Improving Efficiency of Normative Interventions by Characteristic-Based Selection of Households: An Agent-Based Approach

Mohammad Zarei[1] and Mojtaba Maghrebi[2]

Abstract: Energy demand is increasing globally, and the building sector accounts for more than a third of energy use in some countries. Thus, by means of normative interventions (NIs), the authorities have started investing in improving the energy behavior of households as an important factor affecting the energy consumption of buildings. In this regard, ecofeedback programs and the appointment of environmental champions (ECs) in the target community are considered practical solutions. This paper presents a novel approach, characteristic-based selection of households (CBSH), to improve the short-term and long-term effects of such NIs by focusing on characteristics of the energy behavior of households. In the simulation model, the household's energy consumption behavior and social network can be altered to study the effectiveness of different scenarios for a selection of households as ECs or ecofeedback attendants. According to the simulation results, the outcome of NIs can be promoted by using CBSH to select ecofeedback participants as well as integrating ECs with ecofeedback programs.
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Introduction

Globally, rising energy demands and environmental issues together with rising energy costs are the main reasons to invest in energy conservation methods. The building sector accounts for a large proportion of energy consumption in the least-developed countries, which can be responsible for up to 50% of total national energy use (Graham and SBCI 2010). Significant efforts have therefore been made with empirical (Hargreaves et al. 2010; Barry et al. 2015; Sprehn et al. 2015) and modeling approaches (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2011) to increase energy savings in this sector.

Diverse factors with possible impacts on energy demand in buildings have been introduced in the literature. These are the four major categories (Yu et al. 2011):

1. Building envelope
2. Building equipment
3. Climate
4. Human behavior

Although most of the introduced energy-saving methods have traditionally aimed at building physical enhancements primarily related to the building envelope (Ham and Golparvar-Fard 2014) or equipment (Khavari et al. 2016), recent studies with various methodological approaches indicate that improving household energy behavior could lead to better outcomes (Masoso and Grobler 2010; Clevenger et al. 2013). Moreover, due to a phenomenon known as the take-back or rebound effect, whereby households tend to increase their energy consumption after physical improvements (replacing more efficient equipment, etc.), improving the energy behavior of households has a higher priority than technical improvements (Sorrell et al. 2009).

Residential occupants usually have significant control over their energy consumption such that two similar buildings could exhibit up to 500% difference in energy use (Parker et al. 2008). More critically, research into commercial buildings reveals that in nonworking hours, more than 50% of the energy is used (Masoso and Grobler 2010), and for most equipment types, turn-off rates are below 50% (Webber et al. 2006), which is mainly attributable to occupancy-related actions. Thus, improving the energy consumption behavior of households is an effective way of achieving sustainable goals.

Occupant behavior is a constantly changing variable, affected by social interactions (Jain et al. 2013) and energy-saving interventions (Abrahamse et al. 2007; Barry et al. 2015). Among all the methods introduced to modify the energy use pattern, including goal setting (Van Houwelingen and Van Raaij 1989), commitment (Pallak and Cummings 1976), and workshops (Geller 1981), researchers have focused more on normative energy behavior interventions (NIs) such as appointing environmental champions (ECs) or ecofeedback events (Azar and Al Ansari 2017; Bastani et al. 2016; Darby 2006; Fischer 2008; Francisco et al. 2018; Anderson et al. 2013; Taylor et al. 2012). In the feedback programs, occupants are given continuous (Van Houwelingen and Van Raaij 1989) or discrete (Katzev et al. 1980) information about their energy use, which is specifically called ecofeedback, and then, peers can compare their energy consumption amounts to each other (Jain et al. 2013). ECs are individuals who care about environmental issues and can encourage their peers to conduct themselves on a sustainable basis (Taylor et al. 2012; Anderson et al. 2013). The success of NIs can be explained by the findings of the social sciences, which suggest that changes brought on by social influences depend on two psychological needs (Deutsch and Gerard 1955):

[1]M.Sc. Student, Faculty of Engineering, Dept. of Civil Engineering, Ferdowsi Univ. of Mashhad, Azadi Square, 9177948974 Mashhad, Iran. Email: m.zarei@mail.um.ac.ir

[2]Assistant Professor, Faculty of Engineering, Dept. of Civil Engineering, Ferdowsi Univ. of Mashhad, Azadi Square, 9177948974 Mashhad, Iran (corresponding author). ORCID: https://orcid.org/0000-0001-7284-9095. Email: mojtabamaghrebi@ferdowsi.um.ac.ir

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1. People need to be right (informational social influence).
2. People need to be liked (normative social influence).

Studies on ecofeedback programs showed various energy reduction rates, ranging from 0% to 32%, but mostly between 5% and 12% (Abrahamse et al. 2007; Fischer 2008; Petersen et al. 2007; Allcott 2011), and the common problem in most of these studies was that participants returned to their previous behaviors some time after the program ended (Ma et al. 2018). Hence, more research is needed to improve the efficiency of such programs. The main purpose of this study is to investigate the improving methods for NIs, particularly ecofeedback and EC programs. Although earlier efforts have had valuable results in studying energy-saving programs in the field (Francisco et al. 2018; Gulbinas and Taylor 2014) or with simulated models (Anderson et al. 2012, 2013; Azar and Al Ansari 2017; Bastani et al. 2016), it is not clear how much the method of selecting program participants can affect the efficiency of the program and the amount of energy saving in the community. To answer this question, based on the influence, susceptibility, and conformity (ISC) model (Duggins 2014) and previous simulation studies on NIs (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2013), an enhanced agent-based model has been developed to simulate energy behavior change of households through NIs and provide a means to investigate the impact of the proposed approach, characteristic-based selection of households (CBSH), on the efficiency of such programs.

The paper's layout is as follows (Fig. 1): a brief background on normative interventions, social network effects, and agent-based modeling (ABM) is given in the first section. Then, the developed agent-based model is described. The model has been tested in a residential context, and its validity has been investigated. Finally, the results are discussed and concluded.

Background

As mentioned in the previous section, using normative interventions can significantly reduce energy consumption of buildings. With this in mind, a computer simulation model has been developed to examine the methods that can potentially increase energy saving from NIs. The main concepts employed in this model, including energy-use interventions, modeling social effects on energy consumption behavior, and a powerful modeling technique named agent-based modeling, are described as follows, which is the first step toward the research purpose in Fig. 1.

Normative Interventions: Ecofeedback and EC Programs

Since the energy crisis of the 1970s, scholars have introduced many intervention techniques in order to increase energy-saving behaviors, including workshops, commitments, goal-setting, rewards, and punishments (Abrahamse et al. 2005). Of these various methods, several studies have confirmed the positive effect of NIs such as ecofeedback and EC programs on occupants' energy conservation (Hargreaves et al. 2010; Abrahamse et al. 2007; Fischer 2008; Jain et al. 2013; Barry et al. 2015; Sprehn et al. 2015).

