

REPORT



Simulation Modeling of Occupant Behavior in Commercial Buildings January 2013





EEB Hub REPORT

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Table of Contents

Executive Summary
Introduction
Modeling Framework7
Case Study Buildings
Building #1: Single Tenant 11
Building #2: Multiple Tenants 12
Building #3: Multiple Tenants 13
Illustrative Modeling Results
Calibration 14
Building #1: Occupant Responses to Load Shedding 16
Building #2 Misaligned Incentives in Multi-tenanted Buildings 19
Building #3 Misaligned Incentives in Multi-tenanted Buildings 22
Building #2 Locus of Control 25
Building #2 Occupant Engagement Using Dashboards and Serious Games 29
Recommendations for Practice and Future Research
References

Executive Summary

A group at the Energy Efficient Buildings Hub is researching the links between energy efficiency and occupant behavior, and in addition to performing fieldwork and experiments, it has also completed the computer simulation modeling activities summarized in this report. The modeling work continues, but this report provides a useful snapshot of its current state. The modeling work provides a consistency check on the empirical work, while also opening up new ways to bring insights about human behavior to the building design process. The modeling framework used in this report connects commercially available building information modeling (BIM) software to a novel tool that simulates occupant behavior.

Fieldwork confirms that occupant behavior is an important consideration in the design of advanced energy retrofits (AERs) in commercial buildings for three key reasons. First, occupants determine the acceptability of retrofits and resist changes that decrease their comfort or make additional demands on their time and attention. Second, occupants sometimes respond to changes in mal-adaptive ways, such as by bringing in a personal space heater that offsets central system savings achieved by the retrofit. Finally, if occupants gain access to enabling technology and appropriate incentives, they may supportively perform energy-saving behaviors. By capturing these insights about the likely interactions between people and building systems in a simulation modeling framework, designers can explore the "what-if" space thoroughly before carrying out the retrofit.

The modeling framework incorporates the EnergyPlus building energy performance model and drives it using the OpenStudio plug-in to the Sketchup building geometry design tool. The human agent submodel is programmed in the NetLogo agent-based modeling environment, and a connective tissue of Java code links the submodels together into a dynamic simulation system.

Three relatively new multi-story commercial buildings in the Greater Philadelphia region with gross floor areas in the 75,000 – 100,000 square foot range have been modeled. One houses a single tenant and the other two are multi-tenanted. The two multi-tenanted buildings are LEED certified and include a variety of innovative daylighting and thermal comfort features. The single-tenanted building is undergoing an advanced energy retrofit. The buildings and their occupants were studied in detail during a year of fieldwork. The modeling framework was calibrated to produce credible simulations of each building. The modeling team simulated several scenarios for each building to demonstrate the range of questions that designers can explore. These included the following:

- Load shedding was modeled for the single-tenanted building, and the simulation showed that occupants barely noticed, thereby bolstering the owner's confidence that a real event would not alienate the tenant.
- In a multi-tenanted building, a tenant who pays their own energy bill uses less energy than one who does not. Occupants in the cost-conscious tenant space must engage in regular activities to try to maintain comfort.
- In a multi-tenanted building, when much control is centralized into the hands of the building operator, occupants expend little effort in trying to maintain comfort. When control is decentralized, more dynamism enters the system because occupants disagree on optimal settings for thermostats, overhead lights, and window blinds.

Simulating Occupant Behavior

• In a multi-tenanted building, the introduction of enabling technologies including dashboards and serious games yields modest building-wide energy savings while reducing the frequency with which occupants adjust thermostat and other controllable building features.

Key recommendations for practice include the following:

- Consider including representations of occupant behavior in BIMs for both AERs and new buildings.
- Pursue "behaviorally robust" building and AER design strategies that complement the current focus on high-performance designs.
- Pay particular attention to the usability issues associated with design innovations, and consider the user-friendliness of each AER.
- Take advantage of enabling technologies such as dashboards and serious games that open up opportunities for occupants to carry out energy-saving behaviors.

