Towards defining the structural properties of efficient Consumer Social Networks on the electricity grid

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Abstract. Energy markets have undergone important changes at the conceptual level over the last years. Decentralized supply, small-scale production, smart grid optimization and control are the new building blocks. These changes offer substantial opportunities for all energy market stakeholders, some of which however, remain largely unexploited. Small-scale consumers as a whole, account for significant amount of energy in current markets (up to 40%). As individuals though, their consumption is trivial, and their market power practically non-existent. Thus, it is necessary to assist small-scale energy market stakeholders, combine their market power. Within the context of this work, we propose Consumer Social Networks (CSNs) as a means to achieve the objective. We model consumers and present a simulation environment for the creation of CSNs and provide a proof of concept on how CSNs can be formulated based on various criteria. We also provide an indication on how demand response programs designed based on targeted incentives may lead to energy peak reductions.

1 Introduction

The necessity for sustainability has transformed the traditional power production scheme to a distributed energy resource one, while the deregulation of energy markets has generated great business potential for energy-related companies, along however with a number of both technical and policy challenges. In addition, the Smart Grid paradigm is here to stay. The great advancements in ICT have boosted R&D activities aiming to automate the monitoring and control of power grids, enhance their management, offer alternatives to individual electricity consumers, and achieve large scale energy savings. The Smart Grids are extensively researched at academic and commercial level; however, what is even more important, is that they have found their way into international strategic planning directives [Dollen(2009)].

The necessity rises, thus, for the development of dynamic small-scale consumer models, which could be used in order to help all involved energy market stakeholders understand consumers' market power, assess the impact and possible consequences of certain policies applied to them, and identify potential profits/gains. Practically, among all issues of interest to the various stakeholders, two are the ones that draw immediate attention: a) from the power system side, the reduction of peaks in demand and, b) from the consumer side, the potential to reduce costs.

The concept of Consumer Social Networks (CSNs) comprises the basis of the solution proposed in this work. A consumer corresponds to a, macroscopically, insignificant consumption with a rather limited margin for demand control. Obviously, the market power of such a customer is also limited, and the respective incentives offered to him/her may be insignificant for him/her to act. It is only on the aggregate consumption of a group of consumers that power peaks in demand and energy consumption become important. Therefore, the concept of CSNs is expected to increase the consumers' market power, and thus their motivation to optimize their aggregate consumption by controlling their demand.

CSNs may be initiated in various ways and by various stakeholders, in order to support the above scenario:

1. By the small-scale customers themselves, for strengthening their market power and increasing their bargaining options.
2. By ESCOs (Energy Service Companies), as means for performing customer segmentation and for providing different incentives to each identified consumer group, according to their profile.
3. By DSOs (Distribution System Operators), in order to perform demand response and reduce peaks in power curves, thus improving power system stability.
4. Through a custom, energy related social network or through an application inside an existing social network for energy savings through gamification mechanisms [Zichermann and Cunningham(2011),Bartle(1996)], enabling competition among members (badges, campaigns, rankings etc.).

In order to support the CSN concept and its applicability, we designed and developed a simulation model with social characteristics and have worked towards identifying the types of network structures that could lead to stakeholder benefits. Further extending research presented in [Symeonidis et al.(2011)] and [Chatzidimitriou et al.(2013)], we perform analysis for the identification of modeling parameters that should be taken into account in order to build CSNs that can capture behavior dynamics and can lead to peak reduction (and, thus, money savings).

In the remainder of this paper, Section 2 discusses state-of-the-art approaches on CSNs and Demand Side Management (DSM) techniques. Section 3 presents the modeling methodology adopted, while Section 4 discusses results on the various networks created and perform property-based analysis of the generated CSNs. Finally, Section 5 summarizes work performed, comments on future research steps and concludes the paper.

2 Background and Related Work

During the last years, social networks have been in the center of attention for various research communities. Various methodologies based on resource attributes and have been applied in different fields, but their use in energy markets remains limited, despite the fact that they could have an important influence for their operation.