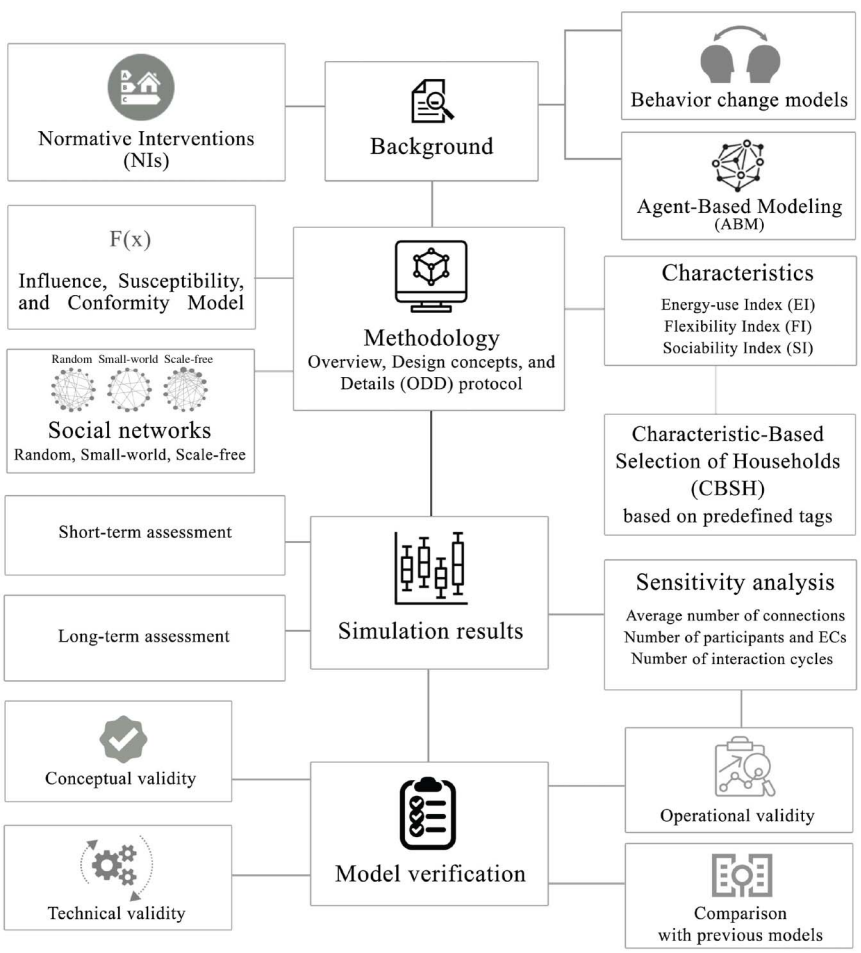

Fig. 1. Paper structure.

Table 1. Feedback program studies

Source	Method	Results
Petkov et al. (2011)	Providing ecofeedback using a prototype mobile application and conducting a semistructured interview with users.	Different mechanisms for choosing relevant people should be considered for different user motivations (competition, comparison, etc.).
Peschiera and Taylor (2012)	Providing daily room-level feedback (22 rooms) and ecofeedback (22 rooms) and comparing with a control group (44 rooms).	Peer networks were more effective in inducing reduction in consumption than impersonal generic norms.
Jain et al. (2013)	Developing an algorithm to assess the social influence impacts on energy behavior that is applied to an empirical data set of users exposed to unit-level ecofeedback.	Both the statistical method and empirical results show that users were influenced to use less energy when exposed to normative feedback.
Murtagh et al. (2013)	Providing individual feedback to 83 office workers in a university.	Statistically significant energy reduction was found; engagement with feedback diminished over time; no measured individual variables were related to energy reduction and only attitudes to energy conservation were related to energy use.
Anderson et al. (2017)	Conducting two yearlong field experiments for ecofeedback messages.	Normative messages should be sent as long as possible, and effort should not be wasted attempting to change people's attitudes or behavioral intention, but rather spent to convey that a positive norm of energy conservation exists.

At the early stages of feedback studies, mostly applied by psychologists, more attention was paid to investigating the impact of receiving energy use data on consumption behaviors (Abrahamse et al. 2007). Recent works, however, have revealed that ecofeedback is more effective than purely historical feedback, given the social influence and peer network (Fischer 2008; Gulbinas and Taylor 2014; Ma et al. 2018). As an illustration, the result of a 9-week ecofeedback study on a commercial building that provided an advanced system for occupants accessing energy data in their organizational network indicated that occupants who had access to the energy information of peers performed considerably better than those who only received personal-level feedback (Gulbinas and Taylor 2014). Another study, which developed a mobile app to provide dormitory occupants with ecofeedback information, showed that ecofeedback programs had significant positive effects, especially in the short and medium term (Ma et al. 2018). This method is therefore considered more effective, particularly in cases where there is no financial incentive to reduce energy consumption, such as commercial buildings, dormitories, hospitals, hotels, or offices. Several other field studies of feedback are presented in Table 1.

Although the positive impact of ecofeedback and EC programs has been confirmed both in experimental (Francisco et al. 2018; Gulbinas and Taylor 2014; Hargreaves et al. 2010; Ma et al. 2018) and simulation research (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2013; Bastani et al. 2016), there is still little information available on how to obtain more energy savings with limited investment. The purpose of this paper is to investigate participants' related factors that can affect short-term and long-term effects of these programs. Considering these factors in the selection of households as the ecofeedback attendants or ECs could help to achieve a higher level of energy savings with limited resources.

Modeling Social Effects on Energy Conservation Behavior

Several mathematical models have been developed in the literature to facilitate the simulation of changes in human behavior through social interactions (Deffuant et al. 2002; Duggins 2014). Because energy-saving behaviors are mutable, as are other behaviors (Karatasou et al. 2014), energy behavior simulation has been the subject of many works (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2011, 2013; Bastani et al. 2016; Du et al. 2016; Zhang et al. 2011). A variety of methods have been implemented in these studies, including the relative agreement model (Azar and Menassa 2013), base diffusion model (Bastani et al. 2016), social influence network theory (Anderson et al. 2013), and the word-of -mouth effect (Azar and Menassa 2011). In addition, several models have been developed to investigate the effect of social networks on the efficiency of energy-saving interventions (Anderson et al. 2012; Azar and Al Ansari 2017; Du et al. 2016; Ekpenyong et al. 2014). In the relative agreement (RA) model, continuous values of opinion and flexibility of agents only change in interactions in which peers have a certain degree of similarity (Deffuant et al. 2002). In a study to evaluate the energy-saving potential from occupancy interventions, the RA model was employed to simulate the behavior of energy consumption of occupants through social interactions (Azar and Menassa 2013). Another simulation study (Bastani et al. 2016) investigated energy-saving policies with the application of Bass diffusion theory (Bass 1969), which describes the process of how new products get adopted in a population. In this study, some of the occupants will spontaneously adopt the policies and change their energy consumption behavior, and then they start to convince others to adopt the same policies. According to Bass theory, the speed and timing of adoption depend on the degree of innovativeness (external effects such as advertising) and the degree of imitation among adopters (Bass 1969).

For this paper's goals, several types of behavior change models were studied, and the influence, susceptibility, conformity model has been chosen as the central logic of the simulation process. Given mathematical rules in the ISC model, simulating the change in energy usage of households through NIs is achievable. As a result, the impact of CBSH on the efficiency of NIs can be examined.

