Quantifying the human-building interaction: Considering the active, adaptive occupant in building performance simulation

Jared Langevin^{1,a}, Jin Wen¹, Patrick L. Gurian¹

¹ Department of Civil, Architectural, and Environmental Engineering, Drexel University, Philadelphia, PA
3141 Chestnut St., Curtis 251
Philadelphia, PA 19104
(215) 895-2341

^a Corresponding author, e-mail: jared.langevin@gmail.com

Keywords: Occupant behavior; agent-based modeling; building performance modeling; thermal comfort; co-simulation

Abstract:

This paper introduces a Human and Building Interaction Toolkit (HABIT) for simulating the thermally adaptive behaviors and comfort of office occupants alongside building energy consumption. The toolkit uses the Building Controls Virtual Test Bed (BCVTB) to co-simulate a field-tested, agent-based behavior model with an EnergyPlus medium office model. The usefulness of the toolkit is demonstrated through a series of zone and building-level case study simulations that examine the wisdom of pairing local heating and cooling options with strategic thermostat set point offsets, judging from the energy, Indoor Environmental Quality (IEQ), and cost perspectives.

Results generally suggest that trading efficient local heating/cooling options for whole space conditioning has both energy and comfort benefits, saving up to 28% of monthly HVAC energy while improving the acceptability of thermal conditions in a Philadelphia climate. Nevertheless, cost analysis shows that the fuel source of conserved energy must be considered – particularly in the case of personal heater use, which adds to electric plug loads and associated utility and CO₂ emissions cost penalties. Moreover, costs from even small changes in simulated occupant productivity tend to overwhelm energy costs, suggesting the need to improve the accuracy and precision of available productivity models across multiple seasons and climates.

1. INTRODUCTION

Real office building occupants interact with and adapt to their surrounding environments in deliberate and meaningful ways that affect both energy consumption and Indoor Environmental Quality (IEQ). Numerous studies have estimated the magnitude of these effects, establishing the high degree of influence that occupant behavior exerts on building energy use and thermal comfort relative to other potentially significant factors [1, 2, 3].

Given the importance of occupants' environmental adaptations to building energy and comfort outcomes, a series of regression-based occupant behavior models have recently been integrated into building performance simulation (BPS) routines. Bourgeois [3], for example, joined a Sub-Hourly Occupant Control (SHOCC) model with the ESP-r building simulation program. The SHOCC module overrides ESP-r lighting diversity profiles at five minute time steps with stochastically determined occupancy, blind use, and lighting behavior information for a single private office. Running the SHOCC scheme for the Quebec, Canada and Rome, Italy climates, the authors found manual versus constant lighting control reduced lighting consumption by 79% in Rome and 77% in Quebec, and also reduced cooling loads by 42% and 57% and primary energy loads by 60% and 43%.

Rijal et al [4] modeled the probability of window opening behavior in terms of operative indoor and outdoor air temperatures once a +/- 2K deadband around the group "comfort temperature" has been breached. The algorithm has been integrated into an ESP-r simulation of a single UK office at an hourly time step.

Haldi and Robinson [2] integrated stochastic, Markov-chain-based models of average occupant window and blind use into the City-Sim urban simulation software, using indoor/outdoor temperature and indoor/outdoor illuminance as inputs to the window and blind use models, respectively. The behavior models were implemented in a City-Sim simulation of a single private office at a five minute time interval, with the energy impacts of the modeled behavior reportedly on the order of a factor of two.

While the above regression models generally describe the probabilities of *group-level* behaviors (i.e., total percentage of windows open in an open plan office), a few recent studies represent *individual-*

level occupant behaviors in BPS via an Agent-Based Modeling (ABM) approach. An ABM represents individual building occupants as autonomous “agents” with unique personal attributes and behavior possibilities, as well as rules for interacting with other agents and their surrounding environment [5]; group-level behaviors then emerge from the adaptive behaviors of individuals. The natural ability for agent-based models to represent individual behavioral diversity makes them particularly attractive for a BPS application, which typically concerns building spaces with multiple occupants [6].

Previous occupant behavior ABMs include that of Azar and Menassa [7], who represent ten low, medium, and high energy consuming occupant agents and their interactions in an e-Quest model of a single graduate office at monthly time steps. The agents vary in their use of blinds, lighting/equipment use schedules, and hot water consumption. The authors found that on average, the simulations showed a 39% difference in electricity consumption and an 11% difference in gas consumption between “Low” and “High” consumers.

Another study by Andrews et al [8] couples an ABM of occupants’ daily lighting use with the RADIANCE lighting simulation software, simulating a five-zone office building at hourly time steps for one day total. The authors use the coupled simulation to determine an optimal window-to-wall ratio of 30% for the building, given the multiple objectives of minimizing visual discomfort; minimizing the number of lighting control actions; and minimizing energy use and costs.

From a review of the existing modeling work above, the following areas for improvement in behavior co-simulation for BPS have been identified:

- **Generality and scope of underlying behavior models.** It is unclear how effectively statistical behavior models can make predictions outside the context of their calibration; moreover, many of these models only roughly account for inter-individual variability in behavior through “active” and “passive” occupant groupings; do not generally address social influences on behavior in non-private offices; and rarely model the most immediate adaptive opportunities (clothing, personal fans/heaters). While agent-based behavior models are better suited to handling individual variability in comfort/behavior and social interactions, available

ABMs are inconsistently reported and few have been validated against long-term field data.

- **Flexibility and performance of behavior/energy co-simulation approaches.** Most existing behavior/energy co-simulation studies simulate behavior and energy in a single thermal zone - often with one occupant - and it is unclear whether multiple building zones with several occupants could be accommodated for studies at the whole building level. Co-simulations that do represent multiple zones and/or occupants are run either across a short time period (e.g., one day) or at a coarse time step (e.g., one month) that may miss short-term behavior dynamics. Moreover, existing studies rarely report the computational time for co-simulation runs, precluding the definition of acceptable thresholds for co-simulation performance.
- **Interpretability and comprehensiveness of co-simulation outputs.** Previous studies typically report energy use changes associated with various occupant behavior scenarios; yet, the definition of “energy use” differs across studies, sometimes signifying overall energy; other times focusing on specific end uses or fuel types; and also varying between site and source energy. Output metrics like cost, which are more meaningful to those outside of the building performance modeling community, are rarely explored; nor are IEQ metrics like thermal acceptability and productivity, though their inclusion would yield a more holistic understanding of behavior impacts on building operation.

This paper introduces a Human and Building Interaction Toolkit (HABIT) that seeks to address the above issues. Specifically, the toolkit co-simulates building energy and office occupant behavior using a field-validated, agent-based model that represents both individual and group-level comfort/behavior outcomes; the co-simulation accommodates whole building-level analyses; and co-simulation outputs allow assessment of energy, behavior, IEQ, and cost together as a guide to the design and operation of low-energy, high quality office building environments.

