Leadership in Sustainable Infrastructure
Leadership en Infrastructures Durables

Vancouver, Canada
May 31 – June 3, 2017/ *Mai 31 – Juin 3, 2017*

EXPLORING AGENT-BASED MODELING FOR HUMAN-CENTERED ENERGY CONSUMPTION PREDICTION

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Abstract: People interact with buildings to make the indoor environment more comfortable thereby impacting energy consumption. However, these occupants' energy-related actions in buildings are not well accounted for using traditional simulation programs and normally are represented in a simplistic manner. Agent-based modeling (ABM) is widely used to predict real world situations and this approach has been used to model human behavior in different contexts. ABM has also been used in relation to energy consumption prediction. This study explores how ABM can be used to better model not only human behavior but also look into how occupant values (for instance thermal comfort, visual comfort, indoor air quality, perceived health and personal productivity) and indoor environmental preferences can be maintained while ensuring energy savings. The human behavior considered in this paper include occupants adjusting layers of clothing, using portable heating and cooling devices, adjusting thermostats, adjusting lighting levels, and using shading devices. Following a review of the available literature, the authors highlight the gaps and present recommendations to better address occupant preferences and behavior.

1 INTRODUCTION

Agent-based modeling (ABM) techniques are versatile and have been used in various disciplines to depict human behavior. Through ABM approaches, real-life problems can be simulated in the agent environment by observing and computing changes sensed by the agent. ABM tools find applications in marketing to study financial markets, in transportation for traffic management (Bonabeau 2002), and in organizations for decision making (Macal and North 2007). They are being increasingly used in the building industry for fire safety egress design (Kuligowski and Peacock 2005), for construction site operations and to improve energy conservation in buildings. Indeed, ABM tools have been beneficial in depicting human behavior to improve safety of systems, gain better understanding of processes and enhance end-user satisfaction in different contexts.

Human behavior is complex and dynamic and as a result, people value different things in buildings in relation to the indoor environmental conditions such as thermal comfort, visual/lighting comfort and indoor air quality (IAQ) so they interact with building systems to improve their comfort and to achieve their preferred satisfaction levels. A number of studies have demonstrated that occupant behavior impacts energy consumption. Hong and Lin (2012) quantified the impact of occupant behavior on energy consumption in office buildings by simulating different categories of occupants based on their energy use habits. The 'wasteful' work style could increase energy consumption by up to 90% compared to a standard energy consumer while the 'austerity' (conservative) occupant can save up to 50% of energy. Some of the behavior people engage in to adjust the indoor environmental conditions to their preferred settings include opening and closing windows, adjusting thermostats, and using shading devices to meet their comfort needs. Occupant behavior could be challenging to model given the complex nature of humans. Considering the link between human behavior and energy consumption, it is important to address occupant-related parameters in buildings. In traditional building energy simulation programs, occupants are represented using simple schedules which do not capture the differences in occupant preferences and behavior. ABM allows occupants to be represented as agents which are able to assume assigned characteristics and behave according to stated rules. ABM is continuously evolving and it provides an avenue for occupant factors to be considered in conducting energy simulations.

In this paper, the authors explore different occupant behavior for under consideration for improvement of energy use predictions from simulation tools. The need to address occupant-related factors is highlighted demonstrating that building occupants should not be seen as similar but diverse, having individual needs and preferences. Studies that have used the ABM approaches are discussed and the opportunities that exist for improving agent-based modeling for improved energy prediction is also shown.

2 METHODOLOGY

A review of available studies on occupant behavior related energy consumption with ABM was conducted using search engines such as Google Scholar, Engineering Village, and American Society of Civil Engineering (ASCE) using a combination of the keywords ‘agent-based modeling’, ‘energy’, ‘buildings’, ‘occupant behavior’. The results of the search were narrowed down to find the relevant studies based on the applicability to ABM to improve energy efficiency in buildings taking the building occupants into account. Since the focus of this study is to explore how ABM can be used to address different occupant behavior, the review was modified to take this into account looking at how existing energy simulation tools may be improved and how ABM tools can be leveraged to address this concern. A few studies were selected from the final results of the search. Tools that can be used for ABM were identified. The tools vary in usability and complexity but the main factors that were considered for a suitable ABM tool are the ease of assigning agent behaviors, the accuracy of energy predictions and the interaction of the agents based on the rules of the environment. The details of the ABM tool comparison are not included in this paper.

