# Agent-Based Modeling of Occupants and Their Impact on Energy Use in Commercial Buildings

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**Abstract:** Energy modeling is globally used during the design phase to estimate future building energy performance. Predictions obtained from common energy estimation software typically deviate from actual energy consumption levels. This discrepancy can mainly be attributed to the misrepresentation of the role that building occupants play in the energy estimation equation. Although occupants might have different and varying energy use characteristics over time, current energy estimation tools assume they are constant. This paper proposes a new agent-based approach to commercial building energy modeling by accounting for the diverse and dynamic energy consumption patterns among occupants, in addition to the potential changes in their energy use behavior attributable to their interactions with the building environment and with each other. The impact of an active modeling of occupancy is then illustrated in a case study of an office in a university building, where more than 25% variation in the predicted energy consumption was obtained when using the proposed method versus a traditional commonly used method with static occupancy parameters. **DOI: 10.1061/(ASCE)CP.1943-5487.0000158.** *© 2012 American Society of Civil Engineers.*

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## Introduction

Buildings are responsible for 30 to 40% of global energy use (UNEP-SBCI 2007) and a similar percentage of green house gas emissions (Yudelson 2010). In 2009, commercial buildings consumed 19% of the total energy used in the United States, with associated carbon dioxide emissions totaling 1.0 billion metric tons (EIA 2010). According to the United Nations Environment Programme (UNEP-SBCI) (2007), 80% of the energy consumed by a building during its life cycle occurs when the building is in actual occupancy and use.

More importantly, in commercial buildings, more energy is often used during nonworking hours (56%) than during working hours (44%) mainly attributable to occupancy related actions (Masoso and Grobler 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 if occupant behavior was modified (Emery and Kippenhan 2006; Meier 2006; Staats et al. 2000). These studies looked at how changes in occupants' behavior can result in energy savings in excess of 40% in the building under consideration when compared with buildings of similar type. Such savings are key to energy efficiency, leading to economical and environmental benefits.

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A number of empirical and simulation models exist and are widely used in the building sector to predict energy consumption during the operational phase of buildings. However, the estimates obtained from these tools typically deviate by more than 30% from actual energy consumption levels (Yudelson 2010; Dell'lsola and Kirk 2003; Soebarto and Williamson 2001). The difference can even reach a value of 100% in particular cases such as laboratory buildings with high process loads (Turner and Frankel 2008).

Although several limiting factors, such as the complexity of buildings, weather, and variations in building schedule and occupancy, are causing the predictions obtained from different modeling techniques to differ significantly from actual energy use, these deviations can mainly be attributed to misunderstanding and underestimating the important role that the occupants' energy use characteristics play in determining energy consumption levels (Hoes et al. 2009; Turner and Frankel 2008). The term "occupant's energy use characteristics" is 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 et al. 2009).

Not only is it important to model occupants with different energy consumption patterns, it is also essential to model and predict their change in behavior over time and the resulting impact on energy consumption (Jackson 2005). Occupants might change their energy usage characteristics by adopting more energy efficient practices or, on the contrary, adopt bad consumption habits, some of which may be attributable to the often called rebound effect (Sorrell et al. 2009). 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 type of behavior change negatively impacts energy consumption by increasing energy use (Sorrell et al. 2009). Factors such as energy conservation campaigns that encourage energy use reduction or financial incentives that incentivize energy savings typically lead to positive changes in



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energy consumption behavior (Jackson 2005). Another important positive factor is the word of mouth or peer-to-peer effect, which is considered to be a very influential channel of communication (Allsop et al. 2007). 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 (Peschiera et al. 2010; Staats et al. 2004).

This paper investigates the use of agent-based modeling as a technique capable of simulating almost all behavioral aspect of agents, where agents in this research represent the building occupants. As defined by Axtell (2000), an agent-based model consists of "individual agents, commonly implemented in software as objects. Agent objects have states and rules of behavior. Running such a model simply amounts to instantiating an agent population, letting the agents interacts, and monitoring what happens." In this study, agents, or building occupants, make decisions based first on their interaction with their environment and, second, based on their interactions with other agents. For example, in a certain room, occupants might choose to save energy and switch their lights off during the day because of good day lighting level (environment interaction) or because the energy conscious occupants of the room are encouraging them to adopt energy saving habits (agent interaction). A computational agent-based model was therefore developed for the purpose of this research, where the qualitative behavioral aspects of occupants are represented in a quantitative way to generate more customized and accurate energy use estimates. The proposed model could supplement traditional energy modeling software to better predict energy use during the design phase of buildings, which is essential to the choice and optimization of building energy systems. So, by making better informed decisions during the design phase, considerable energy and monetary savings can be achieved over time, while also reducing greenhouse gas emissions (Hoes et al. 2009; Turner and Frankel 2008).

## Objectives

The aim of this paper is to present a new approach for energy consumption estimation in commercial buildings by using agent-based modeling to account for different occupant energy use characteristics, their change over time, and finally calculate energy consumption levels that reflect this dynamic aspect of occupancy. This is expected to result in more realistic energy consumption predictions during the building design phase compared with estimates obtained using traditional energy software (e.g., eQuest, Energy Plus), representing occupants as static agents in the energy modeling process. These software programs allow for only few inputs related to occupants, typically limited to the building schedule hours and the maximum number of occupants per building square foot (SBIC 2012; EnergyPlus 2009; eQuest 2009; Hoes et al. 2009; Turner and Frankel 2008). Furthermore, they assume that all occupants have similar schedules, consume energy at the same rates, and never change their energy consumption behavior over time.

One main objective of this research is a computational agent-based model that simulates occupancy as a variable element by assigning attributes and characteristics to building occupants. These occupants are consequently allowed to have different energy consumption behaviors and also interact with each other and with their environment to change behavior. The proposed model finally generates energy consumption estimates that correspond to these different and changing energy consumption behaviors of occupants over time. The model's interface is simple and user-friendly in which users can easily change occupancy related parameters and observe the resulting effect on the overall energy consumption levels.

Finally, the capabilities of the built model are tested and verified on a case study consisting of a conceptual 1,000 sqft graduate student office in a university-type building, accommodating up to 10 full-time graduate students. This helps test and verify the developed algorithm and then allows the comparison of the model's results with those obtained from traditional energy estimation tools.

## Background

A large number of studies analyzed the way building occupants affect total energy consumption levels, mainly through their actions and interactions with the building environment. One set of studies is related to office lighting, where the light switching patterns that occupants adopt depending on room and also outside conditions are monitored and analyzed. Results show that building occupants that actively seek day lighting rather than systematically relying on artificial lighting can reduce overall primary energy expenditure by more than 40% compared with occupants who constantly rely on artificial lighting (Bourgeois et al. 2006).

The second set of studies considered office equipment usage in commercial buildings. Webber et al. (2006) studied office equipment after-hour usage in different commercial buildings in the United States and showed that less than 50% of equipment is switched off by the building occupants during non operating hours. Sanchez et al. (2007) investigated the density, type, and usage of plug load equipment in different types of commercial buildings. The collected data showed that when the building is unoccupied, the average turn-off rates for office equipment were 59% for desktop computers, 45% for copiers, and 41% for scanners.

The third set of studies focused on occupants' schedules, which have important effects on the occupants' level of energy consumption. Davis and Nutter (2010) studied occupancy schedules in common university classroom buildings and developed occupancy diversity factors. These factors help model occupancy in a more realistic way by accounting for different schedules depending on the type of the university building under study. Wang et al. (2005) also studied occupancy schedules but on a smaller scale by modeling occupancy in a single person office. A model was then developed to predict the daily office presence and absence of occupants.

