Human Behavior and Energy Consumption in Buildings: An Integrated Agent-Based Modeling and Building Performance Simulation Framework

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Abstract

A framework is proposed to integrate Building Performance Simulation (BPS) and Agent-Based Modeling (ABM) using a regression surrogate model. Such integration helps overcome the limitations of BPS in modeling human behavior, and those of ABM in modeling building physics and energy systems. The framework is illustrated through a case study where the impact of uncertainty in human actions on the energy performance of a commercial building is quantified. Results indicate that the level of control given to occupants and facility managers over building systems highly influences the sensitivity of the building's energy performance to uncertainty in human actions.

Introduction

Background

There is a growing understanding that the energy consumed by buildings is highly affected by how occupants and facility managers operate various building systems (Azar and Menassa 2014a; Masoso and Grobler 2010). Studies over the past decade have proven the significant influence of human actions on building energy performance, confirming the crucial human role for efficient building operation (Colmenar-Santos et al. 2013; Duarte et al. 2013; Sanchez et al. 2007; Webber et al. 2006).

For instance, Webber et al. (2006) studied the after-hours power status of equipment in offices, schools, and medical buildings located in California, Pennsylvania, and Georgia. Results indicate that turn-off rates for most equipment are under 50 percent, showing a significant potential for energy saving from changes in the energy use patterns of occupants. Similarly, Sanchez et al. (2007) audited 16 buildings in various North American cities and observed low-turnoff rates for various office equipment categories. Masoso and Grobler (2010) confirm the previous findings and highlight the significant quantities of energy wasted during unoccupied building hours. The authors audited buildings in South Africa and Boswana and showed that 56% of the energy is consumed during non-working hour, as opposed to only 44% when the buildings are occupied.

In parallel to the role played by occupants, facility managers have the important responsibility of properly managing and operating various building systems. When advanced building system technologies are used in buildings, building operation becomes a complex and challenging task. Consequently, facility managers may fail to cope with such increased level of complexity, leading to inefficient operation of various building systems. As observed by Colmenar-Santos et al. (2013) and Duarte et al. (2013), inefficiencies or failures in the control systems of complex building systems are very common, typically increasing building energy use by 10 to 30 percent.

In summary, uncertainty in how occupants and facility managers operate various building systems can lead to important variations in the energy performance of buildings. This is believed to significantly contribute to the large discrepancies observed between the predicted energy consumption levels (made during the design phase) and the actual energy consumption levels (observed during the operation phase) (Azar and Menassa 2011; Yudelson 2008; turner and Frankel 2008). Consequently, there is a growing need to better account for human actions in building energy modeling. This is expected to reduce the observed gap in performance and help devise human-focused solutions that reduce the energy intensity of the building sector.

Problem statement

Building performance simulation (BPS) is a commonly used technique to predict the energy performance of buildings (Crawley et al. 2008). However, BPS software typically lack the ability to capture individual actions of building users. Most BPS software (e.g., EnergyPlus, IES, eQuest, TRNSYS, etc.) assume generic profiles of energy consumptions (i.e., diversity profiles), which do not capture how occupants or facility managers can have different and/or changing energy use characteristics over time (Azar and Menassa 2014a; Crawley et al. 2008).

Acknowledging this limitation, researchers have turned to modeling human actions and behaviors in the built environment using techniques such as agent-based modeling (ABM). ABM is a decentralized modeling approach that allows representing occupants and facility managers as individual agents with personal attributes, as well as simulating uncertainty or changes in these attributes over time (Gilbert 2008). However, ABM does not have the BPS capabilities to simulate building physical systems, and as result, cannot translate changes in human behaviors to accurate energy predictions (Menassa et al. 2013). For instance, Azar and Menassa

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(2014b) used ABM to simulate changes in the energy use characteristics of occupants over time. However, the models developed in these studies did not account for the physical properties of the buildings such as the civil, mechanical and electrical systems. Consequently, simplistic assumptions were used to translate the changing energy use characteristics (i.e., behaviors) of occupants to estimates of building energy consumption.