Recommendations for future research include:

- Develop less costly ways to collect occupant perception and behavior data for use in calibrating behavioral models.
- Optimize the computer code to speed up the simulation process and allow the occupant behavior module to become an add-in to commercial BIM software.
- Extend this modeling approach to the domains of interior design and urban design.

Introduction

Occupants play several roles in determining a building's energy use and they can have a strong influence on the success of advanced energy retrofits (AERs). Occupants directly use energy by operating computers, task lights, and other locally controllable equipment that we categorize as plug loads within buildings. Occupants indirectly use energy as beneficiaries of heating, ventilating, and air-conditioning (HVAC) systems, lighting systems, security systems, elevators, water systems, and other building services. Engineers and architects design building services to reflect their understanding of what occupants want, and building operators manage these systems in ways that they hope balance the twin objectives of low costs and high comfort. Occupants can influence the performance of building systems in an active sense, as they adjust thermostats or operate windows and blinds, and in a passive sense as occupancy schedules and usage patterns change over time (Brager and de Dear 1998, Fabi et al 2012, Masoso and Grobler 2010). The successful rollout of AERs depends significantly on whether occupants accept the changes (van den Wylenberg 2012, Indraganti et al 2013, Toftum et al 2009, Karjalainen and Lappalainen 2011).

The literature shows that occupant behavior can measurably affect a building's energy performance. In conventional office buildings, occupants typically focus more on doing their jobs than on saving energy (Lo, Peters and Kok 2012). In high-performance commercial buildings, the very innovations that contribute to technical performance may not be comprehensible to building occupants, raising usability issues that threaten ultimate energy savings (Brown and Cole 2011, Wagner et al 2007). In conventional residential buildings, cooling and lighting are the parameters most strongly affected by occupant behavior, whereas in high-performance residential buildings, it is the random variations in occupants' schedules and their use of plug loads that dominate (Brandemuehl and Field 2011, Emery et al 2006). Physiological factors such as gender, psychological factors such as perceptions of personal control, and availability of adaptive behaviors such as adjusting clothing all have effects on both perceived comfort and building-wide energy use (Karjalainen 2007, Karjalainen 2009, Newsham 1997). Occupant influences on building energy are the same order of magnitude as technological factors, making behavioral robustness an increasingly important design criterion (Schweiker and Shukuya 2010, Hoes et al 2009).

Simulation modeling has become an essential design tool in recent decades, as computers and specialized software have found their way onto desktops in architectural and engineering firms. Building information modeling (BIM) has been a regular part of the professional curriculum for more than a decade and the industry has developed standards that enable file sharing across firms throughout the building industry. BIM is also entering the building management system (BMS) sphere, where it promises to support more sophisticated management and control strategies.

Tools that simulate building energy use have been widely available since the 1970s and energy simulations have become an essential part of both design and regulatory compliance processes. Building energy performance models incorporate important information about occupant behavior, including occupancy schedules, thermal comfort setpoints, internal heat gains due to occupant activities, and target illumination levels. However, they also miss important information such as the variation across occupants in preferred temperatures and lighting levels,

the range of adaptive behaviors occupants perform as they respond to changing comfort conditions, and the amount of effort required of occupants to become effective users of buildings, especially those with novel or complex features (Daum et al 2011, Bourgeois et al 2006, Galasiu and Veitch 2006). For example, designers of thermally activated building control systems need to understand the linked adaptive responses of occupants before they can understand the overall dynamic performance of the building-occupant system (Sourbon and Helsen 2011, Saelens et al 2011). Designs intended to increase personal control, such as task/ambient air conditioning systems, need similar verification (Akimoto et al 2010).

