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Targeted selection of participants for energy efficiency programs using genetic agent-based (GAB) framework

Mohammad Zarei · Mojtaba Maghrebi

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Abstract Many studies show that the human energy-related behaviors have a significant impact on the return of Energy Efficiency Programs (EEPs). However, studies that aimed at increasing the energy savings from the EEPs are still limited. In this paper, a Genetic Agent-Based (GAB) framework has been proposed to enhance the return of a typical EEP by simulating social network and energy behavior attributes and finding the best participants among a target community. Several attributes are considered for creating the agent-based model of households and numerically representing their interactions with the EEP or within their social network. The improvement of the EEP using the GAB framework is tested on a social network consisting of 56 households. The simulation results show that by accurately selecting participants using the presented framework, the amount of energy saving could increase up to ten times. This ultimately indicates the considerable impact of the social network on the EEP performance. In other words, to have an efficient EEP in the long term, the social network attributes such as network degree and strength of connections should be also considered in decision-making along with the energy-related attributes.

M. Zarei · M. Maghrebi (✉)
Department of Civil Engineering, Ferdowsi University of Mashhad, Mashhad, Iran
e-mail: mojtabamaghrebi@um.ac.ir

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Introduction

Recently, global climate change has emerged as an important international issue, and Energy Efficiency Programs (EEPs) research has become a major focus worldwide. Typical EEPs have been traditionally introduced with physical changes to residential buildings such as building envelopes (Cheung et al. 2005; Harvey 2009) and equipment (Lanzisera et al. 2012). Studies on occupant behavior revealed, however, that human actions play a major role in the success of such programs and more attention should be given to this topic (Delzendeh et al. 2017; Hanus et al. 2018; Morgenstern et al. 2016; Hoicka and Parker 2018). For example, due to different occupancy behaviors, one home could consume 2.6 times more electricity than another identically equipped home (Parker et al. 2008), or two similar buildings could have an energy consumption ratio of 5-to-1 (Diamond 1984). Here, a phenomenon known as the "take-back" or "rebound" effect is worth mentioning, whereby the households tend to increase their energy consumption after physical promotions, so that improving households' energy behavior is more important than technical improvements (Sorrell et al. 2009; Abdessalem and Labidi 2016). Therefore, physical improvements without taking human behaviors into account cannot be as effective as expected (Gynther et al. 2012; Winther and Wilhite 2015).

Since running the EEPs require adequate investment, particularly on a large scale, increasing the return on these projects is of great importance for decision makers and investors (Sauma et al. 2016). The return (the amount of energy saving) from an EEP can be divided into short term or direct impact and long term or indirect impact (Ekpenyong et al. 2014). The short-term impact is contributed to the direct energy savings by target individuals (referred as participants in this paper) during the implemented EEPs such as energy feedback programs (Dougherty and van de Grift 2016), workshops (O'connor and Macur 2018), and green marketing (Cho et al. 2015). The long-term impact is the result of social interactions between program participants and nonparticipants, which could change the EEP effect on participants or spread the energy-saving behavior through the nonparticipants.

Valuable empirical (Abrahamse et al. 2005; Vine et al. 2014; Hoicka and Parker 2018) and simulation efforts (Anderson et al. 2013; Azar and Al Ansari 2017; Azar and Menassa 2013; Du et al. 2016; Ekpenyong et al. 2014; Ekpenyong et al. 2015; Chen et al. 2012; Zarei and Maghrebi 2020) have been made to enhance the performance of EEPs considering human factors. The results in (Peschiera and Taylor 2012) show that the energy consumption of a typical building is affected by not only the behavior of its own occupants but also by occupants from neighboring buildings. Residents can thus reduce energy use by sharing information on energy efficiency in a social network (Shimokawa and Tezuka 2014). In addition, the use of energy feedback method shows that individuals tend to decrease their energy use when comparative information about consumption is provided (Anderson et al. 2017; Ma et al. 2018). These studies also reported a gradual decline in the impact of interventions over time.

In the simulation studies, the impact of several factors on the return of the EEPs have been investigated including social network types and their characteristics (Anderson et al. 2013), multilayer program efficiency (Azar and Al Ansari 2017), word-of-mouth effect (Bastani et al. 2016), and indirect energy saving estimation (Ekpenyong et al. 2014), to name but a few. For instance, a mathematical model that describes the reduction of information propagation over time in a social network is proposed for expected energy cost savings (Ekpenyong et al. 2015). The results show that the increase in connections among members of a social network enhances the potential for increasing energy saving over time. This model, however, neglects the differing strength of the links between people covered by another work by (Du et al. 2016). Although the upgraded model has a more realistic representation for social networks, the difference in the susceptibility of people to energy conservation issues is not taken into account.

