IMPACT OF OCCUPANTS BEHAVIOR ON BUILDING ENERGY USE: AN AGENT-BASED MODELING APPROACH

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ABSTRACT
Energy modeling techniques used during the design phase of buildings are failing to accurately predict energy use during the buildings operational phase. The main reason behind this discrepancy is the misrepresentation of the role and impact of occupants' energy consumption characteristics on building energy use. Current energy modeling tools represent occupants as static elements, overlooking their different and changing energy use behaviors over time. These behavioral aspects significantly affect energy consumption levels, hence the need for a new energy modeling approach that overcomes the limitations of traditional energy modeling tools by better accounting for occupants actions and behaviors to predict buildings energy consumption. Therefore, this paper presents a new agent-based modeling approach that accounts for the diverse and dynamic energy consumption patterns among occupants, in addition to the potential changes in their energy use behavior due to their interactions with each other and with the building environment.

Keywords: building energy consumption, occupant behavior, behavior change, agent-based modeling

1. INTRODUCTION

According to the United Nations Environmental Program, buildings are responsible for 30 to 40 percent of global energy use, and a similar percentage of green house gas emissions (UNEP-SBCI 2007). Over the life-cycle of buildings, more than 80 percent of the energy consumed occurs during the operational phase to meet various energy needs such as heating, ventilation, and air conditioning (HVAC), lighting, water heating, and various equipment loads. Moreover, in commercial buildings, more energy is often used during non-working hours than during working hours mainly due to occupancy related actions (Masoso and Groblera 2010).

A number of studies emphasize the role that building occupants play in affecting the energy consumption in buildings and the anticipated savings in energy usage if occupant behavior was influenced over time. A change in behavior could lead to energy savings in excess of 40 percent in some cases, leading to significant economical and environmental benefits (Emery and Kippenhan 2006; Meier 2006; Staats, Leeuwen, and Wit 2000). The Building Sector has therefore a large potential for delivering long-term, significant and cost-effective greenhouse gas emissions reductions, leading governments to shape their policies and programs to reduce energy use during the operational phase of buildings (UNEP-SBCI 2007).

A number of empirical and energy simulation models exist and are widely used in the building sector to predict energy consumption during the operational phase of buildings. Common software programs are eQuest, Energy Plus, Energy-10, and IES (IES 2011; SBCI 2010; EnergyPlus 2009; eQuest 2009). These tools are used at different stages of the life-cycle of buildings, but most importantly during the design phase to optimize the selection and the sizing of mechanical and electrical systems. Consequently, accurate energy predictions are essential to avoid common equipment over-sizing issues, typically resulting in excessive and unnecessary energy use throughout the life of the building under study (Crawley, Hand, Kummert, and Griffith 2008). Furthermore, the need for accurate energy estimates is growing with the increasing demand for Life-Cycle Analysis (LCA) and Life-Cycle Cost Analysis (LCCA), performed to assess the environmental footprint and the economic value of buildings.

However, current energy modeling tools are failing to accurately predict energy use. Their estimates are typically deviating by more than 30 percent from actual energy consumption levels and this difference can even reach a value of 100 percent in particular cases such as laboratory buildings with high process loads (Yudelson 2010; Dell'lsola and Kirk 2003; Soebarto and Williamson 2001).

Although several limiting factors such as the complexity of buildings, weather, and variations in building schedule might affect the accuracy of energy estimates, studies are showing that these deviations are mainly attributed to misunderstanding and underestimating the important role that the occupant's energy use characteristics play in determining energy consumption levels; the term 'occupant's energy use characteristics' being defined as the presence of people in the premises and the actions they perform (or do not perform) to influence the level of energy consumption (Hoes, Hensen, Loomans, DeVries, and Bourgeois 2009; Turner and Frankel 2008). As a matter of fact, current commercial energy modeling software are accounting for occupancy in a static way by making simplistic assumptions about building occupants and their energy consumption behavior.