Building energy performance modelers have explored various strategies for representing the essential elements of occupant behavior. The default strategy is to drive a deterministic engineering physics model with average values for occupant-related variables. Deterministic tools can also be used as modeling engines that explore a variety of scenarios embodying alternative occupancy schedules, temperature set points, and other design assumptions. Modeling engines can perform Monte Carlo analysis (Pfafferott and Herkel 2007). Specific variables can be treated as stochastic instead of deterministic, thereby allowing exploration of what variable behaviors and preferences might mean for optimal design choices (Virote and Neves-Seva 2012, Herkel et al 2008). Specific variable values can be modeled explicitly, such as by representing occupancy schedules as Markov processes in which the variable value in any particular hour depends partly on what it was in a previous hour (Page et al 2008). Multiple user profiles can be developed to characterize succinctly the variations in occupant behavior (Santin 2011). Data mining (Yu et al 2011) and behavioral algorithms that represent reduced-form formulations of complex behaviors can make the prospect of multiple simulations more manageable (Rijal et al 2008). Bayesian networks provide a useful way to manage the complexity of the coupled building-occupant system (Jensen et al 2009). Researchers are now exploring alternative artificial intelligence (AI) approaches that range from machine learning that correlates behavioral inputs with building-wide outputs without attributing causality, to agent-based models (ABMs) that explicitly simulate specific theories and processes of human behavior (Andrews et al 2011, Klein et al 2012). The current research adopts an agent-based modeling approach.

ABM is a computer simulation framework that has been greatly facilitated by the advent of object-oriented programming languages such as Java. In an ABM, software objects interact with one another and their external environment according specific rules. These rules govern their interactive behaviors as well as their internal workings. The rules provide a coherent basis for simulating many phenomena such as the behavior of molecules in a fluid, the behavior of predators and prey in an ecosystem, the behavior of pedestrians on a city street, and the behavior of occupants in a commercial office building. In these examples, the ABM can reveal emergent system properties (turbulent flow, population crashes, sidewalk congestion, building-wide energy use). Among various approaches for modeling human behavior, ABMs are particularly useful when agents are heterogeneous in their preferences and capabilities, have bounded rationality, and respond to changing information. Standard ABM platforms are emerging which reduce the programming burden for potential developers.

The intended benefits of adopting an ABM approach to the representation of occupant behavior in buildings are both practical and aspirational. In practical terms, it is empirically evident that building occupants have heterogeneous preferences and adaptive responses to changing comfort

Simulating Occupant Behavior

conditions. If detailed data are available from fieldwork or experimentation, then calibration of an ABM is a straightforward exercise in populating agent characteristics from occupant survey responses and occupant-specific observations. The ABM framework also has practical value for simulating behavior-change strategies such as occupant education, energy information feedback, and social persuasion that derive from psychological, that is, individual-based behavioral theories rather than theories based on aggregate economic behavior. The ABM approach is also aspirational because it becomes more useful as computing power increases and "big" data become more available.

This report shares results of a modeling effort that characterizes occupant behavior in existing commercial buildings under a variety of conditions. A major purpose of the modeling work is to capture insights harvested from a set of case studies of single- and multi-tenanted buildings undergoing AERs. Once captured within a model, users can apply these insights to future AER projects in a more direct way than they could by simply reading historical case studies.

The rest of this report introduces the modeling framework, shares details from the case study buildings and their occupants, reports illustrative modeling results, discusses the results, and draws conclusions and recommendations for practice and for future research. The modeling work continues but this report provides a useful snapshot of its current state. Models discussed here may be downloaded from greenbuilding.rutgers.edu.

Modeling Framework

There are three motivations for creating this framework for simulating occupant behavior. We



The modeling system requires several types of data, including detailed building design documentation; utility bills and other objective measures of building performance; surveys and

other empirical evidence regarding occupant perceptions, preferences, and behaviors; and exogenous assumptions to guide the formulation of scenarios (Figure 2).



Figure 2: From fieldwork to modeling

The modeling framework consists of several commercially available programming and simulation applications tied together with a connective tissue of Java code. The occupant behavior model is programmed in the NetLogo ABM environment (www.netlogo.org, Wilensky and Rand 2013). The building geometry is entered using Sketchup (www.sketchup.com). Details on building systems, schedules, and other factors are entered using a beta version of OpenStudio (openstudio.nrel.gov). The EnergyPlus modeling engine characterizes the energy performance of the building design (http://apps1.eere.energy.gov/bu ildings/energyplus/). The Eclipse Java programming environment manages the connective code (www.eclipse.org).