The current study focuses on the impact of social network on the performance of EEPs in residential buildings. In most EEPs, it is not possible to directly engage with all households in a target community. A number of households will, therefore, be selected as the EEP participants. In this regard, previous works have shown that the selection of participants could change the energy saving both directly and indirectly (Du et al. 2016; Ekpenyong et al. 2014, 2015). Using agent-based simulation integrated with genetic algorithm, a new framework is suggested in this paper to find the near-optimum targets among a social network of households in order to participate in a typical EEP and provide more short- and long-term energy savings. This framework, called the Genetic Agent-Based (GAB) framework, has been tested in a community of 56 households whose social structure is derived from (Ekpenyong et al. 2014), to identify the best EEP participant combination.

The rest of the paper will be structured as follows. The first section describes the GAB framework and the concepts used. The proposed framework is carried out on a simulation experiment in the subsequent section and the results are discussed. Finally, in the last section, some conclusions are drawn.

Methodology

The first step in a typical EEP is to find the potential participants and encourage them to reduce their energy consumption by either upgrading equipment or improving their energy consumption habits (Gynther et al. 2012). The purpose of this study is to provide a general framework for finding the best EEP participants. The proposed framework, GAB, is made up of two main components (Fig. 1(a))

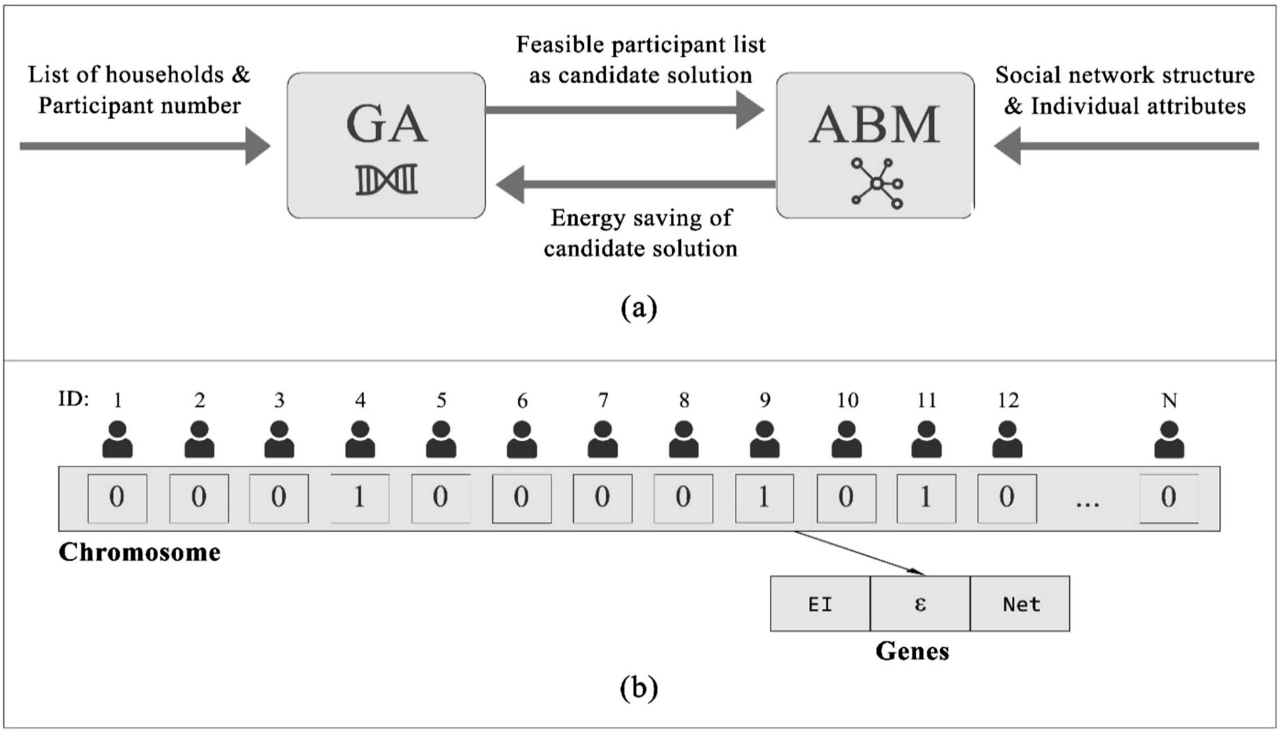

Fig. 1 (**a**) GAB framework; (**b**) Composition of chromosome in GA

(1) Genetic Algorithm module (GA)
(2) Agent-Based Model (ABM)

GA is responsible for heuristically finding the near-optimum solution and producing feasible candidates as the input of ABM. These solutions are a list of IDs representing the potential participants attending in the EEP (Fig. 1(b)). ABM's role is to estimate the energy saving in the target community caused by the EEP. This task is accomplished by simulating the participants' behavioral change during the EEP as well as considering individuals' interactions within their social network. Details of these processes are described below.

