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An agent-based model of building occupant behavior during load shedding

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Abstract

Load shedding enjoys increasing popularity as a way to reduce power consumption in buildings during hours of peak demand on the electricity grid. This practice has well known cost saving and reliability benefits for the grid, and the contracts utilities sign with their "interruptible" customers often pass on substantial electricity cost savings to participants. Less well-studied are the impacts of load shedding on building occupants, hence this study investigates those impacts on occupant comfort and adaptive behaviors. It documents experience in two office buildings located near Philadelphia (USA) that vary in terms of controllability and the set of adaptive actions available to occupants. An agent-based model (ABM) framework generalizes the case-study insights in a "what-if" format to support operational decision making by building managers and tenants. The framework, implemented in EnergyPlus and NetLogo, simulates occupants that have heterogeneous thermal and lighting preferences. The simulated occupants pursue local adaptive actions such as adjusting clothing or using portable fans when central building controls are not responsive, and experience organizational constraints, including a corporate dress code and miscommunication with building managers. The model predicts occupant decisions to act fairly well but has limited ability to predict which specific adaptive actions occupants will select.

Keywords

locus of control,
building energy modeling,
occupant behavior,
load shedding,
agent-based modeling

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1 Introduction

The four major components of electricity demand in commercial buildings are heating ventilation and air-conditioning (HVAC), lighting, plug loads, and non-component-specific features such as elevators (EIA 2016). Expected occupancy schedules drive all of these components, although climate conditions also strongly affect HVAC loads, and daylight availability can affect lighting loads. The peak electricity demand for most commercial buildings and electric power systems occurs on hot summer afternoons (except in heating-dominated climate zones) when buildings are at full occupancy and cooling loads are highest.

The cost of serving peak electricity demand is typically much higher (2–10 x) than that of serving average demand because more generation, transmission, and distribution capacity is needed; and because low-capacity-factor peaking power plants often perform inefficiently and have high operating costs (Faruqui et al. 2012). Demand-side management that attempts to re-shape and flatten the aggregate daily demand profile has long since entered the utility planner's toolkit alongside planning for new power plants and power purchases (Cowart 2016). Load shedding, which attempts to shave or shift peak-hour electricity demand, is a well-established practice that is implemented indirectly, via time-of-use pricing or interruptible power contracts that call on customers to shed load in whatever ways they deem feasible, or directly, via direct load control of key items of equipment in buildings by the utility. In some markets, aggregators bundle together many buildings and thereby expand the degrees of freedom for responding to load shedding requests (Cappers et al. 2010). The economics of the aggregation business, and the incentives for utilities and direct customers to optimize their performance during load shedding events, are driving efforts to make buildings more controllable on an hour-by-hour basis (Stluka 2014).

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Countries around the world have already incorporated load shedding as part of their initiatives for improving the operational security of electric power systems. Italy, for example, combined a load shedding strategy with other demand side management measures during its 2003 power outage (Capozza et al. 2005). In South Korea and South Africa, load shedding programs have been accepted and implemented. The implementation can be as simple as reducing peak-hour demand for various customers to avoid total electric system failure. Time-varying pricing strategies are also commonly implemented with load shedding strategies to reduce peak hour demand (Newsham and Bowker 2010). Sun et al. (2013) evaluate load shedding strategies using three cold thermal energy storage facilities, including building thermal mass, thermal energy storage system, and phase change material. Another variant of load shedding, Distributed Interruptible Load Shedding (DILS), is used in case of emergency by increasing the number of program participants to prevent total electrical system failure (Faranda 2007). In a typical commercial building with load shedding, a building manager responds to a request from the electric utility as the peak hour approaches. The demand for electricity during peak hours, such as 11:00 AM to 5:00 PM, is much higher than during non-peak periods, and demand charges vary between 35% and 65% of the total electricity bill. Load shedding implementation requires demand response control strategies for time-programmable activities and tariffs that aim to reduce peak electric loads, and hence, electricity costs (Huang 2007).The rise of fully-automated demand response, that does not require human intervention in adjusting the electric loads, becomes a challenge to occupant satisfaction and control system designers. The regulatory economists' claim that electric loads in buildings can easily be reduced by 30% or more (Faruqui et al. 2012) needs testing in specific scenarios to determine whether building occupants notice and respond constructively, and that is the purpose of this paper.

Studies on human factors in energy consumption and energy waste have received substantial attention in recent years (Toftum et al. 2009). Previous surveys, energy audits, and studies have shown that occupancy and occupant behaviors affect energy consumption (Seryak and Kissock 2000; Masoso and Grobbler 2009; Mahdavi and Pröglhöf 2009; Ouyang and Hokao 2009). In office buildings, occupants interface directly with plug loads such as computers, task lights, and other locally controllable equipment. Comfort perception, which is triggered by a change in the building's environment, plays a major role when occupants adjust thermostats, open or close windows and blinds, turn on or off task lighting, or call their building manager (O'Brien and Gunay 2014). Building occupants may also change their expectations based on their comfort perceptions that could also lead to shifts in building energy use (Azar and Manessa 2012b). Therefore, it is fair to say that building occupants play significant roles in determining a building's energy consumption, and thus determine the success of advanced energy retrofits.

Since occupant behaviors have been identified to be one of the factors influencing building energy use, building modelers have started to incorporate behavioral factors into building energy modeling efforts (Feng et al. 2015; Hong et al. 2015a). Modelers attempt to develop the closest representation of building occupant and behaviors to a real world building system (Hong et al. 2015b). The most used modeling technique is regression analysis that describes the probability of a given group behavior in response, for example, to thermal stimuli like indoor and outdoor temperature (Yan et al. 2015). Building occupants may have heterogeneous responses to thermal stimuli. One such is window-opening behavior that has been used as a case study for several simulation modeling efforts (Nicol 2001; Rijal et al. 2007; Yun and Steemers 2008; Haldi and Robinson 2009). While regression-based occupant behavior models provide simple communication and implementation, most of the models have identifiable issues such as not accounting for adaptive behaviors and occupant interactions (Langevin et al. 2014).

Modeling occupant comfort perception and occupant adaptive responses to a changing building environment is challenging (de Wilde 2014). Existing regression-based models are successful in estimating building energy use and occupant comfort. However, in real building operations, occupant perceptions of comfort and their responses change over time and vary across occupants (Gulbinas and Taylor 2014). Building energy modeling software platforms, such as eQuest and EnergyPlus, typically account for occupant behavior in a limited fashion by adjusting building and equipment schedules and maximum occupancy assumptions. That approach assumes that all occupants perform a fixed set of adaptive responses, have similar schedules, and use energy at the same rate (EnergyPlus 2009; Hoes et al. 2009).

Agent-Based Models (ABM) have been introduced to address the issues (Li and Wen 2014). In ABM, an agent represents a building occupant with personal attributes, interacting with other agents that may represent other occupants or a building manager or other individual entities that exist in the modeled building, or with building systems themselves. Personal characteristics and a set of adaptive actions that are attributable to each agent define the agent's behaviors (Robinson et al. 2011; Macal and North 2010). Andrews et al. (2011) adopt the Belief-Desire-Intention (BDI) framework to create an ABM model of building occupant behavioral responses to lighting intensity. Azar and Menassa (2012a) model an interaction of building occupant agents in office buildings. Lee and Malkawi (2014) developed an ABM model to mimic adaptive behaviors to energy saving and thermal comfort. Langevin et al. (2014) develop a calibrated ABM model of building occupant behaviors based on Perceptual Control Theory. Several other ABM models also have been developed for different applications, such as the residential context (Chen et al. 2012; Kashif et al. 2011), and household water usage (Linkola et al. 2013; Chu et al. 2009).

The application of ABM to load-shedding, to date, has considered only strategic actions of whole buildings or multi-building portfolios as unitary participants in utility load-shedding programs (Lim et al. 2014; Zhang and Li 2014). Individual occupants within specific buildings have not been considered. The research gap this paper helps fill is to model building occupants' reactions to load-shedding events. We focus specifically on characterizing building occupant behavior in commercial buildings under load shedding events.

In Section 2 of this paper we develop an integrated ABM model which includes three major components: (1) simulation of individual building occupant perceptions, behaviors and satisfaction; (2) simulation of collective behavior and building manager-occupants communication; and (3) a parsimonious building energy model. In Section 3 we present data on building performance and surveys of occupant perceptions and self-reported behavioral responses from two real-world commercial buildings for calibration and verification. Section 4 shares simulation results including calibration runs, verification runs, and hypothetical "what-if" scenarios. Section 5 discusses the results and Section 6 offers conclusions and recommendations for future research.