Consumer social networks have also been leveraged for motivating people into reducing CO_2 emissions as well. [Mankoff et al.(2007)] proposed to explore the use of social networking websites in supporting individual reduction in personal energy consumption. They integrated feedback on ecological footprint data into existing social networking and Internet portal sites which allowed frequent feedback on performance, while enabling the exploration motivational schemes that leverage group membership. Different motivational schemes are compared in three ways: a) reduction in CO2 emission, b) lifestyle changes, and c) ongoing use by users who join the site (retention).

Approaches like the ones followed by `Opower`[3] and `Bidgely`[4], attempt to empower ESCOs with actionable insights for their customers by engaging the latter in a social loop with tips on their energy efficiency and comparative graphs on others' consumption. Consumers become the center of attention in the early 2012, when the `Which?` campaigning charity[5] started the "Big Switch" initiative, a completely new way to buy - and save money on - people's energy. So, using the power of thousands of consumers, `Which?` planned to negotiate with energy suppliers in the UK and seek to secure a market-leading energy deal and help people make the switch.

Reducing peak demand is an important part of ongoing research efforts. To reduce peak demand, smart grid utilities were introduced [Mishra et al.(2013)], that use variable rate electricity prices. Recent efforts have shown how variable rate pricing can incentivize consumers to use energy storage to cut their electricity bill, by storing energy during inexpensive off-peak periods and using it during expensive peak periods. In order to save energy and reduce peak, even control strategies using supercapacitors have been proposed [Ciccarelli et al.(2012)] to store energy that will be used later. Demand side management is also under investigation [Finn et al.(2013)] to limit the requirement for curtailment and further facilitate the integration of renewable energy by shifting the timing of electrical demand in response to various signals. In another approach [Rowe et al.(2014)] propose scheduling algorithms that preprocesses forecast data prior to a planning phase to build in resilience to the inevitable errors between the forecasted and actual demand.

Regarding demand side management, [Kota et al.(2012] envisage the formation of cooperatives of medium-large consumers and the design of a mechanism for allowing cooperatives to regularly participate in the existing electricity

[3] http://opower.com
[4] http://www.bidgely.com
[5] http://www.which.co.uk/

markets by providing electricity demand reduction services to the Grid. The proposed Consumer Demand Side Management (CDSM) mechanism employs agents that proactively place bids in the electricity market, contribute to the flattening of the energy consumption curve for the day ahead and distributes profit among the cooperating agents. [Vasirani et al.(2013)] focus on the concept of a Virtual Power Plant (VPP) and attempt to define a mechanism for creating coalitions between wind generators and electric vehicles, where wind generators seek to use electric vehicles (EVs) as a storage medium to overcome the vagaries of generation.

From an energy cooperatives perspective there are some interesting works such as [Akasiadis et al.(2013)] and [Veit et al.(2013)] that provide incentives to agents to form cooperatives in order to reduce their electricity bills, while on the same time flatten the demand curve through load shifting. In our work there is no need to have a cooperative in order to apply the technique, but the ESCO or DSO can make a virtual CSN from consumers in order to achieve its goals.

From all related work, one may say that work by [Vinyals et al.(2012)] is closer to our approach. However, the hypothesis of [Vinyals et al.(2012)] is different from our approach in three ways. First, authors consider the existence of social interaction between consumers, thus links already exist; we define links based on the "proximity" of consumers, and model consumers accordingly. Second, authors do not consider network topology, and how consumers are assigned under different ML (medium-low) voltage transformers; this is probably not important if applied in large-scale (since authors are referring to the market), nevertheless has to be taken into consideration from the power network perspective. What is more important, though, is that the authors do not focus on the behavioral aspects of the network and how they will act/interact, given specific incentives; we focus on how structural properties of a generated network will influence peak reduction.

Based on this approach, we solve the problem of the formation and response of a CSN as a graph coloring problem with constraints between network nodes. Experiments has shown that, given the appropriate parameters for building the network, it is possible to achieve substantial peak reduction, if the right incentives are given. The modeling methodology followed and the exact problem statement are discussed next.

