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Integrating building performance simulation in agent-based modeling using regression surrogate models: A novel human-in-the-loop energy modeling approach

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A B S T R A C T

Building Performance Simulation (BPS) is an established method used in the design phase of buildings to predict energy consumption and guide design choices. Despite their advanced abilities to model complex building systems, BPS tools typically fail to account for different and changing energy use characteristics of building occupants, contributing to important prediction errors. In parallel, Agent-Based Modeling (ABM) has emerged in recent years as a technique capable of capturing occupants' dynamic energy consumption behaviors and actions. However, ABM lacks the building simulation capabilities to account for the complexity of various building systems in energy calculations. This research proposes a new modeling framework that integrates BPS in ABM using trained regression surrogate models. The framework is unique in its ability to (1) simulate energy use attributes of building occupants and facility managers, (2) translate those attributes to robust energy consumption estimates, and (3) help quantify the impact of uncertainty in human actions on the performance of the built environment. The framework is tested and illustrated in a case study on a prototype office building. Results indicate that providing occupants with control over their building systems can mitigate the effect of uncertainty in human actions on the performance of the built environment.

1. Introduction

1.1. Background

There is a growing body of evidence that actions taken – or not taken – by building occupants and facility managers highly impact the energy consumption of buildings [1–5]. Wasteful energy consumption actions such as occupants leaving office equipment running afterhours, or facility managers failing to detect faults in air conditioning systems, are in fact very common in commercial and residential buildings. For instance, studies by [4] and [5] indicate that more than 50% of equipment in office buildings are typically running during unoccupied periods. In parallel, [2] and [3] found that failures or inefficiencies in the control systems of complex commercial buildings are very common, leading to significant increases in total energy consumption levels.

Building Performance Simulation (BPS) is an established method to predict the energy consumption of buildings and help understand drivers of energy consumption. It is mostly used by designers and engineers to choose and size various building systems (e.g., heating and cooling systems), identify retrofit options, benchmark building performance, or evaluate building standards and specifications [6,7]. While BPS software such as Energy Plus, IES and eQuest, are very powerful in simulating the "technical" characteristics and performance of building systems, they typically fail to account for the uncertainty in this performance from "human" related actions and behaviors. This is contributing to errors in the energy estimates ranging from 30 to 100%, when compared to monitored consumption levels during operation [8,9].

To overcome these barriers, researchers in recent years have turned to Agent-Based Modeling (ABM). Unlike other simulation methods such as System Dynamics (SD) or Discrete Event (DE), ABM is a decentralized simulation technique where the general behavior of a complex system emerges from the interactions of its individual agents [10,11]. An important advantage of ABM over other methods is its bottom-up structure, which allows simulating complex social dynamics among agents. Agents can represent different building stakeholders (e.g., occupants or facility managers) with different attributes such as energy consumption behaviors. Through their control of their built environment, agents affect the level of energy

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Nomenclature

ABM	Agent-based modeling
ACH	Air changes per hour
ANN	Artificial neural network
BPS	Building performance simulation
CL	Control level
EUC	Energy use characteristic
FM	Facility manager
HVAC	Heating ventilation and air conditioning
LHS	Latin hypercube sampling
MAPE	Mean absolute percentage error
R^2	Coefficient of determination
$R_{adj}{}^2$	Adjusted coefficient of determination
SHGC	Solar heat gain coefficient
SSE	Sum of square errors
TSS	Total sum of squares
UAE	United Arab Emirates
US DOE	United States Department of Energy

consumed by the building. Also, agents can potentially change their behaviors due to interactions with their built environment or their peers [12,13].

1.2. Problem statement

In recent years, ABM has been used in various studies to model different and dynamic energy consumption behaviors of occupants [12–21]. While these studies are important steps towards a better accounting of human drivers of energy consumption, they present important limitations that need to be addressed:

First, unlike BPS tools, agent-based models are not equipped to predict building performance while accounting for building material and systems' characteristics, as well as external factors such as weather conditions. Consequently, simplistic assumptions are oftentimes made to translate human behaviors and actions to building energy predictions (e.g., [12,14,16]).

