Application of Opinion Dynamics Models in Energy Eco-Feedback Agent-Based Simulation

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Abstract

Research suggests that curbing consumer demand for energy through behavioral interventions is an essential component of efforts to reduce greenhouse gas emissions and climate change. On this ground, feedback interventions, which make the energy consumption and conservation efforts visible to the consumers, are considered as a practical method increasing the energy saving behaviors. Simulation techniques provide a convenient and economical tool to examine the factors that could affect the energy saving amount as the outcome of such interventions. However, developing a reasonable model that could correctly represent real-world process is a big challenge. In this paper, five common Opinion Dynamic (OD) models that represent how opinion change occur among individuals’ interactions have been investigated and a Revised OD (ROD) model have been proposed to build more efficient eco-feedback simulation models. Findings indicate that influence condition and weight-factor of connected opinions have significant impact on the accuracy of simulation outputs, which have been compared to the field experiment reports. Accordingly, ROD has been suggested for eco-feedback simulations, which shows the closest prediction to the field data.

Keywords: Opinion Dynamics, Occupancy interventions, Social impact, Agent-based simulation, Eco-feedback
Introduction

The growing industrial and residential carbon footprint fuel the ongoing process of climate change. Regulatory legislation can limit industry’s contributions to greenhouse gas emissions. However, the energy consumption of buildings, which accounts for up to 40% of global energy consumption in developed countries and approximately the same percentage of gas-emission production [7], is difficult to regulate without engendering dissatisfaction among residents. In view of this, building occupants can be considered an important target group for energy saving goals. In other words, by targeting energy-related behaviors at buildings, a considerable amount of energy reduction could be achieved [8, 9]. Here, it is worth mentioning a phenomenon, known as the “take back” or "rebound" effect, whereby households tend to increase their energy consumption after physical promotions, improving households energy behavior has higher priority than technical improvements [10]. Consequently, physical improvement without behavioral interventions will not be as efficient as it is expected to be [11, 12].

Generally, occupant energy behavior is an ever-shifting attribute, which could be changed due to social interactions [13] as well as energy saving interventions [1, 12, 14]. Among different types of occupancy interventions for energy conservation (such as goal setting [15], commitment [16], and workshops [17]), feedback method have attracted more attentions from scholars [1, 3, 5, 18, 19]. In a typical feedback program, occupants are provided with their energy consumption information and can observe the effectiveness of their efforts to conserve energy. Therefore, feedback interventions could address the invisibility of energy use and encourage consumers toward sustainable behaviors [20].

Feedback results could be improved through various ways such as increasing the frequency of feedback, providing a time-, room- or application- specific breakdown, improving the visual design, or adding further information, for example, time series, comparisons with an average, or information about environmental impact [3]. However, implementing eco-feedback programs have reported to be more efficient using social influences on occupant energy behavior [8, 13]. In this approach, occupants can compare their energy usage and their energy saving amount with their peers in their social network.

In addition to several empirical studies on feedback [1, 2, 21, 22], some valuable effort have been made to simulate feedback impact on the energy behavior of occupants [23-26]. Developing a valid simulation model is of paramount importance that can provide an economical opportunity to study the effective parameters in feedback interventions. Using these models instead of empirical studies not only could save a lot of time and money but also could enable researchers to study the impact of a wide range of factors on the efficiency of a feedback program to provide practical recommendations.

Recent feedback simulation studies [23-26] have been commonly employed Agent-Based Modeling (ABM) as a powerful approach in simulating complex systems of autonomous agents [27] integrating with Opinion Dynamics (OD) models, which are mathematical formulated models for describing the
process of attitude or opinion change among individuals [28]. Using ABM, this study aims to investigate different types of ODs and to compare them based on their accuracy of energy saving prediction for eco-feedback simulation in the residential context.

The layout of the paper is as follows. The following sections give a brief background on energy feedback interventions, Agent-Based Modeling (ABM) and Opinion Dynamics (OD) models. Then in the methodology section the three-step process, by which different OD models have been evaluated are explained. Finally, the simulations results and sensitivity analysis are presented, discussed and concluded.

