environment, and executing behaviors. In order to make decisions, an agent is programmed to prioritize the level of its thermal comfort, and hence, consider thermal parameters (e.g., temperature, humidity, air speed, etc.) as the main stimulus for behaviors.

Figure 1 illustrates how the use of agent-based modeling (hereinafter ABM) distinguishes itself from the existing method for simulating occupant behavior. The diagram compares the window use behavior in a naturally ventilated space. In an existing simulation program (first diagram from the left in Figure 1), such as EnergyPlus, a fixed occupancy schedule, or "Human Occupancy," is what dictates the schedule for the window use behavior, or "Ventilation Schedule." In addition, a "Predefined Behavior Input," such as equipment use, lighting use, ventilation control mode (elaborated in the EXPERIMENT section), and others that are indicative of various occupant behaviors, is decided and used throughout the entire simulation cycle.

On the other hand, the proposed method (middle diagram in Figure 1) uses the ABM to make decisions solely on the comfort level of an agent. After an agent makes a decision whether to open/close the window, the ABM sends the information to EnergyPlus to calculate the immediate changes in the thermal condition of the space and the energy implications. The communication is through an onion simulation coupling (using *MLE Legacy* and *BCVTB*) so that the ABM and EnergyPlus can exchange information in real-time (Nghiem, 2012; Wetter, 2011). The information consists of the thermal parameters that determine the comfort level of the agent, behavior decisions of the agent, and the behavior implications on thermal conditions and energy uses (exchanged at each simulation timestep).

The "Make Behavior Decisions" process is illustrated in Figure 1 (far right diagram), which basically covers the logic of the ABM and how the agent makes behavior decisions. The detailed background and theoretical framework related to the process are not covered in the paper, while a brief summary is as follows:

1. Perceive, Think, and Act
   - Observe: At each timestep, an agent observes the thermal parameters in the space to determine the level of comfort.
   - Orient: An agent calculates a cost function to identify and rank different behavior options that would maintain comfort or mitigate discomfort in the space.
   - Decide: Based on the thermal comfort model, an agent decides on the behaviors to consider and the magnitude of the behaviors, e.g., wear a light sweater or turn on a personal fan. This is elaborated in the next section.
   - Act: An agent notifies the execution of behaviors to all the ABM components to initiate the learning/training and agent interaction process. In addition, simulation coupling is conducted so as to calculate the changes in thermal conditions and energy uses.
2. Learning/Training
   - Memory: An agent keeps track of the behaviors executed and their effectiveness in achieving the comfort level.
   - An agent cost function can be constructed to maximize its goal to either increase/maintain 'comfort' or achieve 'energy savings.'
   - Update cost function weights: The weight coefficients associated with the cost function are updated based on the effectiveness of the behaviors toward comfort (not covered in the paper).

3. Agent interaction
   - Effects of others: An agent observes how its behavior affects others, and vice versa, by comparing behaviors of others with its own cost function and comfort level.
   - The cost function is consisted of a normative belief of an agent that accounts for these effects of others. The normative belief changes as a result of this agent interaction, but also defined by managerial arrangements that constrict certain agent behaviors.
   - Update cost function weights: The weight coefficients associated with the normative belief in the cost function are updated based on the effectiveness of the behaviors toward comfort (not covered in the paper).

Overall, the assumed advantages of ABM are the following:

- Instead of using zone-averaged thermal parameters, the ABM tries to use those that directly affect an agent in real-time.
- Therefore, multiple agents can incur varied behavior decisions in a zone, and truly realize the ABM mindset – describing a system from the perspective of its constituent units (Bonabeau, 2002).
- Ultimately, the ABM allows a simulation process to closely emulate the real world, helping to increase simulation accuracy by increasing the prediction accuracy of internal heat gains that result of occupant behaviors.

SIMULATION EXPERIMENT

The experiment simulates the window use behavior in a naturally ventilated space in EnergyPlus, coupled with the ABM approach. In a naturally ventilated space, the thermal conditions of the space are regulated primarily by occupants through opening and closing the windows (ASHRAE, 2004). Therefore, the experiment only considers the zone mean air temperature as the stimulus for determining the window use behavior. However, a more comprehensive ABM will calculate the Predicted Mean Vote (PMV) for thermal comfort to capture the effects of multiple behaviors.