Genetic algorithm (GA) module

The Genetic Algorithm (GA) used in this study is a natural selection process inspired by the theory of natural evolution of Charles Darwin, where the best individuals are selected in order to produce next-generation offspring (Koza 1994). In GA, chromosomes are candidate solutions and consist of genes. Each gene contains the value of a variable to be optimized, i.e., a chromosome is a gene string containing the values of all variables of the optimization. A fitness function measures the goodness of the chromosomes. By randomly generating a set of chromosomes called population, GA is initialized. Then there are three main operations: selection, crossover, and mutation to search for the fittest chromosome, which has the highest/lowest value of the fitness function (depending on minimizing or maximizing the fitness function). Two chromosomes are selected randomly as crossover parents. The fitter chromosomes are more likely to be chosen. Some parent genes are randomly swapped in the crossover to produce offspring with inherited characteristics. Lastly, mutation is performed by altering randomly the value of one or more genes to counteract trapping in a local optimum solution. In each iteration of this process, a new generation of chromosomes is created and evaluated by the fitness function. The algorithm ends when the chromosome population has converged. One of the common conditions for stopping iteration is to reach the maximum number of generations [see (Kinnear et al. 1999) for further information about GA].

A chromosome in this study consists of a defined number of binary cells (representing the number of households), the value of which indicates which individuals are selected for the EEP involvement. It should be noted that all acceptable chromosomes are expected to have a similar number of participants as a predefined value. As illustrated in Fig. 2, ABM will calculate the fitness function (details in the next section) for all candidates to find the one with maximum fitness function in the generation after initializing the first generation of possible solutions (participant list for EEP) and randomly setting the optimum candidate. If it has more fitness function than the previous optimum candidate, it will be replaced as an optimum candidate. Next, some candidates will be selected for the GA operations including two-point crossover and swap mutation (Fig. 3). This step is repeated until new acceptable chromosomes are produced that show the exact number of participants. Then in the new generation, the presence of the optimum candidate will be checked. If during GA operations the optimum candidate were changed, it would be added to the new generation again. This so-called elitism strategy will increase the speed of optimum convergence of candidates (Kinnear et al. 1999). Finally, ABM will compute the candidates' fitness function in the new generation, and this cycle will be performed until the number of generations is equal to the maximum number of generations defined.

Agent-based model (ABM)

The main components of an agent-based model are autonomous agents that act intelligently and interact in an environment (Macal 2016). In modeling complex systems, the agent-based structure, flexibility, and computational advantages have made them powerful tools. In addition, a standard protocol with seven steps called Overview, Design Concepts, and Details (ODD) is prepared for researchers to build more reproducible and readable ABMs. The simulated system can behave very similar to the actual system after accurately defining the behavior of each agent and the relationship of agents within the environment. Consequently, to obtain a set of related data, the simulated system's reaction to each strategy or any other plausible intervention can be realistically simulated. Because of the dynamic nature of the