The paper begins by describing the HABIT co-simulation exchange and its underlying agent-based model of thermally adaptive behaviors. The usefulness of the toolkit is then demonstrated through a series of zone-level and whole building-level simulations that explore a range of occupant behavior scenarios,

including multiple cases where wider thermostat set point ranges are paired with the provision of efficient local heating and cooling options for occupants. The relative merits of each scenario are assessed by comparing resulting energy use intensities alongside occupant thermal unacceptability and productivity outcomes; the whole building-level simulations also assess the costs of changes in each of these outcome metrics across the various behavior scenarios.

2. METHODS

2.1 Integrated Modeling Scheme

2.1.1 Co-simulation Overview

HABIT pairs a previously published ABM of office occupants' thermal comfort and adaptive behaviors [9] in MATLAB with whole building energy simulations of office buildings in EnergyPlus [10] using the Building Controls Virtual Test Bed (BCVTB) co-simulation program [11].

The EnergyPlus/MATLAB information exchange runs as follows (see Figure 1): EnergyPlus simulates zone-level thermal conditions and passes these as inputs to the MATLAB comfort/behavior model; the MATLAB model predicts thermal comfort and related behavior outcomes for each occupant (i.e., fan on; window open, etc.) and aggregates these outcomes across all agents in the zone; the aggregated behavior outcomes are passed back to EnergyPlus and used to adjust appropriate zone schedules (i.e., heater/fan equipment gains; thermostat set points) for the next time step; the process repeats until a simulation end time is reached.

The BCVTB negotiates single runs of the above MATLAB/EnergyPlus exchange. However, the MATLAB comfort/behavior model contains probabilistic elements (see below). Thus, the exchange must be re-run multiple times to assess a range of possible outcomes. These re-runs are achieved through a custom MATLAB wrapper that reopens and executes a given BCVTB system.xml file for as many simulation runs as the user specifies. Once all runs are completed, the R Computing software is used to aggregate results and perform uncertainty analysis. The entire co-simulation process is currently configured through a designated Excel file.

[Please insert Figure 1 around here.]

2.1.2 Agent-Based Behavior Model Overview

In the default HABIT setup, each office occupant is represented in the MATLAB comfort/behavior model as a simulated agent that acts adaptively based on the scheme described in [9], which draws upon Perceptual Control Theory (PCT) [12]. Under this scheme, behavior is considered to be the by-product of a negative feedback loop in which an agent acts to bring its current thermal perception into line with a reference range of seasonally acceptable ASHRAE thermal sensations, despite environmental disturbances. This process is diagrammed in Figure 2.

An agent's current thermal sensation and seasonally acceptable thermal sensation range are both modeled probabilistically using the distributions developed in [13]; daily occupant arrival/lunch/departure times are also sampled from a normal distribution around user-defined arrival/lunch/departure times. Agent behavior choices may be constrained by the building management or by other agents in the space that share a given control.¹ The reader is referred to [9] for full details on the HABIT ABM and its validation, whereby simulated agents are assigned the personal and environmental characteristics of real occupants in a field office, the ABM is executed, and simulated agent behaviors are compared to the field occupants' observed behaviors over a one year period.

[Please insert Figure 2 around here.]

Table 1 presents the full set of behavioral adaptations simulated by the HABIT ABM and shows how their feedback on the thermal environment/comfort is represented on both the MATLAB and EnergyPlus sides of the BCVTB co-simulation. Note that certain behaviors like personal heater adjustment are assigned both individual agent-level and zone-level feedback, while others like clothing adjustment and thermostat use are assigned feedback on only one of these levels.

[Please insert Table 1 around here.]

2.2 Case Study Simulations

To demonstrate the usefulness of the above simulation framework, a series of case study

¹ Behavior choice hierarchy and constraint assumptions are discussed at greater length in [9] and [15].

simulations were performed for a medium-sized office building. The simulated building has 3 stories with 5,600 square meters of total floor space and one core/four perimeter thermal zones per floor; masonry construction with 20% glazing; variable-air-volume (VAV) air-handling units (AHUs) with hot water reheat; an occupant density of 0.05 person/m²; and a baseline occupied infiltration rate of 2.4 CFM/m² applied to perimeter zones (see [17] for more details).

Two sets of simulations are performed. The first set simulates two zones on the second floor of the building across the months of January and July, for a city in each of the five primary U.S. Department of Energy (DOE) Building America climate zones [18].² One of the zones is located on the south perimeter face of the building (231 square meters); the perimeter zone is open plan, has 12 occupants, 12 windows, and 1 shared thermostat. The other is a core zone (1099 square meters); the core zone is open plan, with 59 occupants and 1 shared thermostat. The zone-level simulations are aimed at assessing differences in behavior, energy, and IEQ across seasons, climates, and building zone types within a given climate.

The second set of simulations is performed on *all zones* of the case study building, again for the months of January and July, for the Philadelphia climate only. These simulations each cover 15 zones (3 core; 12 perimeter) and 297 occupants. The whole building-level simulations are intended to yield a more complete picture of the link between behavior, energy, and IEQ across multiple thermal zones with different orientations and locations within the general building geometry.

In each of the zone-level and whole building-level simulations, multiple behavior scenarios are run to test the influence of behavior modeling assumptions on energy and IEQ outcomes. These behavior scenarios and their use in each set of simulations are outlined in Table 2. As shown in the table, the behavior scenarios range from a ‘Baseline’ case where no thermally adaptive actions are possible, to a ‘Fully Unrestricted’ case where a full range of actions is possible, and finally to a series of ‘Wider Set Points’ cases where zone thermostat set point ranges are progressively widened and occupants are

² The cities are: Philadelphia (PHL; Mixed-humid); Chicago (CHI; Cold/Very Cold); San Francisco (SF; Marine); Los Angeles (LA; Hot-Dry); Houston (HOU; Hot-Humid).

provided with more efficient local heating/cooling options at their desks. The ‘Wider Set Points’ scenarios are of particular interest in testing the degree to which localized heating/cooling devices can save energy while maintaining or improving occupant thermal comfort levels (as proposed, for example, in [19]).

[Please insert Table 2 around here.]