2 Methods

This section presents a simulation model in which heterogeneous occupants interact with one another in commercial buildings under load shedding conditions. Our ABM combines a building energy use model with heterogeneous occupants in a single methodological platform. In a set of simulation experiments, we start with a calibrated building energy model and modify its output file using side calculations driven by an ABM that simulates occupant behavior. These occupants have varied perceptions of thermal and lighting comfort conditions, leading to divergent adaptive behaviors. The occupants also vary in their roles and exchange information based on their roles. The building manager plays a major role in controlling building systems. An appendix shares additional modeling details. The appendix is in the Electronic Supplementary Material (ESM) of the online version of this paper.

The main focus of the model is on occupant behavior in commercial buildings undergoing load shedding. The application domain of the model is for operating and retrofitting office buildings. We define the following modeling objectives: (1) simulate comfort perceptions and adaptive responses of heterogeneous occupants, and the building's resulting energy consumption; (2) study the effects of controllability and communication among office building occupants under load shedding scenarios; and (3) verify the resulting ABM models with real post-occupancy survey data. The remainder of this section introduces the modeling framework and defines the scenarios.

2.1 Modeling framework

This section explains how we model the behavior of building occupants and building controllability during load-shedding. The agent-based model (ABM) is programmed in NetLogo to represent the occupant adaptive behaviors (Tisue and Wilensky 2004). NetLogo is a Java-based, object-oriented programming platform for ABM in which heterogeneous classes of computational agents follow rules for interactions with one another and their environments, and from which systemic outcomes such as building-wide energy consumption emerge (Wilensky 1999). In our occupant behavior model, the adaptive behavior is estimated by a utility function that reflects a belief-desire-intention (BDI) framework (Andrews et al. 2011). This approach uses a multi-attribute utility function to select an adaptive action based on perceived environmental conditions. The (dis)utility function is defined by 4 parameters that occupants seek to minimize: environmental impact, effort, cost, and discomfort.

Occupant utility = $U(x) = \Sigma k_i U_i(x_i)$

where, x_i: performance level of attribute i (normalized by a max–min range); $U_i(x_i)$: single attribute utility for attribute i (the range is 0–1); k_i: weighting constant for the utility of attribute i (the range is 0–1, $\Sigma k_i = 1$); i: 1 (environmental impact), 2 (effort), 3 (cost), and 4 (discomfort).
Thus occupant multi-attribute utility has a range from 0 to 1.

The model also presents a multi-agent system (MAS) by taking into account communication between occupants, tenant representatives, and a building manager. In a building where occupants do not have access to adjust a thermostat, for example, they communicate their requests via a tenant representative to the building manager. The appendix (in the ESM), gives an overview of the modeling logic for occupant behavior.

The occupant behavior model starts by reading several input files. The first is a multi-zone building model file, created in EnergyPlus, which is used to initialize the building environmental conditions. The second is a comma-separated file of survey responses, containing a list of building occupants and their occupancy and preferences in regard to thermal and lighting comfort. The model continues with a building manager agent entering the building, followed by building occupant agents. The first building occupant agent who enters an empty zone, becomes the zone's tenant representative. Tenant representatives are commonly present in multi-tenanted office buildings with open office space to interface with building managers.

Building occupants take adaptive actions based on their perceptions of the building zone's thermal and lighting comfort levels. Building zone controllability and communication among agents influence occupants' adaptive responses. Controllability and success-of-communication are stochastic variables whose mean values vary according to the scenario definition. Controllability is an exogenously set attribute of a building zone that offers either Local Control or No Control with a high probability. Success of Communication is an organizational attribute that is set exogenously to either Bad (low probability of successful communication) or Good (high probability of successful communication). For example, building occupants may not have control over thermostats and overhead lighting, resulting in them needing to call the building manager to perform adjustments. Figure 1, below, illustrates the locus of control among the three categories of occupant agent.

Building occupant

Building occupants have predefined characteristics that are set based on survey data and they follow specific rules to choose adaptive responses to environmental conditions they experience. There are 40 occupant-agents in each simulated building. These occupant agents are characterized based on the distribution of empirical data from a survey that includes thermal and lighting preferences. Beyond their comfort perceptions, occupant behavior patterns also may be influenced by electricity cost, if they are cost-conscious. Occupants often do not have local control over their local environment, such as the ability to adjust a thermostat or overhead lighting. As illustrated in Fig. 2, an occupant prioritizes possible adaptive actions that include both actions that can be performed locally, such as using space heater or task light, and actions that require collective or aggregate action, such as adjusting the thermostat and overhead lighting. To implement an aggregate action, an occupant needs to ask a tenant representative to call the building manager in order to make adjustments to meet the desired environmental conditions.

Tenant representative

In this paper, tenant representatives make decisions of their own as well as decisions on behalf of the occupants in their zones ("aggregate" action). Similar to the individual occupant's adaptive response, a tenant representative prioritizes possible adaptive actions based on weighted comfort level and electricity cost. Often, myriad requests for adjustment to environmental conditions are passed on to a building manager. Therefore, a tenant representative needs to adopt a specific decision mechanism to maintain the requests. We consider three types of decision processes. The first is a majority decision process, in which a decision is favored if a majority of occupants prefer it. The second one is a proportional decision process, in which the selection with the greatest additive utility is favored. The final one is a hierarchical decision process, in which decisions are structured based on priorities. As illustrated in Fig. 3, tenant representatives mediate the communication between building occupants and the building manager.

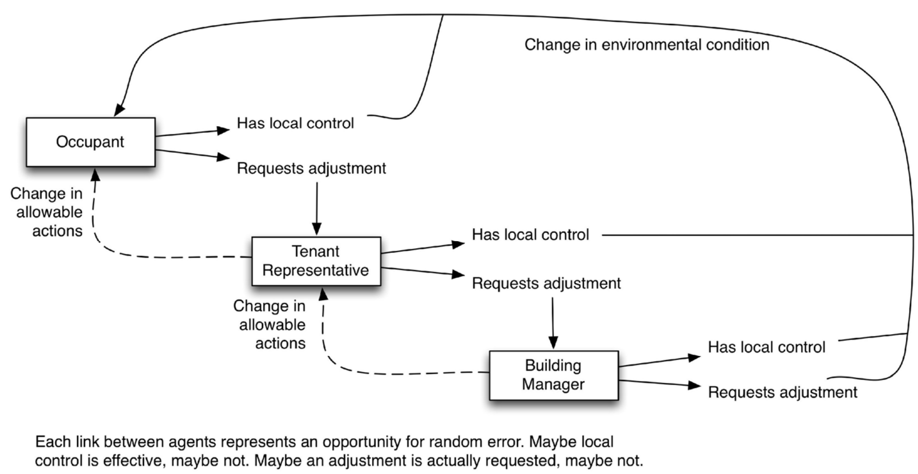


Fig. 1 Locus of control of building occupants (Source: Adapted from Senick (2015))