More specifically, the first assumption made by these tools is that all occupants have similar energy use patterns and consume energy at the same rates. This assumption results from the limited number of occupancy-related inputs that can be entered into the models, imposing a common schedule for all occupants and a common energy consumption pattern. Consequently, these tools are ignoring the results of many studies showing that building occupants typically have diverse energy use behaviors, which significantly affect the accuracy of the generated energy use estimates (Hoes, Hensen, Loomans, DeVries, and Bourgeois 2009; Turner and Frankel 2008)..

The second assumption made by typical energy models is that occupants' behavior remains constant over time. Here again, several studies are showing that occupants might change their energy use characteristics over time by adopting more energy efficient practices or on the contrary, adopt bad consumption habits due to the often called 'rebound effect'. As an example of the 'rebound effect', occupants might tend to use more electric lighting following the installation of energy saving bulbs, assuming that their actions will have less impact on the environment. Such types of behavior change negatively impact energy consumption by increasing energy use (Sorrell, Dimitropoulos, and Sommerville 2009; Jackson 2005). On the other hand, factors such as energy conservation campaigns/trainings that encourage energy use reduction or financial incentives that incentivize energy savings typically lead to positive changes in energy consumption behavior. Another important factor is the 'word of mouth' or the 'peer-to-peer' effect, which is considered to be a very influential channel of communication. Originally used in the marketing field to promote new commercial products, the 'word of mouth' factor in terms of energy use is defined as the influence that each occupant exerts on the other occupants sharing the same building environment to change their energy consumption habits. Lastly, feedback techniques have also proven to induce energy use reduction by providing occupants with information about their energy consumption levels. These better informed occupants typically tend to save energy, especially when they are given access to the energy use levels of the neighboring offices or rooms in the same building (Peschiera, Taylor, and Siegel 2010; Allsop, Bassett, and Hoskins 2007; Staats, Harland, and Wilke 2004).

In brief, there is a need to account for building occupants in a dynamic way by considering and modeling their different energy consumption characteristics in addition to the potential changes in their behavior over time.

2. OBJECTIVES

The main objective of this paper is to present a new energy modeling approach to better predict energy use during the operational phase of commercial buildings. The proposed framework needs to account for different occupants' energy consumption patterns, their change in behavior over time, and finally simulate the resulting impacts on building energy use. This dynamic modeling of occupants is expected to result in more accurate estimates when compared to traditional energy modeling techniques that overlook the significant impact of occupancy actions and interactions on building energy use.

3. AGENT-BASED MODELING

Several simulation tools were identified in literature that are capable of modeling social and behavioral systems. The most common simulation methods are: Discrete Events (DE), System Dynamics (SD), and Agent-Based Modeling (ABM). While DE and SD are considered to a certain extent as centralized structures requiring the user to define the global system behavior (systems), ABM is decentralized where the modeler defines behavior at an individual level. In this 'bottom-up' modeling method, the global behavior emerges as a result of many individuals, each following its own behavior rules, interacting and communicating with each other and with their environment (Gilbert 2008; Edmonds, Hernandez, and Troitzsch 2007; Borshchev and Filippov 2004). More specifically, agent-based models consist of individual agents, commonly implemented in software as objects. Agent objects have states and rules of behavior. Running such models simply amounts to instantiating an agent population, letting the agents interacts, and monitoring what happens (Axtell 2000).

For this purpose, this research investigated the use of ABM as a technique capable of simulating almost all behavioral aspect of agents, which represent the building occupants (Gilbert 2008; Axtell 2000). As detailed in the upcoming sections, agents, or building occupants, are assigned attributes that define their specific energy consumption characteristics and patterns. These characteristics might change over time due to external events (e.g., energy conservation training), or due to the interactions with other occupants (e.g., peer-to-peer influence).

4. METHODOLOGY

Four main steps were required to achieve this research's study objectives: (1) Define different occupancy energy use characteristics and identify factors that cause them to change, (2) build an agent-based simulation model, (3) generate energy use rates for each type of energy use behavior, which are imported into the simulation model, and finally (4) verify the built model through a numerical example.