Simulation outcomes are evaluated from both the energy and IEQ perspectives. For energy, a load or use intensity is calculated³; for IEQ, the percentage of occupants that the behavioral model indicates are outside their acceptable thermal sensation range without any behavioral remedy is recorded at each time step and averaged across the entire simulation period, yielding an overall percentage thermally unacceptable outcome (a thermal comfort indicator). Relative work *underperformance* percentage (a productivity indicator) is also evaluated using the polynomial relationship presented in Jensen et al [20], which describes relative performance in terms of thermal sensation:

$$\text{Relative Work Performance} = -0.0069tsv^2 - 0.0123tsv + 0.9945 \quad (1)$$

Where tsv is an occupant’s thermal sensation vote on the ASHRAE sensation scale. Relative underperformance is then simply 1-Relative Work Performance.

In the whole building-level simulations only, a fourth economic metric - Net Present Value (NPV) - is evaluated alongside the energy and IEQ metrics [21]. Here, three versions of NPV are calculated using a ten year time horizon:

- **NPV 1: Energy Costs.** NPV1 considers energy costs that a scenario affects relative to the baseline scenario (using current U.S. natural gas and electricity pricing).
- **NPV 2: Energy + Carbon Emissions Costs.** NPV2 considers the energy costs and CO₂/SO₂ emissions costs that a scenario affects relative to the baseline. Emissions dollar values are assigned based on the most recent US Government Social Cost of Carbon numbers together with US EPA SO₂ damage estimates [22].

³ Energy load intensity is calculated for the zone-level simulations, since energy load is the only zone-level energy output available from EnergyPlus.

- **NPV 3: Energy + Carbon + Productivity Costs.** NPV3 considers energy costs, CO₂/SO₂ emissions costs, and the cost of changes in work underperformance that a scenario affects relative to the baseline. Work underperformance costs are evaluated by multiplying overall percentage change in work underperformance by the sum of all occupants' salaries across the simulated time period.

Note that a negative NPV value suggests a given behavior scenario is *less favorable* from a cost perspective than the baseline scenario it is being compared against. Key assumptions for the NPV calculations are listed in Table 3.

[Please insert Table 3 about here.]

It is noted that the NPV calculations require annual estimates of energy, emissions, and productivity costs, but our simulations focus on only the coldest and warmest months of the year (January/July). To extend the whole building simulation outcomes to an annual basis, results from January are multiplied across the heating season (three months, approximately December to March); and results from July are multiplied across the cooling season (three months, approximately June to September).⁴

Results from the above case study simulations are subject to the uncertainties inherent in human thermal comfort and behavior modeling. Such uncertainties are represented in the HABIT behavior model through probabilistic, individual-level occupant thermal sensation and acceptability outcomes, which again are based on the sensation/acceptability distributions of [13].⁵ To propagate these probabilistic modeling elements through the case study results, each simulation is re-run ten times to yield a range of possible energy, IEQ, and NPV outcomes.^{6,7,8}

⁴ For example, January and July savings of 1 kWh/sq.m. each become heating gas and cooling electricity savings of 3 kWh/sq.m. (each multiplied across 3 months); a median employee salary of \$50,000 is \$4,167 per month, and thus \$4,167 x 3 = \$12,500 for each of the three-month heating and cooling seasons.

⁵ Note that parameter uncertainty in the distributions from [13] is not currently considered; however, this source of uncertainty is small due to the large number of field observations used to fit the distributions.

⁶ Note that additional uncertainty in NPV assumptions such as the discount rate is also not currently considered.

3. RESULTS

3.1 Zone-Level Simulations

The zone-level case study simulations yield energy, IEQ and behavior results for a perimeter and core zone of the case study building; the two zones were simulated across January and July, in a city from each of the five DOE climate zones, under seven different behavior scenarios, as detailed above.

Figure 3 provides a graphical summary of the energy and IEQ results across all simulated months, zone types, and behavior scenarios in each simulated city. Note that 95% prediction intervals are shown for each point in Figure 3. Accompanying statistics are presented in Table 4 for four of the behavior scenarios: “Baseline” (B); “Restricted” (R); “Unrestricted” (UR); “Wider Set Points” (WSP). Note that the final column for each monthly summary in Table 4, marked Max % Δ_{B-WSP} , indicates the largest magnitude percent change in a given metric between the “Baseline” and “Wider Set Points” scenarios, across zone types. Table 4 also indicates which of three controls (fans, heaters, or windows) is projected for most frequent use in each simulation, and at what average daily frequency.

[Insert Figure 3 around here.]

[Insert Table 4 around here.]

In Figure 3 and Table 4, a few consistent trends in energy and IEQ are observed across the simulated months, zones, and cities. First, HVAC energy load tends to increase slightly from the baseline scenario through the “Fully Unrestricted Behavior” scenario, which adds new sources of consumption to the baseline (i.e., fans, heaters). The energy load then moves back downward for the final “Wider Set

⁷ It is demonstrated in [9] that at least 50 agent thermal acceptability ranges must be sampled per simulated building zone to yield reasonable estimates of the full distribution of thermal acceptability ranges in the building for use in behavior projections. The current simulation has a minimum of 8 occupants per building zone; multiplying this by 10 simulation runs yields at least 80 sampled acceptability ranges per zone, going above the minimum requirement.

⁸ Resulting outcome sets are treated as a sample drawn from a normally distributed population of outcomes for the given metric. Given this assumption, 95% PIs are calculated as: (sample mean $\pm$ 2.26*(sample std. dev.*(sqrt.(1+(1/(n)))) where n is number of simulation runs (10) and 2.26 is the 95% t distribution statistic with n-1 degrees of freedom. Under this approach, 95% of PIs calculated for successive sample sets are expected to contain a single future prediction for the given metric.

Points” scenario, where more efficient local controls are paired with wider thermostat set point ranges. Regarding IEQ, thermal unacceptability is significantly lower relative to the baseline in *all* of the other scenarios, with the lowest unacceptable percentage almost always occurring for the “Fully Unrestricted” case where occupants have complete freedom in determining their personal comfort. Relative work underperformance percentage also remains consistently favorable across the baseline and all other behavior scenarios, with employees predicted to be at most 1-2% off their best possible performance, as shown in Table 4.

Figure 3 and Table 4 also reveal a number of important differences between certain simulation outcomes. Comparing results by simulated month, for example, all July HVAC energy load outcomes for the “Wider Set Points” scenario are significantly *lower* than those of the baseline scenario (up to ~52% reduction in the San Francisco perimeter zone- see Max % Δ_{B-WSP} column of Table 4). This reflects the energy benefits of using low energy fans locally in lieu of whole space air-conditioning. In January, however, some HVAC energy load outcomes for the “Wider Set Points” scenario are *higher* than those of the baseline scenario (up to a ~50% gain in the Chicago core zone - see Max % Δ_{B-WSP} column of Table 4). Indeed, in January the “Baseline” scenario yields the lowest energy load outcome for the colder Chicago/Philadelphia winter climates (more on climate below). This result suggests that in contrast to local fans, which consume only 15 W, the added consumption of multiple 1200 W personal heating devices may be more than enough to outweigh any reductions in space heating consumption for certain building zones and climates under a modestly widened set point scenario. Indeed, it will be demonstrated in the whole building-level simulations that more efficient personal heating devices and more aggressively widened thermostat set points are required to achieve significant energy savings in a localized heating scenario.