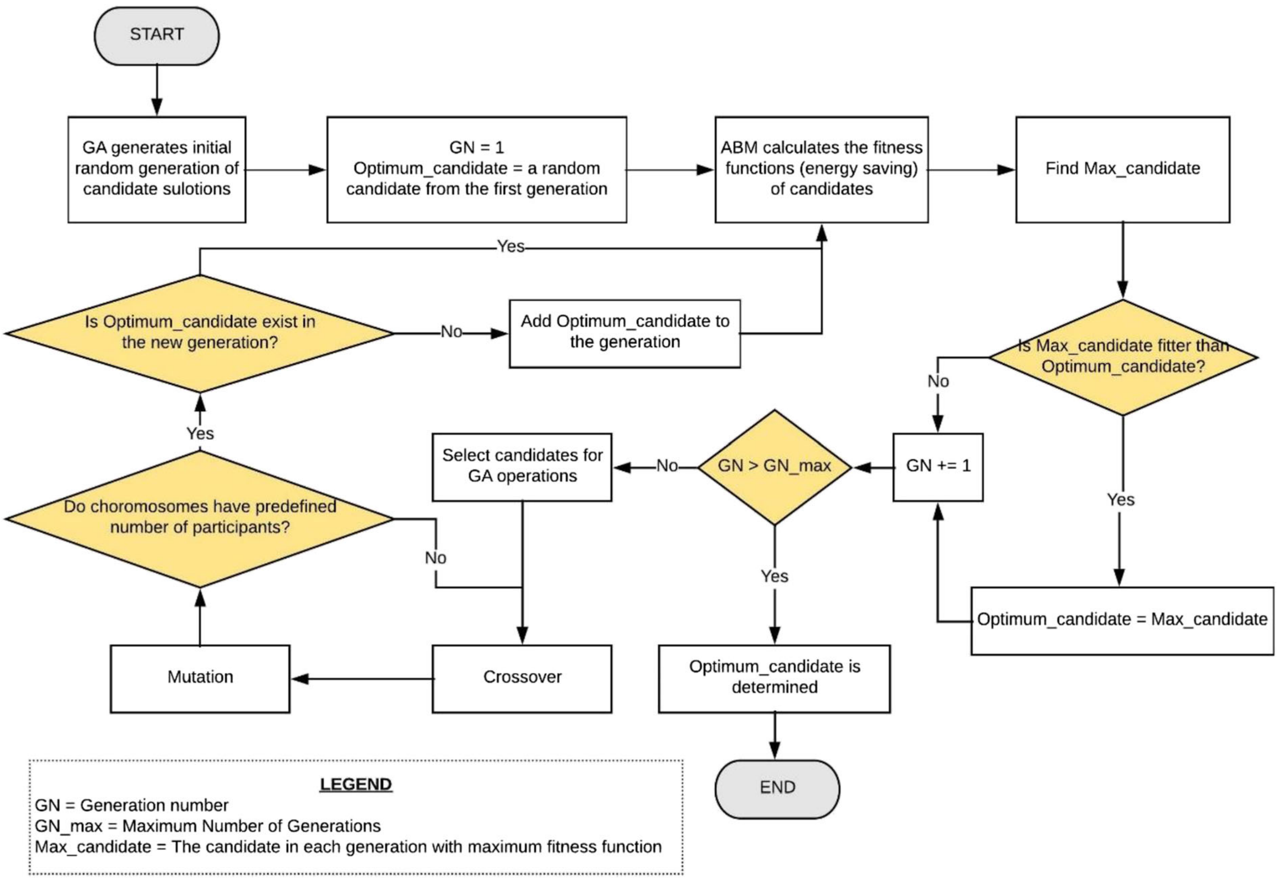

Fig. 2 Finding near-optimum participant list using GAB framework

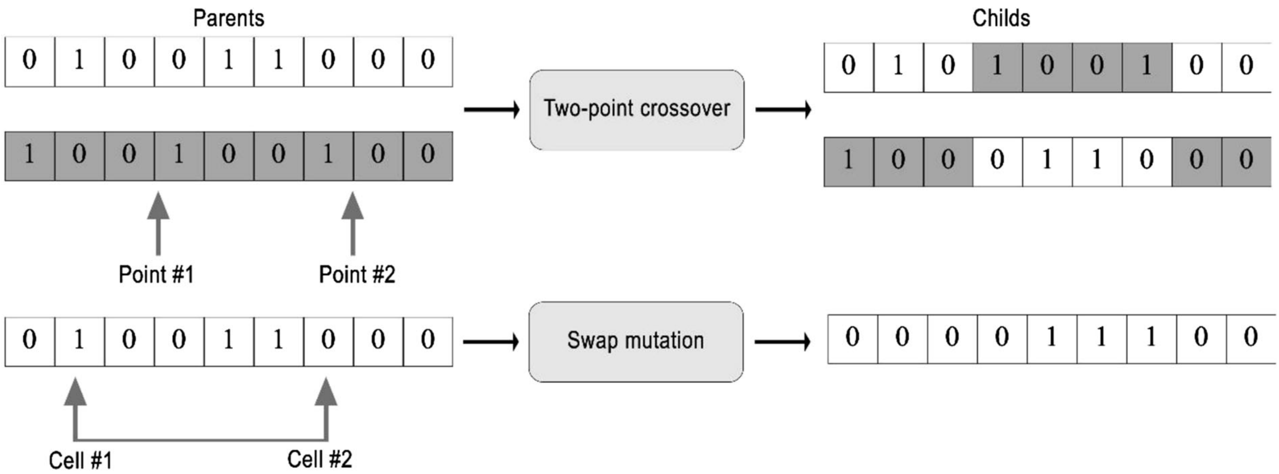

Fig. 3 Two-point crossover and swap mutation

occupants, a residential building with several occupants can be defined as a complex system, and thus agent-based modeling is a suitable tool for modeling such systems.

ABM calculates the fitness function of the proposed candidates by GA in the GAB framework suggested in this paper (Fig. 1). The fitness function is the amount of energy savings in a target community by deploying an EEP. N nodes on a network can represent a community with N agents (households), and edges on the network represent the connections between the nodes. They are said to be connected when there is mutual recognition of friendship between two households. One of the ABM inputs is the social structure of agents in the community. Furthermore, each agent has some variable and constant attributes to be considered in the ABM (Table 1).

Table 1 Agent attributes

Attribute	Description
ID	*Agent ID*. A unique and constant identification code for each agent
EIn	*Energy Intensity*. The annual energy consumption of each household per unit area (kw/m^2) obtained from historical data
A	*Area of the house* (m^2)
EI	*Energy Index*. The annual energy intensity of each household at a scale of 1 to 100
ε	*Susceptibility*. The household's adaptation rate to change their energy-use behavior by external influence on a scale of 0 to 1
Degree	*Degree of connections*. Number of social connections
Net	*Network list*. List of the social connections (relationships)

Energy Index (*EI*), which is dynamic and changes due to the EEP or the social interactions, is the primary attribute of interest. The *EI* of an agent is calculated using the Min-Max method of normalization (Patro and Sahu 2015):

$$EI_i = \frac{EIn_i - EIn_{min}}{EIn_{max} - EIn_{min}} \times 100 \quad (1)$$

where, EIn_{max}, EIn_{min}, and EIn_i are the maximum annual electricity consumption per unit area among the agents, minimum annual electricity consumption per unit area among the agents, and the annual electricity consumption per unit area for agent i, respectively.