These studies emphasize that the building occupants' actions result in excessive and unnecessary energy use. To address these occupancy issues, several methods and tools exist to reduce energy consumption in buildings through changes in their occupancy energy consumption behavior, mainly if energy saving practices are adopted. These typically result in significant reductions in energy use (Staats et al. 2000). Common techniques that induce such behavioral changes are (1) green social marketing or energy conservation training/workshops, (2) information feedback tools, and (3) peer-to-peer or word of mouth information/influence (Peschiera et al. 2010; Jackson 2005; Staats et al. 2004, 2000).

As defined by Kotler et al. (2002), social marketing is "the use of marketing principles and techniques to influence a target audience to voluntarily accept, reject, modify, or abandon a behavior for the benefit of individuals, groups, or society as a whole." The goal of this technique when it comes to this research is to promote good energy consumption practices to reduce energy and water consumption in commercial buildings. Many social marketing programs have already been used in real-life situations and resulted



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in important energy and water savings. These programs typically applied the McKenzie-Mohr's principles of community-based social marketing (McKenzie-Mohr 2000). The best known and documented example is the Ecoteams program established internationally as part of the Global Action Plan for the Earth to reduce household resource consumption. This program successfully induced a reduction of 9–17% for domestic energy consumption and 25–34% for water consumption in the studied United States cities (Pickens 2002).

Feedback is another technique that is believed to result in relevant energy savings. Many experimental studies have shown that sharing energy usage information of a building with its occupants can lead to reductions in the total building energy and water use. This is particularly important when there are no financial incentives for participants to conserve, as is often the case in dormitories as well as in institutional, hospitality, and many commercial buildings (Carrico and Reimer 2011; Faruqui et al. 2010; Peschiera et al. 2010; Staats et al. 2004). Several studies have tested the effectiveness of this method in both the residential and commercial building sectors. For instance, Faruqui et al. (2010) discussed 12 feedback pilot programs that were conducted on residential buildings in North America and abroad. These programs successfully resulted in energy savings ranging from 3 to 13%, with an average of 7%. Other studies tested feedback techniques on commercial buildings, leading to similar results. For example, Carrico and Reimer (2011) provided energy feedback for the occupants of 24 office-type buildings and observed an average reduction of 7% in total energy consumption.

Finally, peer-to-peer influence or the word of mouth effect is originally a marketing concept defined as a type of informal, person-to-person communication between a perceived noncommercial communicator and a receiver regarding a brand, a product, an organization, or a service (Harrison-Walker 2001). In energy related studies, it represents the potential change in energy consumption behavior when people with different energy use patterns or levels share a common space (e.g., office room), frequently interact, and eventually influence each other to change their energy consumption habits. This type of face-to-face interaction regarding proenvironmental behavior can be very effective in convincing people to change behavior, resulting in significant energy consumption reductions (Bartels and Nelissen 2002; Weenig and Midden 1991).

## Energy Estimation Tools

A number of empirical and simulation models exist that provide estimates of energy consumption in buildings. Energy-10 is the least sophisticated of the three mentioned programs and is typically used during the early design phases of the building. It does not include any input for occupant schedule and the output includes hour-by-hour HVAC and lighting loads in addition to the facility energy operating costs (SBIC 2012). eQuest and Energy-Plus have some but limited inputs for occupants' schedules and their spread in the building (e.g., lobby, corridors, rooms, etc.). Although these software allow for variation in hourly occupancy loads, they assume that all occupants have the same energy consumption patterns and that they are constant over time (eQuest 2009; EnergyPlus 2009).

Several studies evaluated the impact of building occupancy on energy simulation models and showed that estimated energy consumption can change significantly when occupants with different energy consumption rates are considered (Yu et al. 2011; Hoes et al. 2009; Clevenger and Haymaker 2006). Furthermore, a change in only one factor such as the level of insulation of a building might result in a 40% change in the total estimated consumption. This rate is not only a function of the design, but also a function of occupancy-related actions such as the frequency of opening of doors and windows, which are typically not accounted for in energy simulation tools (Hoes et al. 2009; Turner and Frankel 2008).

One study by Clevenger and Haymaker (2006) quantified this impact of different occupants' behaviors on building energy use. This was achieved by performing different energy simulations with different input parameters representing high and low energy use levels. The results from these runs showed that energy consumption might change by more than 150% when occupants with different energy characteristics are considered. Although this type of study is important to link the behavior of occupants to energy consumption, no tools or models were found in literature that first account for different energy use behaviors, that simulate changes in these behaviors attributable to the interactions of occupants with their building environment and with each other, and finally predict building energy consumption while accounting for these occupancy-related factors. Actual energy simulation software do not account for these human behavioral aspects of energy modeling (Hoes et al. 2009; Turner and Frankel 2008) and are solely focused on the buildings' technical performance level (EnergyPlus 2009; eQuest 2009; SBIC 2012). Therefore, the main motivation of this study is to propose an agent-based modeling approach to simulate different occupant energy use characteristics and how these characteristics vary over time to better predict building energy use during the design phase.

## Agent-Based Modeling

As previously mentioned, agent-based modeling is a widely used technique to simulate the interaction of agents with their environment and with other agents (Axtell 2000). Agent-based modeling tools have already been investigated to assist energy simulation software for building energy studies. More specifically, Erickson et al. (2009) used agent-based modeling to model the rooms' occupancy in commercial buildings to optimize the HVAC loading and hence avoid typical over sizing problems. This research showed that by simulating occupancy usage patterns, HVAC energy usage can be reduced by approximately 14%.

Another example where agent-based modeling was used to assist HVAC design was presented by Li et al. (2009). In this study, the occupancy of an emergency department of a health care facility was first modeled. The obtained numbers were then used to optimize the sizing of the HVAC system, avoiding unnecessary or excessive air conditioning loads. This organizational simulation model showed that the required capacity of the ventilation system might change by as much as 43% when a building's occupancy is properly modeled.

Literature specific to assisting energy simulation models with agent-based modeling tends to focus mainly on HVAC calculation. Although HVAC accounts for 31% of the total energy consumption for an average United States commercial building, other energy consumption sources such as lighting, computers, and hot water supply account for more than 33% (InterAcademy Council 2007). As a consequence, there is a need to broaden the scope of study to include energy consumption sources other than HVAC, while accounting for the occupancy effect on the levels of energy consumption.

## Methodology

The proposed methodology used to achieve this research's study objectives consisted of five main steps: (1) define different energy



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consumption behaviors, (2) define factors that cause behavioral changes, (3) build a simulation model, (4) generate energy use rates for each type of energy use behavior, which are imported into the simulation model, and finally (5) verify the built model and present a detailed validation plan.

### Define Different Energy Consumption Behaviors

As was previously mentioned, energy consumption can change significantly when occupants with different energy use patterns are considered (Yu et al. 2011; Hoes et al. 2009; Clevenger and Haymaker 2006). This makes accounting for different occupancy behavior essential for building reliable and accurate energy estimation models. For this purpose, three categories of occupants were considered. First, the high energy consumers (HEC) category represents occupants that over-consume energy. Second, occupants that make minimal efforts toward energy savings form the medium energy consumers (MEC) category. 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. It should be noted that the developed model, which is shown in the upcoming sections, can easily be extended to add more patterns if needed by the user.

The main difference between the three proposed categories is the way occupants use the building energy systems resulting in different energy use levels. To understand the differences between HEC, MEC, and LEC, it was important to analyze and understand how these categories use each of the main building energy systems such as lighting, equipment/computers, and air conditioning systems. For this purpose, an intensive literature review was performed to gather studies related to each topic to ultimately understand the different occupancy behaviors.