The steps in building a complete model include:

- 1. Enter building geometry into Sketchup
- 2. Enter buildings systems information into OpenStudio
- 3. Create an EnergyPlus model of the building
- 4. Calibrate the EnergyPlus model using utility bills and other objective data
- 5. Enter occupant perception and behavior data into NetLogo
- 6. Create an integrated NetLogo-EnergyPlus model of the building and its occupants
- 7. Re-calibrate the integrated model using utility bills and occupant behavior data
- 8. Specify what-if scenarios in NetLogo, then run integrated model and analyze the output

The logic of the complete modeling system is summarized in Figure 3. It contains a building performance submodel that tracks and modifies the state of the indoor environment over time. It

Simulating Occupant Behavior

contains a human agent submodel that simulates individual and shared decisions of occupants as they experience and react to changing environmental conditions. It includes a file documenting the current state of controllable and uncontrollable building features. Finally, it contains linked external models that perform detailed engineering and building physics calculations to simulate energy consumption lighting levels, and other results. This modeling framework was introduced in Andrews et al (2011) and extended in Andrews et al (2012).





Source: Andrews et al 2012

The next level of detail in the human agent submodel is shown in Figure 4. The AI community has developed a procedurally-oriented model of human decision making called the Belief-Desire-Intention (BDI) framework. This framework has been applied in a variety of modeling contexts that call for simulations of reasoned (rather than routinized) decision making (Norling 2009). The standard BDI framework includes perception of the current environmental state, cognition that compares the current state to a desired state, deliberation that formulates an intention to remedy the discrepancy, planning that weighs alternative courses of action, and decision making that selects a preferred course of action. In the current application, this framework is enriched with elements from the Theory of Planned Behavior (Ajzen 1991) that offers psychological grounds for developing beliefs about the state of the environment and its controllability, beliefs about what is important in terms of value judgments, and a sensitivity to societal norms that may influence behavioral intentions. The enriched framework was introduced in Andrews et al (2011).



Figure 4: Belief-Desire-Intention Framework for simulation of occupant decision making

Source: Andrews et al (2011)

Usability is the main concept underlying the output metrics of the simulation modeling framework. This framework adopts the standard ISO definition (1998) as discussed in Andrews et al (2011):

- <u>Effectiveness</u>: the probability that the technology performs effectively given the distribution of user behaviors (e.g., % achievement of target lighting level)
- <u>Efficiency</u>: the ratio of the output (e.g., lighting services) of a system to its input (e.g., energy, \$, time, effort, attention).
- <u>Satisfaction</u>: the utility a user derives from a system (weighted function of attributes such as energy, \$, effort)

Case Study Buildings

The modeling framework was initially applied to stylized, simplistic, five-zone buildings, but it has since been extended to more detailed BIM representations of real, occupied commercial buildings in the Greater Philadelphia region. All are Class A, recently-built, multi-story office buildings between 50,000 and 100,000 gross square feet in size. This section introduces the buildings, each of which was the focus of fieldwork to determine its energy performance and to gauge occupant perceptions and behavior. Only summary details are provided here, see the field-study reports for additional information.

Building #1: Single Tenant

The first case study building is a three story office building near Philadelphia that was constructed in 2004, and has 76,692 gross square feet of floor area and 227 occupants. It is owned by a real estate investment trust and, although built as a multi-tenant site, currently functions as a single-tenanted building. The EnergyPlus model for this building was developed and calibrated by another EEB Hub research team whose report shares full details (Xu and Wagner 2012).