From this preliminary study, recommendations for a methodology using ABM for occupant-based energy prediction were presented. The study aims towards exploring the use of ABM (incorporated with other simulation tools) to ensure

- Occupant values are accounted for
- Occupant behavior is captured
- Impact on energy consumption is more accurately quantified
- Occupant satisfaction is maintained

The capabilities of existing simulation tools can be extended to enable the inclusion of occupant values in estimating building energy consumption. For instance, determining the programming requirements, the capabilities of the tool, the interface, limitations, and similar applications of the tool for energy prediction. A critique of available agent-based modeling platforms will also highlight the opportunities for occupant values and behavior prediction.

3 OCCUPANT FACTORS AND BUILDING ENERGY SIMULATION

The building sector in the US consumes about 40% of total energy (EIA 2016). The majority of the energy used in office buildings is apportioned to space conditioning (heating and cooling) and lighting. Energy simulation tools are used to estimate building energy consumption but most buildings have wide variations in the simulated data and actual consumption, some of which is attributed to occupant-related factors. The occupant-related factors include the values, preferences and behavior of people in a building.

3.1 Occupant Values

Occupant values are the things people consider are important to them in buildings. The main occupant values are listed and briefly described below:

- Thermal comfort which is determined by various factors mainly the indoor temperature and humidity
- Visual or lighting comfort influenced by the illuminance levels
- Indoor air quality relates to the cleanliness of the air influenced by the particulate and carbon dioxide levels in a space
- Personal productivity
- Perceived health
- Energy cost savings
- Environmental protection

The ASHRAE thermal comfort standards address the factors that influence thermal comfort in buildings (ASHRAE 2013). From the list of these values, perceived health and personal productivity are affected by the indoor environmental quality (thermal comfort, lighting/visual comfort, and IAQ) while energy cost savings and environmental protection could influence their energy use habits. From a survey conducted by Amasyali and El-Gohary (2016), to identify the values that are important to office building working in three states in the US, they ranked health as the most important to them followed by energy cost savings, indoor air quality, and thermal comfort occupants (based on about 300 responses). This further highlights the need for healthy indoors also energy cost savings will directly translate to energy conservation which is beneficial for the environment. Satisfaction is subjective and dissatisfaction with the indoor environmental conditions could influence occupant behavior. Since people spend a majority of their time indoors, it is important that they have indoor environmental conditions that are conducive and promotes their wellbeing health and productivity.

3.2 Occupant Behavior

The building stock comprises different types of facilities and diverse designs. They provide varying levels of control to the occupants which could cause them to take certain actions that impact energy use. For instance, in some buildings occupants have access to adjust the thermostats, they could make the space warmer or cooler. In situations where they have no control, they may use portable electrical devices such as heaters and fans to improve their comfort. In both instances, energy use is impacted. The building function could also influence occupant behavior. There are several external factors that influence building occupants such as the outdoor weather conditions, economic status, energy conservation habits, and culture. Hong et al. (2016) classified energy-related occupant behavior into two categories namely adaptive and non-adaptive behaviors. In adaptive behavior, occupants could adapt the environment to meet their needs or adapt themselves to meet the environment while in non-adaptive behavior, people use additional equipment like using portable fans or heaters to improve their comfort. The industry is working towards a more uniform way of representing occupant characteristics in buildings by developing a framework for building occupants (Hong et al. 2016).

The most commonly observed occupant behaviors are listed below

- Use of windows
- Use of blinds
- Use of portable electrical equipment
- Adjusting thermostats
- Use of lighting

Various studies have looked into aspects of this for ABM implementation (Azar and Menassa 2012), (Lee and Malkawi 2014)

3.3 Building Energy Simulation

Energy models are not very sensitive to occupant behavior (Azar and Menassa 2012). Occupant parameters are often entered incorrectly and are oversimplified in energy simulation tools. People are seen as static and are identified based on occupancy levels- the number of people in a zone, rather than the individual occupant's preferences and needs. This assumption leads to building systems that are oversized which provide indoor environmental conditions that are not well-suited to the users of the space thus leading to energy wastage. It has been demonstrated that up to 30% of energy savings can be achieved by taking occupant behavior into account in energy simulations (Hong et al. 2016). Clevenger and Haymaker (2006) confirmed the notion that wrongly entering a single parameter in an energy modeling tool can inaccurately estimate energy use by up to 40%.

Building energy simulation tools are used to estimate energy use by building systems such as the heating, ventilation, and air-conditioning (HVAC) systems and lighting systems. They can also simulate different energy sources such as gas and electricity. Energy simulations can be computed for individual equipment or for a whole building. They are used for sizing equipment to provide estimates of energy use based on the inputs provided to the simulation tool. They can predict the building performance over a period of time (e.g. annually) and can be used at various phases of a building from conceptual design phase for a new building to the operation phase (i.e. for retrofit) in an existing building. Energy performance is calculated including outdoor weather conditions, occupancy, building type and other building parameters (Macal and North 2007). Energy simulation tools are based on algorithms that are integrated with the simulation program engine. In order to improve simulation accuracy, dynamic schedules are sometimes used but they still do not reflect the needs of individual occupants.