Simulating Occupant Behavior: Agent-Based Modeling

An agent-based model involves an interactive environment of autonomous and intelligent agents with specific behavioral rules (Axtell 2000). These agents, commonly implemented as software objects, have specific attributes that could undergo changes during interaction with the environment or other agents (Macal 2016).

Buildings occupants as heterogeneous and adaptive agents can communicate through a complex system of social connections; therefore, ABM is a suitable technique for exploratory studies on how individual behaviors, especially energy-related behaviors, change in social networks due to the interactions of occupants. Accordingly, disparate works have employed ABM to simulate the behavior of human energy consumption in buildings. These include but are not limited to building occupancy modeling (Liao et al. 2012), normative energy intervention modeling (Anderson et al. 2013; Azar and Al Ansari 2017), and energy consumption simulation (Azar and Menassa 2011, 2013; Bastani et al. 2016; Zhang et al. 2011). In a study, the energy behavior of occupants was simulated in an agent-based model to calculate the amount of energy consumption for different and changing occupant behavior over a given period of time, based on their interactions (Azar and Menassa 2011). The potential for energy savings in commercial buildings, which can be achieved by modifying the occupancy behaviors, was also assessed through an agent-based model (Azar and Menassa 2013).

In the current study, ABM was employed as a powerful modeling technique to simulate the short-term and long-term impact of NIs on the residential energy. The model used in this paper, which is an enhanced version of previous models (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2013), is intended to identify influential parameters linked to participants on a program's efficiency that could lead to making better decisions for implementing NIs. At this point, the background of the research question is examined, and the research methodology will be described in the next section (Fig. 1).

Methodology

The concepts used to build the agent-based model are explained in the previous section. This section describes the model using an overview, design concepts, and details (ODD) protocol that is introduced for describing agent-based or individual-based models (Grimm et al. 2006). Using this protocol can make ABMs more comprehensible and reproducible. The model was programmed in Python 3.6.

Purpose

The general purpose of the model is to understand whether the CBSH approach can improve the short-term and long-term outcomes of ecofeedback and EC, which are two types of NIs. Additional purposes are to study the program parameters such as social network impacts and average number of connections, as well as to compare the results of these NIs.

Entities, State Variables, and Scales

Model entities (agents) are multiattribute households, as outlined in Table 2. As described in Eq. (4), the energy-use behavior of agents (EIs) is the most important attribute of individuals that can vary by interacting with the environment (e.g., attending an ecofeedback program or interaction with other households). The mechanism for this change will be described in the following sections.

Process Overview and Scheduling

The model, which was programmed in a Python 3.6 environment, started by creating an agent network and then assigning the attributes of agents. During each simulation run, a specific number of agents was selected as ecofeedback attendants based on a set of predefined selection scenarios. The selected attendants were given information about their energy consumption relative to their peers in their social network. This ecofeedback event could modify the energy-use behavior of participants based on the ISC model. The short-term result was calculated just after the event. The long-term result was calculated in the presence of selected ECs among the community after specified periods of agents' interaction within their social network. A detailed description of simulating the program and interaction impact on energy-use behavior of agents is provided in the "Submodels" section.

Design Concepts

Social Influence Modeling: Influence, Susceptibility, and Conformity Model

Social influence can be defined as an exchange information process, through which individuals adapt their opinions, reevaluate their beliefs, or change their behavior as a result of social interactions with other people (Duggins 2014). Several studies have shown that energy-use behavior can also change as a result of social influences (Allcott 2011; Darby 2006; Jain et al. 2013). To understand these phenomena and design appropriate energy-saving interventions, quantitative tools are required to simulate the psychological and social aspects of changes in energy behavior. Based on the ISC model (Duggins 2014), the following general formula was employed in this paper to simulate the change in energy-use behaviors of agents through ecofeedback programs or social interactions:

$$\mathrm{EI}_i^{t+1} = (1 - \mathrm{FI}_i) \times \mathrm{EI}_i^t + \mathrm{FI}_i \times \left(\frac{\sum_1^n \omega_{ij} \times \mathrm{EI}_j^t}{\sum_1^n \omega_{ij}} \right) \tag{1}$$

where EI_i^{t+1} and EI_i^t = energy-use index of agent i at times $t+1$ and t, respectively, which are calculated based on Eq. (4); FI_i = flexibility index of agent i, which is described in the next section; and ω_{ij} = weight factor that represents the strength of the relationship between agents i and j. The number of interactions is also revealed by n.

To calculate the weight factors, two assumptions were made. First, a high similarity of social relationships increases the impact of interaction on the behavior of the parties (Friedkin 2001). Second, the proximity of the individuals' behavior also increases

Table 2. Agent attributes

Attribute	Abbreviation	Description
Agent ID	ID	—
Energy use	EU	The annual energy consumption of each household per unit area ($\mathrm{kw/m^2}$) obtained from historical data
Energy use index	EI	The annual energy consumption of each household on a scale of 1–100
Flexibility index	FI	The household's capability to change its energy-use behavior by external influence on a scale of 0–1
Social relationships	—	List of the household social connections (relationships)
Tags	tags	List of acquired tags based on energy behavior attributes
Sociability index	SI	The level of household influence on the target community

the parties' influence (Deffuant et al. 2002; Duggins 2014). Based on these assumptions and suggestions of the ISC model, the following equation was used to calculate weight factors of each agent connection:

$$\omega_{ij} = C_{ij} \times \left(1 - \frac{|\mathrm{EI}_i^t - \mathrm{EI}_j^t|}{50}\right) \tag{2}$$

where C_{ij} = number of common social relationships between agents i and j; and EI_i^t and EI_j^t = energy-use index of agents i and j at time t, which is derived from Eq. (4). In this way, the similarities of energy behavior and social structure are considered together.

Social Networks

There are two main elements in a social network: (1) nodes and (2) edges. In energy-conservation diffusion models, households (agents) are represented as nodes and social relationships as edges or connections (e.g., kinship, friendship) (Anderson et al. 2013; Azar and Al Ansari 2017). In this model, three types of social networks with the same average connections (random, scale-free, small-world) have been selected. These three networks that are frequently used in simulation studies (Anderson et al. 2012, 2013; Azar and Al Ansari 2017; Azar and Menassa 2013) can provide an environment for simulating changes in energy behavior patterns across a society. They are constructed using *Networkx* (Hagberg et al. 2008), which is a robust Python package for complex network analysis (Fig. 2).

1. Random Erdos-Renyi (ER) graphs are generated by starting with a set of isolated nodes that are then paired with a uniform probability. Most node connections in these networks have the same number, and the degree distribution will be a bell-shaped Gaussian curve (Solé and Valverde 2004).
2. Scale-free networks are characterized by the presence of hubs, which are specific nodes with high degree of connection to other nodes in the network (Fig. 2). This type of network can be constructed by adding nodes and edges to an existing network by considering that the probability of linking to a given node is proportional to its number of edges (Barabási and Albert 1999).
3. In a small-world network, most nodes are not connected to each other; however, the neighbors of any given node are likely to be connected to each other, and most nodes can be reached from every other node by a small number of steps (edges) (Watts and Strogatz 1998).