**Energy feedback interventions**

According to [29], energy consumption is nearly “invisible” to households. A substantial body of research and field experiments has attempted to make energy visible to householders through the provision of various types of feedback [1, 3, 18]. Practically, feedback can be described as an information providing mechanism, through which the occupants could monitor, compare, evaluate their behavior performance, and possibly improve them [30]. Some different types of feedback include informative bills or energy advice via leaflet/email, real time displays, monitors and mobile apps, and more recently enabling peer comparison, which is referred to as eco-feedback [1, 3]. Although at the early stages of feedback studies, more attention was paid to investigating the impact of receiving energy usage data on energy behaviors [1], recent works have deployed the social influence and peer network and have revealed that eco-feedback could delivers more energy saving than purely historical feedback [3, 21, 31].

Implementing a feedback program specially in large scale requires a considerable financial resources. Moreover, different studies reported a wide range of energy saving for feedback interventions [1-3]. So, it is important for investors to obtain more energy saving and the focus of both empirical and simulation studies in this area is on improving the efficiency of feedback programs. Current study intends to enhance the efficacy of eco-feedback simulation models, particularly agent-based models, which are explained in the following.

**Agent-Based Modeling (ABM)**

ABM is a way of representing autonomous entities (‘agents’) and simulating the outcomes of these intelligent agents’ interactions within an environmental via the enactment of rule-based decisions that result in an array of potential outcomes; examples of agents include people, businesses, animals, organizations, and equipment [27, 32]. More specifically, ABM has already been investigated to assist
Azar et al. [34] proposed a novel approach for energy estimation by considering different and dynamic energy behavior among building occupants. This study has been continued in evaluating saving potential from occupancy interventions in typical commercial buildings [25] and energy feedback methods for groups of buildings [24]. The findings of mentioned studies indicate that combining occupants’ energy behavior and the social network influence with energy simulation models could increase the effectiveness of occupancy interventions models.

Another similar work has used Bass diffusion theory in an agent-based environment to represent the spread of energy-saving policies among the occupants and the related impact on energy consumption and emission production [26]. According to simulation results, it has been concluded that the word-of-mouth effect among the occupants had a string influence on persuading the occupants to save energy. This is another evidence for importance of eco-feedback interventions.

In all studies related to the simulation of energy consumption, specifically through occupancy interventions such as eco-feedback, the main challenge is to mathematically describe the energy related behaviors of occupants and their change [23-26, 34, 43,44]. One popular way to overcome this challenge is using Opinion Dynamics (OD) Models, which are discussed in the following section.

**Opinion Dynamics (OD) models**

In the context of sustainability issues, the cumulative sum of individuals’ opinions, which lead to certain actions, has direct impact on both the local environment (air or water quality, noise disturbance etc.) and global environment (climate change, resource scarcity etc.). Fortunately, opinions could be revised [28], which is a complex process affected by interplay of different elements including the individual predisposition, the influence of positive and negative peer interaction (social networks playing a crucial role in this respect), the information each individual is exposed to, and many others [35]. In this regard, models of Opinion Dynamics (OD) can be applied as a quantitative tool that simulate the psychological and social aspects of opinion change to investigate mechanisms driving citizens’ environmental awareness. This awareness eventually could engender more sustainable behaviors.

There are several types of OD models in the literature. In Table 1, several famous OD models that consider continuous opinion are presented. Each model, whose names are shown in the first column, mathematically describe the process of changing opinion ($x_i$ etc.) through interactions with other connected opinions ($x_j$ etc.).
Table 1. OD models