Monthly differences in IEQ are also seen. In January, the increased propensity for Philadelphia and Chicago occupants to use personal heaters with each successive behavior scenario leads to a slight warming trend across scenarios (see Appendix, Figure A.1a); the Jensen work performance model

penalizes this trend, as it was developed using summer-time data and tends to favor cooler sensations. As a result, work underperformance slightly *increases* for these cities in January. This result is incongruous with corresponding thermal unacceptability outcomes, which only improve with the warming trend across scenarios, reflecting the warmer thermal acceptability ranges reported by occupants in the winter vs. the summer (see [13] for more on these seasonal ranges). The disagreement first exposes the inability of the work performance modeling framework to capture effects of seasonal shifts in occupant thermal preferences.

In July, by contrast, projected work performance trends match up well with projected trends in thermal acceptability. Specifically, the addition of behavioral options for cooling through the “Fully Unrestricted Behavior” scenario promotes the cooler thermal sensations that are more widely accepted in this season [13], yielding *decreases* in both thermal unacceptability and work underperformance across all climates. Note, however, that thermal unacceptability and underperformance do tick back up again for the July “Wider Set Points” scenarios, which generally promote warmer thermal environments by raising cooling set points.

Comparing results by simulated zone type reveals some differences in projected HVAC energy load, with the core zone consistently showing a lower load than the perimeter, which is subject to infiltration losses and solar gains. It is also notable that the 95% prediction intervals on expected thermal unacceptability outcomes are narrower for the core zone than for the perimeter zone. This reflects a greater stability in zone-wide thermal unacceptability across each run for the core, owing to its larger number of occupants (59 versus 12 in the perimeter).

Finally, both energy and IEQ differences are observed when comparing simulation results by climate. For energy, Figure 3 shows climatic differences in the January simulations, where the “Wider Set Points” scenario looks less favorable in colder winter climates (Chicago, Philadelphia) than in comparatively warmer ones (San Francisco, Los Angeles, Houston). Table 4 suggests this result relates to differences in behavior frequency between the two types of climate: where higher energy heater use is the dominant behavior in the colder climates in January, low energy fan use dominates in the warmer

climates in January. Figure 4 graphically demonstrates differences in January behavior between a cold winter climate (Philadelphia) and a warm winter climate (Los Angeles) (also see the Appendix for climatic differences in thermostat outcomes). Note that when fan use is projected as the dominant behavior for all cities in July, no climatic differences are observed between the trends in simulated HVAC energy load of Figure 3 across the behavior scenarios.

[Please insert Figure 4 about here.]

Regarding climatic differences in IEQ, the January simulations show slightly higher work underperformance percentages for occupants in warmer climates, which have comparatively warmer daily indoor conditions in the winter. Again, warmer thermal sensations are suboptimal in the work performance model used.

Overall, energy and IEQ results in the first set of simulations show low sensitivity to assumptions about constraints on behaviors. In Figure 3, for example, only small qualitative differences are observed between energy/IEQ results of the “Restricted” and “Fully Unrestricted Behavior” scenarios, where management and social restrictions on fan/heater, window and thermostat actions are successively removed. In the case of thermostats and windows, the modeled effectiveness of more immediate adaptive options in mitigating discomfort (clothing, fans/heaters) appears to preclude the need for the less immediate thermostat and window adaptations in the simulations, even when they are completely unrestricted.

2.2 Whole Building-Level Simulations

The whole building-level case study simulations yield energy, IEQ, and behavior results for the whole case study building; the building was simulated across January and July for the Philadelphia climate only, under seven different behavior scenarios, the first four of which overlap scenarios from the first round of simulations. These results are plotted in Figures 5a-c.

Accompanying statistics are presented in Table 5, which also indicates the dominant behavioral control simulated in each scenario and its average daily frequency, and uses three versions of Net Present Value (NPV) to assess the economic viability of behavior scenarios relative to the baseline scenario.

Table 6 elaborates upon NPV results. Note that in Table 5, the final column for each monthly summary (marked % Δ_{B-WSP3}) indicates the percent change in the given metric between the “Baseline” and “Wider Set Points (Aggressive)” behavior scenarios.

[Please insert Figures 5a-c around here.]

[Please insert Table 5 around here.]

[Please insert Table 6 around here.]

Figures 5a-c show that general trends in energy and IEQ for the second set of simulations are similar to those observed in the first set. Regarding energy, Figure 5a shows that HVAC energy use intensity again increases slightly in both January and July from the “Baseline” behavior scenario through the “Fully Unrestricted Behavior” scenario; the energy use intensity then moves back down across the “Wider Set Points” scenarios, which range from an initial +/- 1°C widening of the set point range (“Wider Set Points”) to a +/- 4°C widening of this range (“Wider Set Points (Aggressive)”).

Energy end use breakdowns in Figure 5a allow a more specific examination of these trends. In January, for example, significant reductions in HVAC energy use for the “Wider Set Points (Aggressive)” scenario (~24%) result from a decrease in gas space heating consumption that more than offsets an associated increase in electrical equipment energy from more frequent use of personal heaters. Similarly, in July, significant reductions in HVAC energy use by the “Wider Set Points (Aggressive)” scenario (~37%) result from a decrease in electric space cooling consumption that more than offsets a small associated increase in electrical equipment energy from more frequent use of personal fans. Further discussion of dominant behavior trends in each month of the whole building simulations is provided below.

Regarding IEQ, Figure 5b shows a significant decrease in percentage of time thermally unacceptable relative to the baseline through the “Wider Set Points (Aggressive)” scenario in January, and through the “Wider Set Points (Moderate)” scenario in July, with the lowest thermally unacceptable percentage occurring as in the zone-level simulations for the “Fully Unrestricted Behavior” scenario in

both months. In July, however, the “Wider Set Points (Aggressive)” scenario yields a thermally unacceptable percentage for July that is close to that of the baseline, with the prediction intervals for the two overlapping. This result also violates the 10% thermally unacceptable threshold used in thermal comfort standards, suggesting that a “Wider Set Points (Aggressive)” strategy for a Philadelphia office in the summer will yield substantial warm discomfort amongst occupants. Work underperformance results for this scenario in Figure 5c reinforce this conclusion, moving up to 3% underperformance as a result of the high cooling set point. Ultimately, a “Wider Set Points (Moderate)” strategy is the better option for achieving significant HVAC energy savings (~28%) while maintaining good IEQ in the Philadelphia summer months.

