A Novel Occupant-Focused Framework to Test Community-Scale Building Energy Feedback

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Abstract

A novel agent-based modeling framework is presented to simulate and test community-scale building energy feedback. The proposed framework expands the scope of previous studies in the literature that were mostly limited to testing feedback on individual, rather than group, of buildings. A case study of 35 office buildings indicates that comparative energy feedback involving occupants from different buildings leads to significantly higher energy savings than one with a single-building approach. The findings motivate the need for community-scale feedback initiatives, which are now made possible through recent advancements in information and communication technologies as well as social networking platforms.

Introduction

There is a growing body of evidence that providing building occupants with feedback about their use of energy can influence their current consumption patterns (Fischer 2008; Abrahamse et al. 2005). Promising results are particularly observed when the feedback provided to occupants includes information about the consumption patterns of people in their social circles (e.g., neighborhood or workplace), as it has shown to increase the social pressure on them to avoid extreme energy use behaviors (Gulbinas and Taylor 2014; Jain et al. 2013).

In recent years, researches have relied on modeling and simulation to test and improve the results of feedback methods (Azar and Menassa 2015; Anderson et al. 2013; Chen et al. 2012). A common technique used for this purpose is agent-based modeling (ABM), which is used to simulate the attributes of occupants (e.g., energy use behaviors), their social connections and networks, as well as the dynamics of their behaviors following exposure to feedback (Gilbert 2008).

Existing studies have mostly covered feedback interventions in individual buildings (i.e., comparative feedback between the occupants of a same building) (Azar and Menassa 2014b, 2011; Andreson et al. 2013; Menassa et al. 2013; Chen et al. 2012). However, there is a growing need to expand the scope of feedback interventions from individual to groups of buildings (e.g., community or city scale) (Gelazanskas and Gamage 2014; Wang and Taylor 2014; Xu et al. 2012). This is mainly driven by the emergence of tools and technologies that can connect people between buildings (Gelazanskas and Gamage 2014; Verbong et al. 2013). One such example is the smart metering technology, which opens the door for community-scale demand-side management programs (Gelazanskas and Gamage 2014). Another example is social media and its popular platforms (e.g., Twitter, Facebook, and Google+), which eliminate geographical barriers for people to interact and exchange ideas or adapt new behaviors (Wang and Taylor 2014).

This paper proposes an ABM framework to test feedback methods on a community-scale level, capturing social networks that can exist or can be induced within – and between – buildings. It provides the first test bed to experiment with the design of large-scale feedback interventions and identify configurations that can maximize energy savings. Two specific research questions are answered through a case study on 35 office buildings:

(1) Does connecting people within and between buildings significantly improve conservation when compared to the current single-building approach?

(2) Does the structure, or topology, of the social network of people impact the effectiveness of the feedback?

Literature review

This section is divided into two parts. The first part summarizes key studies that have employed ABM to simulate feedback interventions in buildings. The second part covers studies that highlight the need to expand feedback interventions from individual to groups of buildings.

In a study by Azar and Menassa (2014b), the authors developed an agent-based model to test how peer-pressure and occupancy interventions can alter the energy consumption behavior of occupants in individual buildings. Results reveal that the diffusion of energy conservation practices can be facilitated by increasing the social connectivity among building occupants. In general, social connections can form in one of two ways: (1) through spontaneous interactions between people sharing a building environment (e.g., peer-pressure between co-workers or interactions between neighbors), or (2) through induced measures such as normative feedback, which provides people with information about the energy consumption patterns of others in their social network or milieu (Xia et al. 2011). Chen et al. (2012) studied how the characteristics of a social network formed by residential building occupants can influence the effectiveness of energy feedback. Various occupancy intervention scenarios are considered and simulated,

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identifying the weights and the degree of networks as main influencing factors of the diffusion of energy-saving actions. The network size, on the other hand, did not have a significant impact on the observed energy savings. Finally, in a similar study by Anderson et al. (2013), the authors found that the social network's type and configuration affect the diffusion of energy-saving actions, mainly through the period that occupants take to adopt and maintain new behaviors.