| Model name                           | Condition | Proposed Model | Parameters |
|--------------------------------------|-----------|----------------|------------|
| Defiant-Weisbuch (DW) [36]           | $|x_i^t - x_j^t| < d$ | $x_i^{t+1} = x_i^t + \mu \times (x_j^t - x_i^t)$ | $x_i^t$: Opinion of person $i$ at $t$ |
|                                      |           |                | $x_i^{t+1}$: Opinion of person $i$ at $t+1$ |
|                                      |           |                | $x_j^t$: Opinion of person $j$ at $t$ |
|                                      |           |                | $d$: Opinion difference threshold |
|                                      |           |                | $\mu$: the strength of influence |
| Jager-Amblard (JA) [37]              | $|x_i^t - x_j^t| < u_i$ | $x_i^{t+1} = x_i^t + \mu \times (x_j^t - x_i^t)$ | $u_i$: the latitude of acceptance |
|                                      | $|x_i^t - x_j^t| > t_i$ | $x_i^{t+1} = x_i^t + \mu \times (x_j^t - x_i^t)$ | $t_i$: the latitude of rejection |
| Social Influence Network (SIN) [38]  | -         | $x_i^{t+1} = (1 - a_i) \times x_i^t + a_i \times \sum_{j=1}^n \omega_{ij} x_j^t$ | $a_i$: susceptibility of person $i$ to the influence of others |
|                                      |           |                | $\omega_{ij}$: influences of the $j$ on person $i$ |
| Relative Agreement (RA) [39]        | $h_{ij} > u_i^t$ | $x_i^{t+1} = x_i^t + \mu \times (x_j^t - x_i^t) \times \left(\frac{h_{ij}}{u_i^t} - 1\right)$ | $h_{ij} = \min(x_i^t + u_i^t, x_j^t + u_j^t) - \max(x_i^t - u_i^t, x_j^t - u_j^t)$ |
|                                      |           | $u_i^{t+1} = u_i^t + \mu \times (x_j^t - u_i^t) \times \left(\frac{h_{ij}}{u_i^t} - 1\right)$ | $u_i^t$: Opinion uncertainty of person $i$ at $t$ |
|                                      |           |                | $\mu$: rate of the dynamics |
| Influence, Susceptibility, and       | -         | $x_i^{t+1} = x_i^t + \frac{1}{k_i} \times \frac{\sum_{j=1}^n \omega_{ij} \times (x_j^t - x_i^t)}{\sum_{j=1}^n \omega_{ij}}$ | $c_j$: inherent willingness of $j$ to misrepresent his/her beliefs in social contexts in order to appear either normal or distinct |
| Conformity (ISC) [28]               |           |                | $k_i$: inherent commitment of $i$ to his/her current opinion |

Second column shows the predefined conditions of each model that numerically determine which opinions in the social network of agent $i$ could change his/her opinion ($x_i$). While SIN and ISC models have no influence condition, other models use the similarity of opinions as a required permit for opinion change. In DW model, an opinion difference threshold is defined and in RA model the overlapping of opinions should be greater than a certain amount (the latitude of rejection), their interaction will lead to the even more different opinions. The calculation method of mentioned parameters is shown in Table 2.

After collecting all acceptable interactions based on influence condition of each OD model, the opinion change occurs in line with the formula that is presented in the third column of Table 1. The formulas
have two common components, which relates the new opinion, $x_{i,t+1}$ to the previous opinion, $x_{i,t}$ and connected opinions, $x_j$:

- **Flexibility-factor** that determines how far an opinion could change through social interactions. This factor has been named as the strength of influence in DW and JA, susceptibility in SIN, rate of the dynamics in RA, and inherent commitment in ISC.

- **Weight-factor** that represent which opinions have more influence on a particular agent. This parameter is considered equally for all opinions in DW model. In JA model, this factor could be equal to -1 or +1 based on comparison of opinion difference with the latitude of rejection and the latitude of acceptance. Other models have more complex definition for **Weight-factors**, which are presented in Table 2.

In the area of occupant energy behavior modeling, some of the mentioned models have been employed as the central logic of simulations. For instance, Azar and Menassa have been applied RA model in their ABM to simulate discrete occupancy focused interventions in addition to continuous peer interactions for the social subnetworks present in a typical commercial building in the United States [25]. In a similar study, Anderson et al take SIN model to investigate the impact of social network type and structure on modeling normative energy use behavior interventions [23].

In this paper, the mentioned OD models in Table 1 have been evaluated to simulate eco-feedback interventions in the residential buildings. The model predictions for energy saving is then compared to the field experiments reports and eventually, a Revised OD (ROD) model is suggested for eco-feedback simulations. In the following section, the methodology, by which the OD models have been analyzed and compared, is described.

**Methodology**

To address the research objective, which is analyzing different OD models in eco-feedback simulation, an agent-based environment is developed using Python 3.6. The simulation process consists of three main steps, generating agents (households), providing eco-feedback information for each agent, and estimating energy saving range (Fig. 2).
Generating agents

The model entities (agents) are a target community of connected households who have different Energy Index (EI) and specific position in the community social network. Energy Index (EI) represents household’s energy consumption behavior on a scale of 1 to 100, which 1 is the least 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 (Fig. 2). The result of Kolmogorov-Smirnov (KS) statistic is 0.032, which is less than the 0.05 common threshold confirming the goodness of fit. In this process each household’s EI is calculated as follows:

$$EI_i = \frac{EU_i - EU_{min}}{EU_{max} - EU_{min}} \times 100$$

Fig. 1. A brief layout on simulation steps
Where, $EU_{\text{max}}$, $EU_{\text{min}}$ and $EU_i$ are the maximum annual electricity consumption per unit area, minimum annual electricity consumption per unit area and the annual electricity consumption per unit area for household $i$ respectively.

