An Agent-Based Simulation of Employing Social Norms in Energy Conservation in Households

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Abstract. Social norms play an important role in shaping human behaviour. They guide people how to behave under certain circumstances by informing what is permitted and prohibited. Research works have shown that social norms can be successfully employed in promoting sustainable practices such as energy conservation. In particular, the combined effect of descriptive and injunctive norms has been shown to bear a positive influence in shaping social behaviour and is being employed by organizations for social norm marketing. Towards the goal of facilitating the reduction of energy consumption in households, this simulation-based study investigates three simple agent-based models (global, local and similarity models) for spreading social norms based behaviour. In this context, first, the effectiveness of adopting a descriptive norm is compared across the three different models. Second, the role of combining both descriptive and injunctive norms on the reduction of energy utilization is investigated. Third, a meta-norm based intervention approach is proposed and investigated which aims at increasing the rate at which a society can converge to a decreased value of energy consumption in a society.

1 Introduction

Social norms are *generalized expectations of behaviour* in a society [9]. When a social norm is in-force, members of a society expect other members of the society to behave in a certain way in a given situation. Norms have been employed by human societies to facilitate cooperation and coordination among agents which enable smoother functioning of the society. Social norms are increasingly being employed in the domain called social norms approach (or social norms marketing) [18], where social norms are used to influence (or nudge) people into pursuing appropriate social behaviour. Examples of such approaches include social norm based campaigns to reduce alcohol consumption among university students [6], reduction in energy consumption in households [18], and increasing recycling [17]. In many of these social domains the actual social norm might not be known to the individuals. However, social-norm marketers are able to infer the social norm at the aggregate level through surveys. The norms thus identified can be used for providing social nudges towards facilitating behaviour modification.

Inspired by the works on social-norms based approach to social problems, this work investigates three different models that can be employed in the reduction of energy consumption in households through simulations. This paper is organized as follows.

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Section 2 discusses the related work. Section 3 presents the three models and compares the amount of energy saving obtained when certain percentage of agents of the society adopt the *energy conservation norm*. Section 4 investigates the effect of employing *injunctive norms* along with descriptive norms in the energy consumption in an agent society. Additionally, Section 5 proposes and discusses a norm-based intervention approach after certain norm emergence threshold is reached in a society to bring about faster convergence towards a reduced energy usage in the society. The limitations of the current work and the pointers towards future is provided in Section 6. Conclusions are provided in Section 7.

2 Background

Social norms, in particular, the combination of descriptive and injunctive norms have been shown to encourage pro-environmental behaviour such as reduction in the amount of energy used by households [18]. According to Kitts and Chiang [11] the definitions of descriptive and injunctive norms are as follows. *Descriptive norms are typical patterns of behavior, generally accompanied by the expectation that people will behave according to the pattern. Injunctive norms are prescriptive (or proscriptive) rules specifying behavior that persons ought (or ought not) to engage in.* According to Reno et al. [14], a descriptive norm defines what is commonly done in a particular circumstance and a injunctive norm defines what an agent should or shouldn't do in a particular circumstance (or what is approved or disapproved by others in a particular circumstance)[1]. Note that the definitions provided by Kitts and Chiang [11] and Reno et al. [14] are in agreement.

A general description of a social norm as given by Elster [7] is as follows: *"For norms to be social, they must be shared by other people and partly sustained by their approval and disapproval. ..."*. Thus, the definitions of descriptive and injunctive norms together capture the essence of what social norms are.

We note that a descriptive norm can be viewed as a convention (i.e. what is normally observed) and the injunctive norm elevates the status of the convention to a proper social norm through prescriptions and proscriptions. For example, assume that left-hand driving is a convention in the society. When it is a convention, the left-hand action is what people normally do in that particular society. However, this convention can become a social norm if it is prescribed (i.e. any deviations from this norm are sanctioned).

2.1 Related Work

This sub-section provides an overview of the related work in the area of social norm based approaches that have been employed in different domains to encourage behaviour modification, with a particular focus on the energy domain.

Researchers have found that social norm based messages help in bringing about positive changes in domains such as littering in public places [4], alcohol consumption [6], resource stealing (petrified wood stealing in Arizona national park [3]), reuse

[1] We note that disapproval and approval can be viewed as sanction and encouragement respectively.