Open source energy simulation tools enable the integration of additional algorithms to improve the occupant-related energy use prediction for different behaviors. Hong et al. (2016) identified three stochastic occupant behavior representations namely the Bernoulli process, Markov chain, and Survival analysis. In the Bernoulli process, occupant behavior does not change with the state of the system but the Markov chain approach takes the past into account while the Survival analysis method is used to predict longevity. The Markov chain model is used in ABM and it was found that for energy use predictions it is important to be able to include the past behavior of occupants to predict future behavior and impact on energy consumption and satisfaction (Khazaii 2016).

In determining occupant values and behavior, it is important to capture behavior through monitoring strategies so a more accurate representation of occupant characteristics including their preferences and satisfaction is determined (Andrews et al. 2011) while also taking the external influencing factors into account. It is important to have the right occupancy levels to estimate the number of people in a space at a specified time so this is also considered along with the behaviors.

4 AGENT-BASED MODELING OF BUILDING OCCUPANTS

Agent-based models have been around for several years and are derived from complex adaptive systems (CAS) (Macal and North 2007). The aim of CAS is to understand how complex behavior is derived from agents. According to Holland (1995), CAS allow for integration, they are non-linear and allow the flow of information. The agents are diverse and can behave differently from each other. CAS are widely used in the biological sciences to model complex and emergent behavior in agents (Holland 1995). This modeling approach is also used in different domains such as social, economic, physiological, ecological, physical, and transportation systems (Davidsson et al. 2007).

With the evolution of ABM systems, increased complexity and functionality have been incorporated into the systems. ABM tools can model systems that comprise autonomous interacting agents. Multi-agent systems, which comprise multiple interacting agents, have also seen increasing applications in various fields of study to predict, analyze or manage different phenomena. Individual agent behavior is modeled to determine the global behavior of the agents as they interact with each other. Intelligent agents are able to predict human behavior, perceive the environment, and act accordingly with minimal human input (Arciszewski et al. 2005).

Agents are autonomous and are capable of acting alone, interacting with each other and interacting with their environment (Bonabeau 2002). The agents can respond based on their own behavior or based on their interaction with other agents. Bonabeau (2002) also listed the best scenarios to use ABM namely when the agents are complex, heterogeneous and not fixed. Building occupant behavior exhibits these agent scenarios. ABM involves the agents, the relationship between the agents and the agent environment. The ABM approach is presented in Figure 1 below extending it to multi-agent systems (MAS). MAS involves multiple agents interacting with each other and with the environment. The agents are assigned different characteristics/attributes and respond based on the rules of the system. They interact with each other and interact with the environment. Their behavior could also be impacted by the environment.

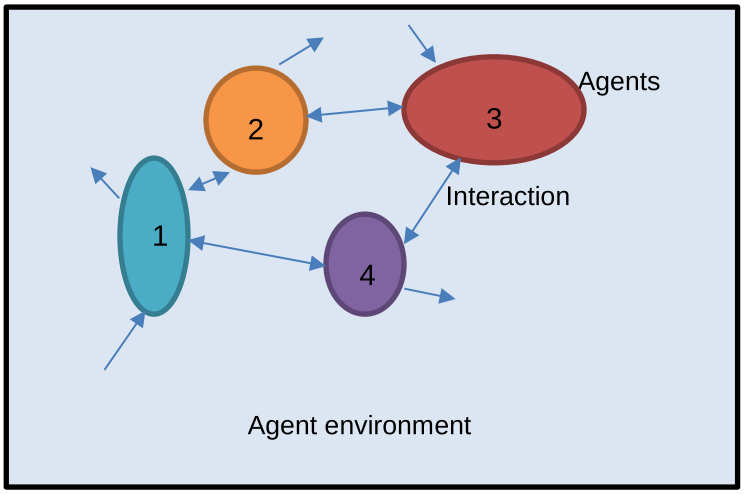

Figure 1: Components of ABM- MAS (Adapted from (C. Macal 2012))

One of the main advantages of ABM includes the ability to reach logical conclusions in situations where it is not feasible and cost effective to perform actual experiments (Khazaii 2016). Kara and Baxendale (2012) created an agent architecture that comprised two types of agents. They represented human and electrical loads integrated with dynamic load control (DLC) algorithms using different an agent-based model which showed good potential for managing building loads taking humans into consideration. Building energy simulation tools are used to model the energy consumption of a building. These tools sometimes take into account a number of occupant characteristics while making several assumptions. Also, people have different perceptions of indoor environmental conditions and energy-related factors (Accenture 2010) so it is important to track these and estimate how they influence energy use.