Figure 5: Case Study Building #1 (a) exterior, (b) interior

Building #2: Multiple Tenants

The second case study building was built in 2005 as a speculative multi-tenant office development of 76,350 square feet. It achieved a green building certification of LEED Platinum Certification – Core and Shell v 1.0 pilot in 2006, and has an EnergyStar Portfolio Manager score of 79. Occupancy of tenanted spaces has exceeded 90% during the study period, with the total number of occupants in the range of 200. Unusual features of this building include extensive daylighting, a four-story atrium, and a high-efficiency HVAC system. See Senick et al (2012) for further details.





Figure 6: Case Study Building #2, (a) photograph, (b) BIM representation

Building #3: Multiple Tenants

The final case study building discussed in this report was built in 2009 as a speculative, multitenanted office building with a floor area of 95,621 square feet. It earned LEED Gold Certification – Core and Shell v 1.2 in 2009 and its ENERGY STAR Portfolio Manager score is 78 once a non-office energy user (healthcare facility) is removed from the tally. It includes a significant level of building automation, performs a substantial amount of daylight harvesting, includes a four-story atrium, and uses a high-efficiency HVAC system. The building's tenanted areas were 100% occupied during the fieldwork period and included approximately 250 occupants. See Senick et al (2012) for further details.





Figure 7: Case Study Building #3, (a) photograph, (b) BIM representation

Illustrative Modeling Results

This section shares illustrative modeling results that communicate key findings from a wide variety of simulations that the research team performed. First, this section discusses the calibration of the EnergyPlus models to utility bills and then it presents results of the coupled building-occupant behavior modeling system.

Calibration

The calibration of the Building #1 EnergyPlus model to utility bills was performed by another research team and the results are summarized in Xu and Wagner (2013). The model closely replicates the normalized utility bills.

Calibration of the EnergyPlus model of Building #2 proceeded in two steps. First, the modeled floor area was confirmed to be within 2.5 % of the floor area of the as-built building. Second, the measured annual energy consumption of 62 kBtu/sq.ft/year compared favorably with the modeled energy use of 69 kBtu/sq.ft/year, yielding an acceptable 11.3% error.

For Building #3, the modeled floor area differed by 1.4% from the measured floor area. Modeled energy intensity excluding the healthcare tenant was 77 kBtu/sq.ft/year, yielding a 0% error relative to the measured energy use excluding that tenant.

To test the validity of the models for Buildings #2 and #3, the modeling team performed 20 sensitivity runs for each building that explore a variety of plausible redesign scenarios. Results are summarized in Table 1, and they suggest that the models are reasonable representations of these buildings.

Table 1: Sensitivity Analyses of Simulation Models of Buildings #2 and #3

Scenario	Change in Annual Energy	
	Use from Baseline	
	Building #2	Building #3
Baseline (2009 ASHRAE 90.1 construction)	0%	0%
Pre-1980-era construction (standard Commercial Building Energy Consumption	+41%	+56%
Survey construction materials, common pre 1980's lighting (20 Watts/m^2) and		
average pre 1980 medium office building electric equipment use (11 Watts/m^2).		
1980 to 2004-era construction (standard CBECS construction materials, average	+26%	+30%
lighting load (17 Watts/m ²) and average medium office building electric		
equipment use (11 Watts/m ²) for the time period 1980-2004).		
Single Pane (all exterior windows are single pane 3mm windows).	+3%	+13%
Triple Pane (all exterior windows are triple pan windows with three 3mm panes each	-3%	-8%
separated by 13mm of air).		
Double Pane Argon (all exterior windows are double pane 3mm glass separated by	-3%	-3%
13mm of argon gas).		
Triple Pane Argon (all exterior windows are triple pane 3mm glass separated by	-6%	-9%
13mm of argon gas).		
Double Reflective Argon (all exterior windows are double pane 3mm glass separated	-4%	-6%
by 13mm of argon gas with a reflective coating).		
Triple Pane low-e Argon (all exterior windows are triple pane 3mm glass separated	-6%	-12%
by 13mm of argon gas. The glass has both low thermal emissivity and reflective		
properties).		
Half Lights (ses 5 Watts/m ² instead of the standard 10 Watts/m ² for the	-13%	-10%
building's lighting load).		
Quarter Lights (2.4Watts/m ² instead of the standard 10 Watts/m ² for the	-17%	-13%
building's lighting load).		
Floor Insulation (triple the amount of floor insulation on external and ground contact	-1%	-5%
surfaces).		
Interior Insulation (triple insulation on all interior walls, floors and ceilings).	-3%	-5%
Roof Insulation (triple the amount of roof insulation on external surfaces).	-4%	-5%
Wall Insulation (triple the amount of wall insulation on external surfaces).	-4%	-5%
Wall and Roof Insulation (triple the amount of wall and roof insulation on external	-4%	-6%
surfaces).		
Wall, Roof and Floor Insulation (triple insulation on all exterior surfaces).	-4%	-6%
Wall, Roof and Floor Insulation with Triple Argon (triple the standard amount of	-7%	-13%
insulation on all exterior surfaces coupled with triple pane argon windows.		
Wall, Roof and Floor Insulation with Triple Argon and Half Lighting (triple the	-14%	-21%
standard amount of insulation on all exterior surfaces coupled with triple pane argon		
windows and uses 4.8 Watts/m ² for the buildings lighting load).		
More Thermal Zones (more localized HVAC thermal zones as opposed to only one	-3%	-6%
thermal zone per floor).		

