Social Networking for Smart Grid Users
A Preliminary Modeling and Simulation Study

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Abstract—**Emerging smart grids have promising potentials to make energy management more efficient than currently possible in today's power grids. Integration of small scale renewables, distributed charging of electrical vehicles and virtual power stations are some of the technological innovations made possible by smart grids. Besides these technological aspects, smart grids also have a clear social component: consumers and small producers can together form energy communities. Such communities can be based on shared geographical location. They can also form based on shared values. This paper assumes that online social networks can be used to form virtual energy communities with shared values such as sustainability and social cohesion, sharing energy. We present an exploratory study on the creation and evolution of *Smart Grid Social Network*s using an agent-based simulation model. Initial simulation experiments show that in this context a large community with members that are occasionally active forms a better predictor for successful energy communities than a smaller community of very active users.**

I. Introduction

*Smart Grid*s have sparked a vast array of research and investment globally for their promising potentials in socio-economical and environmental benefits [1]–[3]. Integration of small scale renewables, distributed charging of electrical vehicles and virtual power stations are some of the technological innovations made possible by such smart grids. A recent trend is that research not only addresses the technological aspects of the grid, focusing mainly on hardware and software of grid infrastructures, but also on the social dimension of the grid [4], [5]. The idea of linking smart grids with (online) *Social Network*s (SNs) as a joint R&D topic has recently caught much attention in the media [6]–[9]. There are many research efforts on both topics individually, but research on combining SNs with smart grids has just started. A number of recent papers propose frameworks or approaches that interconnect smart meters (or smart homes) as SNs for energy management and sharing [10], [11]. In addition, Silva et. al. [12] report on surveys to understand user needs for energy services including SN services. Several frameworks or simulation models for demand side management and value-added web services with SN aspects have been developed [13]–[15]. Others use simulation models to demonstrate the feasibility of social coordination in supply and demand [16], [17]. Our research interest expands on the related work in that it focuses on smart grid user communities. The research is performed within the framework of the EU FP7 CIVIS project[1]. The CIVIS

project has the vision that, in addition to seeing smart grid users as individual entities driven by economic considerations contributing individually to achieve energy goals [18]–[20], users are members of social communities served by a shared smart grid infrastructure and driven by joint sustainable and social goals. The potential and challenges of users' collective action, pro-social values and sense of community are subject of study within CIVIS. The goal in large is to provide ICT support for social participation in smart grids to manage communities and support energy services. This paper focuses on an ICT system that includes features of *Social Networking Site*s (SNSs) providing grid users a web-based platform of *Smart Grid Social Networks* (SGSNs), as a part of the ICT system's functionality, with which users can share interests and values, exchange experiences within their community, and compare (and compete) energy consumption, etc.

This paper focuses on the question whether SGSNs can foster user awareness and engagement to achieve energy goals such as consumption reduction and load shifting. *Modeling and Simulation* (M&S) provides the means to explore how ICT enhanced SGSN can be used to engage grid users, to influence their energy usage, and to examine the evolution of the SGSN. As the model is exploratory rather than predictive at this stage, the model serves as a tool for experimentation allowing model users to observe model responses to different input configurations and their effect. The goal is to identify a set of variables (or metrics) that are potentially critical to model behavior, particularly in terms of positive or negative SGSN growth, to inform further research in the CIVIS project and provide insights into the design of the social energy ICT systems. The main results of this modeling and simulation study are presented in this paper.

II. An Agent-Based Simulation Model for Smart Grid Social Network

M&S are often used as a research methodology to study complex problems [21], [22]. This paper deploys an *Agent-Based Modeling* (ABM) approach [23], [24] with which each agent represents a person or a household. Model development is agile (and adaptive) [25]. During this phase of the project, model features and attributes are represented at a relative high level of abstraction. They will be refined and extended adequately at a later stage when more information and data

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[1] http://www.civisproject.eu/

are at hand. In terms of M&S software, *NetLogo*[2] has been chosen for its rich functionality and simplicity.