4.1. Occupants energy use characteristics and influencing factors

The first step consisted of defining different energy consumption behaviors, which is essential for building accurate energy estimation models (Yu, Fung, Haghighat, Yoshino, and Morofsky 2011; Hoes, Hensen, Loomans, deVries, and Bourgeois 2009; Clevenger and Haymaker 2006). Therefore, three categories of occupants were considered. 'High Energy Consumers' (HEC) represent occupants that over-consume energy. 'Medium Energy Consumers' (MEC) are the average energy consuming occupants. Finally, 'Low Energy Consumers' (LEC) represent occupants that use energy efficiently. These assumptions were made based on a study by Accenture (2010) that classified energy consumers in different countries around the world into eight different categories based on their attitude toward energy management programs. However, after discussions with industry professionals, and because of the main focus on energy modeling, it was assumed in this paper that three categories of occupants are adequate to observe differences in energy consumption levels.

Occupants in the three proposed categories mainly differ by the way they use the building energy systems, resulting in different energy use levels. To understand and quantify these differences, an intensive literature review was performed to understand how HEC, MEC, and LEC use each of the main building energy systems such as lighting, equipment/computers, and heating, ventilation, and air conditioning systems (HVAC). For instance, the study by Bourgeois, Reinhart, and MacDonald (2006) was used to identify the variations in the light switching patterns of occupants in commercial buildings. Regarding equipment/computer use, data collected by Sanchez, Webber, Brown, Busch, Pinckard, and Roberson (2007) and Webber, Roberson, McWinney, Brown, Pinckard, and Bush (2006) were used to determine common rates of office equipment use for different occupancy patterns. Similarly, the studies of Davis and Nutter (2010) and Wang, Federsipel, and Rubinstein (2005) were considered to study occupants' presence in their offices, which significantly affects the energy use levels.

After defining different energy consumption characteristics, it was important to identify the factors that might affect these behaviors and cause them to change over time. Three main factors were chosen for analysis in this paper.

First, energy conservation trainings/workshops were considered, which are informational events that educate occupants about energy saving practices and encourage them to reduce their energy consumption. So, after attending such events, a portion of the occupants is expected to reduce its energy consumption. This is translated into a conversion of some HEC to MEC, and some MEC to the LEC category.

Second, the 'rebound effect' represents the opposite type of behavior change, where occupants counter react to energy reduction initiatives and increase their energy use. In that case, a portion of the LEC becomes MEC, and some MEC convert to HEC.

Finally, the peer-to-peer influence represents the influence that occupants sharing a certain building environment have on each other to change their energy consumption patterns. So, each category of occupants (HEC, MEC, and LEC) might influence occupants from the other categories to change their behaviors, and adopt its energy consumption patterns. So, in this type of interaction, three possible changes in behavior or conversion of occupants can occur as illustrated in Figure 1. The first line shows the case where HEC are influencing MEC and LEC. This change in characteristics is gradual where some MEC get converted to HEC, and some LEC become MEC. Similarly, the second and third lines of Figure 1 respectively show the cases where MEC and LEC are actively converting other occupants. The influence of each category on the others depends on the number of persons in this category in addition to its Level of Influence (LI), which is entered by the user. More details on these conversions are provided in the upcoming sections.

Figure 1: 'Peer-to peer' interactions and conversions

4.2. Agent-Based model

The next step consisted of building an agent-based model to simulate the above-mentioned interactions and predict energy use.

The agent-based software that was chosen for this research is 'Anylogic', which is widely used in the industry (XJ Technologies 2009; Borshchev and Filippov 2004). The choice of 'Anylogic' was mainly due to its Java-based environment that allows the user to develop custom Java codes, and integrate them in pre-built simulation blocks (XJ Technologies 2009). This was essential in this research to optimize and customize the proposed model in order to simulate the complex behavioral aspects of building occupants. The proposed model flowchart is shown in Figure 2 where a five-step iterative process was defined.

First, energy consumption rates for HEC, MEC, and LEC are imported into the agent-based model to be used in the following stages (Step 1). Details on obtaining theses rates are shown in the upcoming section.