3 Modeling Methodology

The core modeled entity in the developed agent-based simulation model is the *Consumer Agent* (CA) - residential, commercial or industrial - which efficiently controls its own power consumption under a personal utility model. CAs may choose whether an electric consumption activity can be avoided, performed at an earlier time or postponed, given appropriate incentives. In order to enhance and better coordinate the aggregate effects and the rewards given for helping ameliorating system emergencies, the CA can join coalitions, in our case defined as *Consumer Social Networks* (CSNs).

In contrast to typical social networks, in an electrical grid there is no obvious link between between nodes (CAs), other than the grid structure (electrical network topology). Thus, a separation between the structure and the behavior of the network should be made. The goal of the CSNs is to manipulate the dynamics (behavior) of the physical network (structure) through information diffusion. Such a diffusion of information could take place via various means, i.e. social media, web campaigns, smart metering etc.

Our objective is to understand and assess behavior changes of small–scale electricity consumers with respect to peak reduction, an outcome highly desirable to various stakeholders, and especially DSOs. Therefore, one must identify the individuals responsible for the power peak, and try to shift their consumption from the peak time to other timeslots. One way of achieving the shift would be by providing appropriate incentives for shifting activities out of the specific (peak-related) timeslots, either in the form of bonus or penalty, or in a more holistic manner, in the form of *Time-Of-Use* (TOU) pricing schemes.

In such a setting, we can pose the problem of CSN construction and behavior manipulation as a *constraint satisfaction* problem and more specifically as a *graph coloring* problem [Kearns et al.(2006)]. The goal is to shift the "peak-related" consumption patterns of the CAs that exhibit similar behavior, i.e. there is a link between them, around the peak timeslots of the day. The CSN can be created in practice over an information channel (existence of smart metering infrastructure); this way the stakeholders can identify the peaks that need to be resolved and create a social network based on the similarity of CA behavior around those times.

Since the electric grid is constrained by its topology (transformers installed in the network), we follow the assumption that the CAs reside under medium-to-low voltage transformers and we focus on a specific branch of the grid (CAs under the same transformer).

When a CA decides to join a CSN, the node representing the CA is linked to one or more of best "matches". To do so, they can assign to a 3rd party mediator the task of making a list of all candidates and evaluating them with respect to certain preferences under specific similarity (or dissimilarity) criteria. For example the mediator could be an application in an existing social network.

Each CA has a number of modeling properties that can be used in the "match-making" and behavior modeling processes. These are:

1. *Consumer Type* (CT): In our case there are eight different types of consumers categorized based on demographics: Bachelor, Elderly person, Elderly couple, Two students, Couple, Two working persons, Couple with a baby, Family with four members [6].
2. *Consumer Load curve* (CL): A vector denoting the load curve footprint of the CA on an average day (Figure 1) per quarter of the hour (96 values in total).
3. *Response Action* (RA): A pre-specified action set (without loss of generality) that a CA can perform when given an incentive. The available action are:

[6] Data were retrieved from the TSO in Cyprus - http://www.dsm.org.cy

   (a) shift activity 30' before peak time (30B)
   (b) shift activity 15' before peak time (15B)
   (c) no shift (NS)
   (d) shift activity 15' after peak time (15A)
   (e) shift activity 30' before peak time (30A)
4. *Preferred Action* (PA): This attribute denotes whether the agent is likely to perform the shifting before or after the peak time. Based on their PA, CAs may select not to respond as requested.
5. *Acceptance* (AC): Whether the CA has accepted to be part of the CSN construction or not.

Other attributes that could be used to perform the matchmaking are:

1. *Trust* (TR): Denotes the degree of whether a user can be trusted or whether we don't have sufficient data.
2. *Environmental awareness* (EA): Describes the degree of environmental awareness of the CA.
3. *Savings* (SV): Describes the savings policy of the CA.
4. *Influence* (IF): Describes the influence the user has to other users. In terms of social media examples could be the number of followers in Twitter, the Klout score[7], the number of friends in Facebook or RSS subscribers.
5. *Prosperity* (PT): The financial status of the CA.
6. *Uptake* (UT): The degree by which a CA is willing to uptake new technologies.