Table 5 shows that all four “Wider Set Points” scenarios yield significant HVAC energy savings in both January and July; however, a benefit-cost analysis of the energy savings paints very different pictures for the two months. For example, in the two NPV calculations that consider utility energy costs (NPV1) and energy and carbon/sulfur emissions costs (NPV2), the January HVAC energy savings for the “Wider Set Points” scenarios yield *negative* NPV1/NPV2 values ranging from -\$18,990 to -\$6,190 (Table 6); again, a negative NPV value suggests the behavior scenario is *less favorable* from a cost perspective than the baseline scenario it is compared against. Meanwhile, the July HVAC energy savings for the “Wider Set Points” scenarios yield *positive* NPV1/NPV2 values ranging from \$20,454 to \$60,176.

Moreover, while in January the NPV2 values are always *less favorable* than the NPV1 values, in July the reverse is true. These results reflect the higher utility and carbon costs associated with electricity vs. natural gas savings in the NPV analyses. As touched upon earlier, the January “Wider Set Points” HVAC energy savings come at the expense of trading lower cost, lower emissions natural gas space heating for higher cost, higher emissions electricity from personal heaters; in July, meanwhile, HVAC energy savings come from replacing space cooling electricity with the far lower electric power requirements of personal fan use. From a utility and carbon cost perspective, therefore, the electricity savings of the July “Wider Set Points” scenarios look more favorable than the natural gas savings of these scenarios in January.

The third set of NPV calculations factors in the costs of changes in occupant work underperformance (NPV3). Here, January and July results for the “Wider Set Points” scenarios are uniformly negative relative to the baseline, ranging from -\$54,150 to -\$26,061 in January and from -\$286,161 to -\$73,776 in July. This results from increased work underperformance in these scenarios (Figure 5c) - particularly in July when the warmer thermal environments promoted by higher cooling set points are suboptimal in the work performance model. Indeed, the most strongly negative result of -\$286,161 occurs in the “Wider Set Points (Aggressive)” scenario in July, in which the building’s thermal environment is the warmest of all the simulated scenarios.

Figure 6 plots average daily behavior intensities simulated by month for the whole office building. The figure graphically demonstrates the dominance of occupant personal heater use in January and personal fan use in July, as was observed for the Philadelphia climate in the first set of simulations. Simulated heater use in January ranges from an expected daily average of 6% of occupants using a heater in the “Restricted Behavior” scenario (sd = 1.2%) to an average of 15% using a heater in the “Wider Set Points (Aggressive)” scenario (sd = 1.5%), where the space heating set point is lowest. In July, simulated fan use ranges from an expected daily average of 8% of occupants using a fan in the “Restricted Behavior” scenario (sd = 1.6%) to an average of 39% using a fan in the “Wider Set Points (Aggressive)” scenario (sd = 2.4%), where the space cooling set point is highest. Simulated heater use tends to ramp up later in the morning (beginning to plateau between 10:00-11:00 AM), with many heaters turned off at lunch and somewhat less heater use simulated for the afternoon hours. Fan use tends to start earlier in the morning (plateauing between 9:00-10:00 AM), dipping down at lunchtime but showing strong tendencies for late afternoon use, when interior temperatures increase (Appendix Figure A.2b).

[Please insert Figure 6 about here.]

It is noted in Figure 6 that window use is significant in July for the “Wider Set Points” scenarios, peaking at an expected daily average of 13% windows open (sd = 2.0%) for the “Wider Set Points (Aggressive)” scenario (statistics not shown in the Table). This again reflects the tendency for a warmer thermal environment in these scenarios, which weakens the influence of an assumed restriction on

window opening when Running Mean Outdoor Temperature exceeds Indoor Operative Temperature (see [9]). Simulated window openings tend to occur in the morning hours, with windows generally left open until departure. Thermostat set points in July (shown in Appendix Figure A.2b) are quite stable for the first three behavior scenarios, but are adjusted down by about 0.5°C on average in the morning hours of the various “Wider Set Points” scenarios. The latter result suggests the higher base cooling set points of the “Wider Set Point” scenarios are pushing thermal sensations above the warm acceptability limit of most occupants, leading to greater use of their 1°C downward thermostat adjustment capability in these cases.

4. DISCUSSION

4.1 Summary of Key Findings

Case study results are discussed in terms of the energy, comfort, and productivity outcomes yielded by the HABIT program. Key findings are drawn from the whole building-level analysis in Philadelphia; the zone-level simulation results are used to assess the applicability of findings across differing climatic contexts and zones within a building.

Energy: In both January and July, whole building HVAC energy use intensity is highest for the “Fully Unrestricted Behavior” scenario, and is lowest for the “Wider Set Points (Aggressive)” scenario. HVAC energy increases are small but significant for the “Fully Unrestricted Behavior” simulations - up to about 10% in July (6.5 vs. 6.0 kWh/m² baseline HVAC energy use intensity, as shown in Table 7). The “Wider Set Points (Aggressive)” scenario, meanwhile, shows large and significant energy *decreases* of about 24% in January and 37% in July.

The energy results make intuitive sense: in the absence of other changes to this air-conditioned building’s operation strategy, unrestricted occupant behavior *should* increase HVAC energy use, as it introduces new sources of energy consumption (personal fans, heaters, thermostat adjustments, outdoor air from windows). Similarly, a conditioning strategy that pairs wider thermostat set point ranges with local heating/cooling options *should* reduce HVAC energy use, given the increased efficiency of heating or cooling the area near an occupant’s desk relative to heating/cooling the whole

zone air volume. HVAC energy reductions from such a strategy are greater in July than in January because the dominant behavior in July is turning on personal fans, which use far less energy than personal heaters (dominant in January). It is notable that HVAC energy results in January for the “Wider Set Points + Education” scenario, where half of occupants are expected to use a halogen heater on a low setting (400 W), are quite similar to the “Wider Set Points” scenario, where all occupants use the heater on a high 800 W setting. Ultimately, energy savings from use of the heaters on a lower setting are offset by associated increases in space heating requirements (Figure 5a).

The zone-level simulations reveal that while general HVAC energy trends across behavior scenarios are similar for different climatic contexts, the potential for HVAC energy reductions in a January “Wider Set Points” scenario are likely greater in a warmer winter climate than in a colder one. This is because fan use is projected to dominate even in January in the warmer climates, while heater use dominates in January in the colder climates. Again, turning personal fans on requires much less energy than turning on personal heaters; thus, a set point adjustment strategy that is coupled with increased fan use will look more favorable from an energy perspective than an adjustment that is coupled with increased heater use.