(e.g. reusing hotel towels [8]) and energy conservation [18]. In particular, these works note that both descriptive and injunctive norms should be used in conjunction for facilitating a positive behavioural change. Descriptive norm on their own do not encourage positive behaviour to a large extent and in some cases boomerang effects were observed [15, 18] resulting in mixed benefits in the usage of social norms. For example, when the messages based on descriptive norm informing users that they consume low energy than their neighbours was sent, *boomerang effect* was observed where the users started consuming higher amount of energy [18] than their previous consumption. The boomerang effect was eliminated when the injunctive norms were added.

In the work of Schultz et al. [18] the objective was to examine the influence of descriptive and injunctive norms on overall reduction in energy consumption in households using a social norm based approach. The messages constructed using social norms approach is based on the average energy consumed in the neighbourhood of 290 houses. The energy consumption of all the houses in the neighbourhood is used to compute the minimum, maximum and average energy in the neighbourhood and these values are used to construct the normative messages. The descriptive norm based messages contained information about an individual household's energy usage and whether its energy consumption was below or above the average energy consumption of the neighbourhood. Households that consumed energy higher than the average tended to decrease their energy consumption. On the other hand, households that consumed less energy than the average increased their energy consumption (i.e. the boomerang effect). The authors have demonstrated that combining injunctive norms with descriptive norms eliminated the boomerang effect. A limitation of the work of Schultz et al. [18] is that they have not considered the different attributes of households that impact their energy consumption. A neighbourhood may contain households that vary in different dimensions. For example, the attributes that may impact energy usage may include: number of individuals living at home, size of homes, different appliances used, lifestyle choices (e.g. using dryer vs. hanging clothes outside) etc. These are not explicitly considered by this model. It treats the entire neighbourhood as one unit without considering the differences in energy usages driven by varying parameters. These parameters can be used to group different households into different groups and can then be used to compare the deviations in energy consumptions between members belonging to the same group.

The social norms approach used by OPOWER [1] makes use of a similarity-based approach to encourage people to reduce their energy consumption. The company sent out letters to 600,000 consumers in the United States indicating the household's energy consumption, the household average energy consumption of similar neighbours, and the energy consumption of the efficient neighbours. The document sent is the descriptive norm based nudge from OPOWER to encourage households to reduce energy consumption. The document also contained an injunctive norm based message. A smiley-based approach was used to indicate approvals for energy usage below average and disapproval for usage above average. For example, to indicate the approval one smiley was used if the energy consumption of a household was lower than average (also described in words as good) and two smileys were used to indicate that the household's average energy consumption was considerably lower than average (less than 20th percentile of energy also described in words as "great"). According to Allcott [10] this leads to 1.1%

to 2.8% reduction in the amount of energy consumption with reference to a baseline model which does not employ norms.

While Schultz et al. [18] employ a neighbourhood model, the approach used by OPOWER as discussed by Allcott [10] makes use of a similarity model. In this work, first, we investigate three types of models for norm-based influence on users behaviour using an agent-based simulation approach. The three models we investigate are the global model, local model and similarity model. These models are discussed and compared in the next section.

3 Investigations of Three Models for Norm-Based Social Influence

The three models investigated for norm-based social influence are the global model, local model and the similarity model. These three models were investigated in the context of the adoption of a descriptive norm in a society of agents using an agent-based social simulation (ABSS) approach [5][2].

3.1 Global Model

In the global model, a society of agents is simulated. Agents represent individual houses. Each agent has certain parameters. The parameters are a) a unique identifier of the house, b) the number of people living in the house and c) the energy consumed per month in Kilowatt hour (KWh) by the household. We used the data available from the Government of South Australia[3] for initializing the average energy consumption of agents. We modelled households with members ranging from one to five. The average energy consumed by the households per month is given in Table 1.

Table 1. Average energy consumption in households based on number of occupants (data from the Government of South Australia)

Number of people in the house	Average energy consumed per month (KWh)
1	479
2	642
3	738
4	829
5	1188

In this model, agents were randomly initialized with the number of people living in a household. Since our model considers households with sizes ranging from one to five, 20% of agents have the same value for the number of members in the household. The energy consumed by a household was initialized with a value that lies within plus or minus x% of the average energy consumed by household. For example, if x is set to 25,

[2] For a general overview of the mechanisms used by researchers in the simulation-based studies of norms refer to the work of Savarimuthu and Cranefield [16].

[3] `http://tinyurl.com/3fhssbf`

an agent representing a household with five members will be initialized with a value that lies between 891 and 1485.