With respect to the modeling properties of a CA, matching preference may be established is various ways. Table 1 illustrates our approach, where with ↓ we define preferences that the smaller their value is, the more preferable it is for the corresponding CA, while with ↑ we define preferences that the greater their value is, the more preferable it is for the corresponding CA.

Table 1. Preferences for choosing the best "matching" CA_n for CA_1.

Attribute	Impact	Formula
Consumption Proximity Metric (CPM)	↓	$euclidean(CL(CA_1), CL(CA_n))$
Physical Proximity Metric ($PhPM$)	↓	$tanh(euclidean(CA_1, CA_n))$
Trustworthiness Metric (TM)	↓	$TR(CA_n)$
Influence Metric (IM)	↑	$IF(CA_n)$
Prosperity Proximity Metric ($PrPM$)	↓	$\|PT(CA_1) - PT(CA_n)\|$
Savings Proximity Metric (SPM)	↓	$\|SV(CA_1) - SV(CA_n)\|$
Acceptance Proximity Metric (APM)	↓	$\|AC(CA_1) - AC(CA_n)\|$
Environmental Awareness Metric (EAM)	↑	$EA(CA_1)$

[7] http://www.klout.com

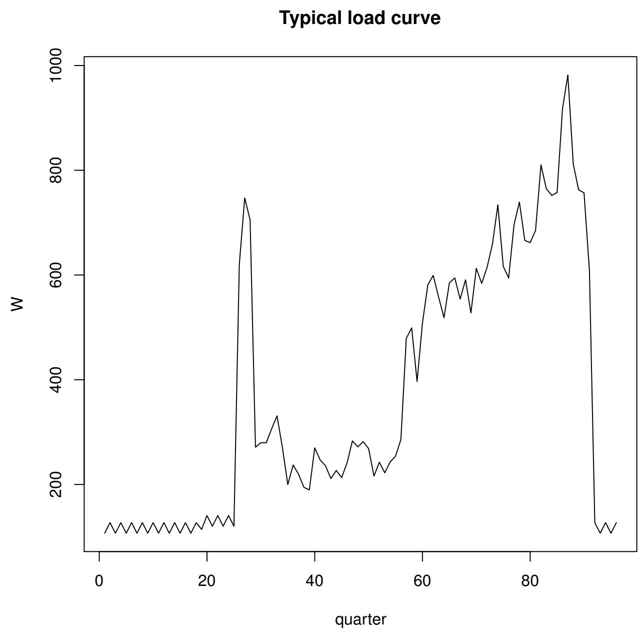

Fig. 1. A typical load curve footprint of a consumer agent.

The CSN construction follows the approach of preferential attachment: each CA is connected with another CA based on how the one ranks the other with respect to a *Preference Metric* (PM) and on the number of links the CA is allowed to have. One May use a preference metric of the form:

$$PM = w_1 * CPM + w_2 * PhPM + \frac{w_3 * TM * IM + w_4 * SPM * PrPM}{EAM} + w_5 * APM \tag{1}$$

Various networks structures can be constructed depending the contribution of each of the properties in the matching preference of one node towards the others [Chatzidimitriou et al.(2013)] (Figure 2). The weights can be determined based on experts opinion or fomr historical data. In addition, some properties contribute to whether a CA will shift activities or not or whether a CA is willing to participate in the overall CSN creation or not.