Second, most studies focus on a single occupancy action (e.g., light switching or window opening patterns), limiting the scope of results to the particular action that is considered. Furthermore, the same studies do not differentiate between end-uses typically controlled by occupants (e.g., plug-loads), and ones controlled by facility managers (e.g., air conditioning) (e.g., [18,21]).

Finally, some studies propose integrating ABM with BPS using a real-time coupling approach, where different modeling tools need to be simultaneously running and communicating. However, these studies face important limitations related to the lack of compatibility between different software programs, coding languages and protocols, as well as the resulting challenges in processing and analyzing data (e.g., [22,23]).

In summary, ABM is helping researchers overcome the limitations of traditional BPS methods, which do not account for different and dynamic energy use behaviors of building occupants. In parallel, current ABM studies are limited by their lack of energy estimation capabilities and scope of application. There is a growing need to merge the capabilities of BPS and ABM to accurately simulate building performance, while accounting for the varying energy use characteristics of building users, namely occupants and facility managers.

1.3. Objectives

This study proposes an integrated approach to incorporate BPS in ABM using trained regression surrogate models. A proof-of-concept model is developed and validated, with the following objectives: (1) simulate the "physical" layer of the building consisting of its civil, mechanical, and electrical systems; (2) simulate the "human" layer of a building environment, consisting of occupants and facility managers, who can have different energy consumption attributes and patterns; (3) integrate the two layers to translate changes in human attributes to accurate building energy consumption levels; and (4) illustrate the capabilities of the framework by quantifying the impact of uncertainty in human actions on the performance of the built environment.

Achieving these objectives will help overcome the limitations of BPS and ABM, which typically lack the human and/or building physics modeling capabilities. This work will also set the ground for a new integrated and multidisciplinary approach needed to capture the human influence on building operation, and help devise effective human-focused energy conservation strategies.

2. Surrogate modeling techniques

Integrating BPS in ABM can be done through surrogate models, which are trained models that can mimic the behavior of a complex system such as a BPS, but in a simplified, flexible, and easy-to-use format [24,25]. There are three major types or families of surrogate models: (a) reduced-order (white-box) models, based on physical equations, (b) grey-box models, based on both physical equations and parameters that are estimated through a statistical process, and (c) statistical (black-box) models, usually trained using a machine learning algorithm.

Reduced-order, or white-box, models are typically based on differential equations and require significant knowledge on building physics, as well as the interactions between different components [25]. In the absence of such knowledge, reduced-order models present the risk of oversimplification and might lead to inaccurate modeling of building systems and performance. Especially in regions where cooling loads prevail, reduced-order models typically fail to capture the complexity of consumption patterns [26]. Additionally, as discussed in the work of [24], although white-box models are based on parameters with physical significance and fundamental principles of physics, they often come with errors related to random variables, such as human behavior (e.g. window opening).

In parallel, grey-box models use stochastic differential equations to describe the physical model structure. They rely on statistical methods to estimate the system's unknown parameters, given measured or simulated data. Examples of building grey-box applications can be found in the works of [27] and [28]. For instance the authors of [27] applied grey-box modeling to simulate the thermal characteristics of a test building. In their approach, they did not consider human actions explicitly, but added a noise term in their model to account for all the unrecognized inputs. In another study [28], the authors developed a new method for building climate control using integrated temperature and humidity models, while accounting for the internal heat gains generated by occupants. In general, such models demonstrate higher predictive accuracy than reduced order models [24]. However, similar to the white-box models, they still require knowledge about building components and systems for accurate predictions [29].

Black-box models, on the other hand, use statistical or machine learning concepts to model and predict building metrics (e.g., energy consumption), given a set of inputs parameters. Their simplistic nature (input-output) and the rapid evaluation of various