After initialization, we assume that normative messages are sent to each agent (either electronically or by post) which informs the agents about the average energy consumption of the entire society and whether their energy consumption is above or below the average. Note that the message is the descriptive norm that is being conveyed to the agents. In this model we assume that $y\%$ of agents that consume more energy than average choose to decrease their energy by $z\%$. For example if y=5 and z=5, that implies that 5% of the agents that consume more than average energy reduce their energy consumption by 5%. We also have set a buffer range, $\pm\alpha$, around the current average energy consumed in the society which governs the limit upon reaching which the agents do not have to reduce their energy any further. This buffer range has been set in order to prevent agents from perpetually decreasing their energy until they reach a value of zero and doing so will not be realistic.

In order to understand these variables better let us consider the following example. Assume that agent A has five members and its current energy consumption for the month is 1680 KWh. Assume that the agent wants to reduce its energy consumption since its consumption is higher than the 1180 KWh which is the average energy consumption as informed to the agent through the normative message. So, the agent decreases its consumption value to 1410.75 KWh (assuming z=5). Assuming the buffer value of α=5, in further iterations if the agent decides to decrease it energy usage, it can do so to a minimum of 1247.4 assuming that average energy consumption in the society does not change in the subsequent iterations. The buffer range of the society in this case is from 1128.6 to 1247.4. Note that the buffer is a sliding buffer and the minimum and maximum values depend upon the current energy consumption average of the entire population.

Each iteration of the simulation corresponds to one month in real-time. After each iteration we record the overall energy consumed in the society. This data is used to plot the average energy consumed by the society in KWh over several months.

3.2 Local Model

In the global model, the whole society is treated as one unit. However, in the local model, agents in a society form several neighbourhoods. In order to simulate the neighbourhood model, the agents are arranged in a two-dimensional toroidal grid. Each agent has eight neighbours. The norm-based message sent to the agent takes into account the average energy consumption of all the eight neighbours around it. In this model, unlike the global model there isn't a unique average energy consumption value that all the agents can use to compare their energy consumption values. Depending upon the neighbours, each agent will have a different value for the average energy consumed in the neighbourhood. Hence, the buffer values for each agent will be different since the neighbourhood is different for each agent. Apart from this change, all the other aspects are the same as the global model.

3.3 Similarity Model

In the similarity model, agents' norm-based messages report the average energy consumed by the agents that are similar to them. In our model the similarity is based on the number of members in the household. Since there are five groups, average energy consumption is calculated for all these five groups. Agents are informed about the average energy corresponding to the groups they are in. The buffer values of agents across the five groups will be different (i.e. there will be five different buffer values, one for each group). Apart from this change, all the other aspects are the same as the global model.

3.4 Comparison of the Three Models

One of the objectives of this work is to investigate the differences between the three models. We believe the three models represent different choices available that can be used under different circumstances. For example, a power company that knows the data about all its consumers, may choose to employ the global model for spreading normative messages. To cater for the differences in neighbourhoods (e.g. changing climatic conditions[4]), the firm may choose to employ the local model. Additionally, the firm can also choose a similarity model, by clustering households into groups based on certain properties.

Note that the work of Schultz et al. [18] has considered a neighbourhood model[5]. OPOWER has employed a similarity model. In this work, we are interested in comparing the three models by keeping the parameters constant across the models. Towards that goal, the questions we investigate are two-fold.

1. How much decrease in energy is possible using each of the models?
2. What is the rate of convergence towards reduced consumption of energy in each of these models?

In order to answer these questions we simulated an agent society with 1000 agents. The parameters that were used in the three models are given in Table 2.

The simulation set-up considers two variations in the nature of the agents that are influenced by norms (i.e. agents that consume high energy that would like to decrease energy consumption). In the first set-up, a fixed percentage of agents are assumed to be influenced by norms in the entire simulation. We call this set-up a static set-up. In the dynamic set-up, a fixed percentage of randomly chosen agents are influenced by norms in each iteration. For example, if the percentage is set to five, then the 50 agents in the society that are under the influence of norm in one iteration will be different from the agents under influence in the next iteration. This represents a society where agents that are influenced by norms are dynamic. However, in the static set-up the same 50 agents are influenced by norms throughout the entire simulation.

[4] Neighbourhoods differing in the number of sunshine hours may impact energy consumption.

[5] Strictly speaking, the model considered is a global model since only one neighbourhood is considered.