In recent years, there has been a rising interest to evaluate occupancy interventions on a group, rather than individual, buildings (Gelazanskas and Gamage 2014; Wang and Taylor 2014; Xu et al. 2012). First, research indicates that the energy consumption behavior of occupants highly depends on their activities and interactions within – as well as between – the buildings that form their neighborhood (Xu et al. 2012). Put differently, residents living in a community have shown to adapt their energy consumption patterns according to those of their neighbors (Xu et al. 2012).

The need to expand the scope of current studies to groups of buildings is also motivated by the advance of Information and Communication Technologies (ICT) (e.g., smart grids and meters), which have created new channels of communication between buildings and their occupants (Gelazanskas and Gamage 2014; Verbong et al. 2013). For instance, demand-side management strategies such as energy feedback can now involve occupants from different buildings, comparing their energy consumption patterns and creating social pressure to induce changes in their behaviors.

Lastly, in addition to ICT, social media platforms (e.g., Facebook, Twitter, and Google+) offer a new virtual environment for people to interact, further expanding the potential of large-scale energy feedback interventions (Wang and Taylor 2014). As a result, online social network can help overcome geographical barriers between buildings and occupants, providing an opportunity to diffuse energy conservation practices across multiple communities or social milieus in order to achieve large-scale group action and behavior change. As an example, Mankoff et al. (2007) have proposed a framework where popular social networking sites are used to deliver people with both individual and group ecological footprint feedback. Similarly, Petkov et al. (2011) have developed a Facebook-enabled mobile application for energy monitoring. The application integrates energy consumption information in a social context with the goal of catalyzing social interaction and energy saving actions among users.

To sum up, while social networks have shown to highly influence energy conservation diffusion, they have rarely been evaluated in the context of a community or groups of buildings. This poses a significant obstacle to devising, testing, and optimizing large-scale occupancy interventions (e.g., city-scale energy feedback), leaving an important potential for energy savings untapped. The following section presents the methodology used in this study to overcome such limitations.

Methodology

An ABM framework is developed using the Anylogic software platform (Anylogic 2015). A main goal of the framework is to experiment with different feedback structures and social network characteristics on a community-scale level, identifying the configurations that maximize energy savings. While the proposed model is general, it illustrated through an application to a group of 35 medium-sized office buildings. The following sub-sections details the key concepts and steps of the methodology, which include: (1) the key behavior change dynamics of occupants and how those affect building performance; (2) the feedback methods and social networks that are tested; (3) the data collection and model's initialization process; (4) the model's execution process and steps; and (5) the verification and validation process.

Behavior change dynamics

The first step consists of defining – based on validated energy behavioral models and theories – how occupants adjust their energy use behaviors when exposed to those of people in their social network (e.g., peers, neighbors, friends, etc.). Eq. 1 illustrates a general behavioral model adapted from the works of Deffuant et al. (2000), Hegselmann and Krause (2002), and Mobilia et al. (2007).

$$OECI_i^{(t+1)} = (1 - FeedbackRecipient_i * Susceptibility_i) * OECI_i^{(t)} + FeedbackRecipient_i * Susceptibility_i * \sum_{j=1}^{N} (OECI_j^t / N_{connected}) \quad (1)$$

Where *Occupant Energy Conservation Index* ($OECI_i^{(t)}$) is a variable that represents the level of actions taken by occupant *i* at time *t* to conserve energy in the building. *OECI* ranges from 0 to 1, where a value of 0 represents an agent (i.e., occupant) that is not putting any effort to save energy, while a value of 1 represents an agent at the other extreme, putting the maximum possible effort to save energy. $OECI_i^{(t+1)}$ is the updated *OECI* of occupant *i* following exposure to the *OECI* average of $N_{connected}$ occupants ($\sum_{j=1}^{N} (OECI_j^t / N)_i$). Also from Eq. (1), $Susceptibility_i$ represents the openness of an agent to change behavior following exposure to the *OECI* of other people. A value of 0 results in occupant *i* not changing behavior (i.e., $OECI_i^{(t+1)} = OECI_i^{(t)}$), while a value of 1 updates $OECI_i^{(t+1)}$ solely based on the values of the connected agents. Finally, $FeedbackRecipient_i$ is a variable used to differentiate between occupants' receiving feedback (i.e., value of 1), and those who are not (i.e., value of 0). In the case of the latter, $OECI_i^{(t+1)}$ is here gain assigned the value of $OECI_i^{(t)}$ (i.e., no behavior change given the absence of feedback).