Further advancing work presented in [Chatzidimitriou et al.(2013)], we mainly focus on the properties of consumer load, response action and preferred action and display how distributed decision making can be applied over the network in order to achieve the goal of peak reduction. A new metric PM is defined (Equation 2), which calculates preference based on consumption proximity at the peak times and on preferred action proximity, with n denoting the n^{th} peak timeslot

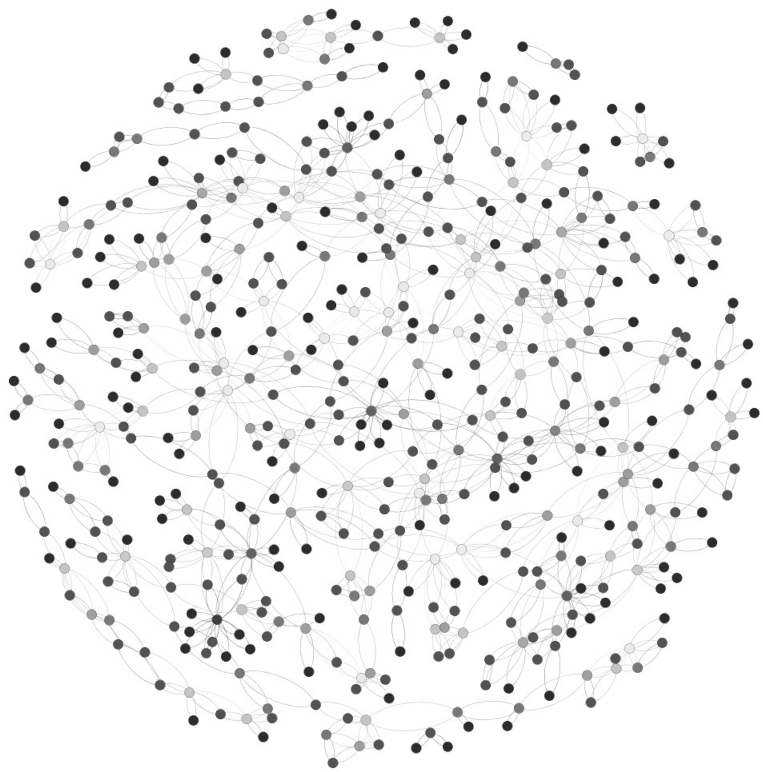

Fig. 2. CSN with weights, $w \in \{1, 1, 1, 1, 1\}$ and 1 connection initiating per CA.

and *euclidean* denoting the Euclidean distance between the consumption load values at peak times.

$$PM = \sum w_n * euclidean(CL_1^n, CL_2^n) + w_{n+1} * xnor(PA_1, PA_2) \qquad (2)$$

Using this preference metric function we also want to add constraints between CAs that have similar loads around peak times in order to assign them with different incentives and, thus spread the peak loads evenly across the peak timeslot. All variables are normalized in the [0,1] interval. The *xnor* function outputs 0 if the preference action is different from what is requested and 1 if it is the same. This way it is possible to produce clusters of greater variety in preferred actions.

Obviously, one may define a different PM function given the problem at hand, based on the modeling approach followed; nevertheless, Equation 2 can be considered adequate for the proof of concept for CSNs, as discussed in the context of this paper. Algorithm 1 presents the code for structuring the CSN and for uptaking the appropriate incentives.

Algorithm 1 CSN construction and application algorithm.

```
{CSN construction}
for all CAs do
  if CA_i is participating then
    for all Other CAs participating do
      values[j] ← PM(CA_i, CA_j)
    end for
    Create links between CA_i and the k most preferable CAs.
  end if
end for
{CSN "coloring"}
while Links with different actions exist or Maximum iterations reached do
  for all Links between different actions do
    for all CAs do
      if CA_i is participating then
        if CA_i has the same incentive as neighbor then
          Action_i ← random(RA)
        end if
      end if
    end for
  end for
end while
{CSN application}
for all CAs do
  if CA_i is participating then
    if PA_i same direction as Action_i then
      if Action_i = 30B then
        Shift consumption 30' before peak time
      end if
      if Action_i = 15B then
        Shift consumption 15' before peak time
      end if
      if Action_i = NS then
        Make no shift
      end if
      if Action_i = 15A then
        Shift consumption 15' after peak time
      end if
      if Action_i = 30A then
        Shift consumption 30' after peak time
      end if
    end if
  end if
end for
```

4 Experiments and Discussion

The agent simulation system has been implemented in Netlogo [Wilensky(1999)], an agent-based parallel modeling and simulation environment developed by the Center for Connected Learning and Computer-based modeling of the Northwestern University.