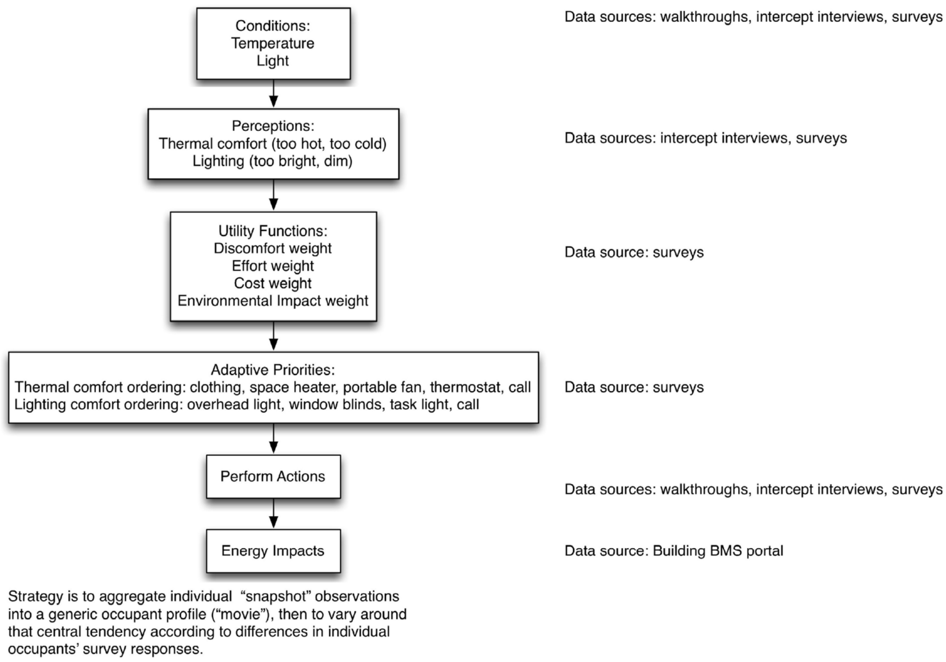


Fig. 2 Model of an occupant's adaptive behavior

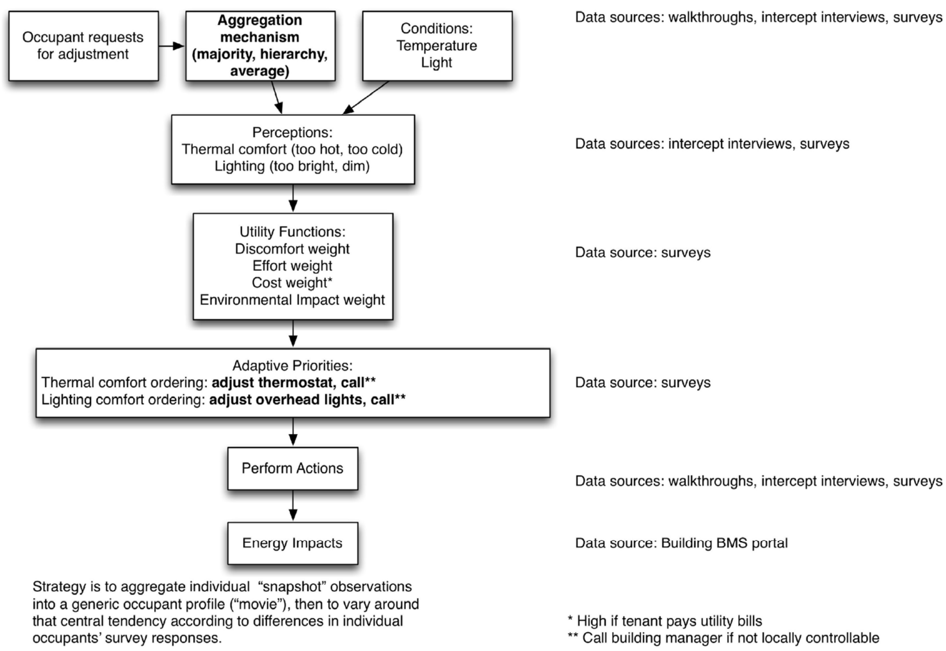


Fig. 3 Model of a tenant representative's adaptive behavior

Building manager

There is only one building manager that operates building-wide HVAC and lighting systems. A building manager receives requests from tenant representatives for environmental adjustments in up to 47 designated building zones. A building manager also performs load shedding by responding to requests from the electric utility. Figure 4 illustrates a model of building manager's adaptive behavior.

2.2 Scenario analysis

We exercise the simulation framework by examining 24 scenarios. Two scenarios calibrate the model to a case study building under normal operation and load-shedding conditions (building "A", Scenarios 1 and 13). Two more scenarios verify the model by testing its results against a second case study building under normal operation and load shedding conditions (building "B", Scenarios 12 and 24).

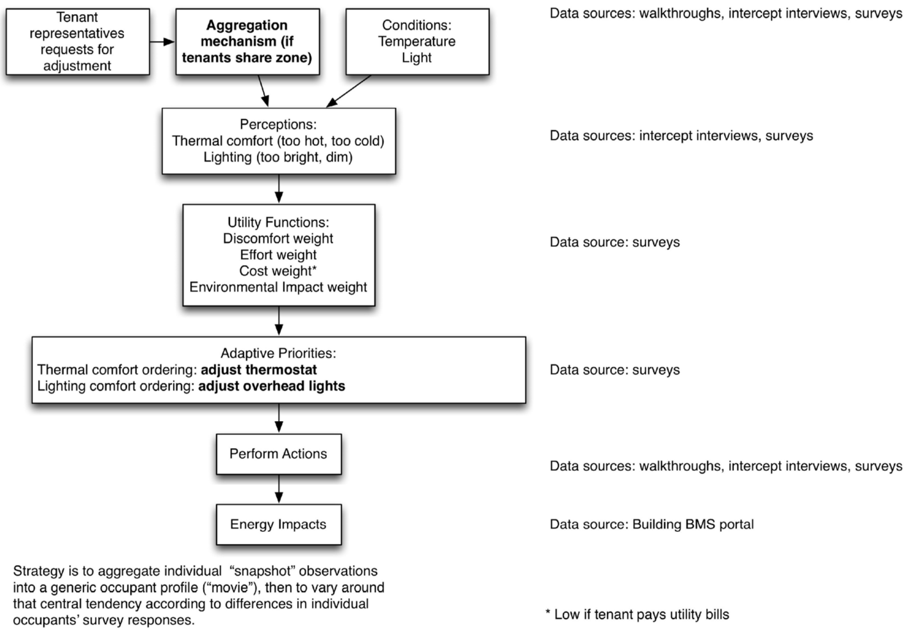


Fig. 4 Model of a building manager's adaptive behaviors

Additional hypothetical "what-if?" scenarios explore the potential effects of organizational factors (communication, local control, and corporate dress code) on occupant comfort perceptions and adaptive actions.

Empirical studies of two buildings, summarized in the next section, suggest that communication and local controllability influence occupant comfort perceptions and behavior. Hence we establish two local controllability scenarios as well as two communication scenarios, under which occupants' requests are likely to be fulfilled by either tenant representatives or a building manager (good communication). Another component worth investigating based on the literature is a corporate dress code. In a typical corporate business office, occupants may be expected to wear business attire that is often heavier (suit with jacket) or lighter (skirt or short sleeves) than what occupants would choose if the office had a flexible dress code. Twenty-four scenarios with different types of communication, controllability, and clothing behavior are compared across buildings either experiencing a load-shedding event or not (Table 1).

Two commercial office buildings that are located in the greater Philadelphia region form the empirical basis for these simulations. The two buildings have load shedding for both lighting and HVAC systems. The buildings are different from each other in the nature of the tenants, building system characteristics, time and scope of retrofit, and building control technologies. Each of the fieldwork sites conducted several load shedding events during 2012 and we collected physical and perceptual data twice daily during those events and also during adjacent control days that had similar weather and building usage. We conducted baseline surveys of occupant attitudes, comfort preferences, and demographic characteristics prior to the load shedding experiments as described in Senick et al. (2013) which provides a full discussion of each case.

2.3 Calibration case study (Building A)

Building A is a three-story office building, constructed in 2004, and has 76,692 (7,125 m^2) gross square feet of floor area and is occupied by 227 people. It is a tenanted building owned by a real estate investment trust. The envelope consists of pre-cast masonry curtain walls with double-pane tinted windows and an insulated roof with a light-colored surface. Most interior lighting uses T-8 32 W lamps in 3-lamp enclosures. The HVAC system includes two 115 Ton DX units, fan-powered terminal boxes for perimeter zones and VAV boxes for interior zones, with electric reheat coils. The building has been retrofitted to include dimmable, IP-addressable lighting ballasts and low-wattage bulbs; variable frequency drives for selected fans in the packaged HVAC systems; retro-commissioning of the HVAC system; updated with more sensors and controls; and advanced building control and monitoring systems that are connected with an enterprise-wide system. This retrofit enables the building operator to perform remote load shedding but provides occupants with little direct control over environmental conditions. Most occupants follow a corporate dress code. We use a detailed, calibrated, 47-zone EnergyPlus model of this building in the simulations, plus occupant behavior data.

Table 1 Scenarios for simulation model

Scenario	Load Shedding	Communica-tion	Zone Control	Clothing
1	Non-LS	Bad	No Control	Heavy Clothing
2	Non-LS	Bad	No Control	Light Clothing
3	Non-LS	Bad	No Control	Allow Change
4	Non-LS	Bad	Local	Heavy Clothing
5	Non-LS	Bad	Local	Light Clothing
6	Non-LS	Bad	Local	Allow Change
7	Non-LS	Good	No Control	Heavy Clothing
8	Non-LS	Good	No Control	Light Clothing
9	Non-LS	Good	No Control	Allow Change
10	Non-LS	Good	Local	Heavy Clothing
11	Non-LS	Good	Local	Light Clothing
12	Non-LS	Good	Local	Allow Change
13	Load-Shedding	Bad	No Control	Heavy Clothing
14	Load-Shedding	Bad	No Control	Light Clothing
15	Load-Shedding	Bad	No Control	Allow Change
16	Load-Shedding	Bad	Local	Heavy Clothing
17	Load-Shedding	Bad	Local	Light Clothing
18	Load-Shedding	Bad	Local	Allow Change
19	Load-Shedding	Good	No Control	Heavy Clothing
20	Load-Shedding	Good	No Control	Light Clothing
21	Load-Shedding	Good	No Control	Allow Change
22	Load-Shedding	Good	Local	Heavy Clothing
23	Load-Shedding	Good	Local	Light Clothing
24	Load-Shedding	Good	Local	Allow Change

The simulation modeling efforts discussed in the next section rely on a detailed EnergyPlus model of Building A that was created based on fieldwork and measurements, and calibrated against measured energy data on a monthly and hourly basis (Wagner et al. 2014). The calibrated model tracked observed performance reasonably well (normalized mean bias error is −2.6%, coefficient of variation of root-mean-square error is 5.9%), although it overstates building energy use during the cooling season (Wagner et al. 2014). Figure 5 shows the modeled and measured peak day hourly electricity use for Building A under normal operation and load shedding conditions. See Wagner et al. (2014) for details on the construction and calibration of the EnergyPlus model for Building A.