A. Model Description

The simulation model assumes the existence of a web-based SGSN platform that allows people (person agents) to join or quit at will. The simulation has a discrete (invariant) time advance ($ta=1$), or time step, that represents a single day. In the model, a *person* agent ($\mathfrak{p}$), as its name implies, represents a human individual who is a resident family member of one household; a *household* agent ($\mathfrak{h}$) represents a household using a smart grid. The person agents and the households agents are defined as follows.

$$\mathfrak{p} := \langle \mathfrak{h}, u, \mathfrak{c}, o, r_{act}, c_{quit}, c_{inact}, c_{idle}, p_{sn}, p_{aw}, k_{ls}, k_{er} \rangle$$

where $\mathfrak{h}$ is $\mathfrak{p}$'s household; u is a boolean value specifying whether $\mathfrak{p}$ is a SGSN user; $\mathfrak{c} \in [0,4]$ is a category indicates how often $\mathfrak{p}$ uses the SGSN (see TABLE I); o is a boolean value that specifies whether $\mathfrak{p}$ is online using the SGSN during a specific day; r_{act} is the probability of $\mathfrak{p}$'s activities (i.e., sharing a message once online), $c_{quit}, c_{inact}, c_{idle}$ are counters that indicate how many times $\mathfrak{p}$ has respectively quitted the SGSN, been online but without activities (i.e., sharing or receiving messages), and not been online during a single day; p_{sn}, p_{aw} are $\mathfrak{p}$'s social networking points or awareness points awarded for message exchange; k_{ls}, k_{er} are $\mathfrak{p}$'s knowledge points awarded for load-shifting or energy-reduction.

$$\mathfrak{h} := \langle \mathfrak{P}, c_u, c_o, p_{ls}, p_{er} \rangle$$

where $\mathfrak{P} = (p_1, ..., p_q) \subset P$ is a set of q family members[3]; c_u and c_o are respective counters of SGSN users in $\mathfrak{P}$, and online (SGSN) users in $\mathfrak{P}$ on a particular day; p_{ls}, p_{er} are $\mathfrak{h}$'s load-shifting points or energy-reduction points.

At model initialization, a set of household agents ($H = \{\mathfrak{h}_{i \in 1..n}\}$) and a set of person agents ($P = \{\mathfrak{p}_{j \in 1..m}\}$) are generated with random cardinalities n and m. A random ratio r_u ($=|P_u|/m$) of person agents $P_u \subseteq P$ are initialted as having joined the SGSN (i.e., P_u is a set of SGSN users, $\forall \mathfrak{p}_j \in P_u \mapsto u_j = true$). Each user ($\mathfrak{p}_j | u_j = true$) is randomly assigned to a SGSN category $\mathfrak{c}_j$. Fig. 1 illustrates a simplified simulation daily routine of a SGSN user.

The likelihood of an SGSN user $\mathfrak{p}_j$ going online during any single day (represented by an increase of the simulation time $t \leftarrow t+ta$) is $\mathfrak{c}_j$. The likelihood of an online user ($\mathfrak{p}_j | o_j = true$) sharing a message of energy-related information or tip is indicated by $r_{act,j}$. A message $\mathfrak{m}$ is defined as

$$\mathfrak{m} := \langle \mathfrak{t}, v \rangle$$

where $\mathfrak{t} \in \{1, 2, 3\}$ is the message type (1. a piece of general information, 2. a load-shifting tip, or 3. an energy-reduction tip) and v is the message value (or weight). The message type determines its effect on the values of a user sending a message: By sharing a message m_g, the user sending the message has a corresponding increase of $p_{aw,j} \leftarrow p_{aw,j}+v_g$, $k_{ls,j} \leftarrow k_{ls,j}+v_g$ or $k_{er,j} \leftarrow k_{er,j}+v_g$ depending on the message type $\mathfrak{t}_g$.
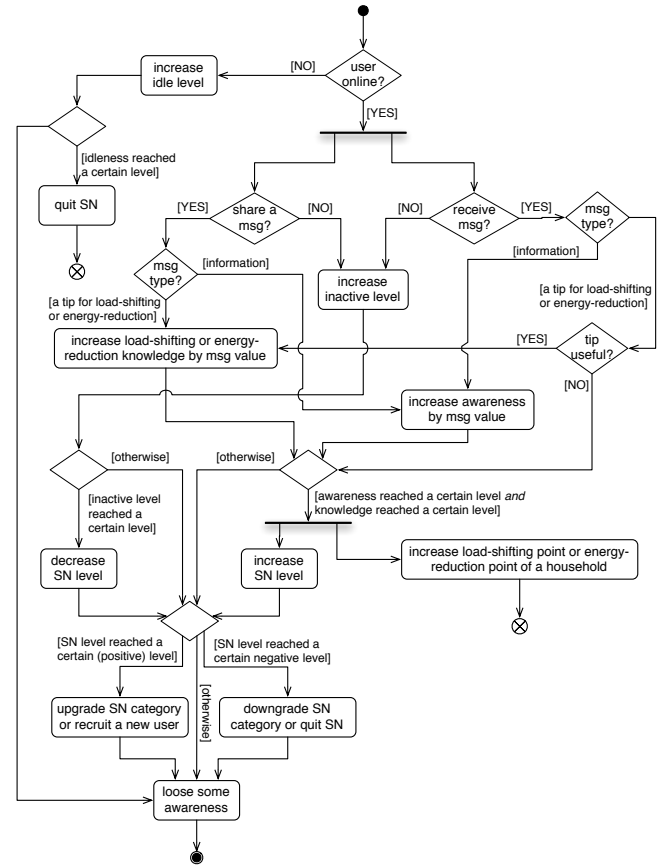
Fig. 1. A simplified simulation daily routine of a SGSN user