The *Building Energy Conservation Index* (*BECI*) is a building level variable that aggregates the *OECI* levels of all of the N_{all} building's occupants (See Eq. 2).

$$BECI_i^{(t)} = \sum_{j=1}^{N} (OECI_j^t / N_{all}) \quad (2)$$

In practice, a change in *BECI* of a building does not necessarily result in a direct change in the building's energy consumption levels, or *Energy Intensity* (*EI*). *EI* also depends on the *Elasticity* in the energy demand of the building. For instance, occupants might only be able to control a portion of the lighting system in the building, which constraints how much energy they can reduce even with the right intent to do so. As shown in Eq. 3, the *EI* of a building *i* at time *t* is a function of its initial level $EI_i^{(0)}$, its $Elasticity_i$, and its $BECI_i^{(t)}$value. A building with an elasticity value of 0 will maintain its *EI* levels throughout the simulation time. As shown later, the values for all parameters (e.g., EI and $Elasticity$) are obtained from previous studies and field experiments).

$$EI_i^{(t)} = EI_i^{(0)}(1 + 2 * Elasticity_i * (0.5\text{-}(BECI_i^t)) \quad (3)$$

Finally, the percentage energy saving in the building is calculated using Eq. 4.

$$Percentage\ Energy\ Saving = \frac{\left|EI_i^{(t)} - EI_i^{(0)}\right|}{EI_i^{(0)}} \times 100\% \quad (4)$$

Feedback methods and social networks characteristics

A social network is defined as a "theoretical paradigm" that outlines the relationships or connections between individuals. It provides the foundation to model social interactions between individuals or "agents", where the spread of ideas, products, or behaviors happens, including both desirable and non-desirable ones. (Newman 2012; Sailer and McCulloh 2012; Rahmandad and Sterman 2008; Mason et al. 2007). In the study of comparative energy feedback in buildings, a social network represents the network of people that participate and receive the energy feedback information (Azar and Menassa 2014b; Carrico and Riemer 2011; Peschiera et al. 2010).

Two configurations of feedback are considered in this study including feedback provided to occupants only 'within' each building, and feedback provided to occupants 'within and between' buildings. This is achieved by either limiting the social connections of occupants to ones that share their buildings, or expanding those connections to occupants from different buildings. In parallel, various social network topologies are considered as they have shown to affect the effectiveness of energy feedback (Azar and Menassa 2014b). Three topologies that are commonly encountered in the literature are tested including the random (RA), small world (SW), and scale-free (SF) topologies (Barabasi and Bonabeau 2003; Wang 2002). While the name of the first is self-explanatory, SF networks use proximity as basis to define the connections between agents. The SF topology on the other hand is characterized by unequal clustering levels between agents, potentially resulting in the formation of hubs (i.e., agents that are significantly more connected than other agents). Finally, a fourth social network combination is simulated in this study named "Mix", where the model randomly selects one of the three configurations for each building. Such configuration is helpful in the absence of information on the social network characteristics of the buildings under study.

Data collection and model initialization

Various sources of information are used to initialize the model's parameters and variables, as shown in Table 1 and detailed next. Firstly, general information about the buildings are gathered from the Commercial Building Energy Consumption Survey (CBECS) (EIA2003). In total, 35 medium-sized office buildings located in the "East North Central" weather zone in the United States are selected as the target of this research. Variables such as the number occupants and the annual energy intensity (in kWh/m^2) of each building are gathered.

Secondly, previous studies are used to initialize specific parameters such as the *Elasticity*$_i$ levels of buildings and the $FeedbackRecipient_i$ variable for occupants (Anderson and Lee 2016; Azar and Menassa 2014a).