The operator of Building A conducted load-shedding experiments during 2012 in order to test for potential effects on occupant comfort perceptions. Normal building operations included a 0% lighting reduction and a cooling setpoint of 74.5 °F. The operator created a pre-defined load-shedding case in its building management system (BMS) that included a 10% lighting reduction and an increase in the cooling setpoint to 78.0 °F. The BMS recorded snapshots of electricity demand (kW), space temperature by zone, and percent lighting reduction before, during, and after each load shedding event.

Our team conducted a baseline survey and a series of daily surveys to document occupant perceptions and self-reported behaviors during normal building operations and load shedding events. We share summary results in the next section. Occupant thermal perception is based on the ASHRAE's predicted mean vote (PMV) measure with −3 being cold, −2 being, −1 being slightly cool, 0 being neutral, +1 being slightly warm, +2 being warm, and +3 being hot. The figures simplify this scale into three categories: Too Cold (−3, −2), Neutral (−1, 0, +1), and Too Hot (+2, +3). See Senick et al.(2013) for additional details.

Building A has limited local controllability. Therefore, a building manager needs to perform adjustments on thermostats and overhead lights whenever the occupants ask for such adjustments via their tenant representatives. This places a premium on successful communication from occupants to tenant representatives to the building manager, which the field research finds is limited. Occupants of this building work in a strict business setting with a traditional corporate dress code. Conditions found in Building A are therefore represented in the simulations by Scenarios 1 (non-load-shedding) and 13 (load-shedding), which incorporate Bad Communication, No Local Control, and a dress code requiring Heavy Clothing that potentially affect both thermal and lighting behavior patterns.

2.4 Verification case study (Building B)

Building B is a research complex that was built in 1960 and it actually consists of 35 attached structures with varying ages and building envelopes. In the research complex, there are 755,540 (70,192 m^2) square feet office space, laboratories, technical shops, and occupied by 450 employees. One of the office portions of this complex was selected to represent a building of approximately equivalent scale to Building A. In contrast to Building A, Building B has an owner-occupant and less integrated building systems; hence, the building manager is well known to the occupants and performs load shedding operations manually. Dress codes are flexible and there is much local control over thermostats and lights.

This building manager, like his counterpart in Building A, conducted a set of load-shedding experiments during 2012 and followed a similar load-shedding protocol. As in Building A, we used the BMS to track building system status and space temperatures in Building B, and we conducted a baseline survey and a series of daily surveys of occupants. For details see Senick et al. (2013). We share summary results in the next section.

The EnergyPlus model of Building A was run repeatedly to create a lookup table of results for different load shedding strategies, occupancy schedules, and internal loads. As a verification exercise, we modified Building A's temperature and lighting setpoints, occupancy and equipment schedules, and occupant behaviors to reflect those in Building B and successfully replicated the essential patterns observed in the fieldwork. As a reminder, throughout this paper the focus is on innovative modeling of occupant behavior rather than capturing detailed building system performance. In the modeling, Scenarios 12 (non-load-shedding) and 24 (load-shedding), which incorporate Good Communication, Local Control, and a dress code that Allows Changes in clothing represent the conditions found in Building B.

3 Results

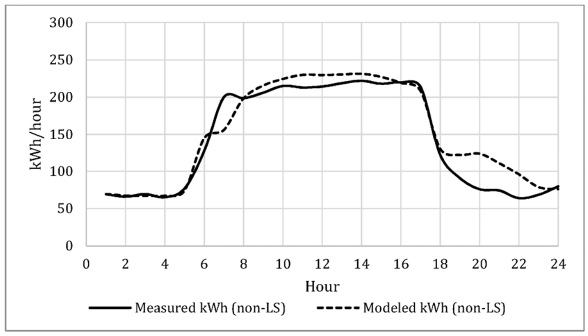
Simulation results for occupant perceptions and behavior comport well with the fieldwork findings. We examine illustrative results for the calibration scenarios (Building A, Scenarios 1 and 13), verification scenarios (Building B, Scenarios 12 and 24), and several what-ifs (Scenarios 2–11, 14–23).

3.1 Calibration runs (Building A, Scenarios 1 and 13)

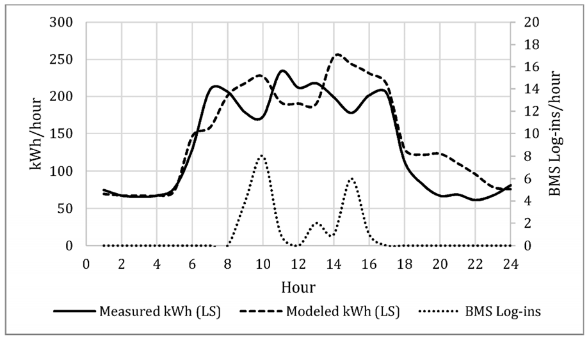
This section compares measured performance of Building A and its occupants to modeled results. It describes the simulation results for Scenarios 1 and 13, "Bad Communication; No Local Control; Heavy Clothing Required". Figure 5(a) compares the measured building-wide electricity consumption in Building A during a control day, with normal building operations, to simulation results for Scenario 1, a non-load-shedding scenario. The Mean Absolute Percent Error (MAPE) for the hourly comparisons is 13%, with the greatest error in the evening hours when the model overestimates electricity usage.

Figure 5(b) compares the measured building-wide electricity consumption in Building A during a load-shedding day, to simulation results for Scenario 13, a load-shedding scenario. Here the MAPE is much higher (22%) because the model includes only one load-shedding event whereas two actually occurred. As the timing of BMS log-ins by the building managers confirms, there was a morning load-shedding event and another one in the afternoon. Visual inspection of Fig. 5(b) suggests that the modeled load-shedding event has a similar energy-reduction signature as the measured events.

Figure 6(a) shows the modeled (Scenario 1) and measured average indoor space temperatures during a non-load-shedding control day in Building A, as well as the cooling setpoints and percent lighting load reduction. The MAPE for hourly comparisons between measured and modeled

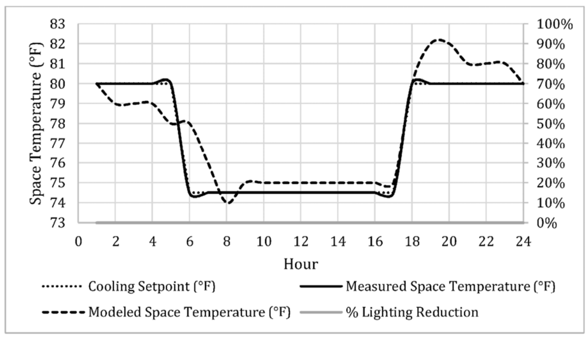


(a) Non-Load-Shedding Day (Scenario 1)

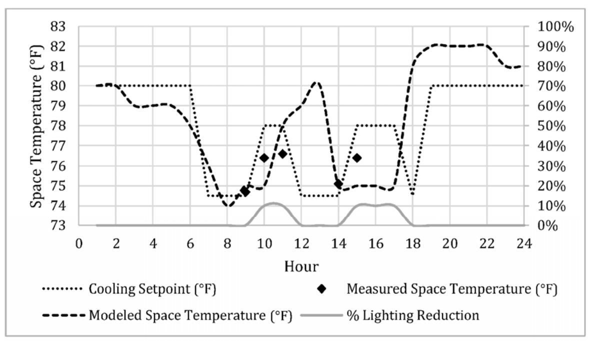


(b) Load-Shedding Day (Scenario 13)

Fig. 5 (a) Building "A" measured and modeled (Scenario 1) hourly electricity use during Non-Load-Shedding Control Day; (b) Building "A" measured and modeled (Scenario 13) hourly electricity use and BMS Log-ins during Load-Shedding Day



