AGENT-BASED MODELING OF COMMERCIAL BUILDING STOCKS FOR POLICY SUPPORT

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ABSTRACT

Achieving energy efficiency targets over time for commercial buildings strongly depends on the dynamics among the diversity of building owners and how they are affected by different physical and institutional constraints. To study this dynamic process and analyze the impact of energy efficiency policies, we propose tackling this issue by using an agent-based approach and developing a prototype called the Commercial Buildings Sector Agent-based Model (CoBAM), which considers commercial buildings of different types and in different climate zones as adaptive agents that are evolving internally and interacting with energy efficiency regulations. This paper describes the development of the simplified energy calculation engine, prototypical buildings, agent behaviors, and preliminary results of this research.

INTRODUCTION

Achieving higher energy efficiency at commercial buildings demands action by both policymakers and end users. Governments and societies, through policymakers, have developed regulations and goals for building design and retrofit, especially for commercial buildings. These goals must be achieved through a combination of market transformation activities and technology developments. Although the innovation and adoption of new technologies will be important, the development of strategies for deploying existing and emerging technologies at the required speed and scale is the most challenging factor. To verify whether an energy efficiency plan is achievable in the long term and to evaluate whether an energy reduction goal is met at a given time, researchers must be able to estimate the energy performance of an entire building stock over time. As this assessment is predictive, we cannot rely on metered usage data. In the implementation phase of a retrofit strategy, it is conceivable that metered usage data and/or auditing of individual buildings in the stock could be used to adjust policies; however, that approach is beyond the scope of this paper. From the perspective of the end user, building owners have diverse attitudes toward policies, incentives, and acceptance levels in terms of adopting energy efficient technologies for their buildings. Hence, to serve the need for policies that address energy efficiency, a building stock energy model must be capable of reflecting current energy performance and projecting the result of future interventions that result from policies and decisions from policymakers and building owners.

To estimate the energy consumption and the CO₂ emissions of building stocks over time, researchers have developed various modeling methods. Groups in Canada (Swan and Ugursal 2009), the United Kingdom (Kavgic et al. 2010), and the United States (Martinez-Moyano et al. 2010) reviewed some of the existing building stock models. Most existing top-down models are too general to capture the impact of physical interventions to building design and operation, whereas most existing bottom-up models are too computationally intensive to model diverse retrofit technologies and owner preferences (regarding energy and cost). To contribute to the building stock modeling community from a different perspective, Martinez-Moyano et al. (2011) proposed an agent-based approach to tackling this issue and developed a prototype called CoBAM. The objective of the CoBAM project is to study infrastructure, policy, and behavioral factors relevant to meeting sector-wide energy efficiency targets by developing an agent-based model of the commercial sector.

The following sections present the detailed approach used in CoBAM to create and simulate building stock agents with respect to building functional types, climate zone, vintage age, and owner preferences. We also develop algorithms to simulate building performance, degradation, and retrofit, which determine the variation of the energy, greenhouse gas (GHG) emissions, and energy costs of each type of building stock over time. A test case is demonstrated in the end of this paper.

METHODOLOGY

In the development of CoBAM, we have used knowledge and insights about the commercial buildings sector identified in the literature and as reported in Martinez-Moyano et al. (2010). In addition, we draw on public data sources and on the modeling approach used to characterize sector participants and their decision and interaction processes. In this section, we describe the organizing framework and the modeling approach used.
Simplified Building Energy Calculator

ISO 13790, “Energy Performance of Buildings—Calculation of Energy Use for Space Heating and Cooling” (ISO 2008), specifies just such a simplified building energy calculation approach, which was developed by the European Committee for Standardization (CEN) in its Energy Performance of Buildings Directive (EPBD) program, as well as by its original developers (Van Dijk and Spiekman 2003; Van Dijk et al. 2005). This standard provides different types of calculation methods, including a seasonal or monthly method, a simple hourly method, and a detailed simulation method. In this study, the monthly method is adapted to serve the objectives.