As mentioned before, the simulation results of OD models have been compared to empirical experiments. Since there is lack of information about the structure of social networks in these experiments, Random ER (Erdos-Renyi) graph with a random average number of connections (ANC) is assumed for the social network of households (Fig. 3). Thus, the possible impact of social network structure has been minimized. However, the sensitivity of outputs to ANC has been analyzed in the last section.

Fig. 2. Lognormal distribution fitting of scaled energy consumption data
Random ER (Erdos-Renyi) graphs are generated by starting with a set of isolated nodes that are then paired with a uniform probability. Most nodes have the same number of connections in these networks and the degree distribution will be a Gaussian bell-shaped curve [40]. To build ER graphs, Networkx [6] as a robust Python package for complex network analysis has been utilized. Fig. 3 depicts three random ER graphs with 100 nodes that have one, five and ten as ANC respectively. The size of each node is related to the number of connections, which commonly referred as node degree.

![Fig. 3. Random ER graphs with 100 nodes, and different ANC using Networkx [6]](image)

**Energy eco-feedback**

In this stage, energy eco-feedback information is provided for agents so that their energy behavior could be modified accordingly. To represent this process mathematically, different types of OD models are deployed. EI is assumed to play as the quantified opinion of each agent towards energy conservation issues. The more this attribute means less care for energy saving. In addition, the agents are only provided with the lower energy consumption feedback.

During each simulation run, Energy Indexes (EI) of agents (households) will be revised according to Eq. 2, which is a general formula from OD models, and the given consumption information:

\[
EI'_i = EI_i + \varepsilon_i \times \frac{\sum_{j=1}^{n} \omega_{ij} \times (EI_j - EI_i)}{\sum_{j=1}^{n} \omega_{ij}}
\]  

(2)

Where \(EI'_i\) and \(EI_i\) are respectively denoted to Energy Index of \(i\) after and before eco-feedback. \(\varepsilon_i\) indicates the flexibility-factor of agent \(i\). This attribute is generated from a normal distribution with a mean value of 0.5 and a standard deviation of 0.3. These values shows that people have different rates of behavior change and adoption to social norms. So that, distribution type and inputs can only make a relative change in system behavior [23, 24, 38, 41]. Finally, \(\omega_{ij}\) reflects the weight-factor that represent
the strength of relationship between agent $i$ and $j$. This factor is calculated based on the selected OD model from Table 2.

Table 2. Weight-factors and influence condition of OD models

| Model name                              | Influence condition | Weight-factor | Parameters |
|-----------------------------------------|---------------------|---------------|------------|
| Deffuant-Weisbuch (DW) [36]             | $|E_i - E_j| < d$   | $\omega_{ij} = 1$ | $d = E_i \times \varepsilon_i$ |
| Jager-Amblard (JA) [37]                 | $|E_i - E_j| < d$   | $\omega_{ij} = 1$ | $d = E_i \times \varepsilon_i$ |
|                                         | $|E_i - E_j| \geq d$ | $\omega_{ij} = -1$ | $d = E_i \times \varepsilon_i$ |
| Social Influence Network (SIN) [38]    |                     | $\omega_{ij} = c_{ij}$ | $c_{ij}$: the number of common social connections between agent $i$ and $j$ |
| Relative Agreement (RA) [39]           | $h_{ij} > \text{var}_i$ | $\omega_{ij} = \frac{h_{ij}}{\text{var}_i} - 1$ | $h_{ij} = \min(E_i + \text{var}_i, E_j + \text{var}_j) - \max(E_i - \text{var}_i, E_j - \text{var}_j)$, $\text{var}_i = \min(E_i, 100 - E_i)$ |
| Influence, Susceptibility, and Conformity (ISC) [28] |                     | $\omega_{ij} = 1 - \frac{|E_i - E_j|}{50}$ | *Since real feedback data is provided for agents, misrepresenting of opinions is neglected.* |
| Revised OD model (ROD)                 | $h_{ij} > d$        | $\omega_{ij} = (1 - \frac{|E_i - E_j|}{50}) \times c_{ij}$ | $d = E_i \times \varepsilon_i$ |

The Revised OD model (ROD) that is suggested in this paper for eco-feedback simulation, is a hybrid OD model. The influence condition of ROD is derived from DW and RA models, which limits the opinion changes from very different EIs and the weight-factor of ROD that is dependent on the proximity of EIs and social networks, is derived from ISC and SIN models.