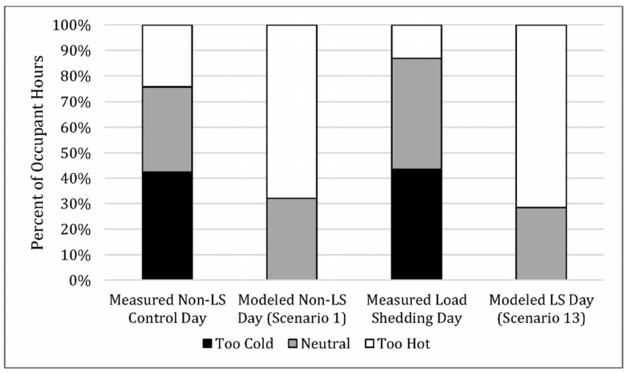
(a) Non-Load-Shedding Day (Scenario 1)



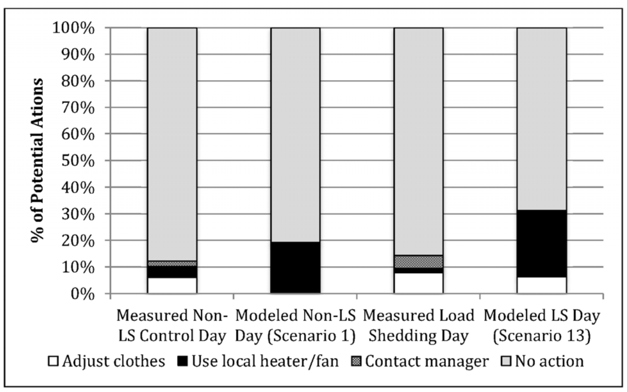
(b) Load-Shedding Day (Scenario 13)

Fig. 6 (a) Building "A" measured and modeled (Scenario 1) space temperatures, cooling setpoints, and % lighting reduction during Non-Load-Shedding Day; (b) Building "A" measured and modeled (Scenario 13) space temperatures, cooling setpoints, and % lighting reduction during Load-Shedding Day values is 1%. Figure 6(b) shows the same information for the load-shedding case (Scenario 13). Note again that the measured data show two load-shedding events whereas the model assumes only one event. Again, the MAPE for comparing measured and modeled hourly data is 1% using available data points. The space temperature increases during the load-shedding period.

Figure 7(a) compares measured (based on surveys) and modeled occupant perceptions of thermal comfort during a non-load-shedding control day (Scenario 1) and a load-shedding day (Scenario 13) in Building A. Modeled results differ significantly from measured perceptions, with the model predicting that many occupants will feel too hot under both scenarios, whereas the measured results suggest more of a symmetrical distribution of occupants feeling too hot and too cold. A clue to the discrepant result is that measured occupant satisfaction with thermal conditions is higher during load shedding in comparison to during the non-load-shedding day, implying that Building A is normally over-cooled. The modeling instead delivers under-cooling. The verification run in Building B will further clarify this matter.



(a) Thermal Comfort Perceptions of Occupants



(b) Adaptive Actions by Occupants

Fig. 7 (a) Building "A" measured and modeled thermal comfort perceptions of occupants during Non-Load-Shedding Control Day (Scenario 1) and Load-Shedding Day (Scenario 13); (b) Building "A" measured and modeled adaptive actions by occupants during Non-Load-Shedding Control Day (Scenario 1) and Load-Shedding Day (Scenario 13)

Figure 7(b) shows the measured and modeled relative prevalence of adaptive responses by occupants to thermal conditions in Building A on a non-load-shedding day (Scenario 1) and a load-shedding day (Scenario 13). The measured and modeled "no action," "contact manager,", and "adjust clothes" response percentages are in approximate agreement, with the model slightly understating those options, and the "use local heater/fan" options are substantially over-estimated by the model.

The next set of figures shows intermediate results at several points in the modeling process to illustrate the relative roles of occupants, tenant representatives, and building managers in managing comfort outcomes. Figure 8 shows occupant perceptions of thermal comfort at three different points in the adaptation process. The number of occupants feeling comfortable with the room temperature is lower at the beginning of each time tick. More occupants feel satisfied with the temperature after adaptive actions are performed. Adaptive actions that require consensus, that is, before the tenant representative is willing to act, adjusting thermostat in this case, are performed first and followed by actions performed by individual occupants (i.e. portable heater, portable fan, change clothes). Similar trends are found in the occupant lighting perception. As shown in Fig. 9, a greater number of occupants feel comfortable with the illuminance level in the room they occupy after they perform lighting adaptive actions. Adjusting overhead lighting that requires consensus or aggregate decision making precedes individual lighting adaptive actions that include adjusting task light and opening (or closing) window blinds. In Figs. 8–10, we only show results between hour 8 and 18 when occupants are present in the building.

In real-world building management, a building manager assumes an important role in adjusting centrally controlled building systems. One influencing factor is requests from the building occupants requesting adjustments, mostly related to their thermal and lighting comfort. As shown in Fig. 10, the building manager acts on requests from occupants to adjust either the thermostat or overhead lighting. In regards to thermal comfort, requests to adjust thermostats are common in the morning, when the HVAC systems are starting up, and during load-shedding events in the afternoon, in this example.

In the simulation, occupants perform adaptive actions after either the building manager or the tenant representative adjusts the consensus-required actions. Occupants adjust portable heaters, portable fans, or clothing layers in order to meet their thermal comfort levels, as shown in Fig. 7(b). The tenant representative, who is also an occupant, may adjust the thermostat setpoint if provided with local control. In regards to lighting comfort, occupants adapt by adjusting task lights or window blinds. Tenant representative behavior includes adjusting the overhead lighting.

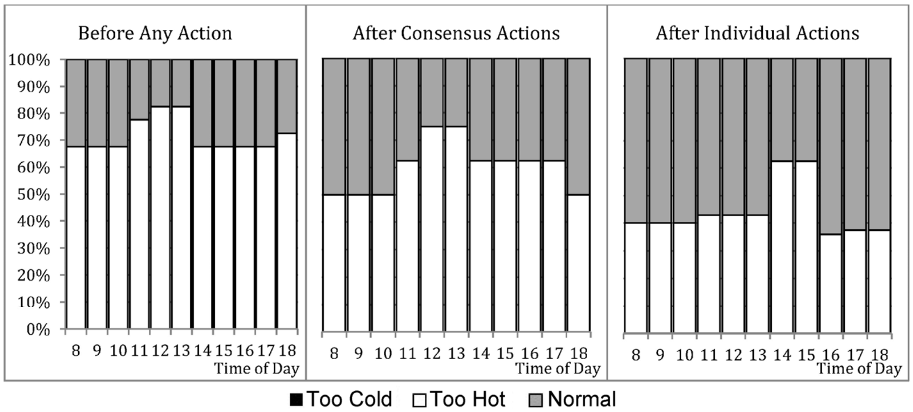


Fig. 8 Simulated building occupant thermal perceptions (percent of occupant-hours) at three different points in adaptation process during load shedding in a building with poor communication and no local control (Scenario 13)

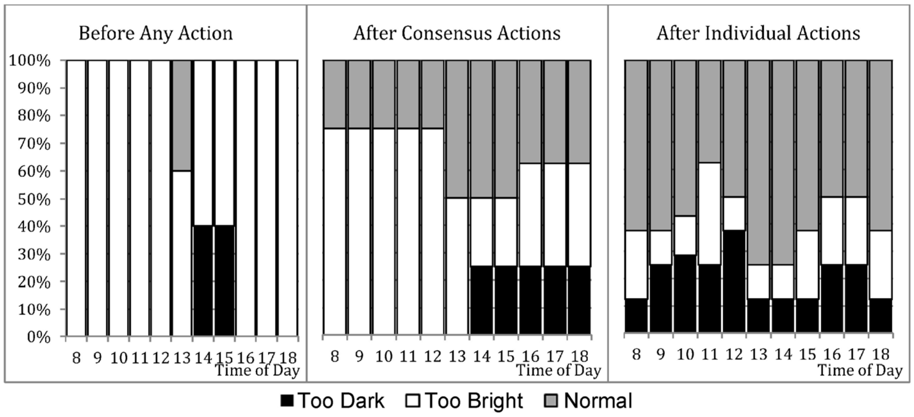


Fig. 9 Simulated building occupant lighting perceptions (percent of occupant-hours) at three different points in adaptation process during load shedding in a building with poor communication and no local control (Scenario 13)