Table 2. Simulation parameters

Parameters	Values
Number of agents	1000
Range of initialization values (x)	$\pm$ 25%
Percentage of agents influenced by norms[6] (y)	5%
Nature of agents influenced by norms	Static or Dynamic
Percentage energy decrement (z)	5%
Buffer range around average (α)	$\pm$ 5%
Number of iterations	1000
Number of runs	1000

3.5 Static Set-Up

We ran the simulation for each of the models under static set-up for 1000 iterations by keeping all the parameters constant across all the three models. The important details of one particular run for all the three models (keeping the random seed constant) are given in Table 3.

Table 3. Static set-up: comparison of three models based on one run of the simulation

Model	Standard deviation (start)	Convergence points (months)	Percentage decrease in energy (end)
Global model	260.16	15	2.03
Local model	245.01	15	1.88
Similarity model	112.97	5	0.81

Column two of Table 3 shows the standard deviation in the initialization values of agents across models. Column three shows the iteration in which convergence to a particular value of energy consumption was achieved in the model. We consider a result to have converged if the difference in the average energy consumption of the society between two consecutive iterations is less than 0.01. Column four shows the amount of decrease in energy at the end of the simulation.

Two observations can be made from the results presented in Table 3. First, it can be observed that the percentage of energy decrease in the global model is the highest and the percentage of energy decrease in the similarity model is the lowest. Second, it can be observed that agents using the similarity model converge the fastest among the three models (i.e. five months for convergence in the similarity model vs. 15 months in the other two models). Results shown in columns three and four of Table 3 can be explained using the data given in column two. It can be observed that the standard deviation for the global model is the highest. Standard deviation represents the variation in energy levels across all the agents in the society. Hence, the agents with high energy utilization in the global model contribute to the substantial lowering of energy by gradually moving towards consuming less energy (i.e. the amount of decrease to a reduced value is high).

The standard deviation for the local model is lower than the global model. So, the energy reduction using this model is lower than the global model. The standard deviation of the similarity based model is considerably lower than the other two models which implies that the agents in the model do not have larger variability in terms of energy utilization when compared to the local and global model which results in reduced lowering of energy consumption values in the end. We believe it is intuitive that similarity model will have the lowest value in standard deviation when compared to the other two models since the agents in this model have 'similar' energy consumption values (since they are grouped based on similarity).

We also conducted experiments by varying the percentage of static agents from 5% to 100% as shown in Figure 1. 1000 runs were conducted for each of the experiments. The energy consumption values obtained for these three models are given as three lines. The observations made from the results obtained for a single run of the experiment also hold for this experiment. Additionally, a third observation can be made from the result shown in Figure 1. The difference between the overall decrease in energy between the global and local models is insignificant. This is because over large number of runs, the difference between the global and local models tend to smooth out.

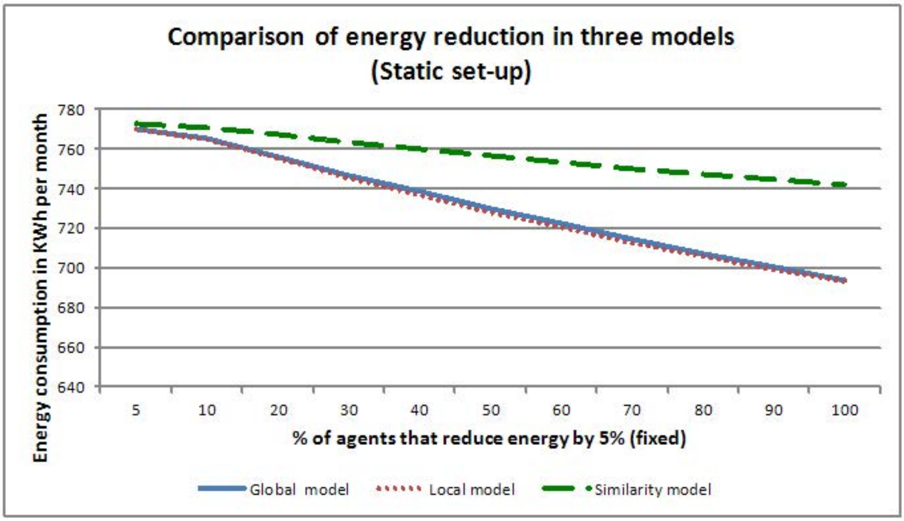

Fig. 1. Static set-up: A comparison of three models

3.6 Dynamic Set-Up

We also conducted experiments by keeping the percentage of agents that are influenced by norm fixed to 5% but allowing these 5% to be made of randomly chosen agents from an agent society[7]. This models the effect that different agents can be influenced by the norms at different points of time by choosing to decrease their energy consumption.