In order to calculate the energy consumption of heating and cooling, this monthly energy model uses the overall efficiencies of the building’s energy generation and distribution systems. Models compute total building distribution loss from normatively defined factors for pipe and duct losses and energy waste due to simultaneous heating and cooling. Models define heating/cooling generation efficiencies as annual system efficiencies that take into account their efficiency under dynamic conditions throughout the year. Using overall efficiencies, this method computes energy consumption levels for heating and cooling from thermal needs. In order to calculate other building energy consumption levels (such as for lighting, equipment, fans, pumps, and domestic hot water), a set of EPBD standards (Hogeling and Van Dijk 2008) describe the empirical coefficients for estimating the performance of building systems, the consumption levels of delivered and primary energy, and GHG emissions.

Prototypical Buildings

This task develops a set of prototypical building energy models that represent the design and operational characteristics of typical commercial buildings in the United States. These prototypical building energy models should represent the diversity of building locations, forms, material composition, HVAC systems, and plug loads that are defined as inputs for the building energy calculator introduced previously. Meanwhile, this study also proposes a method for aggregating these building energy models to estimate the energy consumption of stocks of commercial buildings without simulating every building in the stock.

Representation

It is impractical to model every single commercial building in the building stock energy simulation. Thus, these prototypical building models are created to represent a small number of prevalent building types, the energy consumptions of which are then multiplied by weighting factors to scale the estimation up to the national level. The U.S. Department of Energy (DOE) created reference buildings (DOE 2009) for public research purposes. These models of different building design and operation specifications consist of 16 building types, three age vintages (new, post-1980, and pre-1980), and 16 climate zones. These models are all specified as detailed input files for dynamic simulation tools, such as DOE-2 and EnergyPlus, and are hypothetical models with predetermined operations that meet certain minimum requirements. Using these models to generate useful information involves running thousands of models to cover all of the conditions in the nation. Considering the complexity of every single model, such a massive simulation project can only be performed by developing automated software and using supercomputers. Several recent projects were conducted by the National Renewable Energy Laboratory (Griffith et al. 2008) and Pacific Northwest National Laboratory (Zhang et al. 2010). This study has adopted these 16 commercial reference building types and converted them as base models for the proposed simplified energy calculation. The prototypical building types considered in this project are: large office, medium office, small office, warehouse, stand-alone retail, strip mall, primary school, secondary school, supermarket, quick-service restaurant, full-service restaurant, hospital, outpatient health care facility, small hotel, large hotel, and mid-rise apartment. In applications, this list of building types is neither all inclusive nor necessary to be used for all of the locations. The rest of building types in the literature have different energy consumption patterns and cannot be modeled in a simple straightforward manner. However, because their share in national electricity consumption is small, they are ignored in this study. Meanwhile, a subset of buildings from this list may still form a reasonable abstraction of reality.

Aggregation

Aggregation of building energy consumption exists in many aspects of this study. Aggregation of building energy models on the national level typically uses weighting factors to scale up the energy use of individual prototypical buildings. Because statistical data for real buildings are insufficient, it is difficult to develop reasonable weighting factors to use for national-level computations and almost impossible to do so at the state level or lower (i.e., for smaller regions) (Deru et al. 2011). Jarnagin and Bandyopadhyay (2010) analyzed the McGraw-Hill (2011) database from 2003 to 2007 to develop weighting factors for the new construction reference buildings. However, weighting factors for existing buildings have never been developed in the United States.

Recent attempts to aggregate building energy models at the state or city level benefit from the development of Geographic Information Systems (GIS). Geographic information research and technologies have been developed over four decades, migrating from the mainframe to the workstation to the desktop.
and now to the latest laptop and mobile devices. States that use current GIS technologies have collected massive amounts of data for (1) capturing individual-based data for urban structure and dynamics analysis; (2) modeling urban complexity and hierarchy; (3) simulating urban transportation systems; and (4) analyzing urban growth, changes, and impacts. Several recent studies (Meinel et al. 2009; Tanikawa and Hashimoto 2009) use urban GIS data to explore the impact of urban built form and evolution to the demand of heating energy and construction material at urban scale. The development of GIS databases enables another way of performing aggregation, which is to scale energy use up by actual building floor areas in the city.