In a colder winter climate in January, perimeter building zones have the greatest potential for HVAC energy reductions under a “Wider Set Points” scenario. This result is tied to zone space heating load, which must be reduced substantially from the baseline case if a “Wider Set Points” scenario is to achieve overall HVAC energy use reductions (see Figure 5). While space heating load is sizeable for perimeter zones in winter, this is not the case for the core zones, leaving no energy savings to offset corresponding equipment energy increases from use of personal heaters.

Comfort: In all alternative behavior scenarios aside from “Wider Set Points (Aggressive)” for the whole building analysis, the overall percentage of time occupants find the thermal environment unacceptable is significantly *lower* than that of the baseline (where no behavior is possible). In the “Wider Set Points (Aggressive)” case, lower thermal unacceptability is observed for the January simulations, but not for July, where a 95% prediction interval around the thermally unacceptable

percentage overlaps that of the baseline scenario, and unacceptability reaches above the 10% threshold established by thermal comfort standards.

In general, the comfort results suggest that building simulation models will tend to overestimate occupant thermal unacceptability outcomes if they do not realistically account for occupants' thermally adaptive behaviors. The zone-level simulations show, for example, that simply incorporating realistic daily occupant clothing adjustments ("Clothing Only" scenario) substantially reduces predicted thermal unacceptability – on average, by about 70% across climates in January and about 50% across climates in July (shown graphically in Figure 3). On the whole building scale, simulating the unrestricted use of more efficient heaters and fans in the "Wider Set Points" scenarios reduces thermal unacceptability from a baseline of 12-15% to about 2% in January and to about 3-4% through the "Wider Set Points (Moderate)" scenario in July. These results also demonstrate that the energy savings observed for the "Wider Set Points" scenarios in Figure 5a and Table 5 do not generally come at the expense of thermal comfort (in fact, the opposite is true).

Nevertheless, whole building thermal unacceptability results for the "Wider Set Points (Aggressive)" scenario in July suggest there are comfort limits on how far zone-level thermal conditions can be pushed to save energy, even when occupants have unrestricted local control options. Indeed, while at least some occupants are projected to use these controls (Figure 6 and Appendix Figure A.2), it appears the impacts of the controls on the thermal environment do not satisfy a suitable majority of occupant thermal acceptability ranges. Specifically, in the "Wider Set Points (Aggressive)" scenario, 10% of occupants are projected to find the thermal environment unacceptable on average, and a 95% prediction interval shows this percentage could be expected to rise as high as about 13%. Using the standard unacceptability limit of 10% [14], the "Wider Set Points (Aggressive)" strategy must therefore be rejected for the summer months in Philadelphia in favor of a "Wider Set Points (Moderate)" strategy, which saves significant HVAC energy (~28%)

without compromising IEQ (~5% thermal unacceptability, shown in Table 5).⁹

Examining thermal unacceptability outcomes across the zone-level simulations, few differences are observed between climates or zone types in the case study building. Of note are the narrower prediction bounds for the core zone unacceptability results relative to the perimeter zone, given the greater run-to-run stability in the unacceptability statistic for the core zone with its larger number of occupants.

Productivity: In the whole building analysis, work underperformance outcomes remain around 1-1.5% for January, but show a gradual upward increase across the behavior scenarios in July, ranging from 1.7% underperformance in the baseline to 3.1% underperformance in the “Wider Set Points (Aggressive)” scenario.

Work underperformance results must be interpreted in light of their underlying regression model [20], which predicts minimum underperformance at a thermal sensation of about “Slightly Cool”, and penalizes movements towards the warm side of the sensation spectrum more strongly than movements to the cool side.

As an example of this, the “Wider Set Points (Aggressive)” scenario in July, which raises cooling set points, shows a significantly *higher* work underperformance percentage than all other simulated scenarios, while behavior scenarios simulated in the cold month of January show *lower* work underperformance percentages than the same scenarios simulated in July.

It is noted that work underperformance results sometimes contrast with thermal unacceptability results, though the two metrics might be expected to relate. For example, while whole building thermal unacceptability for the baseline behavior scenarios is significantly *higher* than for the other scenarios (15.5% in January and 12.1% in July, as shown in Table 5), baseline work underperformance percentages are *comparable to* or *slightly lower than* the work underperformance

⁹ The “Wider Set Points (Aggressive)” cooling set point (30°C) may be considered an “upper bound” for this type of building when local cooling options are available. Indeed, the upper limit for indoor operative temperature in ASHRAE Standard 55-2010 is about 30.25°C at the locally controlled air speed assumed for fans in this study (0.75 m/s).

percentages for the other scenarios, across both simulated months.

Such contrasts reflect differences in the modeling approaches for the two metrics: while thermal unacceptability is determined by comparing one's currently predicted thermal sensation against a personal range of acceptable sensations sampled for each season [13], work underperformance is determined using a group-level regression model fit from European occupant responses in the summer, which has only thermal sensation as an input and includes no seasonal adjustment. Recent work by Lan et al [23] found a warmer optimal thermal sensation for work effectiveness than in the Jensen modeling work; the authors suggest the difference lies in their measurement of a wider range of work tasks. Moreover, to the authors' knowledge, no existing studies have directly explored the degree to which occupants' optimal thermal sensations for work effectiveness change seasonally. Season is likely to be an important productivity factor, given its association with changes in thermal comfort preferences [13] and the probable links between thermal comfort outcomes and productivity outcomes.

Moreover, thermal acceptability may not be an appropriate thermal comfort variable to link with occupant productivity outcomes. Indeed, the model of [20] describes maximum work performance in terms of a single *optimal* thermal sensation; acceptability, meanwhile, defines a *tolerable set* of multiple thermal sensations, suggesting "what the occupant is agreeable to, or approves of" [24]. Ultimately, thermal preference may be a more appropriate comfort variable to link with such productivity metrics, defined as "the ideal, referring to the conditions you would favour if you could have exactly what you wanted at any given moment"- this definition better aligns with the idea of a thermal optimum for performance. Future research must further explore this hypothesis using field data that include occupant thermal sensation, acceptability, and preference responses alongside objective measures of relative work performance.

Finally, the zone-level simulations show similar trends in work underperformance across climates and thermal zones. January results do show slightly higher underperformance percentages for warmer winter climates, further demonstrating a tendency for the work performance model to favor cooler

497 thermal environments.

498 Taken together at face value, the energy, comfort, and productivity results of Table 5 suggest that for
499 the Philadelphia climate, an “Wider Set Points (Aggressive)” is the best strategy in winter (~24%
500 expected HVAC energy savings relative to the baseline case; 2.3% occupants thermally unacceptable;
501 1.3% work ineffectiveness); as mentioned, in summer a “Moderate Wider Set Points” is the best strategy
502 (~28% expected HVAC energy savings; 4.9 % occupants thermally unacceptable; 2.4% work
503 ineffectiveness).