Participants are encouraged in a common EEP toward efforts to save energy. For example, energy-efficient products known as green marketing will be given or introduced (Ekpenyong et al. 2014) or eco-feedback programs are conducted (Francisco et al. 2018), in which the participants are given comparative information about their energy consumption. This process could be mathematically described as the following general equation:

$$EI_i^{t+1} = (1 - \varepsilon_i \times \epsilon) \times EI_i^t \quad (2)$$

where EI_i^{t+1} and EI_i^t are respectively denoted to the energy index of i after and before the EEP. ε_i indicates the susceptibility of agent i, which should be obtained for all of the households in the target community. Finally, ϵ reflects the success rate of the EEP. This factor represents the program quality and the other potential issues that could limit participants' maximum change in energy consumption (interest in change, ability to change, change effectiveness, etc.). For all EEP participants, the Eq. 2 is implemented.

Social interactions in the target community could change the energy use of all agents after the program. The amount that an agent changes its *EI* during the interactions with the other connected agents is calculated on the basis of Eq. 3 derived from the models of mathematical opinion change in psychological studies (Friendkin 2001; Deffuant et al. 2002).

$$EI_i^{t+1} = (1-\varepsilon_i) \times EI_i^t + \varepsilon_i \times \sum_{j \in Net(i)} \omega_{ij} \times EI_j^t \qquad (3)$$

where EI_i^{t+1} and EI_i^t are respectively denoted to the energy usage of agent i at time $t+1$ and t, which are calculated based on eq. 4. ε_i indicates the susceptibility of agent i, and ω_{ij} reflects the weight-factor that represents the strength of the relationship between agent i and j. The weight-factor for each pair of connected agents can be estimated based on (Friendkin 2001):

$$\omega_{ij} = \frac{C_{ij}}{\sum_k C_{ik}} \qquad (4)$$

where C_{ij} is the estimate of the probability of an interpersonal attachment from agent i to agent j; and $i \neq \{j, k\}$; $0 \leq \omega_{ij} \leq 1, \sum_j \omega_{ij} = 1$.

In the final step, the average energy saving amount from the EEP that is represented as the fitness function of each participant list is assessed by the following equation:

$$ES = \frac{\sum_1^{n'} \left(EI_i - EI_i'\right) \times A_i}{n'} \qquad (5)$$

where n' is the number of agents, EI_i and EI_i' are respectively the energy index of agent i before and after the EEP and social interactions, and A_i is the house area of agent i. The purpose of this framework is to maximize the Eq. 3 by choosing proper participants for the EEP.

To sum up, GA produces the potential lists of participants as the candidate solutions in the GAB framework, ABM calculates the candidates' fitness function and returns the value of fitness functions to the GA to generate new candidates. This cycle will continue until the maximum number of generations is reached. The proposed framework will be tested in a simulation experiment in the next section.

Simulation experiment

A small community of 56 households with their social connections will be considered in order to examine the GAB framework and five households will be selected as the participants of the EEP (searching among $\binom{56}{5} = 3,819,816$ different possible combination of participant list). Clearly, by expanding the community's population, the number of possible solutions will increase significantly, further justifying the need to use the presented framework to find the near-optimum solution, which is the best combination of participants. For example, the total number of possible combinations to select 10 people among 100 people is approximately 10 trillion ($\binom{100}{10} = 1.73 \times 10^{13}$).

The social network between the households is depicted in Fig. 4 that is taken from (Ekpenyong et al. 2014). The size and the color for each node represent `Degree` and `EI` of each household (see Table 1). The range of values for `Degree` and `EI` are between (1 to 17) and (13.7 to 84.8), respectively.

Table 2 provides the details of the required attributes for the households. Note that it is beyond the scope of this paper to develop a method for quantifying household susceptibility and remains for future works. There are, however, some primitive questionnaires used to capture this attribute in previous studies (Azar and Al Ansari 2017; Zhang et al. 2011). This experiment also aims to demonstrate the applicability of the framework if the required data are already available. Thus, a random constant value is assigned to each agent from a normal distribution ($\sigma = 0.3$, $\mu = 0.5$), which is a common approach in the study of human energy behavior (Anderson et al. 2013; Azar and Menassa 2013). `EI` for each agent was derived from a lognormal distribution ($\sigma = 0.388$, $\mu = -0.924$, $\gamma = -0.099$), 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 (Fig. 5). The result of Kolmogorov-Smirnov (*KS*) statistic is 0.032, which is less than the 0.05 common threshold confirming the goodness of fit (Massey Jr 1951). Finally, all houses are assumed to be similar in the total area (90 m^2).