Thirdly, data is gathered from an ongoing project by the authors that analyzes the energy conservation behaviors of 227 university campus users. The collected information is used to estimate the *OECI*$_i$ and *Susceptibility*$_i$ values of occupants. More specifically, the first was estimated from 5 questions regarding the energy use patterns of occupants when they leave their workplace. These include questions on the turn-off frequency of lights, computers/laptops, printers/scanners, and other equipment, as well as the adjustment of thermostat set points to reduce the heating, cooling, and ventilation (HVAC) loads. The questions were designed in 5-point Likert type (i.e., 1- never, 2- rarely, 3- sometimes, 4- often, and 5- always) and then normalized to the [0,1] range of the *OECI* variable. Next, a curve fitting process helped identify a Gaussian distribution as the best fit for the collected data. The fitted curve (i.e., distribution) was then used to initialize the *OECI*$_i$ values of occupants in the model. The equation is shown in Table 1, with an adjusted R^2 of 0.98 and an F-statistic of 97.8, both confirming the goodness-of-fit. As for the *Susceptibility* values, two questions were used covering the interest of people to know how much energy their peers consume, in addition to their willingness to reduce their energy consumption levels at the workplace. A similar data normalization and fitting process to the *OECI*$_i$ values was performed, resulting in a Gaussian distribution with an adjusted R^2 values of 0.97 and an F-statistic of 58.9 (See Table 1).

Execution steps

The general execution process of the model is illustrated in Fig. 1. Once the model is launched, it initializes the parameters and variables of the model based on the values identified in the previous section. Then, based on the user's selection, specific feedback method and social network topologies are simulated and tested. Throughout the process, Equations 1 to 4 are applied to estimate any changes in occupants' OECI values, and the corresponding impact on the energy intensity of the buildings. It is important to highlight that the model iterates through 3 nested loops: (1) the agent loop (to go through all occupants and study their behavior), (2) the time step loop (to go through multiple time steps, 104 in this case to simulate 104 weeks, the equivalent of a 2-year study period), and (3) the iterations loop. In the case of the latter, 200 iterations of the model are run for each combination of parameters. This helps overcome the stochasticity nature of ABM and capture the variability of the runs (Azar and Menassa 2014b). As shown in the upcoming sections, the outcome of this process is the simulated percentage energy savings observed in the buildings for different combinations of feedback configurations and social network topologies.

Table 1: Initialization values of model variables

Variable	Value	Source
Number of buildings	35	CBECS (EIA 2003)
$EI_i^{(0)}$ of buildings	Ranges from 130.8 to 544.1 kWh/m^2 with an average of 287.0 kWh/m^2 and a standard deviation of 109.9 kWh/m^2.	CBECS (EIA 2003)
Number of full-time occupants in each building	Ranges from 9 to 95 occupants with an average of 35.8 and a standard deviation of 22.0.	CBECS (EIA 2003)
Elasticity$_i$ of buildings	Set to 19% as observed in a study on similar medium-sized office buildings in the United States.	Azar and Menassa (2014a)
$FeedbackRecipient_i$ variable for occupants	Changes dynamically to limit feedback to those that consume more energy than the norm (i.e., 1 for more-than-average consumers and 0 for others). This has shown to enhance energy conservation (Anderson and Lee 2016).	Anderson and Lee (2016)
OECI$_i$ of occupants	Follows the following distribution: $y = a\,.\,e^{\left(-\frac{(x-b)^2}{2c^2}\right)}$, where *a* = 69.274, *b* = 0.710, and *c* = 0.373. Parameter "*a*" is set to 1 for normalization purposes (i.e., *OECI* cannot exceed 1).	Data collected by the authors
Susceptibility$_i$ of occupants	Follows a similar distribution as *OECI$_i$* but with the following values: a = 55.606, b = 0.292 and c = 0.604. Parameter *a* is also set to 1 for normalization.	Data collected by the authors