To understand lighting systems energy use, one of the considered studies is by Bourgeois et al. (2006) in which the variation in the light switching patterns of occupants was investigated in several commercial buildings. For equipment/computer use, data collected by Webber et al. (2006) and Sanchez et al. (2007) were used to determine common rates of office equipment use for different occupancy patterns. Similarly, the studies of Davis and Nutter (2010) and Wang et al. (2005) were considered to study occupants' presence in their offices, which affects the level of energy use. For instance, it was assumed in the case study example shown in the upcoming sections that LEC turn their computers off whenever they are out of their offices. Although current energy modeling software assume that occupants' schedules are similar to building operating schedules (e.g., from 8 a.m. to 5 p.m.) with no absences from their offices during workdays (e.g., lunch, meetings, etc.), the studies of Davis and Nutter (2010) and Wang et al. (2005) were therefore needed to predict the duration of their absences and predict the resulting energy savings for LEC. So, for this specific example, by using the above mentioned studies, occupants' schedules were predicted and potential energy savings calculated.

Although these studies give a good understanding of the differences in behavior of HEC, MEC, and LEC, energy consumption rates for each of these categories of occupants need to be determined on a case by case basis. So, for a specific building environment under study, energy consumption rates for HEC, MEC, and LEC are developed depending on the building characteristics (e.g., construction materials, type of mechanical and electrical systems, etc.) and also on the energy consumption characteristics of its occupants. This is explained in detail through a numerical example shown in the upcoming sections, where three energy consumption rates were derived from studies found in literature, from building energy standards, and from consulting with industry experts to confirm the made assumptions.

### Determine Factors behind Energy Characteristics Change

As was previously mentioned, not only might different occupants have different energy consumption patterns, they also might experience behavior changes over time (Jackson 2005). This can be attributable to different factors such as (1) energy conservation trainings/workshops or (2) the word of mouth influence.

In this research, energy conservation trainings/workshops were considered to be informational events that make a portion of the occupants of the building/room under study change behavior and reduce their energy consumption. An example would be a seminar on good energy consumption practices or energy saving techniques that the building occupants might attend, resulting in a potential reduction in energy use. These events are discrete occurrences (e.g., yearly), resulting in instantaneous change in behavior to a less energy consuming category. As a result, a fraction of the HEC in the environment under study convert to MEC, and a fraction of MEC change to become LEC.

The word of mouth or peer-to-peer effect represents the influences that people sharing the same room have on each other to change their behavior and modify their energy consumption habits (Sorrell et al. 2009). This type of interaction was originally studied in marketing when a new product is launched in the market. The buyers of this product become adopters, interact with potential adopters, and influence them to buy this product (Morecroft and Sterman 2000). By doing so, they shift from the potential adopters category to become themselves adopters. In this model, each category of occupants (HEC, MEC, and LEC) is considered to be an adopter category, where its members are constantly trying to influence other occupants sharing the same environment to change behavior and adopt their energy use characteristics. So, the three types of conversions are possible and are summarized in Fig. 1. The first line shows the case where HEC are influencing MEC and LEC. In this case, some MEC get converted to HEC and some LEC become MEC, showing the gradual change in characteristics. Similarly, the second and third lines of Fig. 1 respectively show the cases where MEC and LEC are actively converting other occupants. More details on these conversions are explained in the upcoming sections.

### Simulation Model

So far, different energy consumption behaviors were defined and potential sources of behavior change identified. The next step was to build an agent-based model that simulates the changes in behavior and generates corresponding energy consumption estimates.

The agent-based modeling platform that was chosen for this research is Anylogic, a widely used simulation software in the

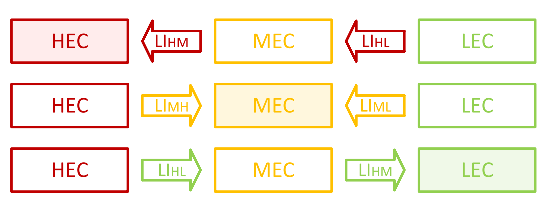


**Fig. 1.** Conversion of occupants



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industry (XJ Technologies 2009; Borshchev and Filippov 2004). The choice of Anylogic was mainly attributable to its Java-based environment that allows the user to develop custom Java codes and integrate them in prebuilt simulation blocks (XJ Technologies 2009). This was essential in this research to optimize and customize the proposed model to simulate the complex behavioral aspects of building occupants.

In the proposed agent-based model, building occupants are represented by agents assigned with different attributes that define how these agents interact with their environment (e.g., HEC, MEC, and LEC) and with other agents, potentially leading to changes in their attributes (e.g., peer-to-peer interaction and influence to change behavior). The model flowchart is shown in Fig. 2 in which a four-step iterative process was defined to ultimately generate energy consumption estimates.

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

Step 2 simulates the interaction of agents and the potential change in behavior attributable 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) their 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%/person/month means that each HEC person has a 5% 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 simulates the conversion between the three categories of occupants and stores the updated numbers of HEC, MEC, and LEC for the current time step.

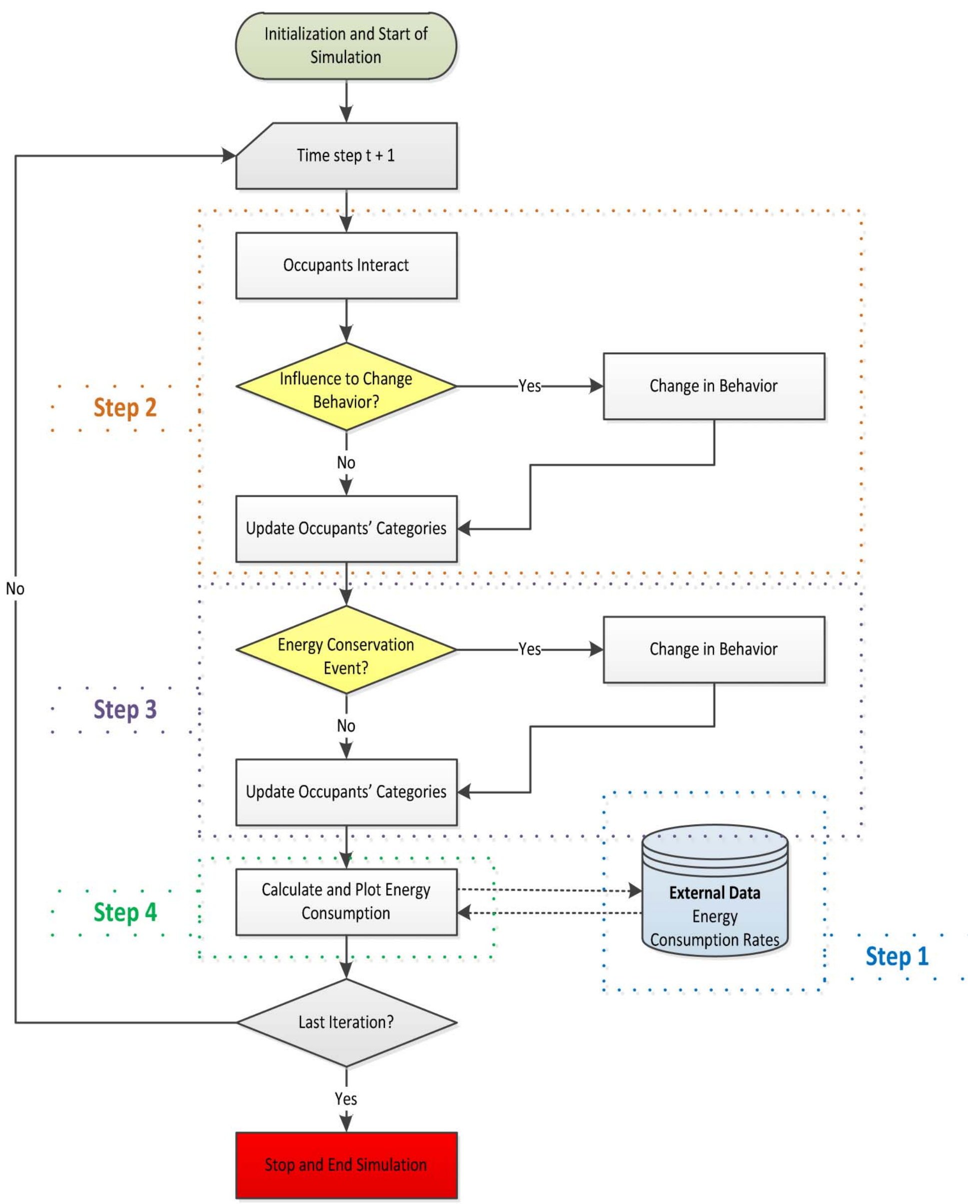


**Fig. 2.** System flow chart





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Next, the model moves to Step 3 to check if an energy conservation event is scheduled for this time step. Here again, the user can schedule events and specify their efficiencies before running the model to simulate energy conservation trainings/workshops and their impact on behavior and energy use. For instance, an event scheduled for month 12 with an efficiency of 30% results in the conversion of 30% of HEC to MEC and 30% 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.