In parallel, recent studies have coupled different ABM and BPS modeling tools in an effort to leverage their computational capabilities. For instance, Hong et al. (2015) developed an occupant behavior functional mock-up unit that supports co-simulation of ABM with various BPS tools. However, co-simulation methods in general present important limitations that can limit their applications such as the lack of compatibility between different coding languages and protocols, difficulties in data handling and analysis, as well as lengthy computing run-times (Yan et al. 2015; Menassa et al. 2014; Lee et al. 2013).

Objectives

This paper proposes an integrated modeling framework that combines the human and building simulation capabilities of ABM and BPS, respectively. It provides an alternative to the traditional co-simulation approach by using regressions surrogate models to integrate BPS in an ABM environment. The framework helps capture the human dimension of building performance and overcome the limitations of existing building tools and frameworks. It is then illustrated through an application on a prototype office building, where specific research questions are investigated:

(1) What is impact of uncertainty in human actions on building energy performance?

(2) How does this impact change for scenarios where building systems are controlled by occupants as opposed to a facility manager? The studied systems include lighting, equipment, and Heating, Ventilation, and Air conditioning (HVAC).

Methodology

Overview

The core of the proposed methodology consists of training a regression surrogate model that mimics the performance of a BPS model (e.g., developed using the EnergyPlus software), and integrating it in an ABM framework. This helps overcome the lack of integration between the two modeling approaches. Next, an uncertainty analysis is conducted using ABM on parameters related to human actions in buildings. The generated scenarios are then translated to building energy predictions within the ABM framework using the regression surrogate model. The steps of the methodology are illustrated in Figure 1 and detailed in the upcoming section.

Framework components

Firstly, a BPS model of the building under study is needed, which is a prototype office building developed for the US Department of Energy (DOE) (Deru et al. 2011). A BPS model was developed for this building using the EnergyPlus software, and is available for download at US DOE (2014). This model, as well as other similar ones developed by DOE (2014), are commonly used for a variety of applications including the evaluation of building technologies and retrofits, building energy standards, green building certification, and other research activities.

Secondly, key BPS input parameters that are linked to building operation are then identified. These include lighting intensity (X_1), equipment intensity (X_2), occupied cooling setpoints (X_3), occupied heating setpoints (X_4), unoccupied cooling setpoints (X_5), and unoccupied heating setpoints (X_6). Then, 1200 combinations of the input parameters above are generated using a Latin hypercube sampling scheme. The simulated dataset using the BPS model is split between 80% for training and 20% for testing. It is important to note that the upper and lower limits for each parameter are set based on acceptable limits defined by building standards (ASHRAE 2013) as well as sensitivity analyses conducted in Azar and Menassa (2014a). The ranges are as follows. For occupied periods, cooling temperatures of 22-26°C, and heating temperatures of 18-22°C are used. As for unoccupied periods, cooling temperatures of 26-30°C, and heating temperatures of 14-18°C are used. Finally, for lighting and equipment energy consumption intensity, a maximum variation of ± 30% is applied to the base case energy intensity values of 19.9 W/m^2 and 10.8 W/m^2, respectively.

Thirdly, a MATLAB-EnergyPlus coupling engine is used to automatically run the EnergyPlus model using the sampled combination of parameters. A regression model is then trained resulting in a regression equation with X_1-X_6 as independent variables and the building's monthly energy consumption Y (in kWh) as dependent variable. Dummy variables (m_1-m_{11}) are added to the independent variables in order to distinguish between the different