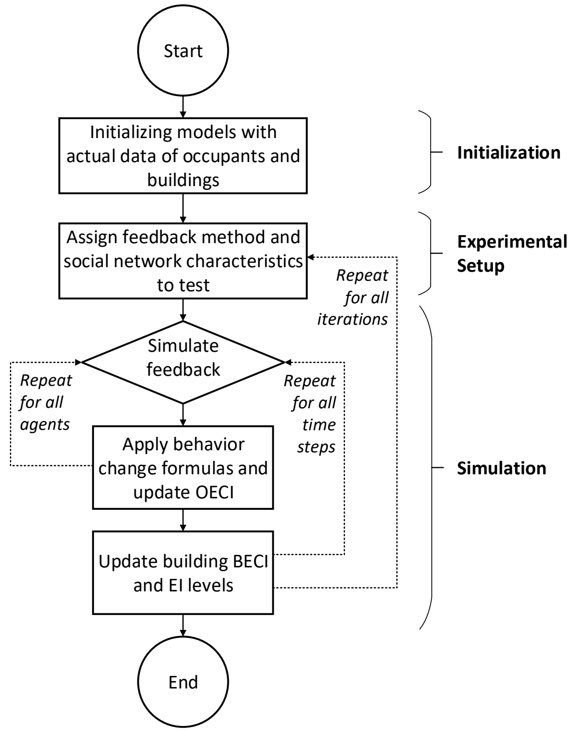

Figure 1: Model schematic view

Technical verification and validation

Prior to proceeding with the results of the experiments, it is important to highlight some of the verification and validation methods used to ensure the technical validity of the model. These are adapted from the works of Ormerod and Rosewell (2009) and Yilmaz (2006), and include: *conceptual validity*, *structural validity*, and *internal validity*.

Conceptual validity consists of defining the interactions of agents based on validated concepts, principles, and models from the literature, similar to the ones used in this study (Mobilia et al. 2007; Hegselmann and Krause 2002; Deffuant et al. 2000). Also this validity is reinforced when actual data is used to initialize model parameters, as was highlighted in Table 1.

For *structural validity*, a combination of "sensitivity analyses" and "tracing" was used through the model development process; tracing consists of closely monitoring individual agents through the simulation time. Both methods help ensure that all of the model's variable are reacting in a logical manner to changes in input parameters.

The *internal validity* of the model is tested by changing the seed of the random number generator used and compare the output of the model. As expected, minor differences are observed in the results (i.e., less than 1% variation over 200 iterations), confirming the independence of the model from the particular random generation function that is used.

Finally, the *predicative validity* of the model has not been tested as this would require gathering data from a large number of buildings over extended periods of time.

Acknowledging this limitation, the results of the simulations are compared to identify the best performing combination of input parameters in term of percentage energy savings, without necessarily projecting absolute energy saving values (e.g., in kWh). This approach is very common in ABM studies given the lack of available data in the literature for predictive validation purposes (Azar and Menassa 2014b).

Results and discussion

Figure 2 summarizes the results for the two tested configurations of feedback (i.e., 'within' and 'within and between' buildings) and the four social network topologies (i.e., RA, SF, SW, and Mix); a total of 8 combinations. For each combination, the results for the 200 iterations of the model are presented, where each circle shows the percentage energy saving predicted by the model at the end of the time steps (i.e., 104th week) (refer to Figure 1 for more details about the difference between the time steps loop and the iterations loop). Confidence intervals (95% level) are also overlaid on the data points in shaded grey rectangles along with box-and-whisker plots.

The discussion of the results is organized around the two research questions that this study aims to answer (repeated below for easy reference):

(1) Does connecting people within and between buildings significantly improve conservation when compared to the current single-building approach?

(2) Does the structure, or topology, of the social network of people impact the effectiveness of the feedback?

Starting with the first, the results of Figure 2 indicate that for all topologies, the scenarios with social connections 'within and between' buildings have significantly higher energy savings than the ones with connections only 'within' buildings. In order to further confirm this observation, two-sample t-tests are computed to compare the means of the different scenarios (H_0–the means are the same, H_1–the means are different). The results are shown in Table 2 where p-values lower than 0.05 are observed for all scenarios. This leads to the rejection of the null hypotheses and the confirmation that the means are different. In summary, the findings confirm that feedback mechanisms that connect people between buildings show higher savings that ones that follow the traditional single-building approach. As mentioned earlier, new channels of communication such as social network platforms can play an important role in that regard, leveraging the social networks that exist between people in different communities and cities.