These numbers are then combined to the energy consumption rates from Step 1, and total energy consumption levels are calculated for the current time step (Step 4). 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.

Fig. 3 presents the model statechart, which is the engine of the proposed agent-based model. This statechart is executed for each time step to simulate the changes in HEC, MEC, and LEC for one room/area of the building under study and estimates the electric and gas consumption levels for this section of the building over the specified simulation time. Later in this section, it is shown how this statechart is replicated in the proposed model to simulate a whole building environment.

The first three states in the statechart (HEC_Conversion, MEC_-Conversion, and LEC_Conversion) represent the respective conversion of occupants to the HEC, MEC, and LEC categories. For instance, if the HEC_Conversion is activated, this means that a HEC successfully influenced another occupant to change behavior and become a HEC (refer to the first line of Fig. 1). So, for each time step, the model starts at decision node 1, where two possible paths can be taken: One that goes through the HEC_ Conversion state, activating the conversion of occupants to HEC, and one that bypasses this state, when no changes in behavior are occurring. The activation of this state is determined by the number of HEC for the current time step, in addition to their level of influence, $LI_{HIGH}$. So, more HEC in a space and/or higher $LI_{HIGH}$ will likely lead to more MEC and LEC occupants, if any, getting converted to HEC. This is shown in the Java code of Box A, where the current number of HEC is multiplied by the $LI_{HIGH}$, and the value of this product is fed into a uniform distribution to simulate the probabilistic aspect of the interactions of occupants and the chances of having a successful HEC influence. So, the used distribution determines the chances that the HEC_Conversion state is actived, which executes the Java code shown in Box B. This code changes the number of HEC, MEC, and LEC according to the flow of people toward HEC that was previously shown in the first line of Fig. 1. The model then moves to node 2 and later to node 3, following the same logic for the MEC_Conversion and LEC_Conversion states respectively, in which the number of HEC, MEC, and LEC are constantly updated and stored in the model. Here again, the flows of occupants for these two conversion states are shown in the second and third lines of Fig. 1.

Next, the model moves to decision node 4 to simulate the change in behavior attributable to energy conservation events. As was previously mentioned, the occurrence and the efficiency of these events are initially entered by the user. So, for each time step, the Energy_Event state is activated only if an event is scheduled for this time step. This state triggers the execution of the code shown in Box E, calculating the flow of people toward the LEC categories, which depends on the efficiency of the event.

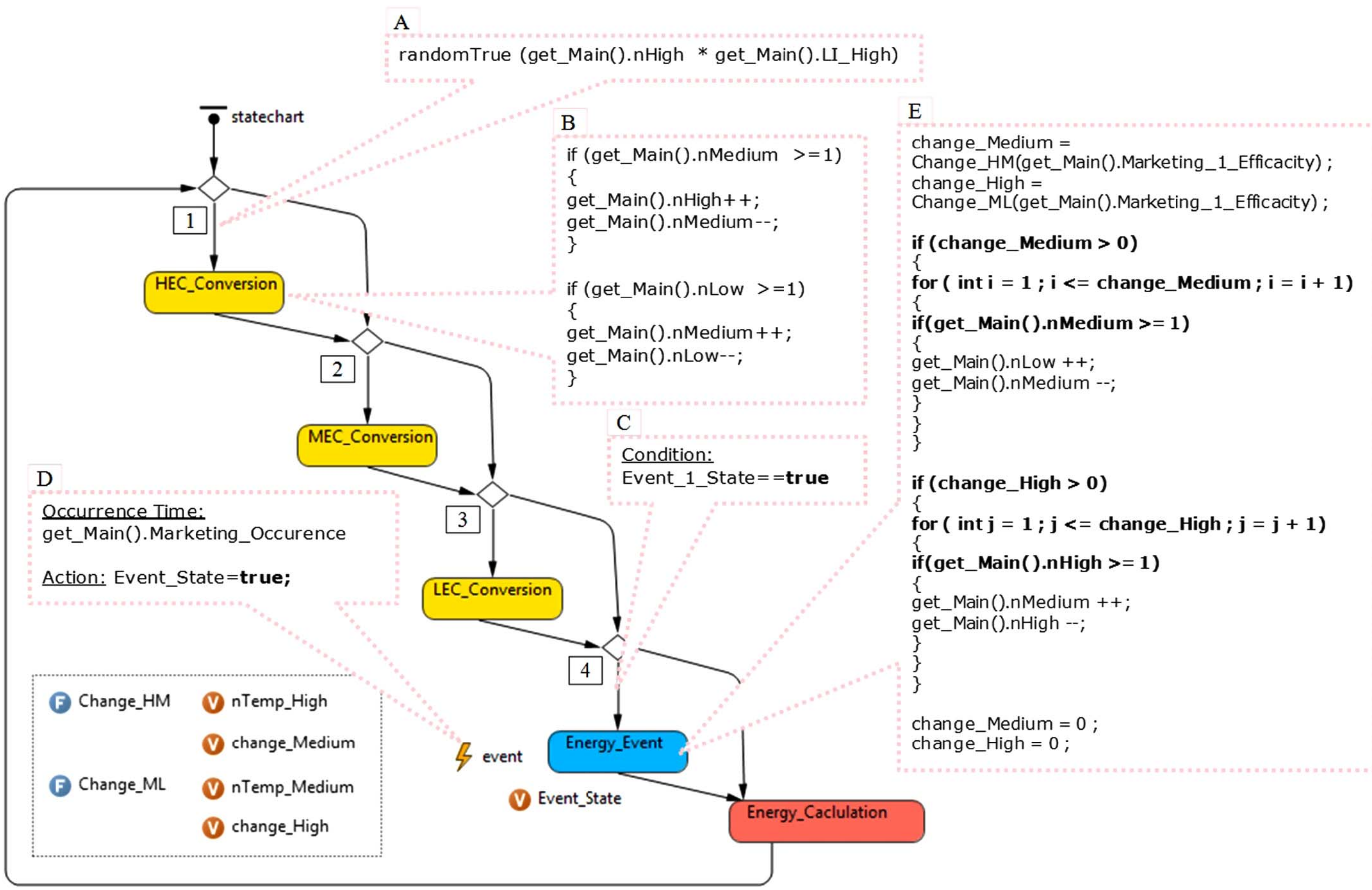


**Fig. 3.** Model statechart



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The last step of the statechart is the Energy_Calculation state that is activated at the end of each time step (see Fig. 3). The code in this state consists of taking the most updated numbers of occupants in the HEC, MEC, and LEC categories for the specific room under study and applying corresponding energy use rates to generate the electric and gas consumption for this time step. Then, the model moves to the next time step and restarts the process at Node 1. This process keeps repeating until the total simulation time is reached.