**Energy saving estimation**

The change in the $EI$ of agents during eco-feedback intervention means that their energy consumption rate have been modified. As a result, the energy saving percent after providing feedbacks for all agent population can be calculated as follows:

$$\text{Energy saving (\%)} = \frac{\sum_i^n (E_i' - E_i)}{\sum_i^n E_i} \times 100$$

(3)
where \( n \) is the population of agents, \( EI_i \) and \( EI_i' \) are respectively Energy Index of agent \( i \) before and after the intervention.

To put into perspective, after building the random social network of agents and assigning their attributes \((EI, \varepsilon)\), the energy consumption of connected agents are given to them (each agent could only see the lower consumers in his/her social network) to modify their energy behavior \((EI)\) based on the eco-feedback information, Eq. 2 and OD parameters from Table 2. In the next section, the results of using each OD model for simulating eco-feedback impacts on the energy behavior of households is compared to the field data.

**Simulation results and discussion**

According to research objective that is evaluation of different OD models for eco-feedback simulation, an agent-based environment, which has been explained in the previous section, is programmed using Python 3.6. To have a benchmark, a wide range of observed energy savings feedback experiments extracted from feedback review studies. The results varied considerably, but mostly between 5 and 12% [1-5, 19] (Fig. 4). Selected parameters for model initiation is surmised in Table 3. These values have been set based on the case study conditions and previous models feedback models [23, 24, 26, 34, 42-44].

**Table 3. Model parameters**

| Parameter name                     | Description                  | Further information                                                                 |
|-----------------------------------|------------------------------|-------------------------------------------------------------------------------------|
| Number of agents                  | 100                          | A typical residential complex                                                       |
| Agent’s \( EI \)                  | Lognormal \((\mu, \sigma)\)  | \( \mu = -0.924, \sigma = 0.388 \)                                                |
| Agent’s \( \varepsilon \)         | Normal \((\mu, \sigma)\)     | \( \mu = 0.5, \sigma = 0.3 \)                                                       |
| Social network type               | Random ER (Erdos-Renyi)      | Using Networkx package                                                              |
| Average number of connections (ANC)| Random \((1,10)\)            | The average number of connections (ANC) is randomly selected from 1 to 10 to cover different communities’ structure, from which the field results are gathered. |
| Simulation run                    | 1000                         | -                                                                                    |

Fig. 4 illustrates the outputs of 1000 runs per each OD model as a box-and-whisker diagram comparing with field data. The vertical axis indicates the percentage of energy reduction, which is computed based
on changes in the \( EI \) of all agents before and after the \textit{eco-feedback} (Eq. 3). The horizontal axis categorizes the results according to the OD model. The field experiment reports of energy saving are also given as the benchmark.

![Energy Reduction Chart](image)

**Fig. 4.** Energy reduction in accordance to different OD models and field experiment reports [1-5]

The first finding of Fig. 4 is that using different OD models could bring about different range of energy saving through \textit{eco-feedback} interventions. In other words, applying proper OD model is of paramount importance to have an accurate model. For instance, SIN and RA provided the widest and lowest range of energy reductions respectively. This observation could be due to high dependence of SIN on ANC (see Fig. 5) and absence of influence condition, in contrast to hard influence condition of RA (Table 2).

Here, it should be mentioned that since the agents only receive lower consumptions of their social network as the \textit{eco-feedback} information, all the OD models predict a negative average energy reduction similar to field data. The field experiment results obtained a wide range of energy saving, which are mostly between 5 to 12 percent [1-5]. Except RA model, which fairly presents a close prediction about
energy saving, other OD types show higher amounts of energy reduction than field reports. Again, this could be related to harder influence condition of RA model, which limits the influence of very low consumption feedback on very high consumers.