The experiment is not only to test the new ABM methodology, but also to quantify the impact of occupant behavior on building performance. Also, it compares how the results from the default EnergyPlus simulation differ from those that utilize the presented ABM. Figure 2 is a diagram of the simulation process that is part of EnergyPlus. The different 'Control Mode' (also in Figure 1) implies how behavior decisions on window use are calculated in EnergyPlus (DOE, 2011). The ones that are tested in the paper are as follows:

- Constant: All of the zone's operable windows and doors are open, independent of indoor or outdoor conditions.
- Temperature Driven: All of the zone's operable windows and doors are opened if $T_{zone} > T_{out}$ and $T_{zone} > T_{set}$.
- Adaptive thermal comfort: All of the zone's operable windows and doors are opened if the operative temperature is greater than the comfort temperature (central line) calculated from the ASHRAE Standard 55-2010 adaptive comfort model.

Simulation Settings

Figure 3 illustrates the space used to simulate window use behavior in the experiment. The simulation settings are as follows:

- Simulators: EnergyPlus version 7.01 and Matlab
- Weather: Philadelphia, PA, USA
- Gross floor area: 669.3 m^2 (Single zone)
- Program: Generic office area
- Window to Wall: 30% (5 windows at North and South façade)

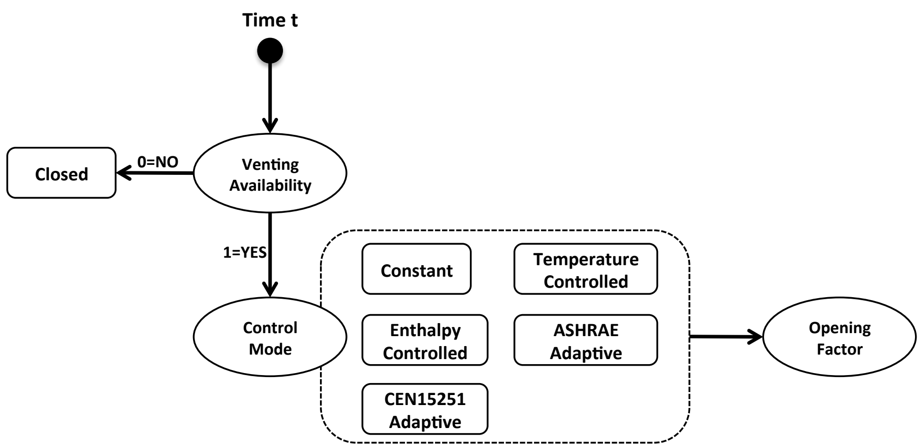


Figure 2 Window use behavior simulation process in EnergyPlus

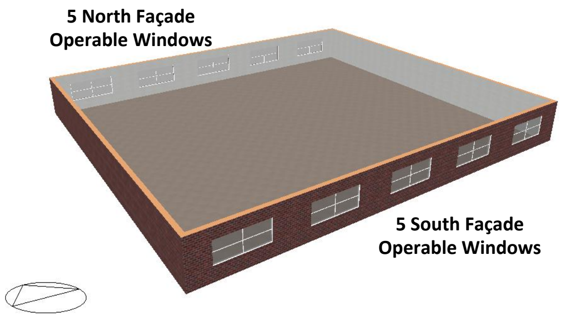


Figure 3 Simulation space

- Hours simulated: 8760 hours
- Number of agents: a single agent
- Mechanical: Fan-coil unit
- Ventilation: Mixed-mode ventilation

Figure 4 explains how the ABM is coupled with EnergyPlus, which can be compared with the process shown in Figure 2. Instead of the embedded control mode provided by EnergyPlus, the ABM conducts an onion coupling, i.e., at each timestep it will perceive the level of occupant comfort satisfaction and determine whether to open/close the window. First, an agent perceives the environment as it observes the zone air temperature that is related to the space, which is information transferred from EnergyPlus to ABM. If an agent is comfortable (based on adaptive thermal comfort), there is no window use behavior, but otherwise, an agent will think about its options to respond to the comfort dissatisfaction – or 'Calculate Cost.' In this case, only a single agent and a single window use behavior are considered, hence, the cost primarily calculates the sum of an agent's belief on the effectiveness of window use for comfort and the ability to actually control the windows (Fishbein et al, 2010), without consideration for agent interactions. If the cost exceeds a certain criteria, behavior is executed.