Studies have looked into using an agent-based approach to model building occupant behavior and assess the impact of occupant behavior on energy consumption. In the study conducted by Azar and Menassa (2012), they found a 25% variation between using traditional modeling approaches and using ABM by changing the occupant characteristics. They had three different categories of occupants - high energy consumers (HEC), medium energy consumers (MEC) and low energy consumers (LEC) adapted from a study by Accenture (2010). The HEC use too much energy, the MEC make the least effort to consume energy while the LEC are energy efficient. They validated their tool using a simulation model case study building. They mentioned the need for using actual energy measurements to validate the tool.

Lee and Malkawi (2014) developed an agent-based model and identified how the agent handles the five behaviors mentioned in the previous section. The approach taken for the model was simulation by coupling using a numerical computation tool and an open source simulation tool. They considered how the agent adapts to dynamic thermal changes and optimizes comfort and energy savings. They also emphasized the need for validation with actual measured data from buildings and occupants. The use of multi-agent simulation to imitate real life behavior was discussed.

Zhang et al., (2011) applied ABM to electricity consumption by computers and lights. The objective was to integrate organization energy management policies, energy management technologies, electrical appliances and occupant behavior in an office into one model. They also developed a multi-agent framework using multiple agents to study practical energy management issues and found it could be a useful tool for energy management in offices.

Cao et al (2015) used ABM for a scheduling framework to determine the prioritization of maintenance by facilities managers in buildings. Impressively, they observed a 30% and 97% increase in occupant satisfaction and building energy efficiency respectively. ABM has been explored for incorporation into the design of building control systems in HVAC applications (Treado and Delgoshaei 2010). They mentioned the potential of these tools to be used for control and configuration of autonomous building systems. The use of ABM to simulate the influence of energy saving policies among different occupants was explored by Bastani et al. (2016) and they found a 13-20% variation in energy savings between two ABM approaches that were used.

The application of agent-based modeling focusing on energy source was explored by Macal (2012). For instance, an ABM tool was used for scenario development for offshore wind energy and for residential energy generation. It has also been used to model micro-combined heat and power (CHP) for residential energy generation (Houwing and Bouwmans 2006).

In Table 1, the ABM representation of some occupant behavior is presented. It is recommended that the table is updated to reflect occupant factors following the identification of how best to quantify measured occupant behavior. Human behavior can be represented implicitly using rules, using artificial intelligence techniques or they can be probabilistic.

Table 1: Agent-Based Modeling Tools and Occupant Behavior

Behavior	**ABM Tool Representation**
Window opening and closing	Open or closed (including percent open)
Use of blinds	Percent open or close from 0-100
Use of portable electrical equipment	Equipment power consumption
Adjusting thermostats	Inputs of preferred temperature set points
Use of lighting	Occupant’s preferred illuminance levels
Occupancy levels	Based on schedules from occupancy patterns

It has been demonstrated that ABM is useful and applicable in human centered studies into energy related behavior in buildings. Accurate prediction of occupant behavior remains a challenge for analyzing occupant impact on building energy performance.

5 RESULTS

A combination of the different occupant behavior (Table 1) can be assigned to individual agents. The cost function or utility function determines the relative value of different behavior assigned to agents and it determines the satisfaction of the occupant (Arciszewski et al. 2005). The agents can be examined based on their interaction with the environment, their interaction with one another and, where their behavior evolves, based on what they learn from another agent. Machine learning methods could also be combined with these to reflect the behavior of a real agent over a period of time under different indoor environment scenarios and contexts. In other words, the reliability of the ABM can be improved by using actual empirical data. The agent could continuously learn from its environment and adapt to changes in the environment.

Two different approaches may be taken to using ABM or MAS, simulation coupling and using ABM on its own. First, the agent environment is defined. The building to be modeled is selected including its form (geometry) and characteristics (For instance, the location of windows). The agent characteristics can be estimated from existing behavioral models or developed from actual measurements using occupant feedback from empirical studies, through previous studies that have been conducted (LEC, MEC or HEC). The occupant-related characteristics that have been defined in a simulation tool can be adjusted to reflect the changes in energy consumption by the occupant. The tool can be adapted to accommodate different occupant-energy-related behavior and validated through case studies using actual buildings.