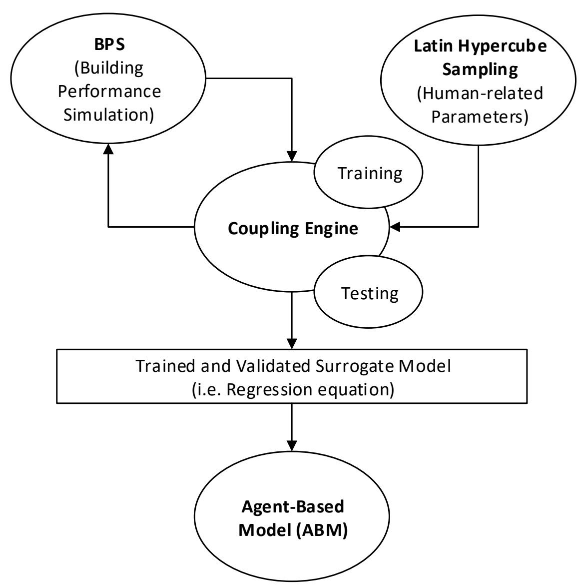

Figure 1: Methodology

months of the year. It is common to use N-1 dummy variables to avoid overfitting the model. The resulting surrogate model equation is presented in Eq. 1.

$$Y = 116.2 + 30.04 * X_1 + 27.81 * X_2 - 2.88 * X + 0.32 * X_4 - 2.09 * X_5 + 0.86 * X_6 + 0.91 * m_1 - 5.54 * m_2 + 8.49 * m_3 + 9.44 * m_4 + 27.06 * m_5 + 35.70 * m_6 + 44.48 * m_7 + 52.37 * m_8 + 36.56 * m_9 + 22.54 * m_{10} + 9.42 * m_{11} \quad (1)$$

The validity of the Eq. 1 is then evaluated using the testing dataset that was unseen by the model (i.e., 20% of the hypercube sampled dataset). Various tests and metrics are therefore applied to verify the goodness-of-fit of the model and ensure that the residuals are independent and uncorrelated (Pham 2006). First, an Adjusted R^2 of 0.975 and a Mean Absolute Percentage Error (MAPE) of 2.35% are obtained, confirming a very strong fit. Then, the Durbin-Watson test for autocorrelation and the Runs test for independence are conducted. P-values greater than 0.05 are obtained, as well as a Durbin-test value of 2.07, all confirming that the residuals of the surrogate model equation are independent and uncorrelated (Wooldridge 2015). The results of the above-mentioned tests confirm the adequacy of the regression equation to mimic the performance of the BPS model given the X_1-X_6 independent variables, and given their ranges of variation specified earlier.

Fourthly, and following the model training and validation, the regression equation is integrated in an ABM model of the building with 101 agents (100 occupants and one facility manager). Each agent has 6 main attributes, x_1-x_6, which represent the energy use characteristics or behaviors of agents towards the operation of the different building systems represented by X_1-X_6 in Eq. 1. For instance, if occupant *i* has an x_3 of 24°C, this means that that he/she will set the temperature setpoint of the HVAC system at 24°C, if given control over this system. In order to model the control level of each agent *i* over various systems, variables c_1-c_6 are introduced (a value of 1 means full control and 0 means no control). Eq. 2 describes how the agent-level variables, x_1-x_6 and c_1-c_6, combine to determine the building-level variables, X_1-X_6. X_1-X_6 are then used in Eq. 1 in order to estimate the building's monthly energy consumption values.

$$X_{1,2,..,6} = \frac{\sum_{i=1}^{Total\,nb.\,of\,agents}(x_i * c_i)}{Nb.of\ agents\ with\ control} \quad (2)$$

As an example, if the facility manager controls the occupied cooling setpoints, then his/her control level over this variable (i.e., c_3) is set to 1, while that of all occupants is set to 0. Consequently, and applying Eq. 2, the building-level X_3 value is equal to that of the facility manager, x_3. In this case, the number of agents with control is 1 (i.e., only the facility manager). As another example, if the occupants have equal control over the lighting systems, then X_1 is computed as the weighted average of the occupants' individual x_1 values. The number of agents with control is 100 in this case.

A general overview of the ABM framework's structure is presented in Figure 2. It illustrates a Unified Modeling Language (UML) diagram of the classes used in the model, namely the "building" and the "agent" classes. The UML diagram shows the names of the classes at the top, their list of attributes in the middle, and their list of methods or operations at the bottom.