504 However, further economic analysis of these whole building energy and IEQ results yields a more
505 ambiguous understanding of the relative benefits of each behavior scenario. Indeed, in January, the first
506 two sets of Net Present Value (NPV) calculations - which factor in energy costs (NPV1) and energy plus
507 emissions costs (NPV2) - indicate *none* of the alternative behavior scenarios yield positive net cash flow
508 over ten years relative to the baseline. Again, this result is attributable to the low cash value attributed to
509 the type of energy that is saved in January – natural gas for space heating - relative to the type of energy
510 that is being added – electricity for personal heater use. Indeed, from the energy cost perspective (NPV1),
511 the current price for natural gas in Philadelphia is \$0.04/kWh, compared to \$0.16/kWh for electricity;
512 when additionally considering the costs of carbon/sulfur emissions from energy use, natural gas is again
513 valued lower at \$0.01/kWh, compared to \$0.04/kWh for electricity, as the former is consumed on site and
514 burns more cleanly, while the latter is generated partially by emissions-heavy, coal-fired power plants,
515 with nearly 70% of the fuel’s energy lost in generation and transmission from source to site (see Table 3).
516 This explains why in January, NPV2 values in Table 8 look even less favorable than NPV1 values across
517 all behavior scenarios.

518 In the July whole building simulations, cooling electricity is always the type of energy being saved,
519 while increases in equipment electricity from greater use of personal fans are minimal. Accordingly, July
520 NPV1 and NPV2 values look favorable for the four “Wider Set Points” scenarios relative to the baseline,
521 given the significant electricity savings seen for these scenarios. Moreover, in July the NPV2 values are
522 now *more favorable* than NPV1 values, since the high utility price assigned to electricity savings is

bolstered by additional consideration for the heavier carbon/sulfur emissions costs of electricity generation.

Nevertheless, the third set of NPV calculations (NPV3) overwhelms any positive cash flows from energy/emissions savings with the much larger costs of changes in occupant work performance. Indeed, the current analysis values a 1% change in annual, whole-building occupant work performance at nearly \$75,000, using occupants' annual salaries as a cost scale (see Table 3). Accordingly, NPV3 values for the "Wider Set Points" scenarios, which all yield higher work underperformance percentages than the baseline, are strongly *negative* in both January and July (Table 5). In fact, only the July "Fully Restricted Behavior" and "Fully Unrestricted Behavior" scenarios fare well in the NPV3 calculations; these scenarios yield lower work underperformance percentages than the baseline by allowing occupants additional ways to cool off (clothing, fans, thermostats, windows) while also leaving cooling set points at their baseline values.

Inevitably, the weights assigned by decision makers to each NPV interpretation of HABIT outcomes will determine how the program guides real-world building design and operation strategies. Looking ahead, for example, the increasing urgency of dealing with climate change may demand that building owners overlook "optimal" work environments in favor of environments that are thermally "acceptable" to occupants while also yielding significant energy costs savings and reductions in greenhouse gas emissions (i.e., prioritize NPV1/NPV2 metrics).

Alternatively, office building tenants may double down on the potential cost benefits of maximizing employee productivity [25], and assign greater weight to the relative work performance considerations of the NPV3 metric. As this and other studies¹⁰ have demonstrated, the cost implications of even small changes in occupant productivity must be considered in building life cycle analyses because the productivity cost scale is far larger than that associated with changes in energy consumption. Before such productivity assessments can be more widely employed, however, current work performance models must be further developed across multiple climates and seasons to yield more realistic "optimums" in thermal

¹⁰ See, for example: [26]; [27].

sensation. Again, such optimums might be tuned to the thermal preferences of individual occupants, and account for seasonal changes in preferences across the year.

4.2 Assessment of Modeling Framework & Limitations

It is clear from the case study results that the HABIT framework yields a comprehensive set of energy and IEQ metrics, which can be used to holistically evaluate sustainable building design and operation strategies that work in tandem with – and not in spite of - realistic adaptive occupant behaviors. In the current study, for example, a series of set point adjustment strategies were evaluated in the context of energy use, thermal comfort, and workplace productivity simultaneously. Results from the analysis clearly demonstrate the link between these key concepts, occupant behavior, and one another across several environmental conditioning possibilities. Moreover, these outcomes were simulated on the scale of a whole office building with a few hundred occupants – a substantial extension of previously reported behavior/energy co-simulations, which tend to focus on a single, private office. The whole building simulation capabilities of HABIT are particularly beneficial in enabling energy fuel source breakdowns from EnergyPlus for the purpose of benefit-cost analyses. As this study shows, such economic analyses add an important layer of interpretation to the energy and IEQ results that would not be apparent in evaluations that do not assign monetary values to simulation outcomes.

Limitations of the HABIT program concern the applicability of its agent-based behavior model in non-air-conditioned buildings and the efficiency of the general co-simulation exchange. The former issue is discussed in [9]. Regarding co-simulation efficiency, the use of a MATLAB wrapper to re-run the BCVTB multiple times adds to simulation overhead by requiring the BCVTB program to be opened and closed for each simulated run, with EnergyPlus warm up routines also re-running each time. One option going forward is to re-implement the co-simulation under a Functional Mockup Interface (FMI) standard approach, allowing the exchange to be managed directly from EnergyPlus (see [28] for more details). For now, a single HABIT run covering one month of the simulated case study building (15 zones, 297 occupants) takes about 6 minutes.

5. CONCLUSION

574 This paper has introduced a Human and Building Interaction Toolkit (HABIT) for simulating the
575 thermally adaptive behaviors and comfort of office occupants alongside building energy consumption.
576 The toolkit uses the Building Controls Virtual Test Bed (BCVTB) to co-simulate an agent-based behavior
577 model in MATLAB with a whole building energy model in EnergyPlus. The paper outlined this co-
578 simulation and its setup by users, and also described the agent-based, field-validated occupant behavior
579 algorithm that the co-simulation incorporates. To demonstrate how the toolkit might be used to inform
580 building design and operation, a series of behavior scenarios were simulated for a medium-sized office
581 building. A first round of simulations examined how energy and IEQ results changed across various
582 climates and between perimeter/core zones in the building; a second round of simulations then examined
583 these results on the whole building scale, for the Philadelphia climate only.