This study uses the second aggregation approach mentioned above. This approach considers a cluster of buildings of the same type (using the same prototypical model) within the same region (using the same weather data) to be one stock (Figure 1). This stock is defined as one agent in the agent-based model created.

Figure 1 Four Levels of Aggregation

Agent-Based Modeling and Simulation (ABMS)

In the development of CoBAM, we use an agent-based modeling approach. Agent-based modeling and simulation is a technique for bottom-up modeling that provides an alternative perspective to those that can be attained by using optimization or general-equilibrium approaches (North and Macal 2007). In agent-based simulations, system behavior emerges from the behaviors of interacting agents. An agent can be an autonomous and potentially self-directed entity that is characterized by a set of attributes. Normally, in agent-based models, agents are situated in a system in which they interact with each other and their environment. The behavior of an agent is usually driven by its goals. In achieving these goals, specific and predefined rules guide the agents’ actions when interacting with the other agents. An agent has the potential to learn based on environmental information and a set of predefined rules. Climate and policy impacts are modeled as the environment. In general, the proposed agent-based model follows the logics shown in Figure 2.

CoBAM is developed in the open-source Repast Symphony environment. The architecture of the model is designed in generic terms to allow for scalability of features, number of agents modeled, and features of the agents. This development philosophy allows for flexibility in model components and offers scalability potential to avoid the need to restructure the model in major ways when additional detail or complexity is added.

AGENT BEHAVIORS

In the ABMS, every building owner agent determines its own behavior when it gets activated. These behaviors can be modeled as a combination of performance degradation and energy retrofit.

Performance Degradation Model

The energy efficiency of building systems degrades every year. In this study, the building performance degradation process is captured with, and defined as, the annual degradation ratio (ADR). The building energy performance decreases by applying a set of degradation factors to the input parameters. For a degrading building parameter \(j\) of building agent \(i\), its value at year \(t+1\), denoted as \(X_{ij}^{(t+1)}\), is:

\[
X_{ij}^{(t+1)} = (1 + ADR)X_{ij}^{(t)}
\]

According to this degradation function, the performance of each building component is consistently reduced every year until system maintenance is performed to that component. In that case, \(X_{ij}^{(t)}\) is reset to its initial value. New technologies can also be applied to achieve higher performance than used for the initial value.

\(^1\) See http://repast.sourceforge.net/.
To quantify building performance degradation, Brown et al. (1996) reviewed past studies of the persistence of energy savings from demand-side management programs and determined an average annual degradation of 0.05–0.20. Hu (2009) surveyed multiple sources in the literature and concluded that the average degradation coefficient due to the partial load operation of heat pumps is 0.10–0.26 for heating and around 0.066 for cooling. In addition, CEN/TC 169 (2006) showed a normative annual maintenance factor of 0.20 for lighting power. In this study, three building model parameters are considered to degrade annually: (1) energy use intensity of the lighting system (ADR_light, unit: W/m²), (2) the cooling system COP [coefficient of performance] (ADR_cool, unit: kW/kW), and (3) overall efficiency of the heating system (ADR_heat, unit: kW/kW). In reality, the ADR values vary by case and have relatively significant impacts to the projection of building energy efficiency levels. Thus, multiple scenarios of degradation shall be considered when applying this model to compare policy making decision options. In this prototype, we conservatively assume the values of ADR_light, ADR_cool, and ADR_heat to be 0.05, −0.05, and −0.05, respectively. Using these values means that the power intensity of lighting fixtures increases by 5% every year, and the efficiencies of cooling and heating systems decrease by 5% every year.