As for the second research question, the results of Figure 2 also indicate important differences between the different social network topologies, however, this difference is less significant for the scenarios with connections 'within and between' buildings. As shown in Figure 2, when agents are only connected 'within' buildings, important variations in the results are observed. For instance, for the SW topology, the results show a clustering of results at two poles, which can be attributed to the distance-based nature of SW connections. Put differently, distant agents with high energy consumption patterns might not be connected to their peers, and as result, may not be subjected to the feedback information that incentivize them to change behavior. On the other hand, when connections are established 'within and between'

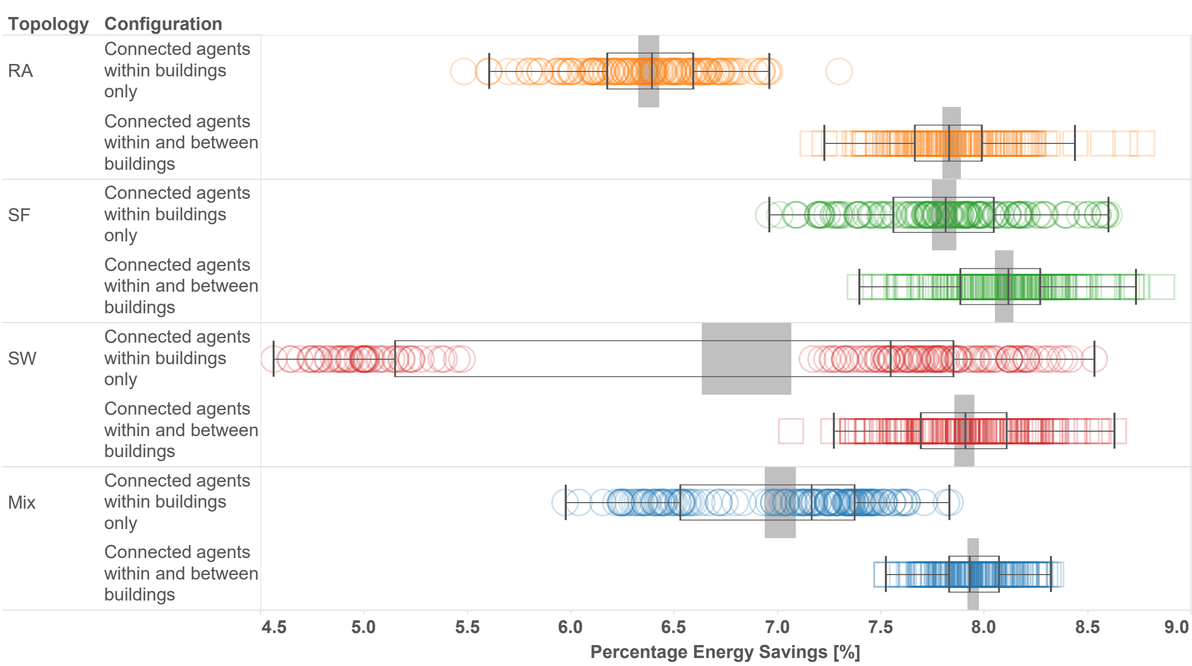

Figure 2: Parametric variation results

buildings, the variations in the results are less significant, with confidence intervals in the 7.8-8.2% energy savings range. Therefore, it can be concluded that connectivity between buildings also helps reduce the variability in the results typically encountered between different social network topologies.

Table 2: T-test for different feedback configurations

Topology	Feedback configuration	Mean	p-value	t-test
SW	Connected agents "within" buildings only	6.85	<2.2e-16	-9.37
	Connected agents "within" and "between" buildings	7.91		
SF	Connected agents "within" buildings only	7.81	<3.9e-13	-7.62
	Connected agents "within" and "between" buildings	8.10		
RA	Connected agents "within" buildings only	6.38	<2.2e-16	-43.90
	Connected agents "within" and "between" buildings	7.84		
Mix	Connected agents "within" buildings only	7.01	<2.2e-16	-23.31
	Connected agents "within" and "between" buildings	7.95		

Conclusion

This study presents a novel ABM framework to test building energy feedback on a community scale. The framework is illustrated through a case study of 35 medium-sized office buildings in the US, where various configurations of feedback and social network topologies are tested. Results indicate that expanding feedback methods from individual to groups of buildings can significantly increase energy savings. Furthermore, such increase in the scale of connectivity can help reduce the variability in energy savings observed in individual buildings. The findings of this study are significant as they motivate the need to expand the structure of existing energy feedback mechanisms to groups of buildings. ICT and social media can play an important role in this regard, creating the needed communication channels to influence behavior and help reduce energy consumption in the building sector.

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