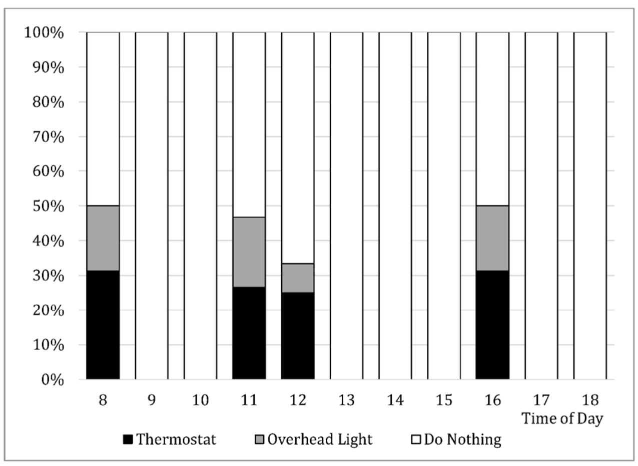
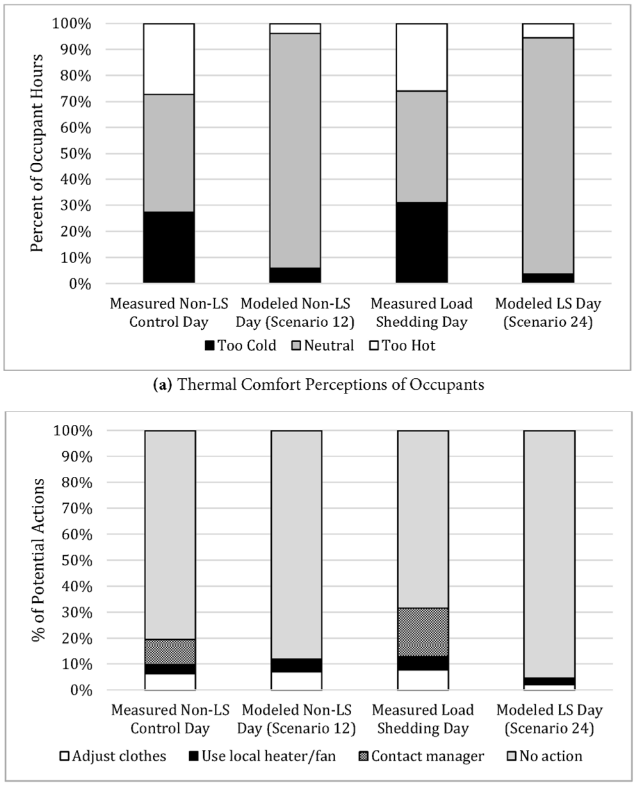


Fig. 10 Simulated building manager adaptive actions during load shedding in a building with poor communication and no local control (Scenario 13)

3.2 Verification runs (Building B, Scenarios 12 and24)

The verification runs apply the occupant behavior model that was calibrated with data from Building A and use it to predict outcomes in Building B. This section summarizes how the results compare to measured data from Building B. In Scenarios 12 and 24, "Good Communication; With Local Control; Allow Clothing Change", which closely resembles Building B, it is expected to see more occupants feeling comfortable with the environment. In contrast to the simulations of Building A (Scenarios 1 and 13), more occupants are found to be comfortable after performing their own individual adaptive actions. Figure 11 shows measured (surveys of occupants in Building B) and modeled results (Scenario 12 and 24) for thermal comfort perceptions and adaptive actions by occupants. Figure 11(a) shows that measured thermal comfort perceptions are normally distributed in Building B. The model mimics that symmetry but produces less dispersion around the mean than in the measured results. Figure 11(b) shows that the model approximately simulates the prevalence of "no action," "adjust clothes," and "use local heater/fan" actions, but it fails to predict the measured level of "contact manager."

In Fig. 11(b), it is noticeable that controllability provides many options for individual occupant behavior. Building occupants perform almost all types of adaptive actions to



(a) Thermal Comfort Perceptions of Occupants

(b) Adaptive Actions by Occupants

Fig. 11 (a) Building "B" measured and modeled thermal comfort perceptions of occupants during Non-Load-Shedding Control Day (Scenario 12) and Load-Shedding Day (Scenario 24); (b) Building "B" Measured and Modeled Adaptive Actions by Occupants during Non-Load-Shedding Control Day (Scenario 12) and Load-Shedding Day (Scenario 24)

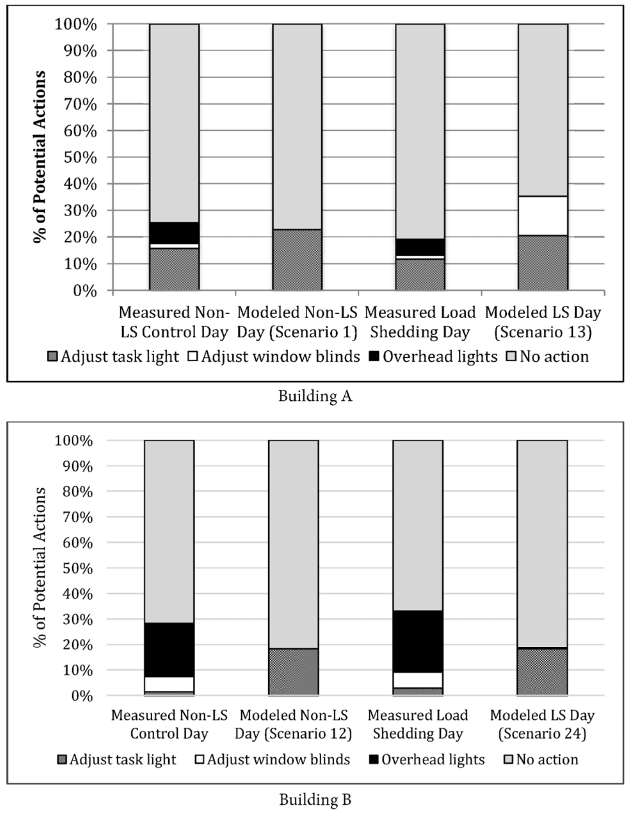


Fig. 12 Buildings "A" and "B" measured and modeled lighting-related adaptive actions of occupants during Non-Load-Shedding Day (Scenarios 1 and 13) and Load-Shedding Day (Scenarios 12 and 24)

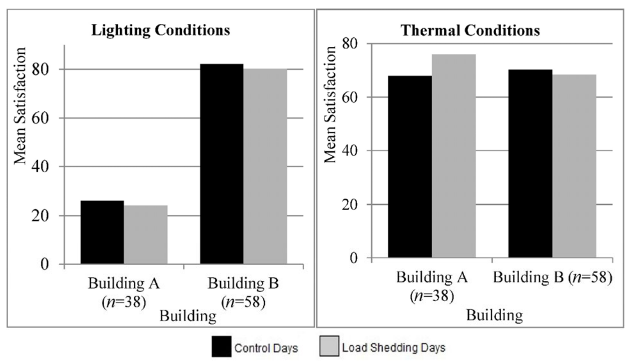


Fig. 13 Observed mean satisfaction across surveyed occupants in Buildings A and B during control and load shedding days (0–100 scale)

meet their thermal and lighting comfort levels. The tenant representative has control over thermostats and overhead lighting.

3.3 Comparing Buildings A and B

Figure 12 compares the measured and modeled lighting-related adaptive behaviors of occupants in Building A and B. In Building A, the model provides a good approximation of the "no action" and "adjust task light" actions, but it under-estimates the "overhead lights" and "adjust window blinds" actions. In Building B, the model also under-estimates the "adjust task light" action.

As a final point of comparison, Fig. 13 shows that occupant satisfaction with lighting and thermal conditions is only slightly affected in a negative direction during load shedding events, with one counter-intuitive exception identified in Senick et al. (2013). Building A shows an *increase* in satisfaction with thermal conditions during load shedding. Investigation shows that this is because the building is over-cooled during baseline operation, hence load shedding brings conditions closer to what a majority of occupants prefer. Changes between control and load shedding days are also found by Senick et al. (2013) to be significant estimators for satisfaction, well-being, and productivity (positively for Building A, negatively for Building B).

3.4 What-if scenarios

One benefit of creating an occupant behavior simulation model is that it allows informed speculation about scenarios that have not yet been empirically verified. This section explores the example of a hypothetical corporate dress code. Clothing choices influence the thermal comfort levels perceived by building occupants. In the model, thermal discomfort is measured as the number of occupants each hour who feel Too Hot or Too Cold on the simplified thermal comfort scale discussed earlier. The model measures lighting discomfort on a parallel basis. Figure 14 illustrates the influence of a hypothetical dress code on thermal comfort experienced during a load-shedding day in a building with good communication and local control. Occupants that are required to wear heavy clothing, such as a business suit are least comfortable, those required to light clothing (e.g., skirt, short sleeves) are more comfortable, but those who have flexibility in what they wear are the most comfortable.