The GAB framework is programmed in Python 3.6 environment using NetworkX (Hagberg et al. 2008) as a robust Python package for complex network analysis. In this experiment, it is assumed that $\epsilon = 1$ and the quality of the EEP is set at maximum influence. However,

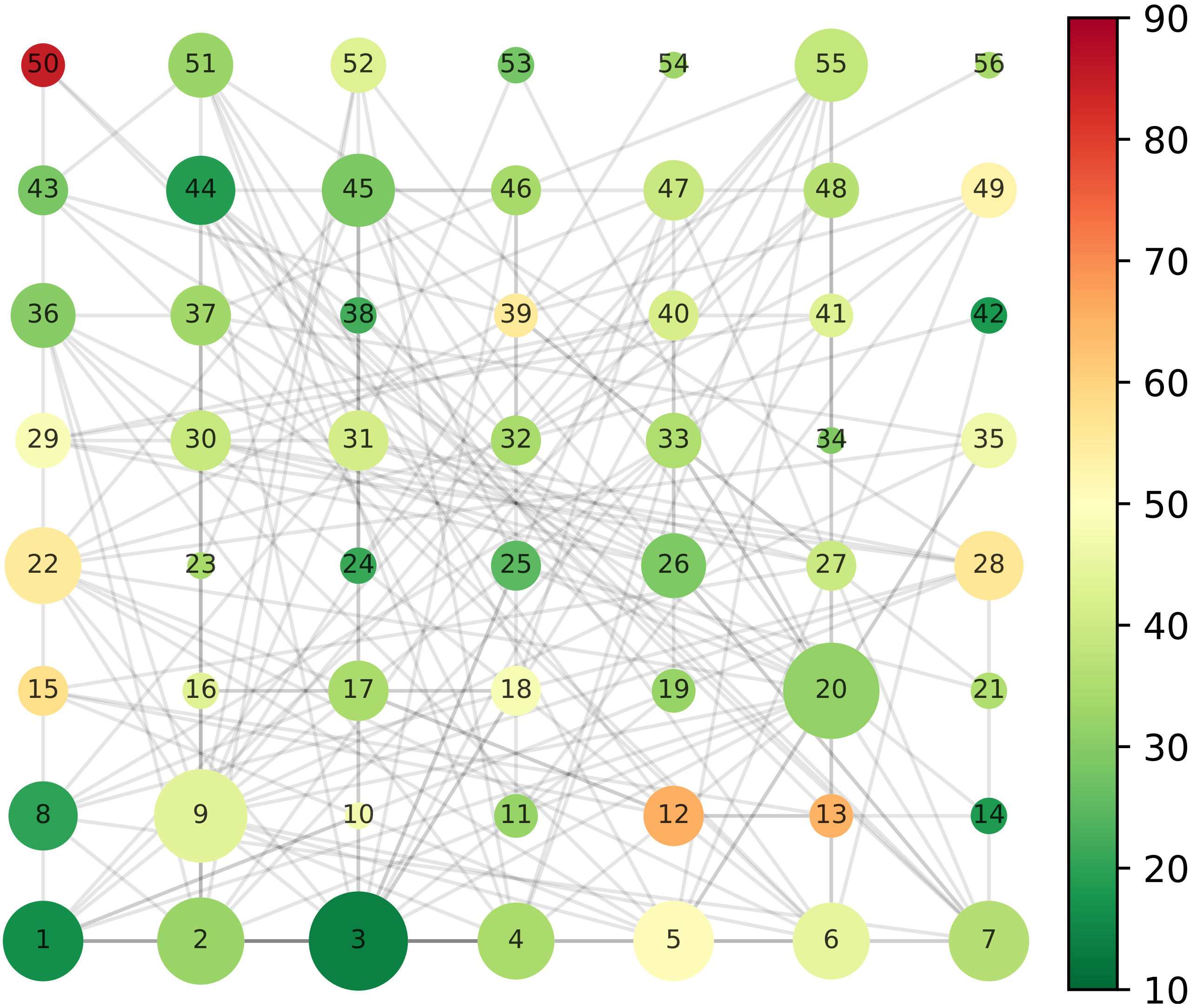

Fig. 4 Social network of 56 household

sensitivity analysis demonstrated relative changes in system behavior with different values for this factor, and the suggested lists remains stable. GA's parameters used in the model are 500, 50, 0.5, and 0.2 for the number of generations, population size, crossover rate, and mutation rate, respectively. Having run the model, the near-optimum participant lists are identified as presented in Table 3.