4.1 Constructing CSNs based on preferential attachment

From a power systems perspective, we assume that the entire population is located under the same medium-low transformer so that they are no electricity distribution constraints in our simulation. In all the experiments performed, we assume a population of 192 CAs, uniformly distributed to the eight consumer types.

Figures 3 and 4 displays the constructed CSNs for two and five allowed connections per CA respectively. Table 2 presents the results of the distributed optimization algorithm with the use of CSNs. Two types of CSNs were constructed, one where preferential attachment was used using the preference metric function (PM) and one where a random network was created (RN). In the random network edges were added randomly and not through some preference metric.

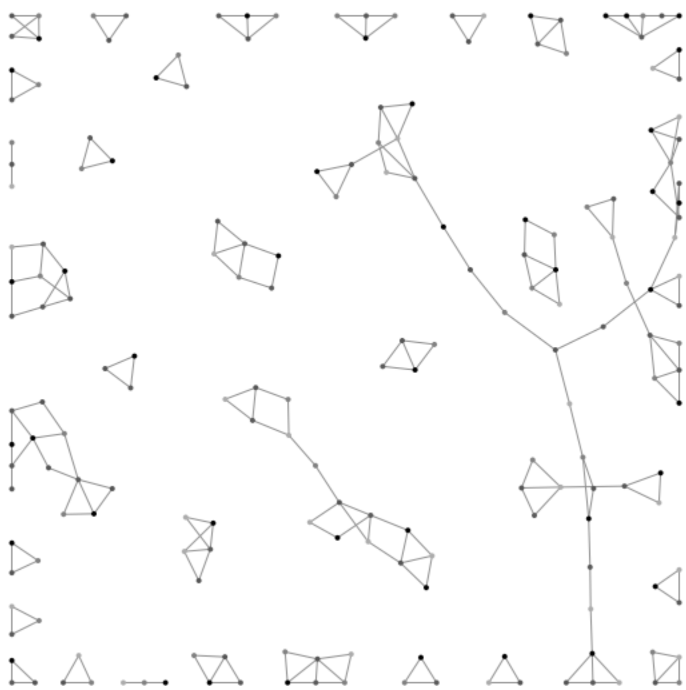

Fig. 3. CSN with two allowed connections per CA.

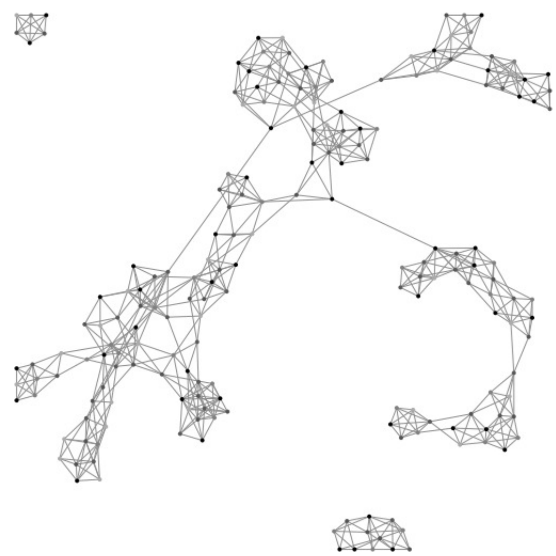

Fig. 4. CSN with five allowed connections per CA.

Figure 5 depicts the peak reduction when 100% of CAs join the CSN and they are allowed to have 5 links. No substantial benefits were found with more than 5 links.