Figure 15 shows that dress codes interact with local control, at least when there is poor communication between occupants and the building manager. The effect is systematic. Local control always improves thermal comfort, especially when the dress code is flexible or requires a light outfit.

Figure 16 summarizes the total daily thermal and lighting discomfort levels for Scenarios 1–24. Superior performance

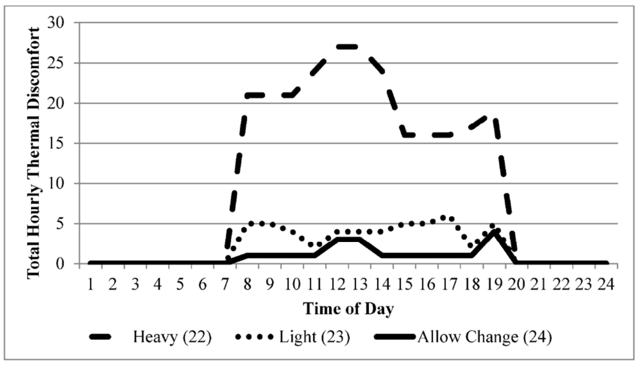


Fig. 14 Simulated effects of dress codes on occupant thermal discomfort during load shedding given good communication and local control (Scenarios 22–24)

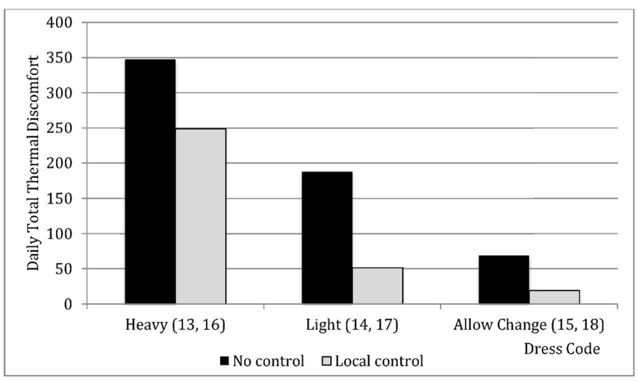


Fig. 15 Simulated effects of dress codes on daily total mean occupant thermal discomfort under buildings with controllability and no control, given poor communications (Scenarios 13–18)

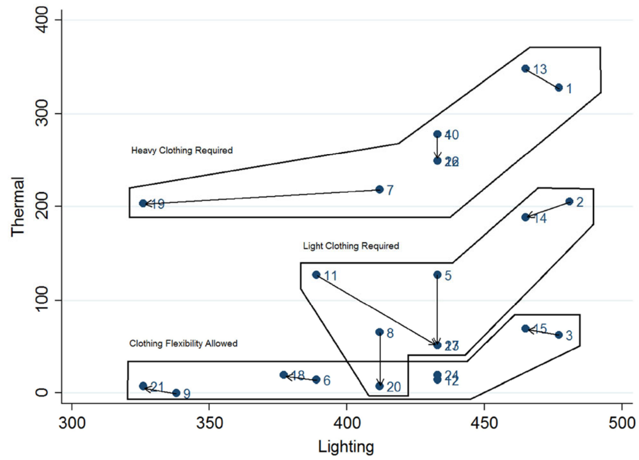


Fig. 16 Scatter plot of total daily thermal and lighting discomfort by scenario (Scenarios 1–24). 0 = Low discomfort, 500 = High discomfort

is toward the lower left corner of the scatter plot (low thermal and lighting discomfort), and poor performance is toward the upper right corner. Arrows connect the non-load-shedding and load-shedding scenarios of each type, providing a visual portrayal of which combinations of local zone control, communication effectiveness between occupants and the building manager, and dress code requirements are most robust. The best performing non-load shedding scenario (9: good communication, no local control, and clothing flexibility) remains the best under load shedding (Scenario 21). The worst performing non-load shedding scenario (1: bad communication, no local control, heavy clothing required) also barely changes under load shedding (Scenario 13). By contrast, the scenario with good communication, no local control, and a requirement for heavy clothing shifts dramatically as the building goes from no load shedding (Scenario 7) to load shedding (Scenario 19), as do the Scenario 5-to-17 and 11-to-23 couplets. Generally, the point cloud shows that a flexible clothing policy is the surest way to reduce thermal discomfort. Good communication between occupants and the building manager reliably reduces lighting and thermal discomfort. Local zone control, by contrast, and somewhat surprisingly, does not guarantee less discomfort but it does reduce range of variation in lighting discomfort.

4 Discussion

The simulation model replicates the occupant/tenant representative/building manager/building system interactions in a relatively transparent way that partially fits the evidence from fieldwork and surveys in two buildings. We do not want to overstate the accuracy of the model and claim only to have verified rather than validated the model. This is one cost of the ABM approach in comparison with regression-based approaches. However, the model delivers abundant insights.

Both the fieldwork and the simulations clearly show the importance of heterogeneous occupant perceptions and behaviors in understanding responses to load shedding events. Figures 8 and 9 usefully summarize the range of comfort perceptions that occupants have before any action, after an aggregate action such as adjusting a thermostat or overhead lighting system, and even after individual actions such as putting on a sweater or turning on a task light. Figures 7, 11, and 12 highlight the diverse set of actions chosen by occupants.

A comparison of Figs. 7 and 11 also shows that local control over aggregate actions by a tenant representative (rather than remotely by a building manager) more quickly returns a greater number of occupants to comfortable conditions.

Figure 10 is helpful for highlighting that the building manager's control responsibilities extend well beyond the time frame of the load shedding event. Morning startup is an equally important time period for addressing occupant concerns. In contrast to owner-occupied buildings, most commercially leased spaces require a pretty tight range for temperature (thermal comfort), which can place contractual requirements in conflict with the thermal comfort preferences of some occupants.

Some occupant actions shown in Figs. 7, 11, and 12 represent positive adaptations but others are mal-adaptations in that using a portable fan or space heater, for example, increases electricity demand at the moment when the building manager is seeking to reduce demand. The electric power accounting framework within the ABM makes marginal adjustments to the EnergyPlus output lookup table to reflect these influences, and they are minor for the cases explored here.

The least well validated aspect of the model appears to be the choice of adaptive actions taken by occupants in response to changing comfort conditions. While the "no action" option appears to be well modeled, the other potential actions chosen by the model do not closely reflect the evidence from case study buildings.

Dress codes are not a normal topic in building simulation papers, but Figs. 14, 15 and 16 show the important interaction between clothing choices and local control of comfort conditions. A flexible dress code gives occupants another degree of freedom when local control is not available. Post-Fukushima Japan famously deployed the "Super Cool Biz" summer dress code to give office building occupants more latitude during the frequent HVAC system curtailments required by the stressed TEPCO electric power system (Tools of Change 2012). This option could become more widely available.

The robustness of specific operating practices across both normal conditions and load shedding is quite varied, as Fig. 16 shows. Some combinations of communication, local control, and dress codes perform better and are more stable than others. The implication is that building managers will want to investigate these dimensions of their buildings before implementing load-shedding programs.

5 Conclusions

This model allows building operators to explore several behavioral and organizational factors that will influence the success of load shedding activities. As the practice of active electricity demand management becomes widespread and increasingly automated, issues of occupant adaptations, local control, and communication will increase in relative importance. They will be especially relevant in remotely-managed, multi-tenanted office buildings where occupants are expected to conform to strict dress codes.

We build confidence in this model by calibrating a building energy simulation modeling tool against a real building, linking the occupant behavior model to the building energy model, driving the occupant behavior model with survey responses from occupants of the subject building, and verifying that the occupant behavior scenario observed in a second building can also be approximated by the model. Many aspects of the model perform reasonably well in comparison to measured data, with the exception of the specific mix of adaptive actions occupants take in response to changing comfort conditions. This is an area for future research.

Future applications can use this model as-is, as a practice tool; calibrate it to different buildings, locations, and occupants; or rebuild the model using a larger database of occupant behavior. Future research should explore the potential for occupant dashboards and other interactive displays that reduce communication problems and personalize the locus of control.

What-if simulations to inform building operators represent a promising application area for occupant behavior simulation modeling. Operators can rehearse load shedding events and anticipate how to manage better the delicate interpersonal and organizational dynamics that accompany service interruptions.

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References

Andrews CJ, Yi D, Krogmann U, Senick JA, Wener RE (2011). Designing buildings for real occupants: An agent-based approach. *IEEE Transactions on Systems, Man, and Cybernetics A: Systems and Humans*, 41: 1077–1091.