Given that all OD models follow Eq. 2, the different results of this simulation shows the importance of influence condition and weight-factor calculation method. Hence, simulation studies should pay more attention to them in order to develop precise models. In this regard, ROD shows the closest results to the field data based on average and range of energy reductions. In the calculation of weight-factors in ROD, the closeness of energy behavior (derived from RA) and the closeness of social connections (derived from SIN) are jointly considered. Moreover, the influence condition depends on the susceptibility of agents (Derived from RA and DW).

To have better insight at micro-level, a snapshot from a simulation run have been provided in Fig. 5. In this figure, the energy saving predictions of OD models for each agent in a 100-agent community whose ANC is set at five (see Fig. 3), are shown. The average energy saving from all agents are also calculated for each OD model.

![Fig. 5. A snapshot from a simulation run. Colors illustrate the energy saving percent for each agent.](image)

Each node (agent) has a size and color. The color shows the amount of energy saving on a range of -20% (red spectrum) to 20% (green spectrum), and the size is directly related to the node degree (connections number of each agent).

With the first look at Fig. 5, it can be seen that most of the agents have positive energy saving (reducing their energy consumption as expected). However, there are few red nodes, which means eco-feedback
has negative impact on these agents (energy consumption increased). The reason of this observation, which exists only in JA and ISC models, is the calculation method of weight-factor. According to Table 2, weight-factors for JA and ISC model could be a negative number if the two opinions are very different. Consequently, the negative impact of eco-feedback information could be expected.

**Sensitivity analysis**

In the previous section for each run, a random number from 1 to 10 has been selected for ANC. In this section the sensitivity of simulation outputs to this factor have been investigated for each OD model. The results are surmised in Fig. 6.

![Fig. 6. Sensitivity analysis of OD models to ANC](image)

It is clear that increasing the number of relationships in the community could directly raise the probability of being connected to low consumers, which could lead to more energy saving. However, the amount of saving with increasing ANC continue to a limited amount. In this example, the amount of energy savings has increased approximately as long as ANC reaches the number of five.

As expected, not all models have same sensitivity to ANC. SIN and ROD has demonstrated the most sensitivity, while other OD models are less affected. This observation might be due to the dependence of weight factors in SIN and ROD to ANC (Table 2).

As the last comment, a summary of the finding from this simulation study and their implications are presented:
• The choice of OD model for eco-feedback simulation is very important so that the result could change up to 50% by different OD model.

• Among five common OD models that have been checked in this study, Relative Agreement (RA) model has predicted more accurately based on field observation on energy saving obtained from feedback interventions. Also, SIN has shown the most sensitivity to the average number of connections (ANC).

• The Revised OD model (ROD), which is a hybrid OD model, represented the most accurate results relatively. This signify that considering the closeness of energy behavior along with the closeness of social connections in simulating the energy behavior change through eco-feedback interventions could enhance the prediction of the model.

Conclusion

Occupancy behavior plays a crucial role in the energy consumption and emission production of buildings. Accordingly, occupancy interventions such as feedback programs are presented as an appropriate way to improve the occupant behaviors and controlling energy demand. Since, empirical studies requires a great deal of time and effort; researchers tend to use simulation models for their analysis. However, building a correct model that could present real world tasks logically is challenging.

Using feedback experiment reports as the benchmark, this paper have analyzed five common Opinion Dynamic (OD) models (DW [21], JA [22], SIN [23], RA [24], and ISC [15]) for simulating eco-feedback programs and have found that RA model shows relatively better results. In this model, a hard influence condition has been considered for interactions, which limits the number of behavior changes and energy savings.

After a thorough analysis on the mentioned OD models, ROD has been suggested, which demonstrates a significant accuracy. In ROD, the weight-factor and influence condition of interactions have been modified and both closeness of energy behavior and social network have been considered.

Finally, this paper has some limitations that could be investigated in the future research. The comparison of models has been carried out in a residential context for short-term results of eco-feedback interventions. However, the model’s behavior could vary in other context (commercial etc.) or long-term impact. Moreover, the more detailed the inputs of the model, the more predictable the model will be. Thus, future studies could provide feasible methods, by which the occupancy factors (flexibility-factor, social connections, and weight-factors etc.) and their possible correlations could be obtained and quantified.
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