By keeping all the other parameters constant, we compared one run of each of the models. Figure 2 shows three lines that correspond to the the energy consumption of the society with different models. The results of this experiment are in agreement with the results of the static set-up. The difference between the results for the global and local model are due to the differences in the standard deviation between agents in the start of the experiment (see Table 4). Two additional observations can be made by comparing Table 4 with Table 3. First, the time taken to reach convergence (i.e. convergence points in months given in Column three of the tables) is longer in the dynamic set-up than the static set-up. This is expected, since the agents that are influenced dynamically change in each iteration. Second, the energy reduction of the societies are higher in the dynamic set-up than the static set-up. Even though the energy reduction is much higher in the dynamic set-up, the amount of time taken for the reduction is high (303 months which is about 25 years for the similarity model). Waiting 25 years for a norm to converge may not be quite reasonable particularly considering faster preventive measures that we would like to undertake in order to avoid greenhouse gas emissions from energy production. We investigate a meta-norm based intervention approach to facilitate faster norm convergence in Section 5.

Table 4. Dynamic set-up: comparison of three models

Model	Standard deviation (start)	Convergence points (months)	% decrease in energy (end)
Global model	263.50	709	25.7
Local model	245.01	653	23.42
Similarity model	115.71	303	9.42

4 The Role of Injunctive Norms

Research has shown that adding injunctive norms helps in negating the effects of boomerang influence [18]. In order to examine the role of injunctive norms, we model a scenario where both descriptive and injunctive norm messages are delivered to the agents. Since agents influenced based on both descriptive and injunctive norms, we assume that the boomerang influence is not present in this scenario. We vary the number of agents that are influenced by both the norms (i.e. combined influence (CI)) by 2%, 5%, 10% and 20%. All the other parameters were the same as the previous experiment

[7] The motivations of this set-up include the following. a) Situations of agents may change over time. An agent may not be able to conserve energy all the time. For example buying a new electric appliance or the arrival of a new-born that requires heating in an additional room may result in a more than average energy bill for the subsequent month. Hence, the change in composition of agents that reduce energy may be inevitable and that needs to be considered while modeling. b) New agents may be influenced by others and they may start conserving energy. These agents may compensate for agents that drop out.

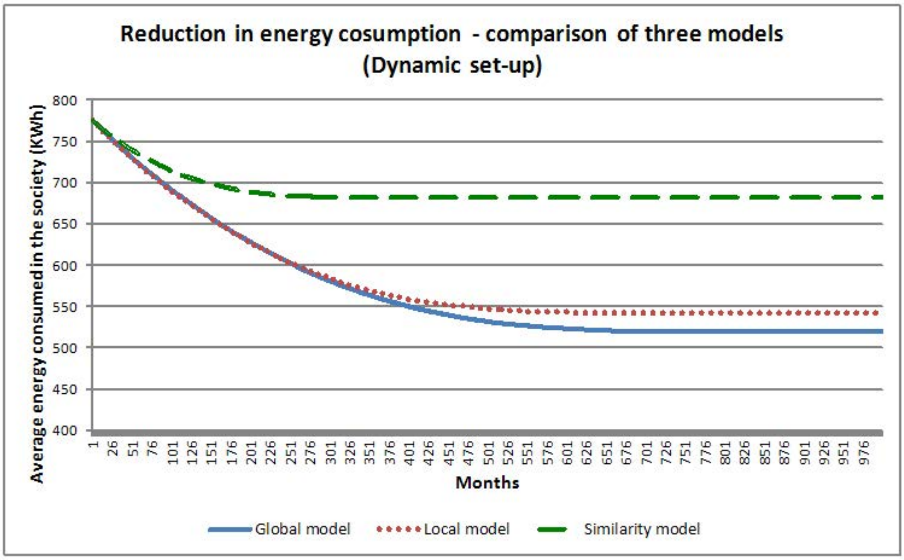

Fig. 2. Dynamic set-up: A comparison of three models

(see Table 2). Our objective in this experiment is to investigate what the implications are by varying the percentage of agents influenced by a combination of injunctive and descriptive norms.