Initialization and Input Data

The initialization process of the ABM is as follows:

1. Social relationships: In each simulation run, a social network is generated based on the network type, number of agents, and average number of connections per agent. Then, the Sociability index (SI), which is used for CBSH scenarios, for each agent is calculated as follows:

$$\mathrm{SI} = \frac{\text{Number of agent connections}}{\text{Average number of connections}} \tag{3}$$

2. Energy-use index (EI): This represents the behavior of the household's energy consumption on a scale of 1–100, where 1 is the lowest energy consumer household and 100 is the highest consumer. This attribute for each agent is derived from a lognormal distribution ($\sigma = 0.388$, $\mu = -0.924$), which is the best obtained fit among known restricted distributions to the energy use data acquired from a typical 100-unit residential building located in Mashhad, Iran. This building is part of a residential complex in an economically mediocre area of Mashhad city that contains about 1,400 units. The units' area is between 80 and 170 m^2, and each has two to three residents. The yearly electricity consumption of 100 units, all of which have two occupants, was acquired from the power utility, and then the energy use (EU in Table 2) of each unit was calculated to acquire EI data [Eq. (4)]. The result of the Kolmogorov-Smirnov (KS) statistic for this distribution fit is 0.032, which is less than the 0.05 common threshold confirming the goodness of fit (Fig. 3). In this process, each household's EI is calculated as follows:

$$\mathrm{EI}_i = \frac{\mathrm{EU}_i - \mathrm{EU}_{\min}}{\mathrm{EU}_{\max} - \mathrm{EU}_{\min}} \times 100 \tag{4}$$

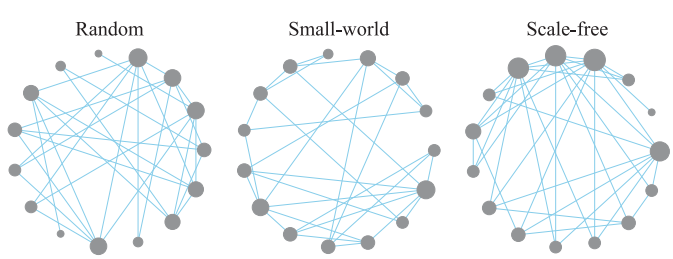

Fig. 2. Common social networks.

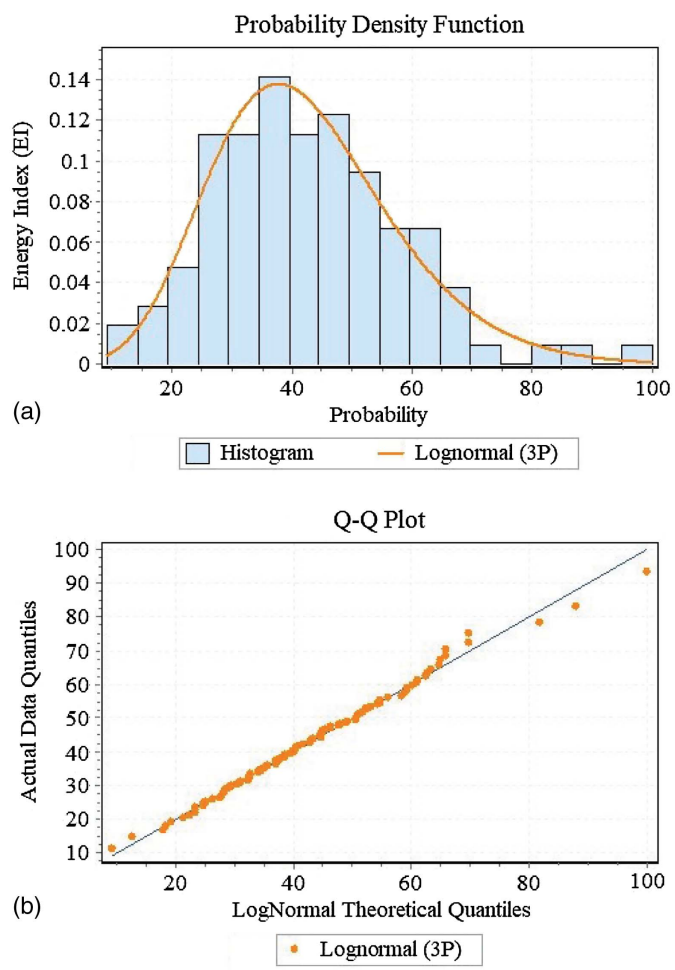

Fig. 3. Lognormal distribution fitting of scaled energy consumption data.

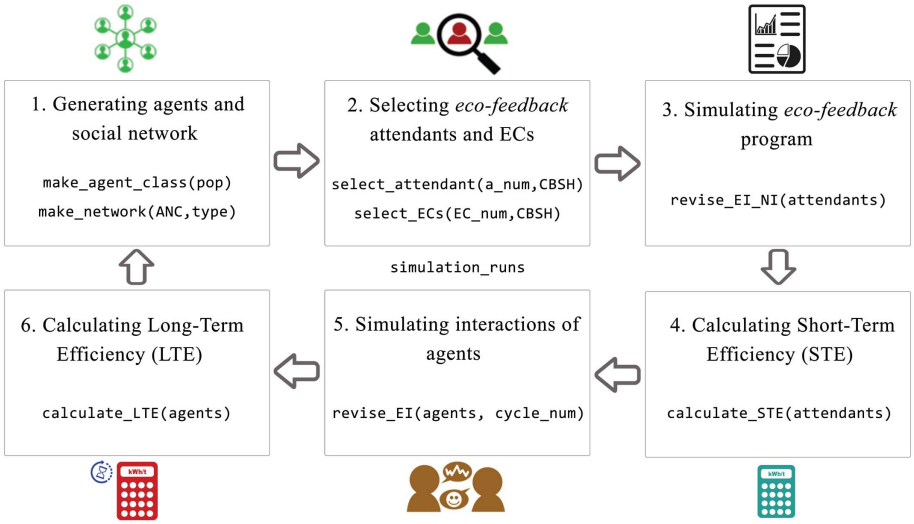

Fig. 4. Submodels.

where EU_{max}, EU_{min}, and EU_i= maximum annual electricity consumption per unit area, minimum annual electricity consumption per unit area, and annual electricity consumption per unit area for household i, respectively.

3. Flexibility index (FI): This is generated from a normal distribution with a mean value of 0.5 and a standard deviation of 0.3. These values indicate that people have different rates of adoption to social norms such that distribution type and inputs can only make a relative change in system behavior (Anderson et al. 2013; Azar and Al Ansari 2017; Deffuant et al. 2002; Friedkin 2001).

Submodels

The simulation model is divided into six separate submodels to effectively manage the simulation process and observe any changes in the system (Fig. 4). The next sections explain each submodel programmed with Python version 3.6.

Generating Agents and Social Network

When the model is launched in each run, this submodel first creates the network of agents (households) with their attributes depending on the total number of agents, social network type, and average number of connections.

Selecting Ecofeedback Attendants and ECs: CBSHs versus Random

The organizers usually choose a small portion of a target community to participate in NI programs because of fund and time limitations. In other words, these programs will only be attended by a limited number of households. To address this real-world task in the simulation model, this submodel selects a predefined number of agents as the ecofeedback attendants or ECs, according to the following selection scenarios, which include different types of CBSH and random selection. These scenarios will provide the decision-maker with insight into the selection of a defined number of agents in an ecofeedback program. Table 3 describes the tags of the agents that are associated with their attributes.