**Energy Retrofit Model**

A large variety of commercial building energy retrofit technologies exist in practice. To model building energy retrofit, we select some common retrofit technologies and group them following the hierarchy of Category, Energy Efficiency Measure (EEM), and Retrofit Technology, as shown in Table 1. Each technology has its physical and financial parameters. During the simulation, when a retrofit technology is chosen by a building owner, affected input parameters ($X_i$) of the building energy model corresponding to that selected technology are updated according to the retrofit equation ($f_j$) in Table 1. This update process derives reduced building energy consumption through the simplified building energy calculator in the next time step (year). This retrofit process can be described as:

$$X_{i,j}^{(t+1)} = f_j(X_{i,j}^{(t)})$$

After quantifying how to retrofit, we also need to define when. We assume that the owner of a building decides to perform retrofit when a performance indicator of that building grows beyond a threshold defined by the policy maker. At the end of every simulated year $t$, building owner $i$ evaluates the performance indicator, denoted as $P_{ti}$. A smaller $P_{ti}$ indicates a lower energy use. If $P_{ti}$ is greater than the policy threshold of that year, denoted as $P_{t \text{th}}$, a retrofit is executed. Depending on the purpose and reference of simulation, many outcomes of building energy calculation could serve as performance indicators, for instance, delivered energy use intensity (EUI), CO₂ emissions, and the energy performance coefficient (EPC), which is defined as the actual energy use of a building divided by a reference value representing the “typical” energy use of similar buildings. In the current CoBAM, we use delivered EUI as the performance indicator. However, we observe that across different building types, EUI does not provide a generic measure, and it is left to the individual policy makers to determine the optimal target performance of each building type. A better performance indicator to trigger the retrofit of different building agents could be a normalized EPC. This philosophy will be tested and implemented in future work.

**Agent States**

As an overall impact of performance degradation and energy retrofit, building model parameters over time are modeled as time series, each year’s state of which depends on its state in the previous year:

$$X_{i,j}^{(t+1)} = \begin{cases} 
X_{i,j}^{(t)}, & \text{if } P_{ti}^{(t)} \leq P_{t \text{th}}^{(t)}, \text{ non-degrading param.} \\
(1 + \text{ADR})X_{i,j}^{(t)}, & \text{if } P_{ti}^{(t)} \leq P_{t \text{th}}^{(t)}, \text{ degrading param.} \\
f_{j}(X_{i,j}^{(t)}), & \text{if } P_{ti}^{(t)} > P_{t \text{th}}^{(t)}
\end{cases}$$

where $X_{i,j}^{(t+1)}$ is a set of building model parameters of agent $i$ at year $(t+1)$, and $X_{i,j}^{(t)}$ is its value at year $t$ when the building owner decides whether to retrofit. This process is computed within ABMS. Figure 3 illustrates the UML State Diagram of this process.