It can be observed from Figure 3 that as the percentage of agents that are influenced by the norms increase, the rate of convergence is faster. The convergence points (in months) are given in Table 5. It should be noted that the values to which they converge are not significantly different. We believe modelling high acceptance rates such as 10% and 20% are reasonable because with the advent of mobile phones and social networks people can be informed and encouraged towards adopting pro-environmental behaviours instead of just using a traditional paper-based approach for spreading normative message. For example, a social-network based application for sharing energy consumption values may induce reduction in energy consumption [12] especially when members are appreciated for taking initiatives to lower carbon foot-print. Mobile phones can be used to spread normative messages instantly (e.g. SMS and Twitter messages). Additionally, a considerable proportion of phones nowadays have the ability to connect to the Internet and can access social networks with ease. Hence, they are a promising tool for spreading norm-based behaviour change. It should be noted that the convergence points achieved through higher percentages of agents changing their behaviour, (e.g., 96 months for 20% of agents reducing their energy consumption), provide some indication that reduction in energy consumption may be achieved in a reasonable time-period in the future without requiring external interventions. However, for smaller percentage of agents, the convergence times are longer.

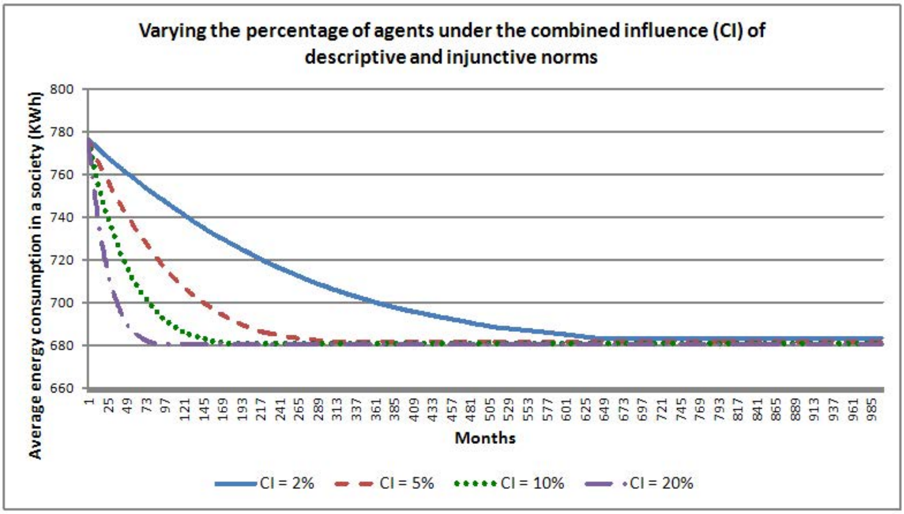

Fig. 3. Varying the percentage of agents that respond to a combination of descriptive and injunctive norms

Table 5. Convergence points on varying the percentage of agents that are influence by a combination of descriptive and injunctive norms

% of agents	Convergence points(months)
2	364
5	303
10	187
20	96

5 Interventions Using a Meta-norm

In this section we present how interventions can be designed based on convergence levels of agents in a society, in order to facilitate faster convergence. These interventions are based on meta-norms. Meta-norms are norms that govern norms. In our case, the meta-norm is based on the convergence value of the average energy consumption in the society.

Let us assume that 75% population of the society consume energy lower than the maximum buffer value allowed around the average energy consumption of a society. The value of 75% is the meta-norm which serves as a starting point for norm interventions at the societal level. The meta-norm is the value agreed upon by the society, where the outlier agents (i.e. agents consuming more energy) are expected to pay higher rates for energy than those who are lower than the range. For example, heavy users of energy may have to pay, say 1.1 times the normal energy price and those who consume energy less than the maximum buffer value may pay 0.9 times the normal energy price. The motivation of this meta-norm based intervention is that similar neighbours should have similar energy needs, hence incentives and disincentives should be used for encouraging and discouraging behaviours. Note that the top-down intervention is built on top of the convergence that emerges in the society using a bottom-up approach.

Note that the intervention is possible only when the society has an agreement on the value for the convergence (e.g. 75% vs. 90%), which is the meta-norm that can be derived based on a bottom-up approach such as voting. Additionally, the society should be motivated in implementing the scheme that rewards lower power consumption and penalizes high power consumption. In this work, we assume that these two conditions hold in a society. Through experimental results we show the effect of interventions, which are facilitated in the society, after certain convergence levels are achieved.

5.1 Effect of Meta-norm Based Interventions at Different Levels of Convergences

We investigated the effect of interventions after different levels of convergences are reached by keeping all the parameters constant. We also assumed that a certain percentage of agents will change their mind after the meta-norm intervention. As a sample value, we chose 10%. This value has been chosen to show that twice the amount of agents change their mind than the original model discussed in Section 3. Our justification for doubling the number of agents is based on the fact that humans are utility driven (most of the times) and they respond to monetary-based incentives than non-monetary based incentives as observed in other domains [2].