The proposed ecofeedback selection scenarios are listed subsequently (Fig. 5):

- R: Random selection with no specified condition
- $S1$: Selecting sociable agents

Table 3. Agent tags

Tag	Condition
Wasteful	EI > median
Austerity	EI <= median
Flexible	FI > 0.5
Sociable	SI > 1

- $S2$: Selecting flexible agents
- $S3$: Selecting wasteful agents
- $S4$: Selecting wasteful and sociable agents
- $S5$: Selecting wasteful and flexible agents
- $S6$: Selecting wasteful, flexible and sociable agents

Similarly, the following EC selection scenarios have been provided:

- R: Random selection with no specified condition
- $E1$: Selecting sociable agents
- $E2$: Selecting austerity agents
- $E3$: Selecting sociable and austerity agents

The defined thresholds in Table 3 are based on the judgments of authors in order to have sufficient participants for each selection scenario. In other words, the condition of assigning each tag depends on the community population, number of participants, and distribution of energy behavior attributes.

Simulating Ecofeedback Program

The ecofeedback program provides attendants with information on the energy consumption of peers. To have better results, in the simulation model, the attendants are only provided with the lower energy consumption feedback, and during each simulated event, energy-use indexes of agents will be revised accordingly based on Eq. (1) and the given ecofeedback information.

Calculating Short-Term Efficiency

Because the energy-use index of agents (households) is generated based on their energy consumption, any changes in this attribute directly affect energy-usage. In view of this, the short-term efficiency (STE) of the ecofeedback program, which determines the energy savings of the attendants, could be defined as the average of EI changes

$$\mathrm{STE} = \frac{\sum_1^{n'}(\mathrm{EI}_i^S - \mathrm{EI}_i)}{n'} \tag{5}$$

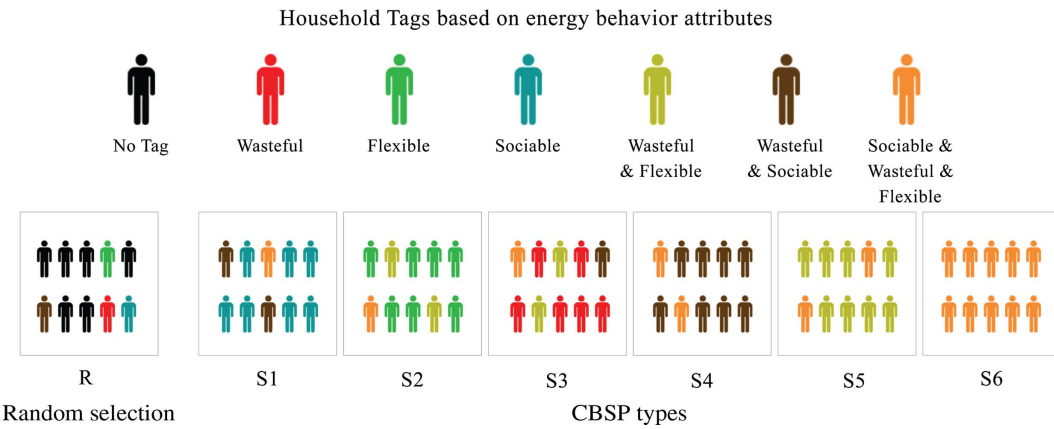

Fig. 5. CBSH scenarios for selecting ecofeedback attendants based on the defined tags versus random selection.

where n' = number of attendants; and EI_i and EI_i^S = initial energy-use index of agent i and energy-use index of agent i after the program, respectively.

Simulating Agents' Interactions

Participants interact with their network and revise their energy-use behavior in each period or simulation run after the ecofeedback program. Given the role of ECs in the community, these agents are not susceptible to negative influence (Anderson et al. 2013). This submodel recalculates the EI of agents using Eq. (1).

Calculating Long-Term Efficiency

The amount of energy savings after the specified periods of agents' interactions in the social network, called long-term efficiency (LTE), is calculated using the following equation:

$$\mathrm{LTE} = \frac{\sum_1^n (\mathrm{EI}_i^L - \mathrm{EI}_i)}{n} \times 100 \tag{6}$$

where n = number of agents; and EI_i and EI_i^L = initial and final energy-use indexes of agent i, respectively.

In the next section, the results obtained using the introduced methodology are presented in order to address the research question (Fig. 1).

Simulation Experiments and Results

The impact of NIs on the energy consumption behavior of residents was studied in three phases:

1. Short-term assessment of ecofeedback program without social interactions
2. Long-term assessment of ecofeedback and EC program with social interactions
3. Sensitivity analysis of main parameters in ecofeedback and EC program

Phase I: Short-Term Assessment of Ecofeedback Program

The first experiment tested the short-term efficiency of the ecofeedback program before any interaction between agents. The main inputs for this experiment are shown in Table 4.

These values have been selected based similar previous models (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2011; Bastani et al. 2016; Ekpenyong et al. 2014). However, the effect of these parameters on the outputs of the model has been investigated through sensitivity analysis in Phase III.

Table 4. Model inputs for short-term assessment of ecofeedback

Parameter	Values
Agents' numbers	pop = 100
Average number of connections	ANC = 5
Selection scenario for ecofeedback	CBSH = [R, S1, S2, S3, S4, S5, S6]
Number of program attendants	a_num = 10
Selection scenario for EC program	CBSH = [R, E1, E2, E3]
Number of ECs	EC_num = 0
Number of interaction cycles	cycle_num = 0
Social network type	type = [Random, Small-world, Scale-free]
Number of simulation runs	simulation_runs = 500

The simulation results for seven selection scenarios and three social network types are illustrated in Fig. 6. The vertical axis indicates the program's percentage of energy savings in the STE term, computed based on changes in the EI of all agents before and after the program [Eq. (5)]. The horizontal axis categorizes the selection scenarios and social network type. Finally, the output of 500 runs per each scenario is plotted as a box-and-whisker diagram.

The first finding of Fig. 6 is that the selection scenarios could have significant effects on the success rate of the program. This observation might help to explain why a wide range of energy savings from 0% up to 30% has been reported in energy intervention experiments (Abrahamse et al. 2007; Darby 2006; Fischer 2008; Gulbinas and Taylor 2014; Hargreaves et al. 2010; Jain et al. 2013; Ma et al. 2018). In other words, more energy savings can be achieved by targeted selection of households (e.g., flexible and sociable top consumers) relative to random selection. One explanation is that each household has different energy saving potential and targeting the households with more energy saving potential could lead to more efficient programs.

As a minor finding, Fig. 6 shows that different types of social networks have a slight effect on the program efficiency and a similar trend in CBSH scenarios. This is consistent with the observations of previous models that reported social network type has less impact on the program results (Anderson et al. 2012; Azar and Al Ansari 2017). These comparisons with other similar validated models can support the validation of the proposed model (Sargent 2009).