Step 2 simulates the interaction of agents and the potential change in behavior due to the 'word of mouth' or peer-to-peer effect. So, for the first time step (e.g., first month), HEC, MEC, and LEC sharing the same simulation environment (e.g., office) interact and try to influence each others to change behavior. The chances of success for each category are dependent on two variables: (1) the number of persons in this category at the current time step, and (2) its Level of Influence (LI) on other categories. Initially, three LIs are entered by the user before the beginning of the simulation: LI_{HIGH}, LI_{MEDIUM}, and LI_{LOW}. For instance, a LI_{HIGH} of 5 percent/person/month means that each HEC person has a 5 percent chance of successfully converting another occupant every month. So, a high number of HEC at a specific time step or a high LI_{HIGH} results in high pressure on the other occupants sharing the same environment to increase their energy consumption and become HEC. At the end of Step 2, the model updates and stores the numbers of HEC, MEC, and LEC for the current time step.

Next, the model moves to Step 3 to check if an energy conservation event (e.g., training, workshop, etc.) is scheduled for this time step. Here again, the user can schedule 'events' and specify their effectiveness before running the model, then track their impact on occupancy behavior and energy use. For instance, an event scheduled for month 12 with an efficiency of 30 percent result in the conversion of 30 percent of HEC to MEC and 30 percent of the MEC to LEC when the simulation time reaches 12 months. So, for each time step, the model checks if any 'event' is scheduled and updates the number of HEC, MEC, and LEC.

In step 4, the model checks if a rebound effect is occurring at this time step, leading to a change in behavior and an increase in energy consumption. In this case, the conversion of occupants occurs towards the high energy consumption categories, where some LEC become MEC and some MEC convert to HEC. Here again, the occurrence time and the effectiveness of the rebound effect is previously specified by the user.

The updated numbers of HEC, MEC, and LEC are then combined to the energy consumption rates obtained from Step 1, and total energy consumption levels are calculated for the current time step (Step 5). Once this iteration is completed, the model moves to the next time step and keeps repeating the cycle until the total simulation time is reached.

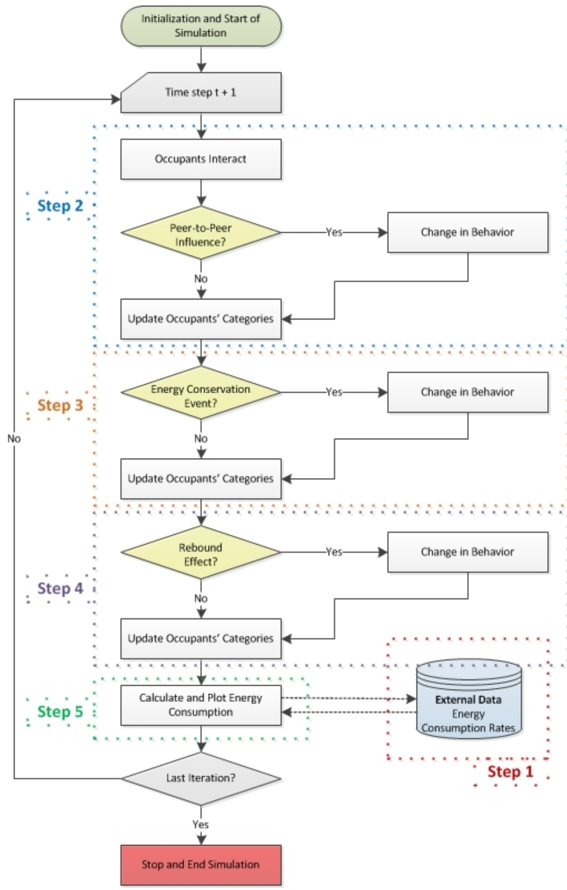

Figure 2: Model's flowchart

4.3. Energy use rates for different types of energy use behavior

This section presents the proposed method that was used to obtain energy consumption rates for HEC, MEC, and LEC using traditional energy modeling software (e.g., EnergyPlus, eQuest, etc.). In this study three sets of simulations were particularly needed, each set having specific inputs representing the different energy characteristics of the three defined categories of occupants. In general, two types of inputs are required to build these models: (1) building related inputs which are the same for all the simulations, and (2) different occupancy related inputs that will lead to the three different energy use rates.