'S1' and 'S2' in Figure 4 refer to the two states of the behavior, closed and opened, respectively. The four arrows between the two states refer to the four transitions: closed to open, opened to close, remain opened, or remains closed. This information is exchanged from the ABM to EnergyPlus to not only calculate the behavior impact on energy use, but also the microclimate of the space that would affect decision-making process at the next timestep ('Time t+1').

The simulated space is conditioned with a fan coil unit, with mixed-mode ventilation (alternate) allowed during the simulation period.

RESULTS AND DISCUSSION

Figure 5-(a) is a graph showing temperature trends populated by the ABM, from January to March (first 1200 hours) of the site. It compares the zone mean air temperatures dictated by three control modes for window use behavior: *Reference* case with no window use behavior (existing EnergyPlus default settings), *temperature-based* control mode (using an existing EnergyPlus algorithm), and *adaptive comfort* control mode. One of the most noticeable observations is that allowing control to adjust the windows resulted in decreased diurnal temperature swings. This is consistent throughout rest of the colder months (Nov-Dec). Even between the two control modes for window uses (temperature and comfort), comfort-based adaptive comfort control mode seems to have smaller temperature fluctuations.

As for the hotter months from July to September, as in Figure 5-(b), all the temperature trends seem to parallel each other. The average zone air temperatures for the reference case, temperature-based control mode, and adaptive comfort control mode are 24.4°C, 24.3°C, and 25.9°C. This indicates that comfort-based behavior decisions result in larger zone air temperature, and ultimately incur higher internal heat gain in the space.

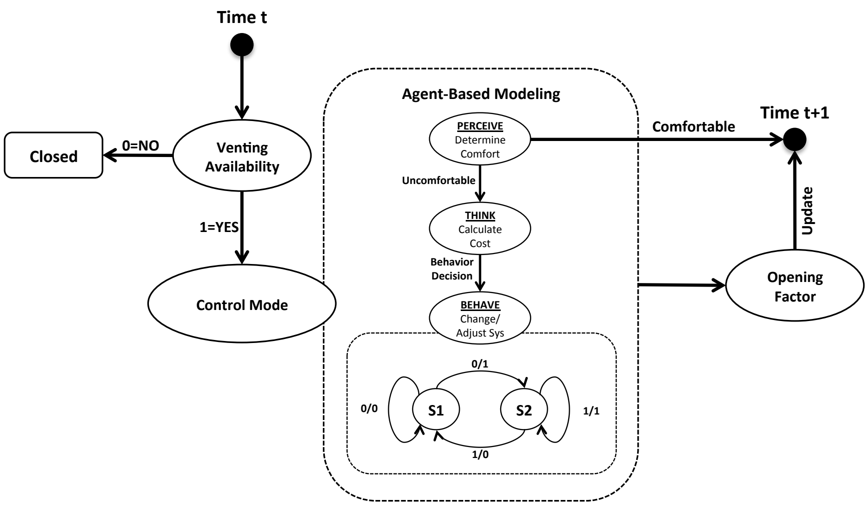
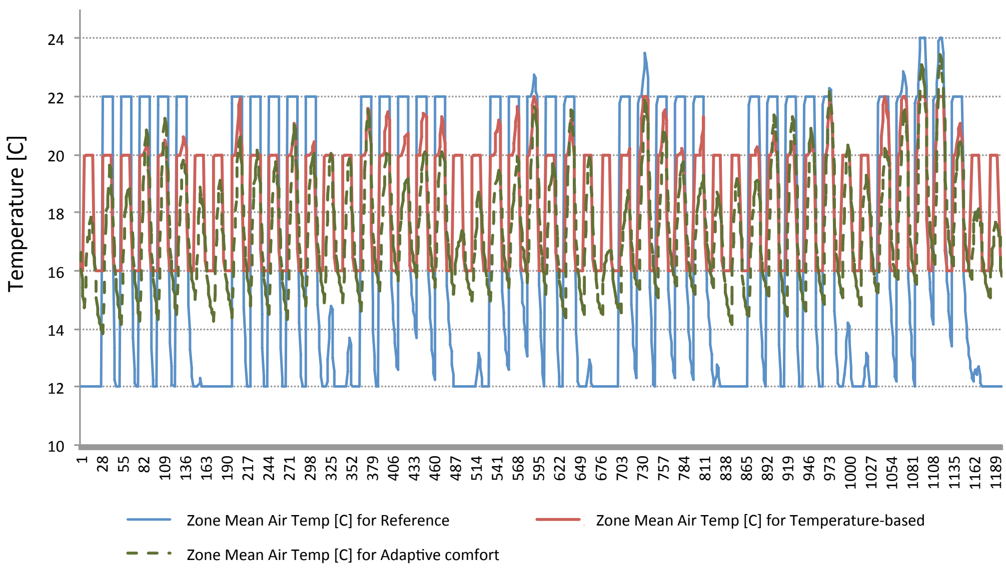