Uncertainty analysis

The last step consists of using the ABM model to simulate uncertainty or variability in the agents' attribute, and translate them to energy consumption estimates using Eq. 1. Monte Carlo simulations are used for this purpose where uncertainty is applied to the initialization of the x_1-x_6 values of each agent. Given the lack of information in the literature on uncertainty in human behavior in buildings, various configurations (i.e., probability distributions) are used when simulating uncertainty. These include uniform, normal, and lognormal distributions. For consistency when comparing the different scenarios, the parameters of these distributions are chosen in a way to generate the same average values of x_1-x_6. These values correspond to the parameters of the base case BPS models that were obtained from DOE (2014). Such a measure helps focus the analysis on the difference in the distribution of the data rather assuming

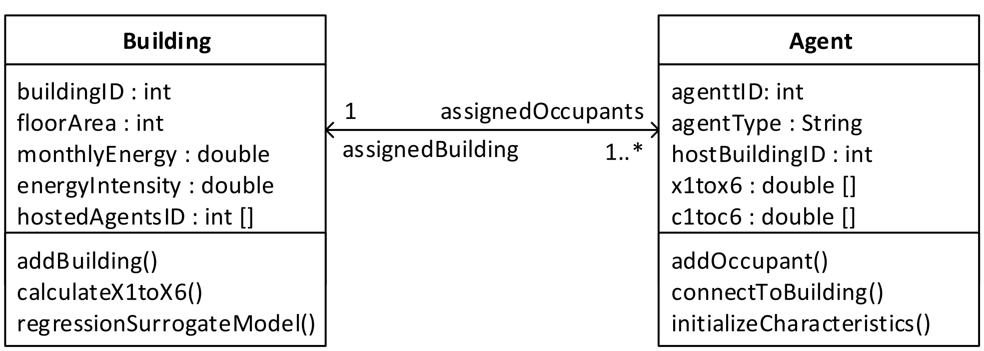

Figure 2: UML class diagram

different means without supporting evidence. Also for consistency, the upper and lower limit of these distributions correspond to same ranges of variation defined earlier.

For each scenario (i.e., distribution), 100 iterations of the model are run to study the variability in the results given the stochastic nature of the model. Finally, the entire process is repeated 3 times, one run with a total control given to occupants over building systems (i.e., no facility manager control), another run with the opposite case of full facility manager control (i.e., no occupants control), and a final run with equally split control between the occupants and the facility manager. In this case, if the facility manager's occupied cooling set point variable (x_3) is 22°C, and the average of all occupants is 24°C, then the building is assigned an X_3 value of 23°C.

Results and discussion

The results of all the tested scenarios are summarized in Figure 3. Each one of the 9 graphs illustrates the estimated energy intensities of the building for a specific control configuration (i.e., full occupant control, shared control, and full facility manager control) and a specific distribution when simulating uncertainty (i.e., uniform, normal, and lognormal). As mentioned earlier, 100 iterations are performed for each configuration of parameters; each dot in this case is the result of one run. Box-and-whisker plots are overlaid on the data points in order to better illustrate the variability and spread of the results. Two main trends can be observed in the results of Figure 3 as detailed in the upcoming sub-sections.

Impact of control levels

There is a clear increasing trend in the variability between the runs (i.e., building energy intensity results) when moving from the scenarios with full occupancy control to ones with full facility manager control (i.e., from left to right in Figure 3). In the former case, the control of the building is divided between its 100 occupants, therefore, the simulated uncertainty in the occupants' energy use characteristics is mostly cancelled out. In such scenario, the risk of observing large variations in building energy performance is low. However, the flexibility to improve this performance is also low, as shown in the box-and-whisker plots' boundaries that are within the narrow range of 220-240 kWh/m^2. Therefore, a large portion of the occupants needs to simultaneously adopt more energy efficient practices in order to shift the building's energy intensity towards lower values (e.g., raising HVAC set points to minimize cooling or reducing equipment and lighting use afterhours). This can in part explain why