The next step in the development of the model was expanding it to simulate building environments with multiple floors/rooms and different number and types of occupants. By replicating the Java blocks in addition to the custom Java codes that were developed to build the statechart of Fig. 3, multiple statecharts can be generated to model multiple areas and achieve whole building energy simulation. This was feasible attributable to the Java-based nature of the developed code and its generic programming capabilities. More specifically, generic programming aims to find the most general formulations of algorithms, which makes it possible to adapt and replicate the code efficiently (Naftalin and Wadler 2006; Gregor et al. 2005). So, before the start of the simulation, the user is required to provide the number of floors, number and type of rooms on each floor, number of occupants in each room, and other information related to occupants' behavior and potential sources of behavioral change. These inputs activate the required number of statecharts to simulate behavior and estimate energy consumption for each room/area in the building under study. For example, Fig. 4 shows the case in which the user specified a three-story building with one common area on the ground floor, two classrooms on the second floor, and three offices on the top level with different initial numbers of HEC, MEC, and LEC for each office. Six statecharts were then activated by the model and connected to form one big statechart loop (see Fig. 4). This loop is executed at each simulation time step, sequentially activating the individual statecharts that represent the different rooms/areas of the building. The following section presents the detailed method that was used to obtain the energy use rates for HEC, MEC, and LEC used in the Energy_Calculation state shown in Fig. 3.

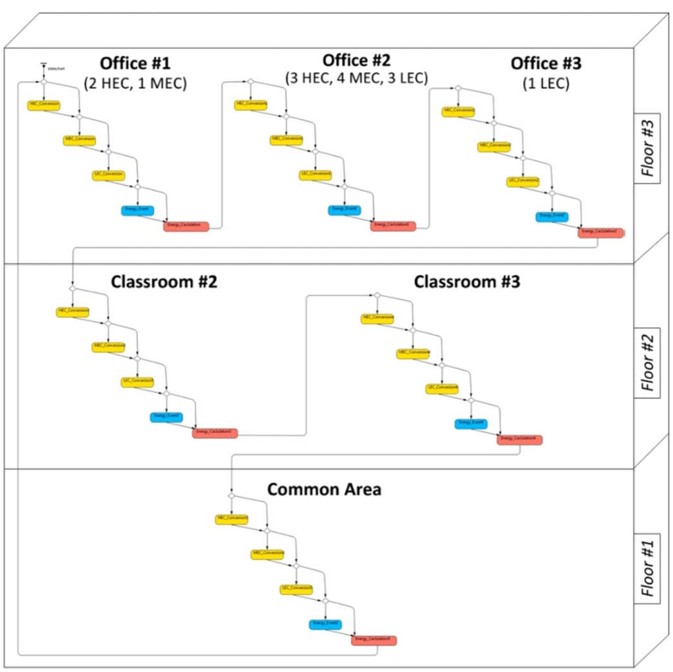


**Fig. 4.** Example model for multiple floors/rooms

### *Energy Consumption Rates per Occupancy Behavior Type*

The main goal of this section is to show how to use a traditional energy modeling software (e.g., Energy-Plus, eQuest, etc.) to obtain energy consumption rates for HEC, MEC, and LEC. In this case, three sets of simulations are needed, each set having specific inputs representing the different energy characteristics of the three categories of occupants. In general, two types of inputs are required to build these models: (1) building related inputs that are the same for all the simulations and (2) different occupancy-related inputs that will lead to the difference in the three energy use rates.

So, the first step consists of defining the building environment under study (e.g., building, area, room, etc.) accommodating occupants that 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'Isola and Kirk 2003).

The next step consists of defining occupancy-related parameters, leading to the difference between the energy consumption levels of HEC, MEC, LEC. These differences in behavior can be entered in traditional energy simulation software through 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 nonoperating 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 generate the corresponding energy use rates.

To sum up, by using parameters that characterize each of the three studied energy consumption behaviors, three energy use rates can be obtained, translating the change in behavior into a change in energy consumption levels. These rates are then imported into the simulation model as was shown in Step 1 of Fig. 2 to be used for the total energy use calculation.

### *Sensitivity Analysis and Model Validation Plan*

The main objective of this paper was to present a methodology or an approach for modeling occupancy interaction and its impact on energy consumption in buildings, which was supported by the developed agent-based model. So, validation in this paper was limited to technical validation, focusing on the technical and computing aspects of the model. Future research will involve actual data collection to test and verify the assumptions that were made about occupancy characteristics.

The testing process adopted for this model and the proposed future validation plan are shown in Fig. 5, combing the works of Gilbert (2008) and Sargent (2000). Three main phases are identified: a sensitivity analysis stage (Phase I), a data validation plan (Phase II), and finally a model validation plan (Phase III). Phase I has already been completed with satisfactory results, whereas Phases II and III present some future research steps that will be necessary before the model can be disseminated for real-life applications.

So first, starting with Phase I, sensitivity analysis is where the computerized model is run for different values of the input parameters and the model's response is analyzed and compared with the theoretical expected response. Ideally, one would like to perform



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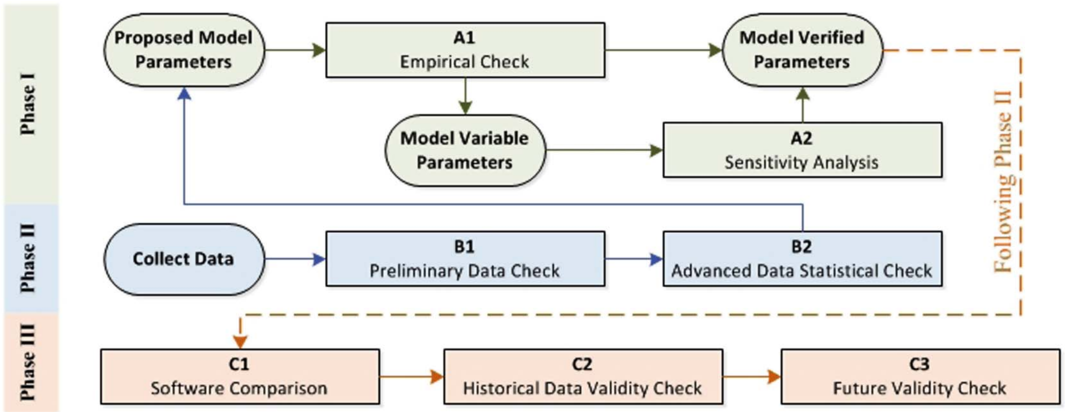


**Fig. 5.** Model verification and validation plan

the sensitivity analysis on all the model's parameters with all possible combinations. However, this activity is very time consuming and can be shortened by cutting down the number of possible parameters' values (Gilbert 2008). For this purpose, an empirical check (Step A1) based on an extensive literature review is first performed on the model's preliminary parameters to determine their levels of variability. If these parameters prove to be constant, they skip the sensitivity analysis phase (Step A2) and become model verified parameters. For example, some of the building design parameters (e.g., HVAC air exchange ventilation rates) are typically set by building standards such as ASHRAE 90.1 and California Title 24 to ensure certain indoor air quality levels; Title 24 being the code used by eQuest (eQuest 2009; ANSI/ASHRAE/IESNA 2010). Thus, such parameters can be assumed constant and remain fixed throughout the study. Parameters that are harder to estimate go through the sensitivity analysis process (Step A2) as the best alternative to verify their validity and also to make sure that the model is reacting in a logical manner to changes in their values. In this research, despite the numerous studies that were found on occupants' energy characteristics, the model's related occupancy parameters were hard to fix and hence required extensive sensitivity analyses. These include the levels of influence that occupants have on each other in addition to the occurrence frequency and efficiency of energy conservation events. An example of the several sensitivity analyses that were performed is shown in the upcoming case study example section. The completion of Phase I resulted in the verification of the technical aspects of the model.