Building #1: Occupant Responses to Load Shedding

In this pair of scenarios, occupants of the single tenanted building experience a load shedding event during a summer day. This is similar to a well-documented set of events that actually took place at this building, as reported in Xu and Wagner (2013) and Senick et al (2013). The hourly simulations cover a 24-hour period in midsummer. The first simulation assumes normal operations, whereas the second includes a late morning load shedding event. The simulation scope includes both thermal comfort and illumination levels. Thus, the range of sensations that occupants can perceive includes Too Hot, Thermally Neutral, Too Cold; and Too Bright, Illumination-Neutral, and Too Dim. The set of actions that occupants may take to adapt to changing thermal comfort conditions includes Do Nothing, Adjust the Thermostat, Turn On/Off a Personal Space Heater, Add/Remove Clothing. For illumination, the set of possible adaptive actions includes Do Nothing, Adjust Window Blinds, Turn Task Light On/Off, and Turn Overlight On/Off.



Figure 8: Building #1 Hourly Energy Use under Normal and Load Shedding Conditions



Figure 9: Building #1 Average Hourly Indoor Air Temperature (F) under Normal and Load Shedding Conditions



Figure 10: Building #1 Average Hourly Occupant Discomfort Level under Normal and Load Shedding Conditions



Figure 11: Building #1 Average Hourly Occupant Adaptive Effort Level under Normal and Load Shedding Conditions



Figure 12: Building #1 Count of Hourly Occupant Adaptive Responses to Improve Thermal Comfort under Load Shedding Conditions (blue = do nothing, red = adjust thermostat, green = use personal space heater)



Figure 13: Building #1 Count of Hourly Occupant Adaptive Responses to Improve Illumination Levels under Load Shedding Conditions (blue = do nothing, red = use task light, green = adjust overhead light, purple = adjust window blinds)

Figures 8-13 show that the load shedding event was barely perceptible to occupants. Although indoor air temperatures rose during the event, the adaptive behaviors of occupants did not show a dramatic shift. The story was similar for lighting. For both thermal comfort and lighting, the bigger adaptive responses were associated with normal daily building startup and operations.

Building #2 Misaligned Incentives in Multi-tenanted Buildings

One of the barriers to improved energy performance identified by fieldwork in multi-tenanted buildings is the problem of misaligned incentives. Tenants are often not sub-metered, or they may be charged for energy use on a pro-rata rather than measured basis. Even if the tenant company has signed a lease that makes it responsible for paying utilities, the actual bills may go to a distant headquarters office rather than to the local supervisor. In short, it is common to find that occupants of multi-tenanted buildings to not experience meaningful energy cost feedback. The following pair of simulations compares two building operation strategies: cost-minimizing versus comfort-maximizing (and effort-minimizing). The energy cost-minimizing strategy represents the case where tenants have well aligned incentives to save energy, whereas the comfort-maximizing strategy approximates the more prevalent situation of misaligned incentives. The simulations show hourly results for a winter day.