Figure 4 Window use behavior simulation process in ABM

(a)



(b)

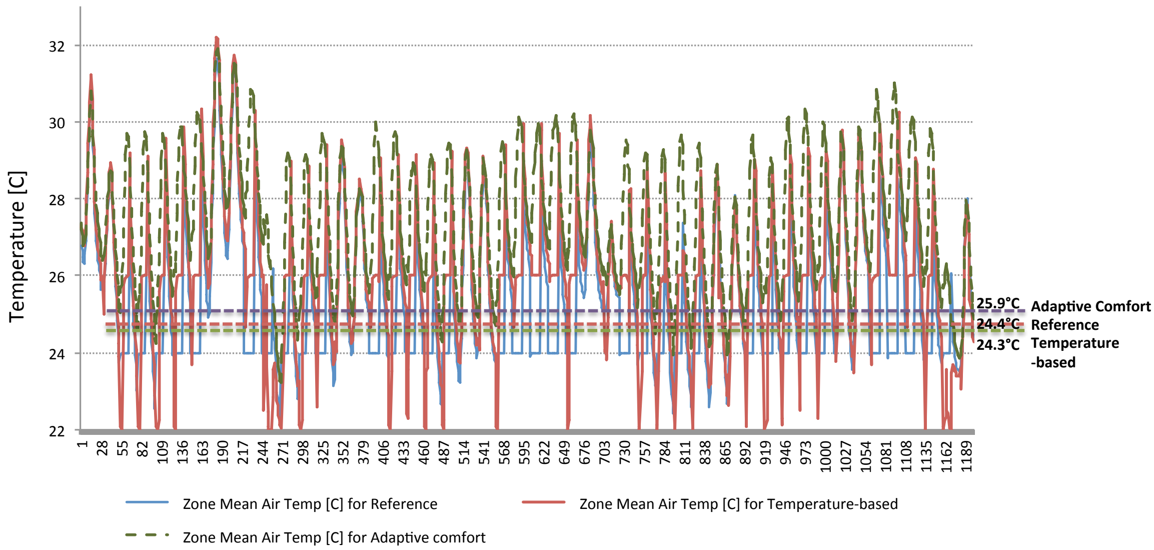


Figure 5 Zone mean air temperature trend comparison for different behavior control modes, (a) January to March, (b) July to September

The results may imply that having some control over building systems to manipulate the built environment may increase the tolerance for operative temperature, which resembles the adaptive model for thermal comfort (de Dear et al., 1998).