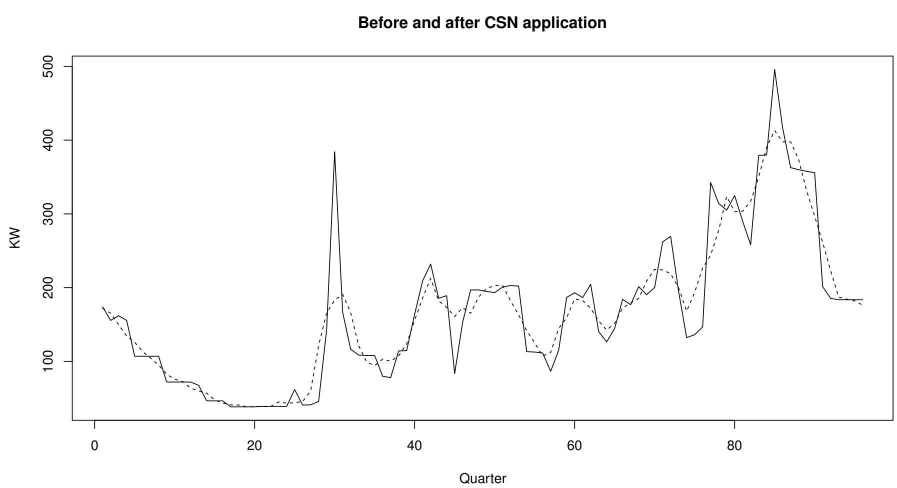

Fig. 5. The final curve (dotted line) of the population load curve after the incentives are applied. The curve is a snapshot of one of the 100 runs of the experiment.

Table 2. Peak reduction percentages (PRPs) are reported for the two identified peaks using CSNs for different acceptance percentages (AP), connections allowed (CA) and construction type (PM and RN). For each of the experiments (#) 100 runs of the algorithm where made and the averages are reported.

#	AP (%)	CA	PM PRP 1 (%)	PM PRP 2 (%)	RN PRP 1 (%)	RN PRP 2 (%)
1	25	1	2.54	7.89	3.38	10.80
2	25	2	2.88	9.02	3.89	12.25
3	25	3	3.63	11.01	3.78	11.75
4	25	4	4.12	12.99	3.67	11.44
5	25	5	4.06	12.39	3.85	11.74
6	50	1	5.00	15.50	6.03	18.65
7	50	2	5.87	17.63	8.01	24.94
8	50	3	6.8	21.00	7.95	24.34
9	50	4	8.01	24.30	7.9	24.21
10	50	5	8.34	26.07	7.73	23.67
11	75	1	7.3	22.72	8.22	25.42
12	75	2	8.52	26.05	11.42	34.84
13	75	3	10.18	31.42	12.01	37.68
14	75	4	12.11	37.19	11.90	37.19
15	75	5	12.31	37.93	11.74	36.08
16	100	1	9.82	30.63	10.6	32.20
17	100	2	11.19	34.66	14.00	43.39
18	100	3	13.25	41.08	16.61	49.80
19	100	4	15.81	48.09	16.25	49.29
20	100	5	16.47	49.94	15.84	48.42

Table 3 provides the results when random incentives are given to a CA without the existence of any CSN.

Table 3. Reduction percentage of the two peaks with random incentives. For each experiment (#) 100 runs where made.

#	Acceptance (%)	Peak 1 reduction (%)	Peak 2 reduction (%)
1	25	2.15	6.95
2	50	4.30	13.02
3	75	6.68	20.80
4	100	8.87	27.27

From observing the results, it is evident that when users coordinate with the help of their peers, better performance can be achieved than in the case where random incentives are given. Additionally, as more connections are available for the CAs, the CAs can better coordinate their actions and achieve higher gains. Last but not least, when the CSN with five allowed connections is constructed (PM type CSNs), results are much better than when a random network is constructed (RN type CSNs).

5 Conclusions and future work

Summarizing, the deployed agent-based simulation system aims at providing a tool for modeling consumer agents with respect of forming CSNs for upgrading their role and market power from small-scale electricity consumers into important stakeholders. This is performed through bottom-up modeling, where the agents, through simple rules, create complex structures with emergent behavior. This preliminary analysis for CSN formation in the area of consumer energy systems illustrates obvious potential benefits.

Future goals include more realistic energy and social modelling for CAs. With the incorporation of more elaborate demand-side mechanisms, we will be able to study demand-response scenarios and their effect on the power system through the use of CSNs.

Acknowledgment

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