Figure 4 shows four lines that represent energy consumptions in societies under different intervention criteria (IC). The solid line shows the energy consumption of the society without norm interventions. The other three lines show the energy consumption of the same society before and after norm intervention. The interventions were applied for the same society under three conditions. The interventions were applied after 60%, 70% and 80% of the agents had converged to an energy consumption value below the maximum buffer value. The interventions corresponding to the three conditions were investigated in three different experiments.

It can be observed from Figure 4 that when the intervention starts earlier, the decrease in the energy consumption of the society also starts earlier (see the line corresponding to IC=60%). This results in faster norm convergence. Table 6 shows the iteration in which norm intervention was introduced (i.e. the iteration in which the society converged to a particular convergence value) and the iteration in which the society converged to a reduced energy consumption value (i.e. the difference in decrease in energy between two consecutive iterations for the entire society is less than 0.01).

5.2 Effect of Modifying the Percentage of Agents Influenced

For two different values of intervention criteria (65% and 75%), we varied the percentage of agents influenced (IA) by the intervention by 10%, 20% and 50%[8]. It can

[8] We believe utilitarian agents will start reducing their energy consumption once a price-based incentive measure has been introduced in the system through the meta-norms. The three different percentages reflect the what-if scenarios that we consider in our simulations.

Table 6. Intervention points and convergence points at different levels of convergence

% Intervention Criterion (IC)	Intervention points (months)	Convergence points (months)
Without IC	-	302
With IC=60%	3	179
With IC=70%	44	197
With IC=80%	112	227

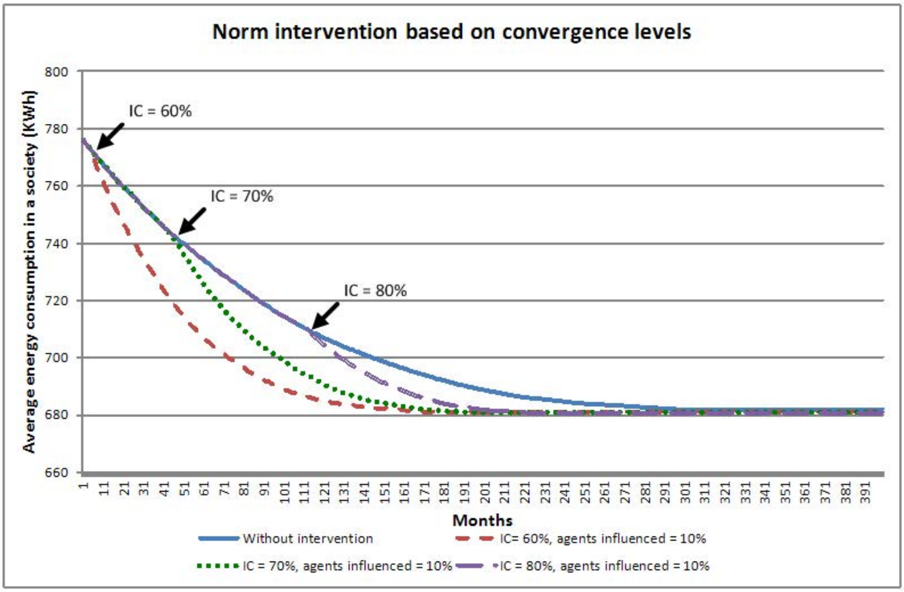

Fig. 4. Norm intervention based on convergence levels

be observed from Figure 5 that when the percentage of agents that are influenced increases, the convergence to a decreased energy consumption value is fast. Table 7 shows the three convergence points for different percentages of agents influenced for both the intervention criteria. It can also be observed from Figure 5 that the iterations in which the intervention comes into effect is the same for all the four cases of each of the convergence criteria (shown using arrows inside the Figure 5). However, the convergence points reached depends on the percentage of agents being influenced. Greater the percentages of agents influenced, the faster is the convergence. This graph thus shows how a meta-norm based intervention can bring about faster convergence towards reduced energy consumption in an agent society. Faster convergence towards a reduced consumption will result in cost reduction in the society. This is because the extra energy does not have to be produced. This also may have other indirect effects on the environment such as decreased CO2 emissions.