In terms of the annual heating and cooling demand, allowing the window use behavior resulted in higher overall demands. As shown in Figure 6, the temperature-based control for window use resulted in the highest annual heating ($35.4kW/m^2$), and the adaptive comfort mode in annual cooling demand ($46.4kW/m^2$).

The two results make it clear that even accounting for a single behavior could result in dissimilar simulation results compared to the reference mode.

The experiment also compared the window use behavior in the two simulation platforms. Given the same simulation settings, a window use behavior based on temperature-based control mode was simulated in the default EnergyPlus model and the ABM coupled EnergyPlus model. Figure 7 is the sum of total temperature difference in the zone mean air temperature between the two cases. The results illustrate how the ABM approach creates different thermal conditions in the space from a non-ABM approach, despite using the same calculation algorithm.

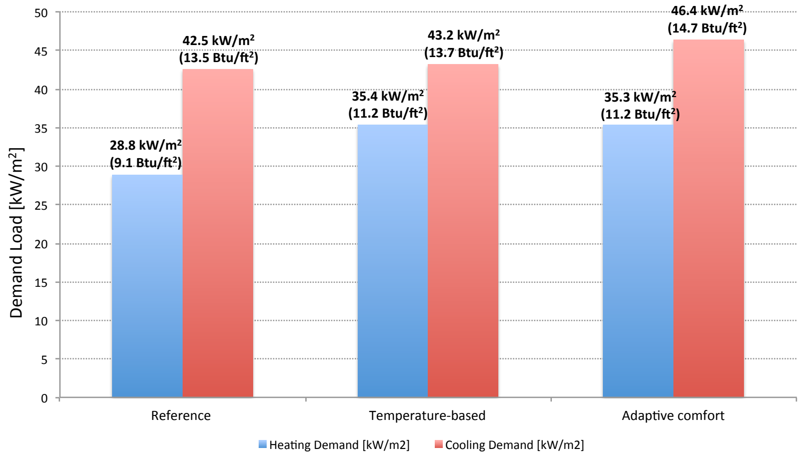


Figure 6 Annual heat and cooling demands for different window use behavior control modes

This is more evident during the hotter months of the year – up to almost 12°C hourly.

CONCLUSION

In response to the limitations of current simulation practices that oversimplify human behaviors, the paper has presented a new simulation methodology that couples existing energy simulation program with agent-based modeling.

The biggest advantages of agent-based modeling (ABM) is that it closely mimics the behavior of an actual occupant, i.e., from an occupant perspective, rather than relying on external forces such as occupancy schedule, which are not always representative of the entire occupant population.

The experiment using ABM was compared to the existing simulation process, investigating window use behavior in a naturally ventilated space. ABM was able to capture the behavioral impact on energy consumption, and also dynamically update the thermal conditions of a space. That is, while the existing simulation program was only concerned with a behavior-energy causality, the ABM was sensitive to the subtle effects of the behavior on occupants' thermal conditions in real-time, which implies that behavior events are not entirely dependent on the environmental stimuli, but also on other behaviors.

The energy results were not as intuitive as we had initially expected – the increase of window use behavior (for natural ventilation) should have lowered the overall energy consumption due to the lesser use of mechanically conditioned air. Our results indicate that adaptive comfort control mode for window use behavior yields the highest end use energy demand, which we can conclude with the following possibilities:

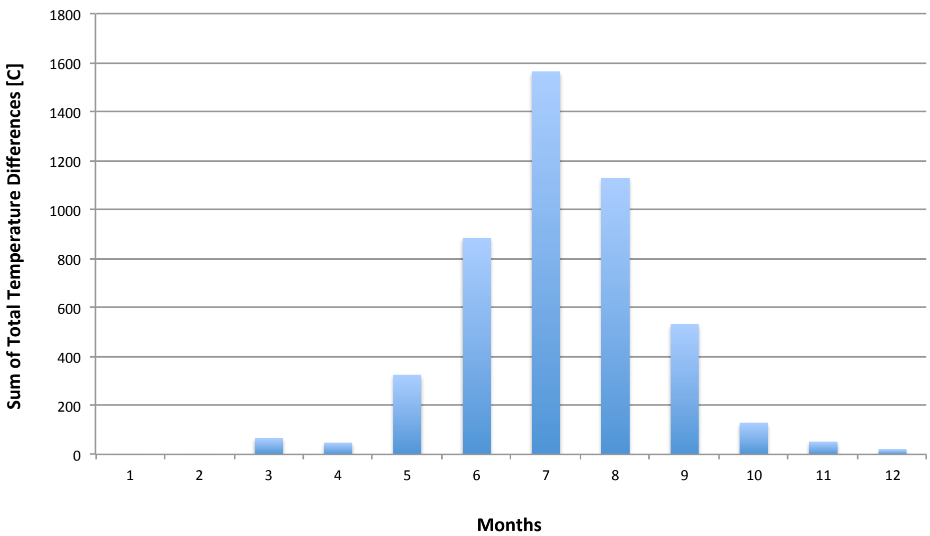


Figure 7 Zone mean air temperature differences (monthly sum) as a result of window use behavior based on temperature-based control mode, between existing and ABM simulation results

- Maintaining the level of comfort in a space incurs other emerging energy demand, e.g., a ventilation heat loss due to opening the windows.
- The logic used in the ABM was not robust enough to fully account for the expected energy savings.
- Overall increased zone air temperature, for the comfort-based ventilation control, was compensated by other mechanical entities to meet the HVAC setpoints.

Our next step is to incorporate other behaviors into the picture – such as lighting use, thermostat adjustment, personal cooling/heating equipment, adjusting clothing level, etc. By optimizing the ABM logic and validating the model with actual data, we expect to have a holistic understanding of occupant behaviors in buildings, and ultimately, use the knowledge to increase the prediction accuracy of building simulation programs.

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AUTHOR RESPONSE TO REVIEWER COMMENTS

Comments from Reviewer #1:
1. Comparison of mean radiant temperature with mean air temperature between the different simulations should not be done. Mean radiant should be compared with mean radiant and dry bulb air temperature should be compared against dry bulb.

→ Fixed. This was a simple typo overlooked from transferring graphs to the paper.

2. How does the ABM relate to external temperature (agents should be satisfied with higher indoor temperatures in summer and lower temperatures in winter, this is a characteristic occupant response)?

→ As mentioned in the INSTRUCTION section, determining comfort/discomfort was based on Adaptive Thermal Comfort Model (ASHRAE) as this paper (mostly the simulation experiment) only dealt with the window use behavior in a naturally ventilated space. In our more developed agent-based modeling, we calculate the PMV for thermal comfort to account for multiple behaviors and their relationship to other thermal properties.

3. How is y-axis scale of fig 7 obtained?

→ Fixed. It should have been the “Sum of monthly temperature differences.”

4. ABM logic should be presented (even if at a high level). It is not sufficient to just say that an ABM has been used.

→ We have added the higher-level ABM logic in Figure 1.

Comments from Reviewer #2:
1. Change the names of the three control modes: Benchmark to Reference; temperature based OK, ASHRAE to adaptive comfort.

→ DONE.

2. Give illustration of the position of the windows (opened or closed) for a typical day for the 3 modes. It is not clear if you run 2*3 simulations or 3: the 3 modes with or without ABM or only the modes with ABM. On fig 6, only 3 simulations appear.

→ For the purposes of presenting a simple simulation experiment, we were not concerned with the positioning of the window (only OPEN vs. CLOSE for now), but more with comparing how our ABM approach yields different simulation results from the existing simulation process. Basically, the three simulation modes point to the three different logics associated with accounting for window use behavior. Note, that the ‘Reference’ case assumes no behavior, so as to highlight that even a single behavior can make a difference both in thermal conditions and energy uses of a space.

3. Fig 7 is not understandable: what is the y axis (values of temperature reaching 1800)? Is that a cumulative difference for one month? What are the consequences?

→ Fixed. Refer to comment #3 from Reviewer 1. The reasoning for the comparison (consequences) is now added in the text.