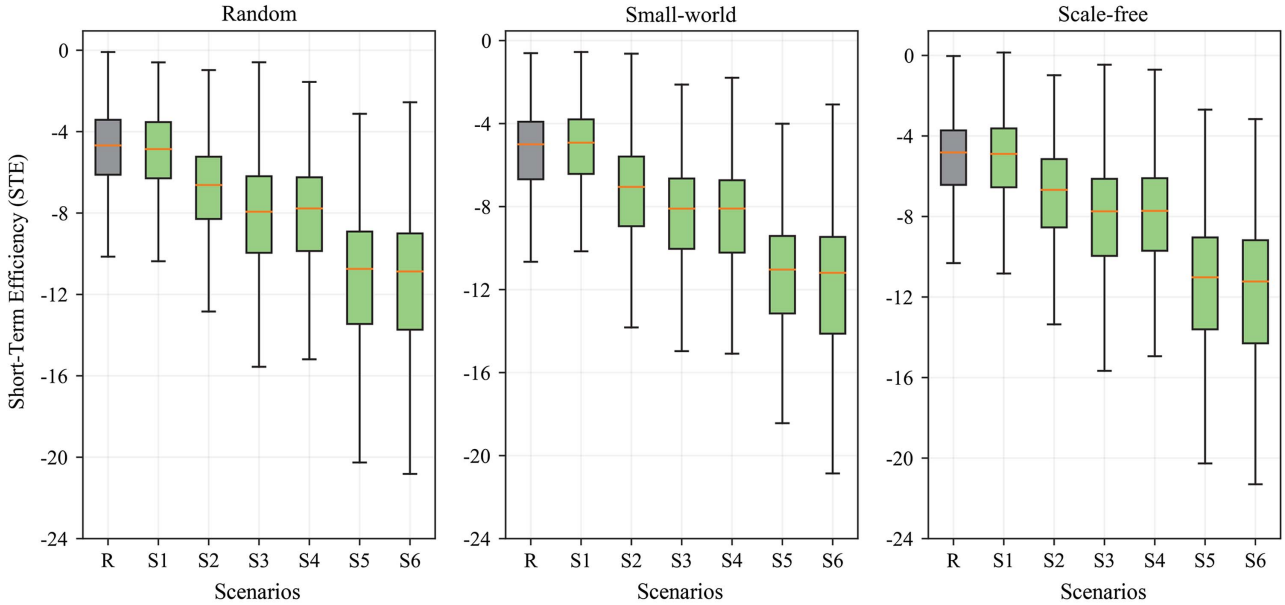

Fig. 6. Short-term efficiency of the ecofeedback program in accordance to network type and selection scenarios.

Phase II: Long-Term Assessment

In this phase, the interactions of agents among their social network, which cause changes in their energy consumption behavior, are considered. Table 5 illustrates the main inputs for this phase.

The most important difference between Phases II and I is the social interaction of residents after the ecofeedback program. In Phase I, residents only tracked the information of the people who consumed less energy, but in Phase II, all connected residents can affect the energy behavior of each other through social interactions. In each interaction cycle, all agents revise their energy behavior based on Eq. (1), and the program efficiency is calculated based on the change in the EI of agents after a specified period of social interactions.

The long-term efficiency of ecofeedback and EC programs are shown in Fig. 7. Although the selection scenarios of CBSH have less importance in the LTE of the ecofeedback program [Fig. 7(a)], the proposed approach has improved the EC program efficiency [Fig. 7(b)]. Based on these results, the E3 scenario could be introduced as the most efficient method, in which austerity and sociable agents are chosen as EC. In detail, the range of outputs has increased relative to short-term outputs, and this is more evident in the scale-free network. Consequently, in this social structure, the prediction of the energy savings from the ecofeedback event is associated with greater uncertainty. This observation could be due to the presence of high-degree nodes in scale-free networks called hubs, which are the most effective nodes on the state of the system (Barabási 2009). Finally, Fig. 7(c) provides a comparison of the results of EC and ecofeedback programs, in which the outputs of the simulation have been classified into four groups (no NI, ecofeedback, EC, and both).

It is evident that integrating both NIs (EC together with ecofeedback) could increase the energy saving of the target community more than single programs. However, selecting ECs (in the E3 scenario) instead of placing households in an ecofeedback program (in the S6 scenario) could generate more long-term energy reductions in the target community. The reason for the centrality of LTE values in the no EI condition around a nonzero number is that the agents' EI follows a lognormal distribution, which leads to a decrease in consumption through social interactions in the long run. Decision-makers could use this model with the available data from the target community to decide which interventions could have better returns considering the required funding for each.

Table 5. Model inputs for long-term assessment of ecofeedback and EC programs

Parameter	Values
Agents' population	pop = 100
Average number of connections	ANC = 5
Selection scenario for ecofeedback	CBSH = [R, S1, S2, S3, S4, S5, S6]
Participant number for the program	a_num = 10
Selection scenario for EC program	CBSH = [R, E1, E2, E3]
Number of ECs	EC_num = 10
Number of interaction cycles	cycle_num = 5
Social network type	type = [Random, Small-world, Scale-free]
Number of simulation runs	simulation runs = 500

Phase III: Sensitivity Analysis

With regard to the results of previous phases, in both the short and long term, S6 and E3 showed relatively better results among other CBSH scenarios. They were therefore chosen as the most optimal selection methods for further parametric analysis. Because the type of social network has little impact on the simulation results, random structure was used for sensitivity analysis. The parameters of the model are described in Table 6.

As shown in Table 6 and Fig. 8, the average number of connections, number of attendants and ECs, and interaction cycles are considered the variable inputs of the model, along with three normative energy interventions. Fig. 8(a) demonstrates that a low average number of connections can significantly limit the results of the NIs, and increasing the value of this factor could improve the outcome of NIs up to a certain limit. By increasing the number of connections in the model, the likelihood of being connected to low