A few of the items to take into consideration for the agent-based model development include

- Identify behavior of agents (or occupants) and associated impacts
- Assign occupant behavior to the agents
- Predict energy consumption taking into account different behavior
- Determine how the comfort of the agents will be maintained
- Track the agent location in the building model
- Enable agent interaction and allow them to respond to changes in the indoor environment
- Consider and react based on the rules and the relationships between the agents
- Leverage existing tools to improve comfort

6 DISCUSSION

Drawing from this initial exploratory study, we emphasize that it is important buildings and conducive and healthy for occupants since health was one of the most important factors to occupants from the survey by Amasyali and El-Gohary (2016). We identify the main features of an ABM for occupant-related energy use behavior and stipulate that more accurate representation of occupant factors is beneficial to move towards attaining more accurate simulation results and providing comfort to the occupants. Oversimplification of some of the occupant values introduces errors and resulting in inaccurate estimates of energy use. Also, the importance of using empirical data is discussed since buildings are operated differently, buildings with identical features and systems are also operated differently partly due to the uniqueness of individual occupants. To estimate the occupant parameters more empirical data can be acquired through actual studies with the building occupants on a large scale to obtain representative data. Learning algorithms can be developed from these for better behavior representation. This could be linked back into the simulation tool for the parameters that cannot be handled by the ABM tool.

Opportunities for more accurate prediction of occupant behavior using ABM approaches have been identified. Identifying the right inputs for the ABM tool and ensuring interoperability and also having a standard methodology could be beneficial in achieving a more accurate prediction of occupant factors and energy consumption.

Different aspects of occupant behavior have been discussed. Incorporating the energy cost savings and the environmental awareness still requires further exploration to quantify how this might affect behavior. The comfort of the occupants is addressed by providing the agents (occupants) with their preferred indoor environmental conditions and assigning these to the agents. A robust methodology will be subsequently developed leveraging existing tools. A simulation to estimate other occupant characteristics while maintaining the building envelope features but changing the agent preferences and maybe agent location could be beneficial to find the optimum placement of occupants in a building based on their preferences.

In developing the tool, a range of behaviors will be considered and an average of standard user identified to estimate the impact on energy consumption taking into account their satisfaction. The occupant parameters should be more accurately defined so weighting factors are assigned to them. We could leverage existing tools and identify how the occupants in buildings being monitored under the categories of occupants of whether it is beneficial to have individual profiles for different occupants especially those in private offices.

Some of the recommendations that can be drawn out are enhancing energy simulation tools using ABM has proven to be beneficial. MAS will be more appropriate to resolve the simultaneously attain occupant satisfaction and energy savings in buildings (Rafsanjani et al. 2015). Therefore, including intelligent autonomous agents that are able to think and act on their own could improve the simulation accuracy of the tool. Since the agents are observed to mirror human behavior, including more behavioral patterns that take place in buildings improve the representativeness of the models. Using adaptive agents that can intelligently predict and respond to changes in the environment could be a new frontier for ABM in energy simulation.

7 CONCLUSION

People can impact energy use in buildings so exploring how occupant parameters can be included in the simulation of energy consumption could provide opportunities for energy conservation. This paper explores existing studies into how occupant behavior might be accounted for or represented in buildings and identifies the opportunities that exist to improve existing systems relying on simulation tools alone. This can be achieved using multi-agent systems or ABM and simulation coupling with an open-source energy simulation tool. Further research into developing a conceptual model and integrate it with empirical occupant-related and energy use data is still ongoing.

The key is exploring how actual occupant feedback data can be used to represent occupant parameters and also attain the occupant values to maximize satisfaction and minimize energy consumption. Focusing on an office building context, a scenario where agents can be introduced to an environment and their preferences are taken into account for energy use prediction while maintaining the building features could enable quicker adoption of this type of technology. The interaction of an agent with other agents in a building in relation to their energy consumption patterns could also provide a beneficial contribution. The agents could be mobile so when they are placed in a different location in a space the optimum location of the agents that provide the highest energy savings in a new building based on their preferences can be selected.

Since the agents are diverse and the behavior of the agents is determined by different rules, their interaction with other agents could bring about a difference in the system as a whole. It is recommended that ABM results are validated with real data so they can be reliably used for decision making for future systems. As researchers seek to simultaneously achieve all the goals of the ABM for simulations to be more human-centered, there still remains a lot to be learned about the feasibility of achieving and applying the proposed recommendations. Future work will involve the development and implementation of a building model with actual energy measurement and occupant data using an office building case study to explore the feasibility of addressing various aspects of occupant-related energy use.

8 ACKNOWLEDGEMENTS

The authors acknowledge the support of Qatar National Research Fund (QNRF), a member of Qatar Foundation (Grant No. 6-1370-2-552).

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