![Figure 3 UML State Diagram for Commercial Building Agents](image-url)
<table>
<thead>
<tr>
<th>EEM</th>
<th>Retrofit Technology RT&lt;sub&gt;j&lt;/sub&gt;</th>
<th>Affected Parameters X&lt;sub&gt;j&lt;/sub&gt; (Unit)</th>
<th>Retrofit Eq.:&lt;br&gt;( f_j = \frac{X_j^{(1)}}{X_j^{(0)}} )</th>
<th>Invest.&lt;sup&gt;a&lt;/sup&gt; ($/m&lt;sup&gt;2&lt;/sup&gt; Ref. Area)</th>
<th>Ref. Area</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Envelope</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Roof insulation</td>
<td>R5 insulation: extruded polystyrene, 25 PSI&lt;sup&gt;ii&lt;/sup&gt;, 1”</td>
<td>Roof U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>( \frac{1}{X_j^{(0)} / X_j^{(1)}} )</td>
<td>10.66</td>
<td>Roof</td>
</tr>
<tr>
<td></td>
<td>R20 insulation: extruded polystyrene, 25 PSI, 4”</td>
<td>Roof U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>( \frac{1}{X_j^{(0)} / X_j^{(1)}} )</td>
<td>35.63</td>
<td>Roof</td>
</tr>
<tr>
<td>Wall insulation</td>
<td>R5 insulation: extruded polystyrene, 25 PSI, 1”</td>
<td>Opaque Wall U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>( \frac{1}{X_j^{(0)} / X_j^{(1)}} )</td>
<td>12.16</td>
<td>Wall</td>
</tr>
<tr>
<td></td>
<td>R15 insulation: extruded polystyrene, 25 PSI, 3”</td>
<td>Opaque Wall U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>( \frac{1}{X_j^{(0)} / X_j^{(1)}} )</td>
<td>23.03</td>
<td>Wall</td>
</tr>
<tr>
<td><strong>Window upgrade</strong></td>
<td>Double glazing clear U2.95 SC0.88</td>
<td>Window U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>2.95</td>
<td>12.16</td>
<td>Window</td>
</tr>
<tr>
<td></td>
<td>Double glazing low-e U2.90 SC0.55</td>
<td>Window U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>2.9</td>
<td>30.45</td>
<td>Window</td>
</tr>
<tr>
<td></td>
<td>Triple glazing low-e 12mm argon</td>
<td>Window U-factor [W/(m&lt;sup&gt;2&lt;/sup&gt;·K)]</td>
<td>0.8</td>
<td>85.00</td>
<td>Window</td>
</tr>
<tr>
<td><strong>Shading device</strong></td>
<td>Overhangs, fins, blinds</td>
<td>Window Shading Coefficient</td>
<td>0.7</td>
<td>100.00</td>
<td>Window</td>
</tr>
<tr>
<td><strong>Inf. reduction</strong></td>
<td>Infiltration reduction</td>
<td>Infiltration Rate (ACH&lt;sup&gt;iii&lt;/sup&gt;)</td>
<td>0.9*X&lt;sup&gt;(0)&lt;/sup&gt;</td>
<td>5.00</td>
<td>Floor</td>
</tr>
<tr>
<td><strong>Cooling and heating system retrofit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooling system</td>
<td>Cooling system tune-up</td>
<td>Cooling COP (kW/kW)</td>
<td>0.9*X&lt;sup&gt;(retro)&lt;/sup&gt;</td>
<td>1.08</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td>High-efficiency chiller</td>
<td>Cooling COP (kW/kW)</td>
<td>7.3</td>
<td>14.05</td>
<td>Floor</td>
</tr>
<tr>
<td>Heating system</td>
<td>Heating system tune-up</td>
<td>Heating Efficiency (kW/kW)</td>
<td>0.9*X&lt;sup&gt;(retro)&lt;/sup&gt;</td>
<td>1.08</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td>High-efficiency natural gas boiler</td>
<td>Heating Efficiency (kW/kW)</td>
<td>0.96</td>
<td>89.51</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td>Electric rooftop heat pump</td>
<td>Heating Efficiency (kW/kW)</td>
<td>3.4</td>
<td>216.54</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heating Energy Carrier (1: Electricity, 2: Natural gas)</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heating Energy Carrier</td>
<td>1</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>Cooling COP (kW/kW)</td>
<td>3.5</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Ground source heat pump</td>
<td>Heating Efficiency (kW/kW)</td>
<td>4.9</td>
<td>380.80</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Heating Energy Carrier (1: Electricity, 2: Natural gas)</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cooling COP (kW/kW)</td>
<td>8.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Energy recovery</strong></td>
<td>Air-to-air heat wheel</td>
<td>Heat Recovery Efficiency</td>
<td>0.7</td>
<td>5.00</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td>Pump system upgrade</td>
<td>VSD&lt;sup&gt;iii&lt;/sup&gt; pump system</td>
<td>Pump Control Factor (3: No auto-control; 2: More than 50% auto-control)</td>
<td>2</td>
<td>5.00</td>
</tr>
<tr>
<td><strong>Lighting</strong></td>
<td>Lighting fixture replacement</td>
<td>Lighting Power Intensity</td>
<td>8.6</td>
<td>8.82</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td>Day-lighting control</td>
<td>Day-lighting sensor factor (1: No sensor; 2: With sensor)</td>
<td>2</td>
<td>8.82</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td>Occupancy sensor</td>
<td>Occupancy sensor factor (1: No sensor; 2: With sensor)</td>
<td>2</td>
<td>8.82</td>
<td>Floor</td>
</tr>
<tr>
<td><strong>DHW</strong></td>
<td>Heater replacement</td>
<td>DHW&lt;sup&gt;iii&lt;/sup&gt; Efficiency</td>
<td>0.94</td>
<td>1.50</td>
<td>Floor</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DHW Energy Carrier (1: Electricity, 2: Natural gas)</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Plug</strong></td>
<td>High-efficiency appliances</td>
<td>Equipment power intensity (W/m&lt;sup&gt;2&lt;/sup&gt;)</td>
<td>0.7*X&lt;sup&gt;(0)&lt;/sup&gt;</td>
<td>2.40</td>
<td></td>
</tr>
</tbody>
</table>