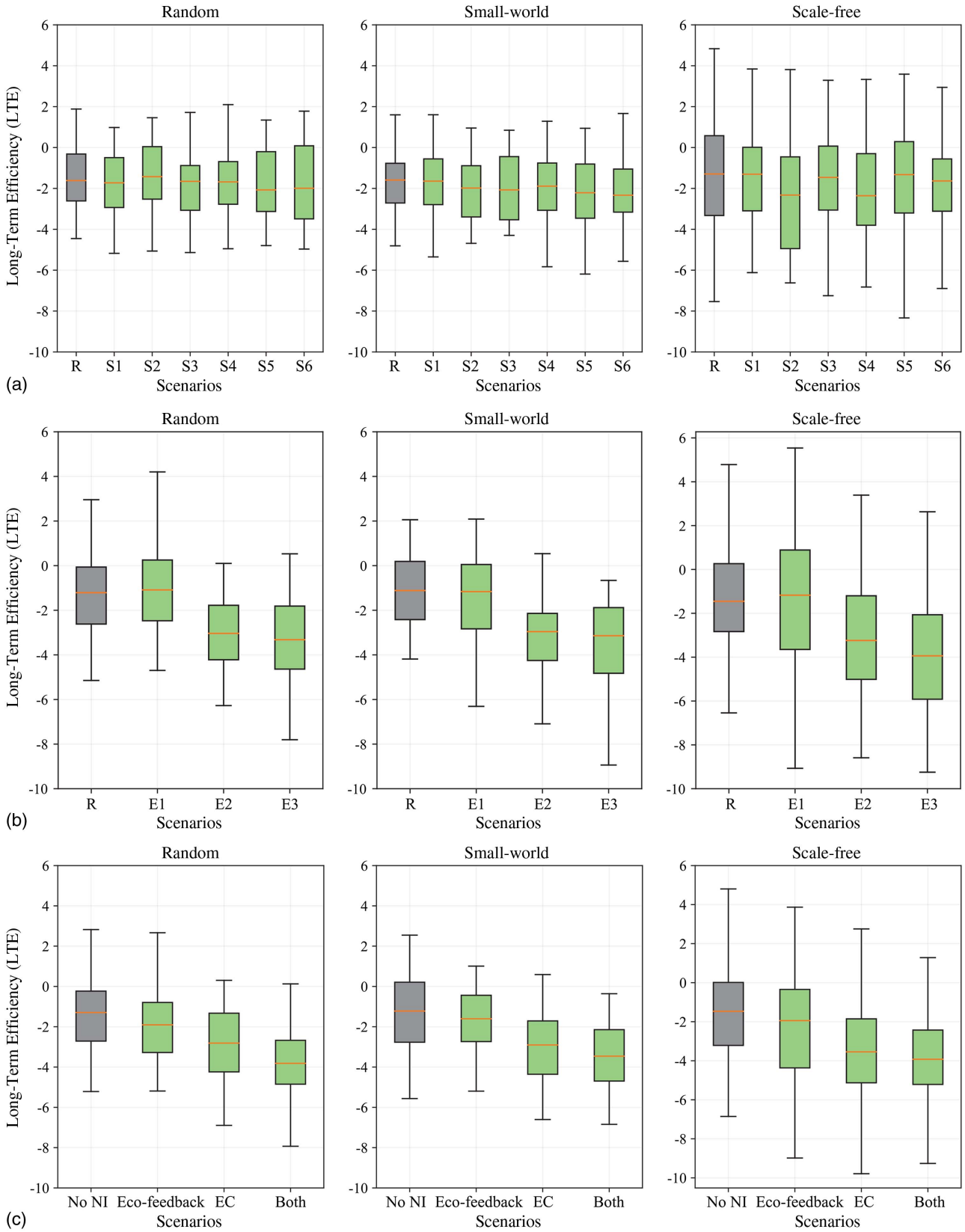

Fig. 7. Long-term efficiency of EC and ecofeedback programs: (a) ecofeedback program without EC; (b) EC program without ecofeedback; and (c) comparing EC (E3 scenario) and ecofeedback (S6 scenario) results.

consumers and ECs increases, and this can continue in this experiment to a limited amount, that is, five connections per agent. As a result, it is not suggested to use these programs in low-connectivity communities.

Although the evaluated NIs show similar sensitivity to the average number of connections, the number of attendants and ECs has different impact on the LTE of these NIs [Fig. 8(b)]. Raising the number of participants increases the long-term efficiency of NIs,

Table 6. Model inputs for sensitivity analysis

Parameter	Values
Agents' population	pop = 100
Average number of connections	ANC = [1,2,3,4,5,6,7,8,9,10]
Selection scenario for ecofeedback program	CBSH = S6
Participant number for the program	a_num = List [1,2,3,4,5,6,7,8,9,10]
Selection scenario for EC program	CBSH = E3
Number of ECs	EC_num = [1,2,3,4,5,6,7,8,9,10]
Number of interaction cycles	cycle_num = [1,2,3,4,5,10,15,20, 25,30]
Social network type	type = Random
Number of simulation runs	simulation_runs = 500

but it is less striking in ecofeedback. One reason for this observation is that ECs encourage the other households in each interaction cycle to make more energy savings without being influenced by high consumers. Nevertheless, ecofeedback participants would increase their consumption if they interacted with high consumers. Determining this factor in the real world depends on the funding available and required for each NI. This finding, which emphasizes the influence of social interactions, suggests that appointing more ECs could have better long-term impacts than increasing the attendants of ecofeedback.

Finally, the effect of the number of interaction periods on the model outputs is presented in Fig. 8(c), which can be interpreted as the impact of time on the energy consumption behavior of individuals. A wider range of possible outcomes for the final state is generated as time progresses and more interactions occur in the system. This impact is more intense in the single ecofeedback program that has no meaningful improvement over time and has gradually reduced its impact. A similar observation was reported in a recent work (Ma et al. 2018) that developed a prototype app-based ecofeedback system. The program effect was significantly positive in the short term, then became slightly positive in the medium term, and further faded to an insignificant level in the long term.

On the contrary, the presence of ECs or the use of both strategies is showing a growing trend with increasing the interaction cycles. Again, the EC strategy or combination of EC with ecofeedback is more practical than just a single ecofeedback in order to enhance the long-term improvement of energy behavior of households. To put the current section into perspective, the short-term and long-term impacts of NIs include ecofeedback and EC, and combination of both interventions has been investigated in the introduced model, which has revealed the reliability of the CBSH approach for selecting program participants. It has also been revealed that employing such normative energy behavior interventions in the target communities with a low average number of connections is not an effective option.

Model Verification

The final step toward addressing the research purpose in Fig. 1 is model verification. Validation of a simulation model is of paramount importance. Based on similar works on simulation of occupancy interventions (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2013; Bastani et al. 2016), four common types of validation techniques are considered in this paper to determine whether the obtained results actually represent the ground truth and proposed CBSH could enhance the outcomes of NIs. These techniques are (1) conceptual validity, (2) technical validity, (3) operational validity, and (4) comparison with previous models (Sargent 2009).

Conceptual validity of the presented model was provided by constructing the model based on validated and state-of-the-art concepts and theories from the literature, notably social psychological research (Friedkin 2001; Duggins 2014), as well as using actual data for model initialization in order to properly present real-world behaviors.

Technical validity was achieved by comparing the results of manually computing key equations implemented in the model to the values calculated by the model for a given input. As expected, the same result of manual calculations with the values generated by the model confirmed the correct implementation of the equations.

Operational validity, which ensures that the sequence of submodels presented in Fig. 4 is working well, was provided by monitoring and sensitivity analysis. Monitoring consists of meticulously tracing the characteristics and interactions of a defined number of agents through each submodel. At each step, any interaction of agents with the environment or other agents and changes in their characteristics is evaluated according to the called functions. In addition, the sensitivity analysis, which was detailed in the previous section, shows that the model reacts to the changes in the inputs in a logical manner. Eventually, the consistency of the results derived from the proposed model with previous simulation works (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2013), as well as empirical works (Abrahamse et al. 2007; Anderson et al. 2017; Darby 2006; Fischer 2008; Ma et al. 2018), provided the final evidence of model validity.

Discussion and Recommendations

Because the energy problem is becoming a critical crisis in the world, much attention is being given to energy-use interventions, which require relatively large investments. As a result, providing methods to improve the return on these investments is of great importance. Because of this, a number of influential factors related to efficiency of NIs have been analyzed in a simulation environment that can estimate the relative energy savings in different NI scenarios. These factors can be categorized into two main groups:

- *Community-related factors:* population, social network type, average number of connections (ANC)
- *NI-related factors:* NI method, number of ecofeedback participants, number of ECs, selection approach

The following recommendations were proposed after investigating and examining the impact of the aforementioned factors on the efficiency of NIs.