So, the first step consists of defining the building environment under study accommodating occupants who consume energy over time through their daily activities. Common inputs related to the building under study are determined such as the building type and size, floor plan layout, construction materials, HVAC equipment, lighting systems, miscellaneous equipment (e.g., computers), and hot water supply (Dell'lsola and Kirk 2003).

The next step consists of defining occupancy related parameters, leading to the difference between the energy consumption levels of HEC, MEC, and LEC. These differences are generated in traditional energy simulation software by varying occupancy related parameters such as 'equipment rates of use' or 'building operating schedules'. For instance, to illustrate how HEC leave their computers ON more frequently than MEC and LEC during building non-operating hours, parameters such as equipment use rates can be increased for the HEC simulation to represent this over-use of energy. Similarly for the rest of the energy consumption sources (e.g., lighting, HVAC, etc.), specific inputs are used to customize each of the three simulations and translate the differences in behavior into differences in energy consumption levels. The obtained rates are then imported into the simulation model as was shown in Step 1 of Figure 2, to be used for the total energy use calculation of the building under study.

It is important to note that the input parameters are determined on a case by case basis, depending on the building environment and on the specific occupancy characteristics. A detailed example of the proposed method is presented in the following section.

5. MODEL VERIFICATION THROUGH A NUMERICAL EXAMPLE

This section highlights the capabilities of the model through a numerical example and presents some of the sensitivity analyses that were performed to verify the model.

5.1. Environment description

First, an experimental energy simulation model was built for the purpose of this study using eQuest. This conceptual 2000 square feet (186 square meters), two-story university type building, is located in the city of Madison, Wisconsin (See Figure 3). The first floor contains two open space offices accommodating 16 and 10 graduate students respectively. The second floor contains one classroom with a maximum capacity of 50 students.

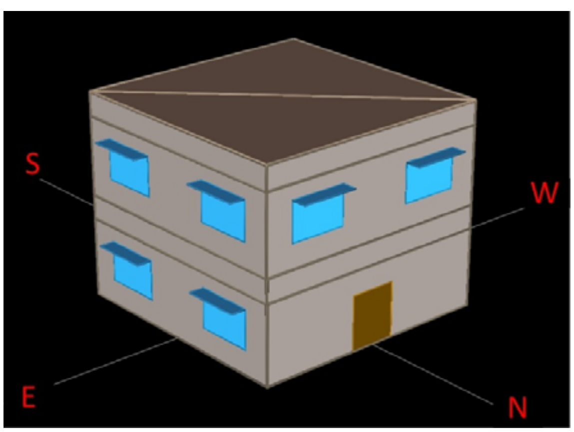

Figure 3: Building environment in eQuest

5.2. Inputs and assumptions

Six energy consumption sources were considered in this example: (1) HVAC heating, (2) HVAC cooling, (3) area lighting, (4) task lighting, (5) equipment (computers), and (6) hot water supply. For each occupant categories (HEC, MEC, and LEC), energy consumption rates were obtained using eQuest by running different experiments using specific inputs that reflect their behavioral differences (Refer to Section 4.3 for more details about the method used). More specifically, three types of inputs were varied in the simulations to differentiate between the energy use behaviors of HEC, MEC, and LEC: (1) lighting schedules, (2) equipment schedules (computers), and (3) hot water use.

In this example, the parameters were first derived based on several studies in literature on occupants and the different energy consumption patterns they adopt (Masoso and Grobler 2010; Mahdavi, Mohammadi, Kabir, and Lambeva 2008; Sanchez, Webber, Brown, Busch, Pinckard, and Roberson 2006; Webber, Roberson, McWinney, Brown, Pinckard, and Bush 2006). Some parameters were also suggested by eQuest, which follows the California's Title 24 building code requirements (eQuest 2009). Additional occupancy related assumptions had to be made about the differences between the high, medium, and low energy use levels. These hypotheses were then reviewed and confirmed by industry experts and were as a result considered acceptable. A summary of the used parameters is shown in Table 1.