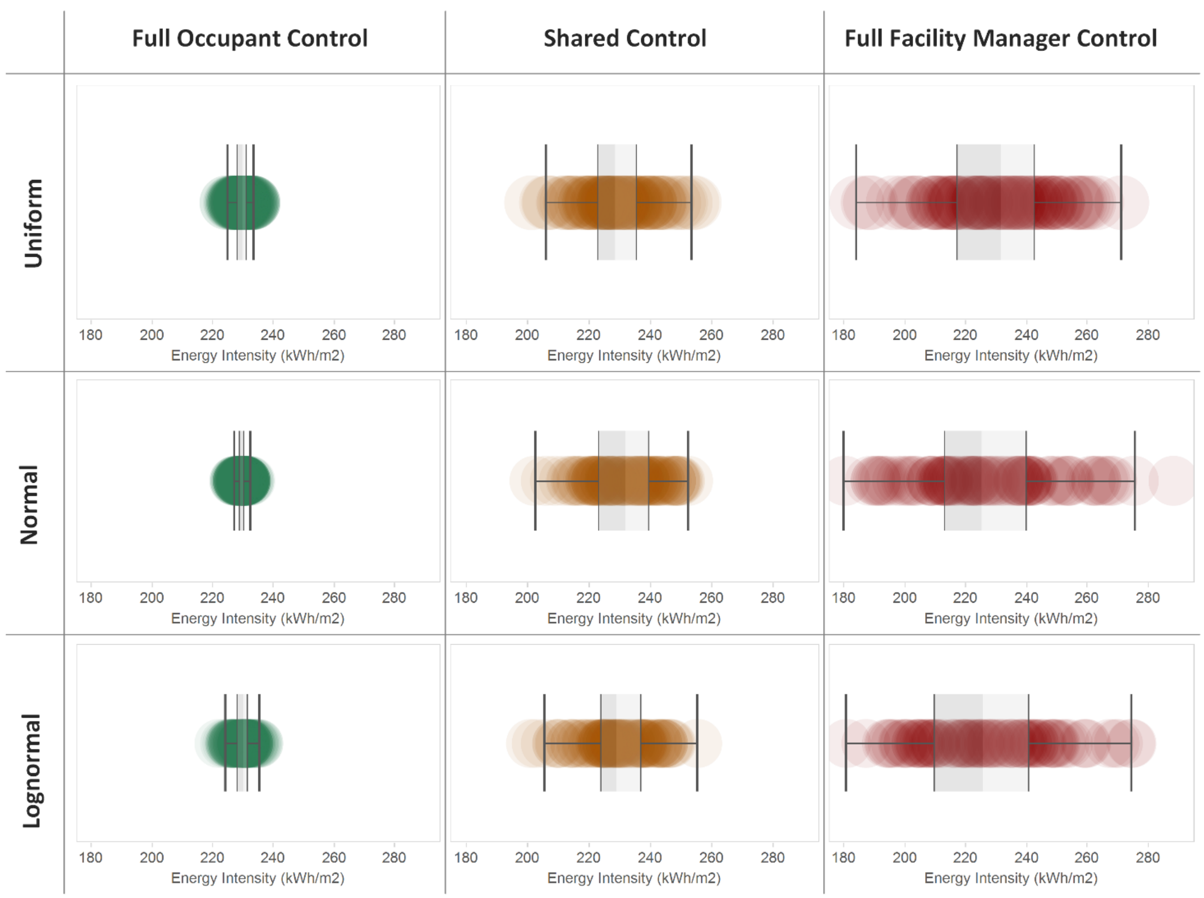

Figure 3: Uncertainty Analysis Results

interventions such as energy education or feedback mechanisms often fail to make strong and lasting changes in building energy performance.

On the other hand, in the scenarios with full facility manager control, larger variations are observed with energy intensity values ranging from 180 and 280 kWh/m^2. This is due to the direct link between the single facility manager energy characteristics (x_1-x_2) and those of the building (X_1-X_6), where any uncertainty in the former directly translates to an uncertainty in the latter. In such scenario, the risk of observing large variations in building performance is high. In parallel, the potential to achieve low energy intensity levels (e.g., kWh/m^2) is higher than the scenarios with full occupant control. The findings confirm and reinforce the crucial responsibility of facility managers in ensuring an efficient operation of various building systems. The failure to do so can have important negative consequences on building energy performance, including large uncertainty or variability in energy building performance (Colmenar-Santos et al. 2013; Duarte et al. 2013).