Azar E, Menassa CC (2012a). Agent-based modeling of occupants and their impact on energy use in commercial buildings. *Journal of Computing in Civil Engineering*, 26: 506–518.

Azar E, Menassa CC (2012b). A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. *Energy and Buildings*, 55: 841–853.

Capozza A, D'Adamo C, Mauri G, Pievatolo A (2005). Load shedding and demand side management enhancements to improve the security of a national electrical system. In: Proceedings of 2005 IEEE Russia Power Tech, St. Petersburg, Russia, pp. 3267–3295.

Cappers P, Goldman C, Kathan D (2010). Demand response in U.S. electricity markets: Empirical evidence. *Energy*, 35: 1526–1535.

Chen J, TaylorJE, Wei HH (2012). Modeling building occupant network energy consumption decision-making: The interplay between network structure and conservation. *Energy and Buildings*, 47: 515–524.

Chu J, Wang C, Chen J, Wang H (2009). Agent-based residential water use behavior simulation and policy implications: A case-study in Beijing city. *Water Resources Management*, 23: 3267–3295.

Cowart R (2016). Demand Response as a Power System Resource—Growing Experience in the US. Paper presented at the Forum for Energy Analysis, Warsaw, Poland. Available at http://www.raponline.org. Accessed 6 Jan 2017.

de Wilde P (2014). The gap between predicted and measured energy performance of buildings: A framework for investigation. *Automation in Construction*, 41: 40–49.

EIA (2016). 2012 Commercial Buildings Energy Consumption Survey: Energy Usage Summary, Table 6: Electricity consumption by end use. Energy Information Administration, U.S. Department of Energy. Available at https://www.eia.gov/consumption/commercial/reports/2012/energyusage. Accessed 6 Jan 2017.

EnergyPlus (2009). Input/Output Reference: The Encyclopedic Reference to EnergyPlus Input and Output. The Board of Trustees of the University of Illinois and the Regents of the University of California through the Ernest Orlando Lawrence Berkeley National Laboratory. Available at http://apps1.eere.energy.gov/buildings/energyplus/pdfs/inputoutputreference.pdf.

Faranda R (2007). Load Shedding: A new proposal. *IEEE Transactions on Power Systems*, 22: 2086–2093.

Faruqui A, Hledik R, Palmer J (2012).Time-varying and dynamic rate design. Report 4 in Brattle Group Global Power Best Practice Series. Available at http://www.raponline.org. Accessed 6 Jan 6 2017.

Feng X, Yan D, Hong T (2015). Simulation of occupancy in buildings. *Energy and Buildings*, 87: 348–359.

Gulbinas R, Taylor JE (2014). Effects of real-time eco-feedback and organizational network dynamics on energy efficient behavior in commercial buildings. *Energy and Buildings*, 84: 493–500.

Haldi F, Robinson D (2009). Interactions with window openings by office occupants. *Building and Environment*, 44: 2378–2395.

Hoes P, Hensen JLM, Loomans MGLC, de Vries B, Bourgeois D (2009). User behavior in whole building simulation. *Energy and Buildings*, 41: 295–302.

Hong T, D'Oca S, Turner WJN, Taylor-Lange SC (2015a). An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework. *Building and Environment*, 92: 764–777.

Hong T, D'Oca S, Taylor-Lange SC, Turner WJN, Chen Y, Corgnati SP (2015b). An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAs Framework using an XML schema. *Building and Environment*, 94: 196–205.

Huang J (2007). Scorecards of the commercial building prototypes. LBNL Report, Berkeley, CA, USA.

Kashif A, Le Binh X, Dugdale J, Ploix S (2011). Agent based framework to simulate inhabitants'behaviour in domestic settings for energy management. In: Proceedings of the 3rd International Conference on Agents and Artificial Intelligence, Rome, Italy.

Langevin J, Wen J, Gurian PL (2014). Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors. *Building and Environment*, 88: 27–45.

Lee YS, Malkawi AM (2014).Simulating multiple occupant behaviors in buildings: An agent-based modeling approach. *Energy and Buildings*, 69: 407–416.

Li X, Wen J (2014). Review of building energy modeling for control and operation. *Renewable and Sustainable Energy Reviews*, 37: 517–537.

Lim Y, Kim H-M, Kinoshita T (2014). Distributed load-shedding system for agent-based autonomous microgrid operations. *Energies*, 7: 385–401.

Linkola L, Andrews CJ, Schuetze T (2013). An agent based model of household water use. *Water*, 5: 1082–1100.

Macal CM, North MJ (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4: 151–162.

Mahdavi A, Pröglhöf C (2009). Toward empirically-based models of people's presence and actions in buildings. In: Proceedings of the 11th International IBPSA Building Simulation Conference, Glasgow, UK, pp. 537–544.

Masoso OT, Grobler LJ (2009). The dark side of occupants' behaviour on building energy use. *Energy and Buildings*, 42: 173–177.

Newsham GR, Bowker BG (2010). The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: A review. *Energy Policy*, 38: 3289–3296.

Nicol JF (2001). Characterizing occupant behavior in buildings: Towards a stochastic model of occupant use of windows, lights, blinds, heaters, and fans. In: Proceedings of the 7th International IBPSA Building Simulation Conference, Rio de Janerio, Brazil, pp. 1073–1078.

O'Brien W, Gunay HB (2014). The contextual factors contributing to occupants' adaptive comfort behaviors in offices: A review and proposed modeling framework. *Building and Environment*, 77: 77–87.

Ouyang J, Hokao K (2009). Energy-saving potential by improving occupants' behaviour in urban residential sector in Hangzhou City, China. *Energy and Buildings*, 41: 711–720.

Rijal HB, Tuohy P, Humphreys MA, Nicol JF, Samuel A, Clarke J (2007). Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy and Buildings*, 39: 823–836.

Robinson D, Wilke U, Haldi F (2011). Multi agent simulation of occupant's presence and behaviour. In: Proceedings of the 12th International IBPSA Building Simulation Conference, Sydney, Australia.

Senick JA (2015). Why energy-saving measures in commercial office buildings fail: Deep versus shallow use structures. PhD Thesis, Rutgers University, USA.

Senick JA, Wener RE, Feygina I, Sorensen AM, Andrews CJ (2013). Occupant Behavior in Response to Energy-Saving Retrofits and Operations. Prepared by the Center for Green Building at Rutgers University for the Energy Efficient Buildings Hub, Philadelphia, PA, USA.

Seryak J, Kissock K (2000). Occupancy and behavioural affects on residential energy use. In: Proceedings of American Solar Energy Society (ASES) Annual Conference, Madison, WI, USA.

Stluka P (2014). Control for energy-efficient buildings. In: Samad T, Annaswamy AM (eds), The Impact of Control Technology, 2nd edn. Available at http://ieeecss.org/general/IoCT2-report. Accessed 6 Jan 2017.

Sun Y, Wang S, Xiao F, Gao D (2013). Peak load shifting control using different cold thermal energy storage facilities in commercial buildings: A review. *Energy Conversion and Management*, 71: 101–114.

Tisue S, Wilensky U (2004). Netlogo: A simple environment for modeling complexity. In: Proceedings of International Conference on Complex Systems, Boston, USA, pp. 16–21.

Toftum J, Andersen RV, Jensen KL (2009). Occupant performance and building energy consumption with different philosophies of determining acceptable thermal conditions. *Building and Environment*, 44: 2009–2016.

Tools of Change (2012). Cool Biz, Japan. Case study designated with Landmark status. Available at http://www.toolsofchange.com/en/case-studies/detail/662. Accessed 6 Jan 2017.

Wagner S, Xu K, Delgoshaei P (2014). Measurement and verification report for. Liberty Property Trust PECO-DOE Project Pilot Phase Buildings. Report prepared for the U.S. Department of Energy by the Consortium for Building Energy Innovation, Pennsylvania State University, State College, PA, USA.

Wilensky U (1999). NetLogo Software. Available at http://ccl.northwestern.edu/netlogo. Accessed 7 Jan 2017.

Yan D, O'Brien W, Hong T, Feng X, Gunay HB, Tahmasebi F, Mahdavi A (2015). Occupant behavior modeling for building performance simulation: current state and future challenges. *Energy and Buildings*, 107: 264–278.

Yun GY, Steemers K (2008). Time-dependent occupant behaviour models of window control in summer. *Energy and Buildings*, 43: 1471–1482.

Zhang D, Li S (2014). Agent-based modeling and simulation of competitive electric power markets. In: Proceedings of Power Systems Conference, Clemson, SC, USA. Available at http://dx.doi.org/10.1109/PSC.2014.6808096