<sup>i</sup> Building parameter values are denoted as follows: \( X_j^{(1)} \) is the value at year \( t \), \( X_j^{(1+1)} \) is the value at year \((t+1)\), \( X_j^{(0)} \) is the initial value at the beginning of simulation, and \( X_j^{(retro)} \) is the initial value after the previous retrofit.

<sup>ii</sup> Sources of these cost values include U.S. EIA (2009), Navigant Consulting (2007), Crawley (2008), Augenbroe et al. (2010), Wulfinghoff (2000), ISO (2008), and Mewis (2010). We have not yet found reliable references for the underlined values.

<sup>iii</sup> PSI = pounds per square inch; ACH = air change per hour; VSD = variable speed drive; DHW = domestic hot water.
Figure 3 depicts the following steps within each time step of the simulation:

1) The agent initially remains at its state in the previous time step.
2) If the performance indicator of the agent does not reach the retrofit threshold, the degradation loop starts to look up and update all degradation input parameters for the energy calculator. This action then ends the agent’s behavior at this time step.
3) If the performance indicator of the agent reaches the retrofit threshold, the retrofit loop starts to look up and update all retrofit input parameters for the energy calculator.
4) When the retrofit loop is finished, the degradation is then started as step 2.
5) Agent finishes the update process and brings its state to the next time step.

A TEST CASE

To demonstrate the use of CoBAM, we have created a population of 50 building stocks based on 10 building types (i.e., large office, medium office, small office, warehouse, retail, strip mall, supermarket, hotel, and mid-rise apartments), two U.S. climate zones (4A and 5A), and three vintage categories (new, post-1980, and pre-1980) all located in six representative cities of the region being modeled (i.e., all located in Illinois, specifically Chicago, Belleville, Bloomington, Quincy, Rockford, and Springfield, as shown in Figure 4).

**Scenarios of Simulation**

Three owner decision scenarios are modeled:

1) **No retrofit**: The building owner does nothing to improve the energy efficiency of its buildings, letting the building(s) degrade over time;

2) **Undirected retrofit**: When the threshold is met, the building owner randomly chooses one retrofit technology from Table 1; and

3) **Directed retrofit**: When the threshold is met, the building owner selects the 12 most effective retrofit technologies recommended by experts.

These three scenarios are designed to (1) capture likely extremes in a continuum of possible decision options that building owners may face, and (2) identify the resulting overall behavior if these decision strategies are adopted by building owners. We place these three scenarios into two “step-down” energy policies, of which Policy 2 is more restrictive than Policy 1:

1) **Policy 1**: Buildings are required to maintain their 2005-level energy use before 2010, reduce 10% by 2010, and reduce another 10% by 2020.
2) **Policy 2**: Buildings are required to maintain their 2005-level energy use before 2010, reduce 20% by 2010, and reduce another 20% by 2020.

**Results and Discussions**

We run the model for the period of 2005–2030 to calculate the yearly energy use of each agent. Figure 5 depicts the average EUI of all building stocks over 25 years of degradation and retrofit.

![Figure 5 Comparison of Average Delivered EUI under Different Decision Scenarios and Policies](image)

Figure 5 shows that the **No retrofit** scenario under both policies generates continually increasing EUI because no retrofit has ever been adopted, making the building stock increasingly inefficient. This trajectory can be considered as the “business-as-usual” path with no improvements attempted. Meanwhile, the other two decision scenarios under both policies both yield an overall reduction in energy use.