Table 1: Input Parameters Variation

	HEC	MEC	LEC
Lighting Schedules	30% of time running after building operating hours	10% of time running after building operating hours	0% of time running after building operating hours
Equipment Schedules	60% of time running after building operating hours	20% of time running after building operating hours	0% of time running after building operating hours
Hot Water Use	20% more than MEC	1.20 Gallon/Pers/Day	20% less than MEC

So, by using the above-shown sets of parameters, energy consumption rates for HEC, MEC, and LEC were obtained, and then imported into the proposed agent-based model.

5.3. Agent-Based model outputs

The next step consisted of executing the steps of the flowchart shown in Figure 2 to simulate occupancy and predict the building's energy consumption levels. An example of the proposed model's output is shown in Figure 4, showing the change in behavior in one of the offices of the building (upper graph), along with the resulting changes in energy consumption (lower graph). Similar graphs are generated for each of the building's rooms, allowing to track occupancy behavior and energy consumption changes both on a room and on a whole building level.

At the start of the simulation, and for this particular office, 5 of the students were assumed to be HEC, 6

MEC, and 5 LEC, reflecting average energy use characteristics. LEC were assumed to have a higher LI than the other categories, showing a strong influence of energy efficient occupants on others. The occupants of the studied room were also assumed to attend an energy conservation event at month 12 encouraging them to reduce their energy consumption and adopt energy saving practices. In this example, the efficiency was set at 50 percent, which means that after attending the event, 50 percent of the occupants were expected to reduce their energy consumption. Also, a rebound effect with a 25 percent efficiency was scheduled for month 24, resulting in an increase in the occupants' energy consumption, and a conversion from the LEC and MEC categories to the MEC and LEC categories respectively. It is important to note that the specific choice of parameters in this example was made to highlight the capabilities of the model. All of the parameters can be specified by the user through a user-friendly interface to customize the model and better represent the specific building and occupants under study.

Figure 4 illustrates how the occupants of the office were changing behavior over the 36 months simulation time due to their interactions with each other, and also due to the external events that were scheduled for months 12 and 24. So, by sharing the same office, the 16 occupants were influencing each other according the LIs that were entered for this particular example. This resulted in a change in behavior represented by the change in the numbers of HEC, MEC, and LEC over time. Moreover, the energy conservation event at month 12 caused a sudden conversion of occupants towards the LEC with their number increasing from 6 to 9. The opposite type of conversion occurred at month 24, with a drop in the number of LEC and an increase in HEC and MEC.

These changes in energy behavior were reflected on the energy consumption levels of the office. More specifically, as the room occupants were becoming LEC, energy consumption (electric and gas energy combined) was decreasing, with a total drop of 12 percent as shown in the lower graph of Figure 4. It is important to note that over the 36 months studied period, the peeks of the total energy consumption curve occurred during the winter season. This was expected in a cold weather region such as Wisconsin, where heating loads are significant and typically exceed air-conditioning cooling loads required during the warmer seasons.