Table 3 shows that the selection of participants has a significant impact on the EEP return. The community's best combination of participants has nearly ten times more energy saving than the worst combinations. This conclusion could persuade the EEP planners to give more attention to the selection process of the participants. Analyzing the attributes of the agents selected as the optimum participants reveals that considering only one attribute for selection (having a high degree of connections, high energy consumption, high susceptibility, etc.) is not sufficient to achieve a near-optimal solution. On the basis of Table 4, it is not easy to identify the best participants simply by inspecting their characteristics, and the final result depends on many factors. Separate studies on this ground (Du et al. 2016; Ekpenyong et al. 2014; Chen et al. 2012) also found that people with the highest connections do not necessarily result in maximum energy savings during EEPs. In other words, there are many factors involved in determining participants' energy saving through an EEP such as the energy consumption level, susceptibility, social connections, and strength of connections, to name but a few. The GAB framework is, therefore, an applicable tool to help decision-makers search for the appropriate EEP participants and achieve more energy savings within the community.

Table 2 Community data

ID	EI	ε	Degree	ID	EI	ε	Degree
1	16.5	0.79	11	29	48.4	0.58	5
2	32.6	0.22	13	30	39.2	0.7	6
3	13.9	0.17	17	31	41.3	0.23	6
4	35.0	0.12	10	32	34.4	0.8	4
5	50.8	0.76	11	33	35.3	0.29	5
6	45.2	0.7	10	34	29.6	0.87	1
7	36.5	0.78	11	35	46.6	0.4	5
8	20.3	0.55	8	36	30.4	0.53	7
9	44.1	0.22	15	37	33.5	0.38	6
10	47.2	0.48	1	38	22.4	0.13	2
11	32.3	0.17	3	39	55.3	0.65	3
12	65.8	0.61	6	40	41.7	0.25	4
13	65.3	0.61	3	41	43.4	0.51	3
14	18.6	0.21	2	42	18.4	0.4	2
15	57.8	0.57	4	43	28.6	0.78	4
16	43.6	0.39	2	44	19.1	0.58	8
17	34.9	0.79	6	45	29.1	0.26	9
18	48.1	0.93	4	46	34.2	0.67	4
19	32.3	0.12	3	47	39.7	0.93	6
20	31.8	0.52	16	48	36.7	0.02	5
21	35.8	0.26	2	49	53.1	0.42	5
22	55.2	0.39	10	50	84.8	0.13	3
23	34.2	0.75	1	51	32.6	0.83	7
24	21.4	0.8	2	52	43.3	0.66	5
25	25.1	0.72	4	53	28.1	0.2	2
26	29.3	0.31	7	54	33.2	0.77	1
27	39.8	0.64	4	55	38.7	0.16	9
28	56.0	0.1	8	56	34.3	0.92	1

Implications

This paper presents the GAB framework as a practical solution for finding the near-optimum combinations of participants in an EEP. As the evaluator of potential participants, the framework integrated ABM with GA as the generator of the potential lists. Although some aspects of this issue have been addressed in the previous works (Du et al. 2016; Ekpenyong et al. 2014), the model in those papers has not considered the fact that people have different reactions to the energy conservation efforts. While in this paper, by using a behavior change model from psychology studies in an agent-based environment, the quantified influence of individuals is more reliable. Moreover, the connections weights in (Du et al. 2016) is obtained by using a questionnaire survey, which could be inaccurate. However, in the GAB framework, the weights of connections are calculated by considering the closeness of connections in the social network that eliminate the weight acquisition step.

Limitations of the framework

There are some limitations to the GAB framework presented in this paper. First, survey data including the details of social network connections and the attributes of households (energy consumption and susceptibility) are required. This reduces the scale of the social network being targeted. One possible solution in the future might be to find possible relationships between the different attributes of households. Another limitation is to quantify household susceptibility. Although this attribute is captured by some primitive questionnaires (Azar and Al Ansari 2017; Zhang et al. 2011), further studies are required to achieve more accurate methods. One suggested way to gather social network details is to ask people about their connections in person. For example, Ekpenyong et al. provided a list of all 56 neighbors for each household and asked them to select their friends (Ekpenyong et al. 2014). Second, the GAB framework's reliability of the result depends on whether the sampled social network is sufficiently representative. The results will be less representative due to inappropriately selected network. Finally, through social interactions or the EEPs, many factors are responsible for the energy behavior dynamics. Although a validated model of behavior change is used in the presented framework, future studies could add more elements and details to bring the outcome closer to the real-world events. Finally, the behavioral change of participants by an EEP is simulated in a general form. Since various EEPs have different factors, they could be modeled separately in the future works.