Figure 14: Building #2 Winter Day Hourly Energy Use with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 15: Building #2 Winter Day Average Hourly Indoor Air Temperature with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 16: Building #2 Winter Day Average Hourly Occupant Discomfort Levels with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 17: Building #2 Winter Day Average Hourly Occupant Effort Levels with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 18: Building #2 Winter Day Average Hourly Occupant Adaptive Responses under the Energy Cost Minimizing Tenant Behavioral Strategy



Figure 19: Building #2 Winter Day Average Hourly Occupant Adaptive Responses under the Comfort Maximizing (and Effort Minimizing) Tenant Behavioral Strategy

As one might expect, the cost-minimizing strategy uses less energy, yields lower temperatures during most working hours, and decreases comfort relative to the more typical comfort-maximizing strategy. Adaptive responses related to lighting differ dramatically between the two cases, with the comfort-maximizing (and effort minimizing) strategy relying heavily on task and overhead lights, while the cost-minimizing strategy harvests more daylight, avoids the use of overhead lights, and requires regular adjustments of lights and blinds by occupants.

Building #3 Misaligned Incentives in Multi-tenanted Buildings

The same scenario was replicated in Building #3 which is newer, larger, has more exterior glass, and different occupants than Building #2. Results differ in their details, as shown below.



Figure 20: Building #3 Winter Day Hourly Energy Use with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 21: Building #3 Winter Day Average Hourly Indoor Air Temperature with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 22: Building #3 Winter Day Average Hourly Occupant Discomfort Levels with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 23: Building #3 Winter Day Average Hourly Occupant Effort Levels with Tenant Behavioral Strategies to Minimize Energy Cost (blue) and Maximize Comfort (While Minimizing Occupant Effort) (red)



Figure 24: Building #3 Winter Day Average Hourly Occupant Adaptive Responses under the Energy Cost Minimizing Tenant Behavioral Strategy



Figure 25: Building #3 Winter Day Average Hourly Occupant Adaptive Responses under the Comfort Maximizing (and Effort Minimizing) Tenant Behavioral Strategy

Comparing Building #2 to Building #3, the patterns of energy use, temperature, discomfort, and effort are quite similar within each of the two scenarios. This supports the general prescription that it is important to align incentives for better tenant management of energy costs. The one area of significant difference is in the adaptive choices made by occupants: in Building #3 they are much more likely to adjust their clothes to improve comfort than is the case in Building #2, and they do not choose to use personal space heaters.

Building #2 Locus of Control

One of the challenges identified in fieldwork on occupant satisfaction in multi-tenanted buildings is confusion over the locus of control, that is, understanding who has control over which systems. The following simulations in Building #2 examine three cases: temperature, overhead lights, and window blinds are controlled by (1) the building operator, (2) a properly-incentivized tenant who minimizes costs, and (3) majority vote of the occupants within each zone. In all three cases, occupants directly control their task lights and plug loads. The simulations show hourly results for a winter day.



Figure 26: Building #2 Winter Day Average Hourly Energy Use under majority vote of occupants on central temperature and lighting controls (red), cost-minimizing tenant's control (blue), and building operator's control (green).



Figure 27: Building #2 Winter Day Average Hourly Indoor Air Temperature under majority vote of occupants on central temperature and lighting controls (red), cost-minimizing tenant's control (blue), and building operator's control (green).



Figure 28: Building #2 Winter Day Average Hourly Occupant Discomfort Levels under majority vote of occupants on central temperature and lighting controls (red), cost-minimizing tenant's control (blue), and building operator's control (green).