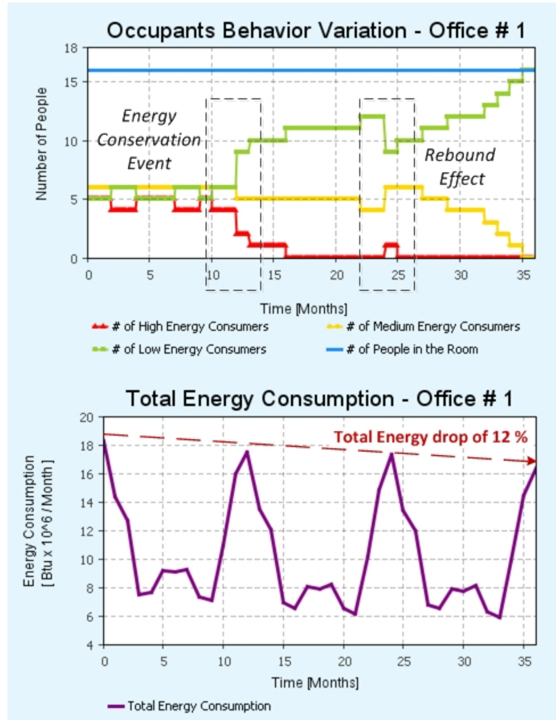

Figure 4: Agent-Based model output (Office)

As was previously mentioned, similar graphs are generated for all of the other rooms in the building. For instance, Figure 5 shows the change in behavior and the resulting change in energy consumption for the classroom area of the building in Figure 3. Unlike in an office where occupants interact on a daily basis and influence each other, students in a classroom have less influence on each other to change behavior. As result, it was assumed in this example that the change in behavior of occupants can only be induced by independent events such as energy conservation events or the rebound effect. This is illustrated in Figure 5 where changes in behavior only occurred when events were scheduled at months 12 and 24.

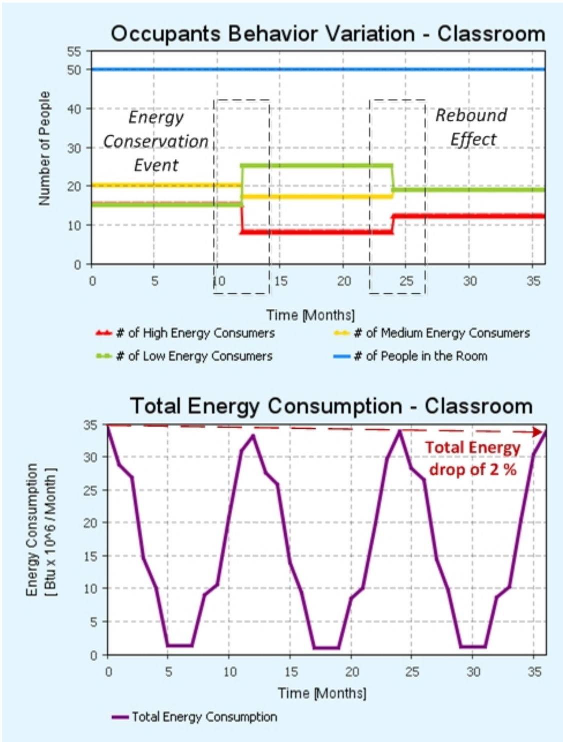

Figure 5: Agent-Based model output (Classroom)

In this example, the relatively low drop in energy consumption of 2 percent for the classroom can be attributed to two main reasons. First, by the end of the simulation time, only 19 of the 50 occupants were LEC, hence the remaining 31 occupants were consuming energy at medium or high levels. Second, the occupants of a classroom have a low level of control over the classroom energy consumption when compared to office occupants that use computers, task lights, etc. So, even if behavior changes in a classroom, the resulting impact on energy use remains limited.

So, by simulating occupancy behavior in all of the rooms of the studied building, the proposed model performs a whole building analysis and predicts the total energy consumption levels.

5.4. Sensitivity analyses

This section shows an example of the sensitivity analyses that were performed to test the model's reaction to changes in input parameters. In accordance with the study's objectives, a specific emphasis was put on the role played by occupants by varying parameters related to their behavior and interactions, and ultimately tracking the resulting changes in energy use.

Four different scenarios were considered in this analysis, and compared to the base case model built using eQuest (See Table 2). This base case represents traditional energy modeling software programs that do not allow for different nor changing occupancy characteristics throughout the simulation time. The first scenario represents the extreme case where all of the occupants are HEC with no peer-to-peer influences or events scheduled to change the high energy consumption behavior of the occupants. In scenario 2, the occupants are evenly divided between HEC, MEC, and LEC, however, the occupants are expected to convert to the HEC category since the highest LI was given to HEC and a rebound effect is scheduled for the 12th month. Scenario 3 is the opposite of scenario 2 with the highest LI given to the LEC, in addition to an energy conservation event scheduled for the 12th month. Finally, scenario 4 represents an extreme case with all occupants being LEC and no peer-to-peer influence or events to change behavior.