Finally, the scenarios of shared control between the facility managers and the occupants show a middle ground between the two extreme scenarios presented earlier. The results shown in the middle column of Figure 3 are characterized by relatively moderate variations in the energy intensity results, while maintaining a relatively good potential for energy reductions.

Impact of uncertainty characteristics

The second main trend in the results of Figure 3 is the low impact of the distribution used to simulate uncertainty (i.e., uniform, normal, and lognormal) on the variability in energy intensity. As shown in the figure, the graphs in each column follow very similar patterns. To further confirm this observation, a one-way analysis of variance (ANOVA) of the means is conducted to determine whether the different distributions show a statistically significant difference in their means. The test is repeated for the three different levels of control separately (i.e., full occupant control, shared control, and full facility manager control). The tested hypotheses are as follows: H_0 – The three means for the runs with uniform, normal, and lognormal are equal, and H_1 – The three means are different. The results of the ANOVA tests are summarized in Table 1. All p-values are greater than 0.05, failing to reject the null hypothesis. Therefore, we are 95% confident that the means of the runs with different uncertainty distributions are equal. It is important to note that given the lack of available data on human behavior in buildings, it is common to test different variations of uncertainty, similar to what was done in this paper. However, the results of Figure 3 and Table 1 motivate the need to further investigate this practice as part of future research.

Discussion, limitations, and future work

While the results presented in this section cannot be directly generalized to other buildings, they shed light on the significant role of control allocation on the overall performance of building systems. Such results are very significant given the trend over the past decades to increase building automation and reduce occupants' control over various building systems. In practice, and as shown in this paper, centralizing the decision-making of building operation with facility managers can lead to a high variability in building performance (e.g., from mishandling building systems or adopting inefficient energy use patterns). It is therefore essential to expand the recent interest in the literature to study occupants' actions and behaviors to include those of facility managers. Then, a study of the ultimate level of control given to each stakeholders can be assessed in order to minimize uncertainty in building performance while preserving a certain flexibility to lower the consumption of energy.

Table 1: ANOVA results

Control groups	F-Statistic	P-value
Occupants	0.258	0.773
Shared control	0.498	0.608
Facility manager	0.355	0.701

It is also important to acknowledge some of the limitations of the current study, which can guide future research on the topic. First, human behavior is modeled by aggregating the energy use characteristics of occupants into single parameters (e.g., zone-level temperature set points). Future research can consider expanding the model to connect individual human actions to the operating schedule of specific building systems in a more direct manner, as well as accounting for the interactions of occupants in shared spaces. Such step would require gathering large sets of occupant-level behavior data, which was beyond the scope of the current study. Additional factors can also be included such as water consumption patterns or the operation of windows and shades. Finally, additional data can help provide more realistic distributions when simulating occupant behaviors and their level of control of various building systems. A good example to follow is the work of Langevin et al. (2014), who developed an ABM of occupant behavior using data from a one-year field study.

Conclusion

An integrated BPS-ABM approach is proposed in this study to incorporate and study human actions in building energy modeling. The proposed framework consists of training a regression surrogate model to mimic the performance of a BPS model, and integrate it in an ABM framework where uncertainty in human actions can be studied. The proposed framework is then illustrated through a case study where the impact of uncertainty in human actions on building energy performance is assessed. Results indicate that the level of control that occupants and facility managers have over various building systems dictates how the building performs under uncertainty in human actions and energy use patterns. On the one hand, high control for occupants reduces the energy performance risk but also reduces the opportunities for energy savings. On the other, high control for facility managers results in a high potential for energy reduction but increases the performance risk. The findings of this study motivate the need to further research and develop energy management solutions that involve both occupants and facility managers. Such an integrated and participatory approach can help ensure that different stakeholders understand and act upon their responsibilities in operating their built environment efficiently.

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