Figure 29: Building #2 Winter Day Average Hourly Occupant Effort Levels under majority vote of occupants on central temperature and lighting controls (red), cost-minimizing tenant's control (blue), and building operator's control (green).



Figure 30: Building #2 winter day hourly occupant adaptive responses under majority vote of occupants on central temperature and lighting controls.

When the building operator is in charge of setting temperatures, overhead lights, and window blinds, the scope of the tenant organization's and the occupant's control over building systems shrinks. The tenant and occupant expend less effort trying to adapt, and they end up focusing on task lights and brief use of personal space heaters. Building-wide energy use is not much

Simulating Occupant Behavior

different than in the two other scenarios, but indoor air temperatures are higher and occupant discomfort levels are lower.



Figure 31: Building #2 winter day hourly occupant adaptive responses under cost-minimizing tenant's control of central temperature and lighting.



Figure 32: Building #2 winter day hourly occupant adaptive responses under building operator's control of central temperature and lighting.

When a cost-minimizing tenant representative is in charge, average discomfort is a little higher than in other scenarios, but little else changes. Finally, when occupants use a majority vote to set the thermostat and other features that are not personally controllable, much dynamism is introduced into the building-occupant system.

Building #2 Occupant Engagement Using Dashboards and Serious Games

Occupant feedback is a potentially powerful way to encourage energy-saving behavior. This pair of scenarios provides occupants with information about their energy consumption, personally and building-wide. These scenarios approximate the field experiments with dashboards and serious games conducted by the EEB Hub in Fall 2012. The actual field experiments addressed only personally-controllable plug loads, whereas these simulations assume a level of control of the full range of energy-using equipment. Shown are a scenario without any occupant feedback tools deployed, and one with two such tools. In both cases, occupants use a majority vote to determine the appropriate thermostat setting, overhead light setting, and window blind setting for each zone. The simulations show hourly results for a winter day.







Figure 34: Building #2 winter day average hourly indoor air temperature under majority vote of occupants on central temperature and lighting controls with feedback to occupants (blue) and without feedback (red).



Figure 35: Building #2 winter day average hourly occupant discomfort level under majority vote of occupants on central temperature and lighting controls with feedback to occupants (blue) and without feedback (red).



Figure 36: Building #2 winter day average hourly occupant effort level under majority vote of occupants on central temperature and lighting controls with feedback to occupants (blue) and without feedback (red).



Figure 37: Building #2 winter day hourly occupant adaptive responses under majority vote of occupants on central temperature and lighting controls *with* feedback to occupants.



Figure 38: Building #2 winter day hourly occupant adaptive responses under majority vote of occupants on central temperature and lighting controls *without* feedback to occupants.

Providing feedback to occupants yields a very modest decrease in building-wide energy use and no visible change in indoor air temperatures. Feedback seems to reduce occupant discomfort and effort levels. The one visible change in adaptive behaviors is that occupants receiving feedback less often adjust the thermostat.

Recommendations for Practice and Future Research

This project has demonstrated that a coupled building-occupant modeling system can be calibrated to data from field studies of real buildings, and used to explore energy performance challenges especially associated with multi-tenanted buildings. The scenarios included in this report are a small sample of the possibilities. Readers are welcome to download the models and try out additional scenarios themselves at greenbuilding.rutgers.edu.

Key recommendations for practice include the following:

- Consider including representations of occupant behavior in BIMs for both AERs and new buildings.
- Pursue "behaviorally robust" building and AER design strategies that complement the current focus on high-performance designs.
- Pay particular attention to the usability issues associated with design innovations, and consider the user-friendliness of each AER.
- Take advantage of enabling technologies such as dashboards and serious games that open up opportunities for occupants to carry out energy-saving behaviors.

Recommendations for future research include:

- Develop less costly ways to collect occupant perception and behavior data for use in calibrating behavioral models.
- Optimize the computer code to speed up the simulation process and allow the occupant behavior module to become an add-in to commercial BIM software.
- Extend this modeling approach to the domains of interior design and urban design.

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