584 Results generally suggest that building managers can pair the use of more efficient local heating
585 and cooling options with strategic thermostat set point adjustments as a simple way of saving significant
586 amounts of energy (up to ~24/28% in heating/cooling months, respectively) while also promoting better
587 occupant thermal comfort outcomes. Here, however, it is shown that the source of energy being saved
588 must be considered, as personal heater use ends up *adding* to energy and emissions costs by replacing
589 natural gas space heating with comparatively more expensive, higher-emissions equipment electricity
590 from the new heater plug loads. Moreover, occupants' simulated work underperformance slightly
591 *increases* under both heating and cooling set point adjustment scenarios, and the monetary costs from
592 even these slight productivity changes overwhelm any financial benefits from energy savings. Given the
593 clear importance of the productivity outcome to the cost-benefit analysis, supporting work performance
594 models must be further developed against larger occupant datasets collected across multiple seasons and
595 geographical locations, to improve model accuracy and generality.

ACKNOWLEDGEMENTS

This work was supported by a U.S. National Science Foundation Graduate Research Fellowship.

REFERENCES

[1] T. Hong, H.W. Lin, Occupant Behavior: Impact on Energy Use of Private Offices, Lawrence Berkeley

- National Laboratory, Berkeley, CA, 2013.
- [2] F. Haldi, F., D. Robinson, The impact of occupants' behaviour on building energy demand, *Journal of Building Performance Simulation* 4(4) (2011) 323-338.
- [3] D. Bourgeois, C. Reinhart, I. Macdonald, Adding advanced behavioural models in whole buildings energy simulation: A study on the total energy impact of manual and automated lighting control, *Energy and Buildings* 38 (2006) 814-823.
- [4] H.B. Rijal, P.G. Tuohy, M.A. Humphreys, F. Nicol, A.A. Samuel, An algorithm to represent occupant use of windows and fans including situation-specific motivations and constraints, *Building Simulation* 4 (2011) 117-134.
- [5] C.M. Macal, M.J. North, Tutorial on agent-based modelling and simulation, *Journal of Simulation* 4 (2010) 151-162.
- [6] D. Robinson, U. Wilke, F. Haldi, Multi agent simulation of occupant's presence and behaviour. 12th Conference of International Building Performance Association, International Building Performance Association, Sydney, Nov. 14-16, 2011.
- [7] E. Azar, C. Menassa, A Conceptual Framework to Energy Estimation in Building Using Agent Based Modeling, 2010 Winter Simulation Conference, Baltimore, MD, IEEE, Dec 05-08, 2010.
- [8] C. J. Andrews, D. Yi, U. Krogmann, J.A. Senick, R.E. Wener, Designing Buildings for Real Occupants: An Agent-Based Approach, *IEEE Transactions on Systems, Man, and Cybernetics: Part A: Systems and Humans* 41(6) (2011) 1077-1091.
- [9] J. Langevin, J. Wen, P.L. Gurian, Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors, *Building and Environment* 88 (2015) 27-45.
- [10] U.S. Department of Energy, EnergyPlus Energy Simulation Software, Retrieved June 24, 2015, from: <http://apps1.eere.energy.gov/buildings/energyplus/>
- [11] Lawrence Berkeley National Lab, Building Controls Virtual Test Bed, Retrieved June 24, 2015 from: <http://simulationresearch.lbl.gov/bcvtb>

- [12] W.T. Powers, Behavior: The Control Of Perception, Benchmark, New Canaan, CT, 1973.
- [13] J. Langevin, J. Wen, P.L. Gurian, Modeling thermal comfort holistically: Bayesian estimation of thermal sensation, acceptability, and preference distributions for office building occupants, Building and Environment 69 (2013) 206-226.
- [14] American Society of Heating, Refrigeration, and Air-Conditioning Engineers, Standard 55-2010: Thermal Environmental Conditions for Human Occupancy, American Society of Heating, Refrigeration, and Air-Conditioning Engineers, Atlanta, GA, 2010.
- [15] J. Langevin, P.L. Gurian, J. Wen, Tracking the human-building interaction: A longitudinal field study of occupant behavior in air-conditioned offices, Journal of Environmental Psychology 42 (2015) 94-115.
- [16] S. Borgeson, G. Brager, Comfort Standards and Variations in Exceedance for Mixed-Mode Buildings, Building Research and Information 39(2) (2011) 118-133.
- [17] L. Hendricken, K. Otto, J. Wen, P.L. Gurian, W. Sisson, Capital Costs and Energy Savings Achieved by Energy Conservation Measures for Office Buildings in the Greater Philadelphia Region, SimBuild 2012, International Building Performance Simulation Association, Madison, WI, Aug. 1-3, 2012.
- [18] Building Technologies Program, Building Science-Based Climate Maps, U.S. Department of Energy, Washington, D.C., 2013.
- [19] T. Hoyt, E. Arens, H. Zhang, Extending air temperature setpoints: Simulated energy savings and design considerations for new and retrofit buildings 88 (2015), 89-96.
- [20] K.L. Jensen, J. Toftum, P. Friis-Hansen, A Bayesian Network approach to the evaluation of building design and its consequences for employee performance and operational costs, Building and Environment 44 (3) (2009) 456-462.
- [21] J. Berk, P. DeMarzo, Corporate Finance, The Core, third ed., Pearson/Addison Wesley, Prentice Hall, Upper Saddle River, NJ, 2014.
- [22] L.T. Johnson, S. Yeh, C. Hope, The social cost of carbon: implications for modernizing our

- electricity system, *Journal of Environmental Studies and Sciences* 3(4) (2013) 369-375.
- [23] L. Lan, P. Wargocki, Z. Lian, Quantitative measurement of productivity loss due to thermal discomfort, *Energy and Buildings* 43(5) (2011) 1057-1062.
- [24] G. Brager, M. Fountain, C. Benton, C., E.A. Arens, F. Bauman, A comparison of methods for assessing thermal sensation and acceptability in the field, *Thermal Comfort: Past, Present and Future*, Building Research Establishment, Garston, UK, 1993.
- [25] V. Loftness, V. Hartkopf, B. Gurtekin, D. Hansen, R. Hitchcock, R, *Linking Energy to Health and Productivity in the Built Environment*, GreenBuild, U.S. Green Building Council, Pittsburgh, PA, Nov. 12-14, 2003.
- [26] A. Lovins, *Transitions to Sustainable Energy Systems: Energy End-Use Efficiency*, InterAcademy Council, Amsterdam:, 2005.
- [27] B.C. Lippiatt, S.F. Weber, *Productivity Impacts in Building Life-Cycle Cost Analysis*. National Institute of Standards and Technology, Gaithersburg, MD, 1992.
- [28] X. Feng, D. Yan, T. Hong, Simulation of occupancy in buildings. *Energy and Buildings* 87 (2015) 348-359.

APPENDIX

[Please insert Figure A.1a-b around here.]

[Please insert Figures A.2a-b around here.]