By comparing the results from all simulated cases, we can make two observations based on the results. The first is that the **Directed retrofit** scenario always yields a lower EUI than does **Undirected retrofit**. This result implies that having both awareness of and directed selection of the retrofit technologies results in more effective energy efficiency improvement. Although implementation of the **Directed retrofit** strategy always yields lower EUIs, the **Undirected retrofit** strategy is an acceptable strategy because it...
generates improvements that, while they are not as
dramatic, therefore allow for more frequent
improvements over time. Using the Directed retrofit
strategy generates changes that take more time to
degrad, resulting in longer periods between
improvement efforts and making the long-term result
closer to that of the Undirected retrofit strategy.

Another observation to be drawn from the results is
that a more restrictive policy regarding energy
efficiency yields lower building energy use across the
entire stock. In Undirected retrofit and Directed retrofit
scenarios, building EUIs decreased further
when policy thresholds were changed in 2010 and
2020. Since Policy 2 applies more pressure toward
energy reduction, EUIs of buildings under Policy 2
are generally lower than those in Policy 1. In this test
case, simulation results prove that energy efficiency
targets defined in Policy 1 and 2 are always
achievable. However, if there are fewer retrofit
technologies available in the market or if their energy
saving capability is not adequate, the building stock
may not be able to meet energy efficiency targets
after 25 years of continuous retrofit. Thus, as a
method and a tool, CoBAM could be used to justify
whether energy targets are achievable given a set of
retrofit technologies and their physical specifications.

Besides energy use figures, CoBAM also projects the
CO$_2$, NO$_x$, and SO$_x$ emissions of the simulated cities.
Figure 6 illustrates the CO$_2$ emissions projections of
the six cities simulated. In contrast to EUIs, CO$_2$
emissions are not averaged by gross building floor
area, so different cities have different annual CO$_2$
emissions because of their measured building floor
areas. In this test case, the actual building
composition and floor area are all assumed for the six
cities. Thus, we cannot learn anything at this time by
comparing the outcomes for different cities. In an
ongoing PhD study, the first author will collect floor
areas and building types from public GIS and tax
assessors’ databases. Then, the calculated CO$_2$
emissions can be validated against published data.

![Figure 6 CO$_2$ Emissions Projections of the Simulated Cities under Undirected Retrofit, Policy 2](image)

Other features of CoBAM include evaluation of the
effectiveness (i.e., energy reduction potential and costs) of retrofit technologies and capture of building
owner behaviors (i.e., different energy efficiency
goals and financial capabilities). These features will
be introduced in future publications.

CONCLUSIONS

This paper proposes an ABMS simulation method to
estimate the energy performance of multiple building
stocks over time. This model is built up via
aggregation of a set of prototypical building designs
calculated by a simplified building energy calculator.
Both performance degradation and energy retrofit
models determine the annual energy performance of
each building stock agent. Simulation results suggest
that policy-initiated changes to baseline decision
thresholds yield adequate results and tend to stabilize
the results observed. In addition, simulation results
support the idea that promoting energy efficiency
technologies, even in a random way, has the potential
to yield interesting results in the marketplace.

The work described in this paper implies that
achieving commercial building energy efficiency
targets most likely depends on the dynamics between
the various market participants and the way those
dynamics are impacted by different physical and
institutional constraints. Studying infrastructure,
policy, and behavioral factors relevant to meeting
sectorwide energy efficiency targets by developing
an agent-based model of the commercial buildings
sector generates promising results. CoBAM is still
under development and verification. Although
validation per se (the determination of the degree of
validity) is generally not achievable in models of
social systems, our approach is to increase our
confidence in the usefulness of the model for the
purpose intended. In this sense, we are interested in
gaining confidence in both the structure of the model
and in its simulation output. In addition, to increase
confidence in model results, we are looking at data
sources that can help us identify trends in behavior of
the system and will closely inspect model results and
its corresponding explanations with subject matter
experts and market participants.

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