Phase II contains the data collection step in addition to the required data checking processes. This phase is essential mainly due to the limited literature on occupants' behavior, especially on the influence that occupants exert on each other to change behavior in addition to the effect of energy conservation campaigns. In the current model, the user is required to make some assumptions about occupancy-related parameters such as the levels of influence ($LI_{HIGH}$, $LI_{MEDIUM}$, and $LI_{LOW}$), or the energy consumption characteristics of the three categories of occupants. So through data collection, more input parameters can be fixed, hence reducing the range and uncertainty of the model's generated outputs. As shown in Fig. 5, two steps are then required to verify the collected data. First, the data preliminary check (Step B1) consists of a literature review study followed by an analysis of the results to make sure that the collected data are in the expected range of values. The second step is the advanced data statistical check (Step B2) where more in-depth analyses are performed to test the precision and the accuracy of the collected data. This validation step can be achieved by developing confidence intervals and testing the null hypothesis with additional data points. Once Phase II is completed, the collected data that are now validated are imported in the model to update the proposed model parameters shown in Phase I. Then the sensitivity analyses of Phase I are repeated resulting in new model verified parameters.

Phase III is the last step of the validation process in which the generated energy estimates are first compared with the estimates of other commercial energy modeling software (Step C1) and then compared with real-life energy consumption levels from actual buildings in operation (Steps C2 and C3). In Step C1, the proposed model is compared with other energy modeling tools by modeling a certain building environment in both tools and comparing the obtained results. Given that no software programs were found in literature that account for occupants' behavior differences and changes to predict energy consumption, traditional energy modeling software (e.g., eQuest, Energy-Plus, etc.) will have to be used. This phase results in the theoretical validation of the model. The second step in this phase is the historical data validity check (Step C2) in which the model simulates the energy use of an existing building, and the obtained results are then compared with actual energy data collected from that building. The last step in the validation process is the future validity check (Step C3). This step consists of using the model to predict the energy and water consumption levels of an existing operating building for a short period of time and then collect data to test the model's estimated numbers. Once Phase III is completed, the model is then validated and can be disseminated for real-life applications. As mentioned earlier, Phases II and III are part of the future research plan.

## Case Study Example

An experimental energy simulation model was built for the purpose of this study consisting of a conceptual 1,000 sqft university graduate student office, accommodating 10 full-time graduate students. The choice of a conceptual model versus an actual operating building for this paper was made to highlight and measure clearly the impact of occupants' behaviors on energy use, since the main objective of this paper is on energy simulation during the design phase of buildings. This helps better present and explain the proposed methodology, which is the main focus of this paper. However, as was discussed in Phase III of the validation process (refer to Fig. 5), data collection from actual buildings in operation will be needed in future steps to validate the final model energy estimates. In addition, although the proposed model is capable of simulating multiple floors/rooms buildings as was previously





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discussed (refer to Fig. 4), a one-room example was selected as a case study for several reasons. First, a single-space environment allows for an easy visualization of how occupants are influenced to change behavior due to peer-to-peer interactions or attributable to energy conservation events. Second, it is more effective to verify the model's parameters as per Phase I of the validation plan (refer to Fig. 5) using a single space. Finally, in accordance with the study's objectives, the main goal of this section was to show the detailed impact of the proposed methodology on a micro level, to better understand its broader macro level impact. If the impact of occupancy on a single-space of the building is high, then it will directly translate to a higher and more significant impact on the whole building energy use.

### Occupants and Environment Description

The studied room shown in Fig. 6 is located at the ground floor of a multistory university building in the city of Madison-Wisconsin. It has four windows facing the east and one door facing the north. These are the only two faces that are exposed to the exterior. The southern and western faces in addition to the ceiling have no openings. They are assumed to be in contact with air conditioned areas, representing other sections of the building. The room also has internal window blinds (not shown in Fig. 6) that can be manually adjusted, opened or closed, by the occupants. Construction materials include 152-mm (6-in.) concrete exterior walls, metal frame with 610 mm (24 in.) on center, stucco exterior finish, and air-type interior walls. For the HVAC system, single-zone DX coils are used for cooling and a combustion furnace for heating.

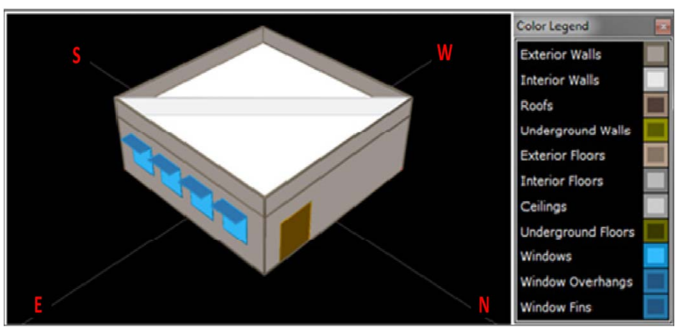


**Fig. 6.** Graduate student office in eQuest

### Model Inputs and Assumptions

Six energy consumption sources were studied in this example: (1) HVAC heating, (2) HVAC cooling, (3) area lighting, (4) task lighting, (5) equipment (computers), and (6) hot water supply. However, the occupants did not have direct control over HVAC heating and cooling sources because a central air conditioning system was assumed to maintain the room temperature at pre-set levels. The occupants, however, indirectly affect the room temperature through human body emitted heat (Prek 2005) and also by controlling the lighting and equipment use in addition to the position of the internal window blinds (Hoes et al. 2009). For example, heat generated from excessive computer use affects the room temperature and might, as a result, increase the cooling load required to maintain a constant temperature. Fig. 7 summarizes the main studied energy systems, where eQuest was used to break them down between electric and gas consumption sources. The main sources that the occupants directly controlled were the area/task lighting and miscellaneous equipment (computers) for electricity consumption and hot water heating for gas consumption.

For each occupant category (HEC, MEC, and LEC), energy consumption rates were obtained using eQuest by running different experiments using specific inputs that reflect their behavioral differences. More specifically, three types of inputs were varied in the simulations to differentiate between the behavior of HEC, MEC, and LEC: (1) blinds positions, (2) lighting/equipment schedules, and (3) hot water use (see Table 1). The values of such parameters are typically determined on a case by case basis, depending on the environment (e.g., level of luminance, type of equipments, etc.) and on the occupants' characteristics. In this example, the parameters were derived first based on several studies in literature on occupants and the different energy consumption patterns they adopt (Masoso and Grobler 2010; Mahdavi et al. 2008; Sanchez et al. 2007; Webber et al. 2006; Reinhart 2004) and, second, based on values suggested by eQuest, which follows California's Title 24 building code requirements (eQuest 2009). Some additional assumptions had to be made about the differences between the high, medium, and low energy use levels. These occupancy-related hypotheses were then reviewed and confirmed by industry experts and were, as a result, considered acceptable. In addition, as was previously shown in the validation plan of Fig. 5, Phase II was specifically added to collect data and validate the assumptions that had to be made about occupants' behaviors and interactions. This step is essential before the final validation of the model's results in Phase III.