First, the social structure and level of connectivity in the target community should be taken into account for the implementation of NIs such as EC or ecofeedback. Employing such NIs in a community with a low average number of connections will not have a proper result, and other options should be taken into consideration. In low-connected communities, households are less likely to have social connections with low consumers or ECs, and normative interventions cannot have the expected influence [Fig. 8(a)].

Second, combining ECs with ecofeedback could lead to more energy savings in the long run. Based on the simulation results, the number of ECs has a direct impact on the long-term energy reduction, which makes a trade-off between the expected energy savings and required investment for NIs. Future research could thus focus on the economical aspects of NIs by developing a cost analysis framework that estimates the required fund for the expected energy savings.

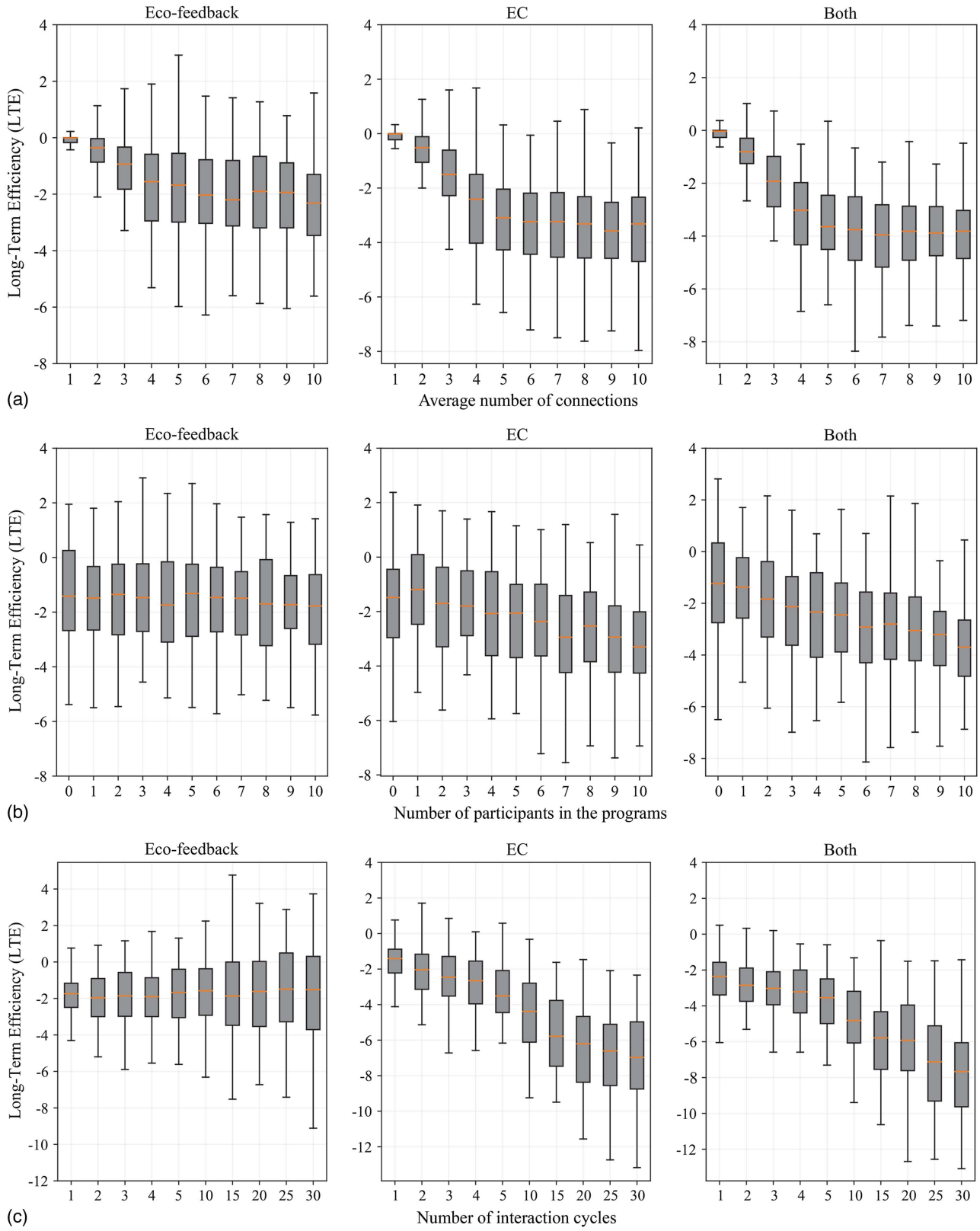

Fig. 8. Sensitivity analysis results (E3 and S7 scenario): (a) average number of connections (E3 and S7 scenario); (b) number of participants in the programs (E3 and S7 scenario); and (c) number of interaction cycles.

Finally, it has been shown that the introduced approach named CBSH could promote the effectiveness of NIs by selecting proper participants as ECs or ecofeedback attendants. Therefore, effective NI programs can be provided by inspecting the energy-related characteristics of the target community. In this paper, three main attributes among several energy behavior–related attributes have been defined for agents, which are applied for CBSH scenarios. Although the suggested CBSH approach is not the optimum answer

and considers a limited number of attributes, it can increases the program efficiency by up to 300% relative to random selection based on the simulation results. Because the importance of the selection process in the NI programs is revealed, the next step of the research would be to develop a framework to consider more related attributes and try to find the optimum NI participants among a target community.

Limitations and Future Work

The model and experiments are not without some limitations that need to be highlighted for future directions of research. One such limitation is the complexity and lack of information about time-related efficiency of ecofeedback programs. Therefore, in order to represent the impact of time on program efficiency, the authors introduced interaction cycles, as well as two efficiency measures (STE and LTE) that represent the passage of time after the program. However, further work is needed to determine the rate of change in energy behavior through program or social interactions. Analyzing this issue accurately would help us evaluate the time feasibility of achieving the expected program results.

Another limitation of this study is the lack of available data and quantification methods on energy behavior parameters reflecting how households form and change their energy behaviors (flexibility index, etc.). Although changing distribution types and their parameter values does not have a critical impact on the reported findings on the CBSH approach, future work should focus on developing feasible methods that can quantify the required energy behavior attributes and describe their possible dependencies.

Conclusion

Many studies attest that occupancy behavior is one of the most influential factors related to energy consumption in buildings. Accordingly, several efforts have been made to improve the energy behavior of households. The current paper has developed an enhanced agent-based model in order to investigate whether applying a characteristic-based selection of participants approach in selecting a limited number of participants as ECs or ecofeedback attendants could improve the program outcome. Similar studies on NIs investigated the impact of different factors such as network type and its characteristics (Anderson et al. 2013), multilayer program efficiency (Azar and Al Ansari 2017), and indirect energy saving through social interactions (Ekpenyong et al. 2014). The main focus of this study, however, is to enhance NIs through targeted household selection. In this research, three characteristics, social relationships, energy-use index, and flexibility index, were considered for selecting program participants among households in different types of CBSH and comparing their outcomes with a random selection approach. Based on the results of this simulation study, some recommendations have been made to increase investment returns and the efficiency of the program, which can fluctuate between 0% and 30%. Appropriate methods for selecting program participants such as CBSH, considering the average number of connections in the target community, and combining EC and ecofeedback programs are the main recommendations that can bring about more energy saving through NIs.

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