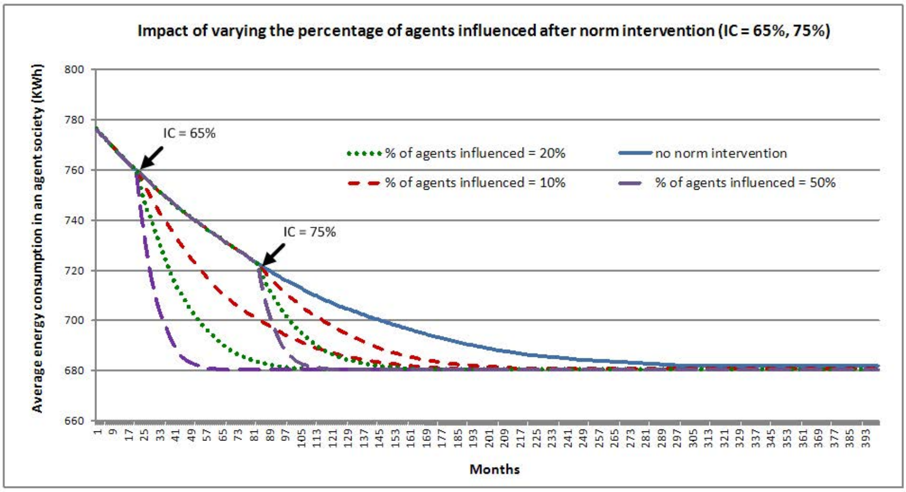

Fig. 5. Impact of varying the percentage of agents influenced after norm intervention

Table 7. Convergence points on varying the percentage of agents that are influenced after intervention

	Convergence points		
Intervention Criterion (IC)	IA=10%	IA=20%	IA=50%
65%	184	113	66
75%	217	168	123

We believe the results shown in Figures 4 and 5 are intuitive and bear real world implications. We note that, as a society we can create meta-norms using a bottom-up approach. The employment of meta-norms and the associated price-based incentive mechanism in addition to the use of descriptive and injunctive norms may better motivate the users towards faster lowering of their energy consumption. Additionally, energy firms and the decision making bodies can use meta-norm based approach to increase the adoption rate of pro-environmental practices such as energy reduction.

6 Discussion

Some works on policy design for institutions have investigated the role of bottom-up (emergent or endogenous) [19] and top-down (prescriptive or exogenous) [20] approaches that facilitate behaviour modification in agent societies. They have shown that the results of policies that arise from an endogenous approach are different from those obtained from the exogenous approach. In this paper we have employed a combination of both these approaches in the context of meta-norm based intervention as discussed in Section 5.

In this paper we have shown that the use of similarity model results in the least decrease in energy consumption in households in comparison with the local and global model. However, it should be noted that similarity model converges faster than the other two models. Additionally, similarity-based approaches have been successful in other domains such as content-based and collaborative filtering techniques for recommendation of articles and books [13]. We believe, similar to other domains, similarity-based approaches may become the de-facto model for energy-domains. Applications that provide such a service have started to emerge in the marketplace that provide comparison of energy usages across households[9]. We believe, using realistic models such as similarity-based approaches may also increase users' motivation in the uptake of the model which may result in further reduction of energy consumption in households.

A limitation of the similarity model presented is that we have only considered one dimension, the number of households, to keep the model simple. We believe a single dimension should suffice for the purposes of demonstrating the approach. Other parameters can be added to the model and also weights can be attached to different parameters which can be used to categorize agents into certain clusters based on the resultant similarity scores. In the future, norm emergence on top of relevant spatial-network topologies can also be investigated. The cost of energy has not been explicitly considered in this work. However, the cost can be calculating by obtaining the product of unit price and the energy consumed.

We believe the next step is to create a social network based set-up in order to study the influence of social networks on normative behaviour. This will involve creating social network applications that would a) provide the ability for individual users to link their own energy consumption data and b) provide normative feedback using similarity-based approach and c) make use of social-network based influence to encourage reduction in energy consumption. The main challenge may lie in the integration of data from independent providers. In cases where the provider does not provide appropriate APIs to access the data, individual users may enter their energy consumption data to the social-network application. However, the trustworthiness of the data posted by users is likely to pose problems.

7 Conclusion

This work aimed at investigating the influence of social norms in facilitating reduced energy consumption in societies using agent-based simulations. First, three models for spreading norm-based influence were investigated namely global, local and neighbourhood models. These three models were compared in the context of spreading the descriptive norm in the society. Second, the impact of the combined effect of injunctive and descriptive norms was investigated. Third, a meta-norm based intervention approach was investigated in order to demonstrate how these interventions can result in faster reduction of energy consumption among households.

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[9] `http://www.energyaverage.co.uk/`

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