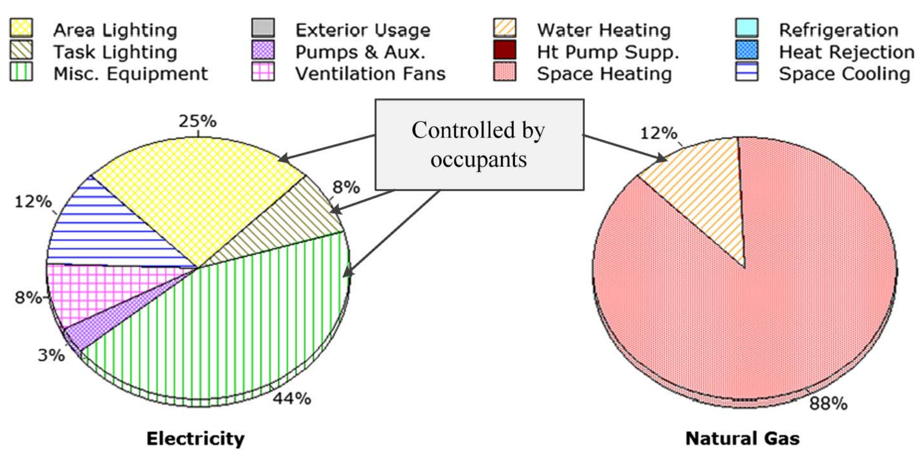


**Fig. 7.** eQuest energy breakdown



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**Table 1.** Input Parameters Variation for Building Energy Consumption

| | HEC | MEC | LEC |
|---|---|---|---|
| Blinds positions | All seasons: 20% of the time closed | Spring/fall/winter: 20% of the time closed; summer: 40% of the time closed | Spring/fall: 20% of the time closed; summer: 60% of the time closed during operation and 90% after hours; winter: 10% of the time closed during operation and 90% after hours |
| Lighting and equipment running schedules | Building opening hours+additional hours | Building opening hours | Half of the building opening hours time |
| Hot water consumption | 20% more than MEC | 1.20 gallon/person/day | 20% less than MEC |

So first, parameters related to blinds positions were considered because important energy savings can be achieved by using blinds to block the sun during the hot season and by keeping them open in the cold season to use the sun as a lighting and heating source. As shown in Table 1, HEC were assumed to close the blinds for 20% of the time during all seasons, without adjusting the blinds to weather conditions. This value was recommended by eQuest based on the California building standards code. MEC make some energy saving efforts during the summer by closing the blinds 40% of the time, hence reducing the solar heat and, consequently, the air conditioning cooling loads. Finally, LEC optimize the use of blinds first by closing them more often during the summer and, second, by opening them during winter days and closing them at night to trap the heat inside the office and avoid heat dissipation and losses through radiation.

The second type of input is the lighting/equipment schedules where the eQuest occupancy schedules were adjusted to account for the overuse of equipment by HEC and the energy savings made by LEC. As shown in Table 1, HEC were assumed to leave the equipment (computers) and lights on not only during the building opening hours but also during additional hours. Additionally, MEC only use equipment and lights during working hours, whereas LEC minimize their energy consumption by taking advantage of day lighting and by turning the equipment and lights off whenever they are out of the office.

The last input is water consumption in which eQuest default value of 1.20 gallon/person/day for typical university buildings was used for MEC. HEC and MEC were assumed to consume 20% more and 20% less, respectively.

The obtained results for electric and gas consumption rates per occupant category are summarized in Fig. 8. An important observation from these graphs is that the difference in energy consumption between the three occupancy categories is higher for electric consumption that it is for gas. This is mainly attributable to the high level of control given to occupants over electric loads, 77% in this particular example, as opposed to only 12% over gas consumption sources (refer to Fig. 7).

### Agent-Based Model

After generating the different energy consumption rates, the next step consisted of simulating the occupants' interactions and their potential change in behavior over time using the developed agent-based model. An example of the obtained change in energy consumption characteristics over time is shown in Fig. 9 in which the 10 students in the room were interacting and influencing each others' behaviors. At the start of the simulation, and for this particular example, three of the students were assumed to be HEC, four MEC, and three LEC. Furthermore, LEC were assumed to have a higher LI than the other categories. 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%, which means that after attending the event, 50% of the occupants were expected to reduce their energy consumption.

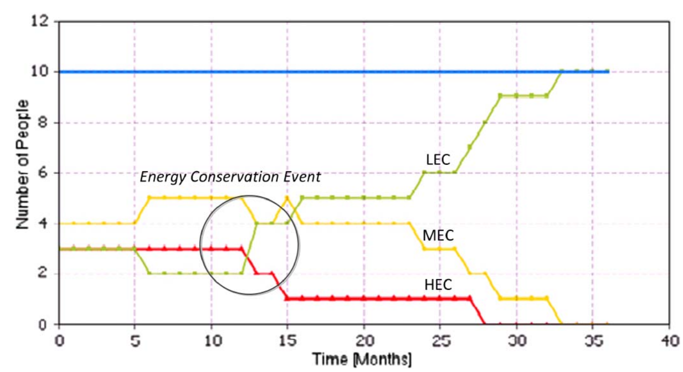


**Fig. 9.** Occupants' energy characteristics change

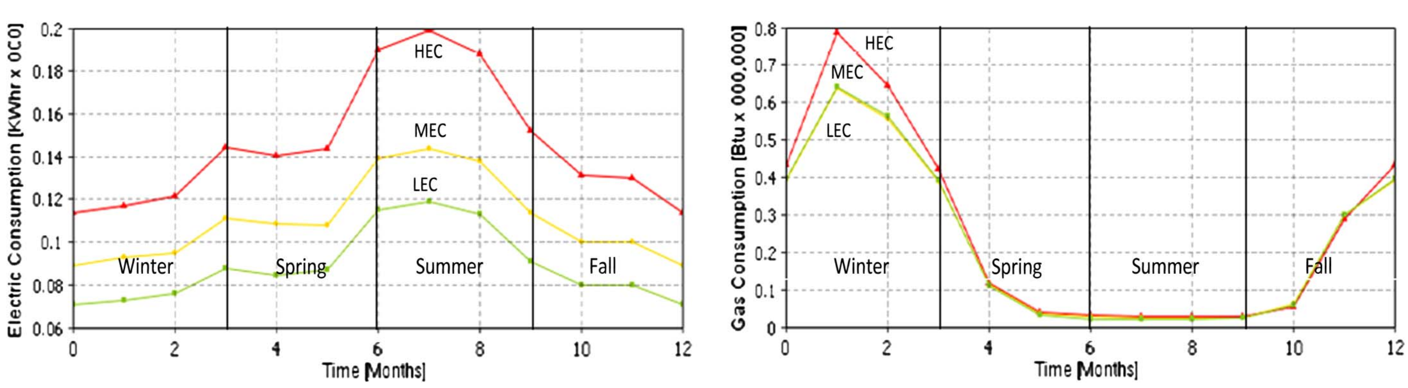


**Fig. 8.** Electric and gas consumption rates



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As shown in Fig. 9, as the simulation time was advancing, LEC were successfully converting all of the MEC and HEC to the LEC category. Consequently, LEC were attracting other occupants at a faster rate than they were being attracted. Therefore, their number kept increasing until all of the occupants became LEC. This conversion was mainly enhanced at the 12th month when the energy conservation event occurred, increasing the number of LEC from 2 to 4. Finally, around the 33rd month, the 10 occupants of the room were at that time LEC.

After calculating energy consumption rates and simulating the changes in occupancy behavior over time, electric and gas consumptions were then calculated by applying the rates shown in Fig. 8 to the number of occupants in each category from Fig. 9. A summary of the results for this example is shown in Fig. 10, where changes in the total electric and gas consumption were plotted over the 36-month study period.

As shown in Fig. 10, there was a significant drop of 23% in the total electric consumption from year 1 to year 3. This was expected because the number of LEC was increasing over time as HEC and MEC were getting converted (Fig. 9). By having the room occupants becoming LEC, less electric energy was then being consumed. The drop in the gas consumption was less significant (5%) because the occupants did not have direct control over the major portion of the gas consumption (see Fig. 7). Behavior changed and occupants were consuming less energy, but this did not reflect in a very considerable way on the gas consumption as it did on the electric consumption.