Conclusion

The indirect energy saving through a community is due to the individuals' interactions within their social network. This impact should be considered by decision makers to identify the best targets for attending the EEPs. This implies that a proper group of participants will encourage the rest of the network to join the program in a mass roll-out or toward more energy-efficient

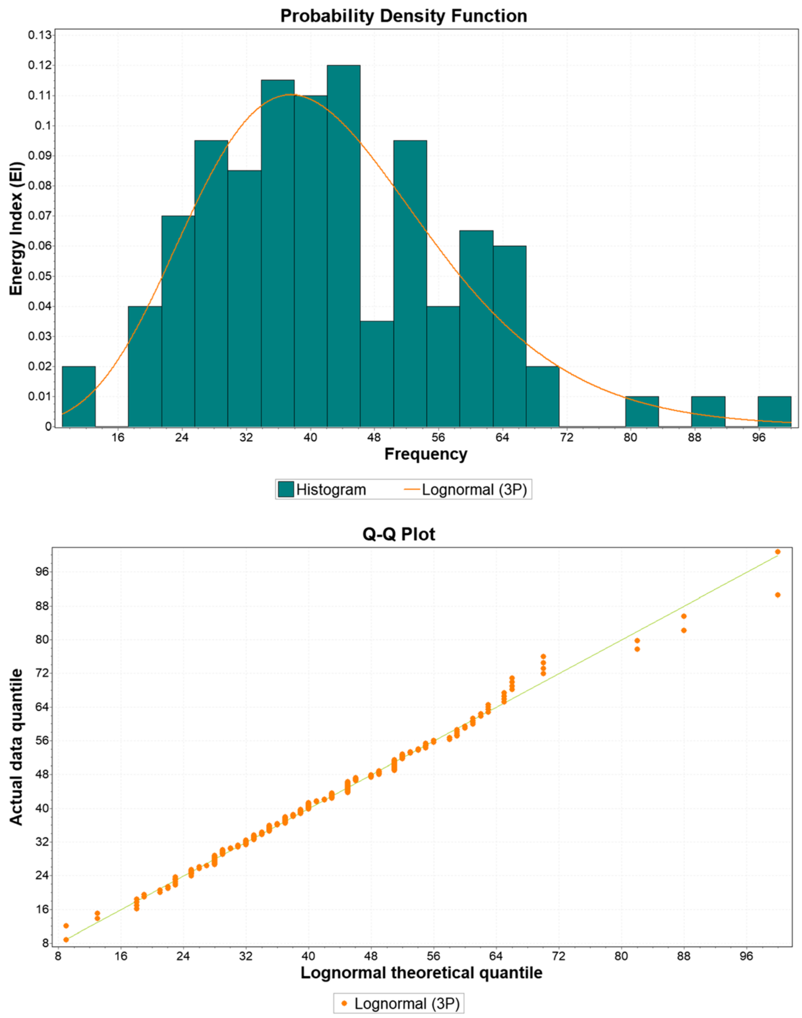

Fig. 5 Lognormal distribution fitting of scaled energy consumption data

behaviors. A Genetic Agent-Based (GAB) framework is developed in this study to integrate the social network and the energy behavior attributes and identifies the best combination of participants in a community. The optimal combination of participants could spread more energy conservation behavior initiated by the EEP. To this end, GA is used to generate the feasible candidate solutions and heuristically search for the near-optimal list of participants. This is integrated with ABM, a powerful method for modeling the social networks and examining the candidate solutions' energy savings. In this framework, households are simulated as the agents with several attributes in a social network, and their interactions with the EEPs or the other households are described using a validated behavior change model. The successful implementation of the GAB framework in the simulation experiment confirmed its applicability by increasing the EEP return. The results show that different combinations of the participants could increase the energy savings rate for the EEP up to 10 times. Additionally, it is revealed that there are several factors that determine the outcome of an EEP such as project type/quality/conditions or the many attributes for a given household. It is not recommended to find the best

Table 3 Energy saving for participant combinations

Participant IDs Best combinations	ES	Participant IDs Worst combinations	ES
5, 6, 12, 13, 18	4.048	3, 10, 11, 23, 34	0.489
5, 6, 12, 18, 20	3.931	4, 11, 24, 39, 54	0.488
5, 6, 12, 18, 30	3.869	10, 14, 24, 48, 54	0.458
5, 6, 12, 17, 18	3.743	10, 11, 19, 34, 39	0.448
5, 6, 12, 15, 30	3.647	23, 38, 39, 48, 56	0.446
5, 6, 12, 30, 51	3.561	10, 11, 24, 38, 56	0.432

Table 4 Information of the best and the worst combination of participants

ID	*EI* ranking	ε ranking	Degree ranking
The best combinations			
5	9	13	5
6	14	17	6
12	2	23	10
13	3	22	13
18	11	2	12
The worst combinations			
10	12	31	15
11	40	48	13
24	50	7	14
38	49	52	14
56	32	3	15

decision by inspecting a limited number of attributes. The influence of the social network is found to be significant among the factors mentioned. As a result, the social network attributes (degree and strength of connections, etc.) should be also considered in the program planning along with the other energy related attributes. The presented framework is a practical and extendible approach for incorporating these attributes. This will lead to better decisions made about the implementation of the EEPs.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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