Table 2: Sensitivity analysis inputs variation

	Initial Energy Use Behavior of Occupants	Peer-to-peer Levels of Influence (LI)	Energy Conservation Event	Rebound Effect
eQuest Base Case	All MEC	none	none	none
Scenario # 1	All HEC	none	none	none
Scenario # 2	Evenly divided between HEC, MEC, and LEC	Highest for HEC	none	Scheduled at t = 12 months
Scenario # 3	Evenly divided between HEC, MEC, and LEC	Highest for LEC	Scheduled at t = 12 months	none
Scenario # 4	All LEC	none	none	none

The results of this sensitivity analysis are summarized in Figure 6 where Scenario 1 resulted in the highest energy use level that is 13 percent higher than the eQuest base case. On the other hand, scenario 4 resulted in the lowest energy consumption level, 17 percent lower than the base case. These results were expected since Scenarios 1 and 4 represented the extreme cases with all the occupants being HEC and LEC respectively throughout the simulation time. Scenarios 2 and 3, in turn, showed variations in energy consumption by plus 8 percent and minus 11 percent. These numbers were also expected since HEC had the highest LI in Scenario 2 in addition to a rebound effect scheduled, while in Scenario 3, LEC were advantaged with a high LI and an energy conservation event. Finally, by comparing the two most extreme cases, Scenarios 1 and 4, a total net difference of 30 percent was observed.

The results from this sensitivity analysis in addition to the other analyses that were performed confirmed that the model is behaving in logical manner to changes in inputs. As a result, the model was considered verified.

Moreover, the significant variations in energy use that were observed confirmed the importance of the impact of occupants on building energy estimation.

More variations are also expected when more types of occupants' interactions are considered, and more control is given for occupants over the building's energy systems.

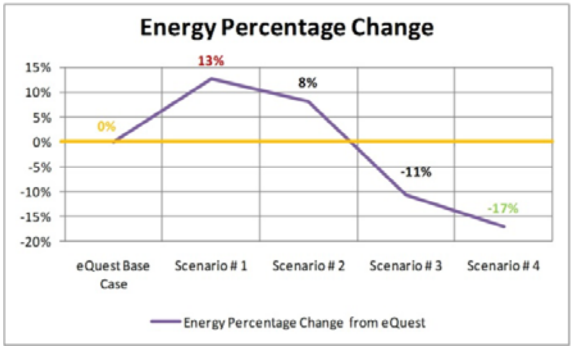

Figure 6: Percentage change in energy from eQuest

6. CONCLUSION

In conclusion, traditional energy simulation software programs are accounting for occupancy in a simplistic way, overlooking the impact of occupants' behavior and actions on building energy use. This is causing their energy estimates to significantly deviate from actual energy consumption levels (Yudelson 2010; Clevenger and Haymaker 2006; Soebarto and Williamson 2001).

This paper presented a new agent-based modeling approach to energy estimation by modeling occupancy in a dynamic way, accounting for both the differences between occupants' energy use characteristics and the changing aspect of these characteristics over time. The proposed approach was then tested and verified through a numerical example, which showed that significant changes in energy predictions can be obtained when occupancy is modeled in a dynamic way.

After successfully verifying the agent-based model, the next step is to validate it by comparing its energy estimates to numbers from actual buildings in operation. This is essential to make sure that the proposed model simulation numbers are consistent with the actual electricity, gas, and water consumption levels of the specific building under study. Once validated, the model can then be disseminated for real life applications.

Finally, the proposed methodology adds a new and important dimension to the energy modeling field by accounting for occupants and their impact on energy use. Consequently, this method overcomes the main limitations of current energy modeling software and results in more realistic and accurate energy predictions, which are essential to the design of more green and energy efficient buildings.

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