Although the results from this example showing the changes in behavior and the resulting changes in energy consumption might seem obvious or intuitive, current energy modeling software (e.g., eQuest or Energy-Plus) do not model these types of interactions, which is one of the main motivation behind this study. Consequently, the proposed method to model occupants' behaviors and their impact on energy use becomes in itself a significant contribution to the energy modeling literature, overcoming an important limitation of traditional energy modeling software. The developed model can supplement these traditional software programs to optimize the design of building systems, leading to significant energy savings over time.

### Sensitivity Analysis

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 of 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 example for the analysis and compared with the base case model built using eQuest, which does not allow for changes in occupancy characteristics throughout the simulation time (see Table 2). The initial conditions for the four scenarios assumed that the 10 occupants at time zero were divided between three HEC, four MEC, and three LEC to start the simulations with neutral energy consumption behaviors. The scenarios first differed by the word of mouth effect represented by the LI that occupants of each category had on those of other categories. The highest LI was assigned to HEC in the first scenario and then to LEC in the three other cases. The second parameter that was varied was the occurrence of energy conservation events,

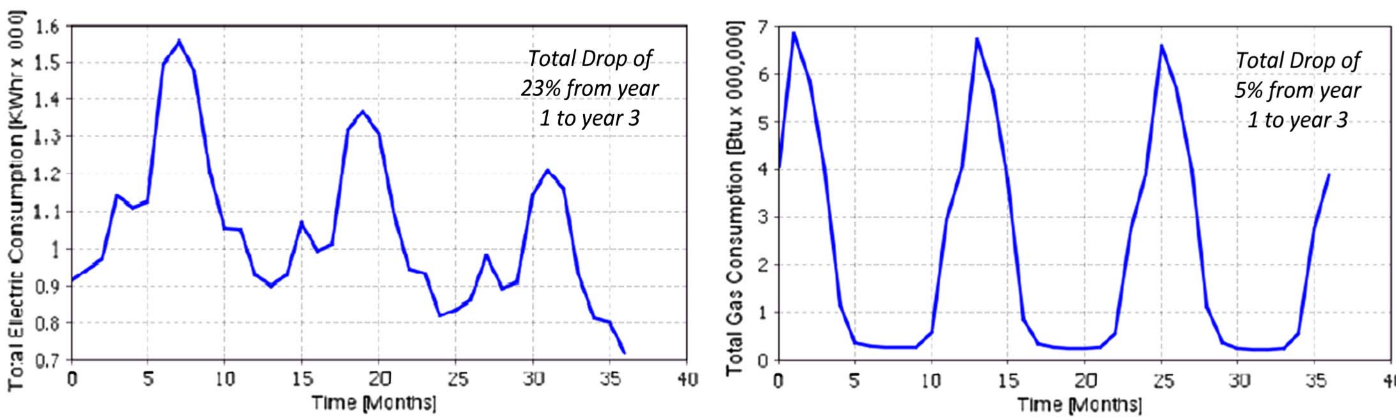


**Fig. 10.** Total electric and gas consumption

**Table 2.** Sensitivity Analysis Results

| Description | Base case | Scenario 1 | Scenario 2 | Scenario 3 | Scenario 4 |
|---|---|---|---|---|---|
| Highest level of influence (LI) | None | HEC | LEC | LEC | LEC |
| Energy conservation events (t in month) | None | None | None | One at $t = 12$ | One at $t = 12$ and another at $t = 18$ |
| Occupants' behavior change from the initial state of 3 HEC, 4 MEC, and 3 LEC | No change | All HEC as of $t = 30$ months | All LEC as of $t = 34$ months | All LEC as of $t = 29$ months | All LEC as of $t = 26$ months |
| Electric percent change from Base case (41.57 kW·h × 000) | 0.0% | +9.4% | −9.1% | −12.8% | −15.8%(Net = 25.2%) |
| Gas percent change from Base Case (80.92 Btu × 000, 000) | 0.0% | +2.4% | −1.7% | −1.9% | −2.3%(Net = 4.7%) |



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where one event was scheduled for Scenario 3 and two events for Scenario 4.

The results of this sensitivity analysis are summarized in the last two rows of Table 2. Scenario 1 resulted in the highest energy use levels because HEC were given the highest LI to successfully convert all of the room's occupants to HEC by the 30th month. In turn, Scenarios 2, 3, and 4 resulted in lower energy estimates with corresponding energy savings when compared with Scenario 1. Furthermore, by adding one energy conservation event in Scenario 3, and two events in Scenario 4, the time needed to convert all the occupants to LEC decreased from 34 months in Scenario 2, to 29 months in Scenario 3, and only 26 months in the last case. As a result, a reduction in the generated energy estimates was observed, reaching a minimum of minus 15.8% for electricity and minus 2.3% for gas consumption. Finally, by comparing the two most extreme cases, Scenarios 1 and 4, a total net difference of 25.2% for electric use and 4.7% for gas use was observed.

These obtained results have several important implications: (1) modeling occupants with different and changing energy consumption profiles can significantly affect total energy predictions, (2) the energy consumption differences are high in the case in which occupants control the energy loads (25.2% for electric) and low with less occupant control (4.7% for gas), and (3) the observed changes represent savings for just one room in the building with particular characteristics and assuming a uniform initial distribution of occupant categories (i.e., 3 HEC, 4 MEC, and 3 LEC). These savings are expected to be significantly higher when the whole building is considered and more aggressive occupancy profiles incorporated with higher levels of control over both electric and gas loads in the building.

## Conclusion

In conclusion, energy simulation software programs are failing to reliably predict energy performance of buildings (Yudelson 2010; Clevenger and Haymaker 2006; Soebarto and Williamson 2001). This is mainly attributable to the misunderstanding and underestimation of the important role that occupants play in determining energy consumption levels (Hoes et al. 2009; Turner and Frankel 2009). 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.

A numerical example that was developed to test the proposed approach showed that with dynamic occupancy being properly modeled, energy consumption patterns might considerably change over time. Furthermore, the more the occupants control the energy consumption sources of their environment, the more a change in their behavior affects total energy use.

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 (refer to Phase III of Fig. 5). 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. For this purpose, our research team is initiating a data collection plan after getting access to a unique building at the University of Wisconsin-Madison campus, providing real time data about the occupants and their energy and water consumptions. This data will also be used to better predict occupancy patterns as further research is required on occupants' behavior and their impact on total energy use levels in commercial buildings. As part of future research, the model will continue to be developed by the researchers to include more types of occupants' interactions, since it is currently limited to interactions within the rooms and with the exterior, not accounting for the influence of occupants in different rooms/areas on each others. Moreover, the model could be adapted in the future to account for different energy profiles of occupants because several studies identified patterns of energy use among occupants of different age, gender, nationality, etc. (Accenture 2010; Marans and Edelstein 2010; Räty and Carlsson-Kanyama 2009).

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, resulting in more accurate energy predictions during the design phase of buildings. These estimates could significantly improve and optimize the choices of buildings' electrical and mechanical systems, resulting in considerable energy and monetary savings while reducing greenhouse gas emissions. The proposed methodology has therefore significant contributions to the field of energy modeling mainly because of its multitude applications. First, the developed method could be integrated into one of the current commercial energy modeling software (e.g., Energy-Plus, eQuest, etc.) to account for the human behavioral side of the energy estimation problem. This framework could also be used independently as the basis for an independent and new energy modeling software. This software will be the first in the industry to focus on the individual level of occupants rather than modeling the system as a whole, which is one of the main advantages of agent-based modeling over other simulation techniques. In the pursuit of this commercial application of this software, the proposed agent-based model has been expanded to perform whole building analyses, simulating behavior and predicting energy use for multiple rooms and floors of building environments. Finally, the model could also be used as a decision-making tool that evaluates different behavioral changing methods (e.g., energy conservation trainings, feedback tools, financial incentives, etc.) and helps owners make more informed decisions about investing in methods to effectively reduce energy use.

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