The message type also determines its effect on the values of an online user receiving a message shared by other users. A user receiving a message has similar increases of $p_{aw,j}$, $k_{ls,j}$, or $k_{er,j}$, depending on the nature of the message. The latter two are increased only when a tip ($\mathfrak{t}_g = 2 \vee \mathfrak{t}_g = 3$) is considered to extend a receiving agent's knowledge. Whether a tip is useful for a receiving agent is determined in this version of the simulation model by a random chance.

Load-shifting points ($p_{ls,i} \leftarrow p_{ls,i}+1$) and energy-reduction points ($p_{er,i} \leftarrow p_{er,i}+1$) are assigned to user households $\mathfrak{h}_i$ once the user has reached a certain level of awareness ($p_{aw,j} = \hat{p}_{aw}$) or knowledge ($k_{ls,j} = \hat{k}_{ls}$ or $k_{er,j} = \hat{k}_{er}$) respectively. Once this has occurred, the value of the user's social networking points is increased ($p_{sn,j} \leftarrow p_{sn,j}+1$), and the user's knowledge is reset ($k_{ls,j} \leftarrow 0$ or $k_{er,j} \leftarrow 0$) to 0 to indicate that this user needs new knowledge to earn more points. In parallel, the value of each user's awareness points decreases by 1 per day ($p_{aw,j} \leftarrow p_{aw,j}-1$) to model the fading effect of interaction and knowledge.

A user who is not online for some time ($c_{idle,j} = \hat{c}_{idle}$) is assumed to have quit the participation in the SGSN ($u_j \leftarrow false$, $c_{quit} \leftarrow c_{quit}+1$). When a user reaches a certain inactive level ($c_{inact,j} = \hat{c}_{inact}$) on the SGSN (i.e., the user does not share or receive messages for a pre-determined period of time), the user's SN points decrease ($p_{sn,j} \leftarrow p_{sn,j}-1$).

When a user's SN points reach a pre-defined upper level ($p_{sn,j} = \hat{p}_{sn}$), the user can either upgrade to a higher category

($\mathfrak{c}_j \leftarrow \mathfrak{c}_j + 1$), or if the user is already online daily ($\mathfrak{c}_j = 4$), a new user is added to the SGSN. Contrarily, when a user's SN points reach a pre-defined lower level ($p_{sn,j} = \check{p}_{sn}$), the user can downgrade to a lower category ($\mathfrak{c}_j \leftarrow \mathfrak{c}_j - 1$) or leave the SGSN ($\mathfrak{c}_j = 0$). In both cases, the user's SN points are reset ($p_{sn,j} \leftarrow 0$). A user who has quit the SGSN may be "recruited" to rejoin only if the maximum number of pre-defined quit actions has not been reached ($c_{quit} < \hat{c}_{quit}$).

Each agents is evaluated according to the aforementioned rules on a daily basis ($t \leftarrow t + ta$). The simulation terminates when the SGSN user ratio reaches a predefined level ($|P_u|/m = \hat{r}_u$) or the simulation reaches a predefined maximum simulation time ($t = \hat{t}$).

B. Model Parameters

This section presents some model configuration choices for the SGSN simulation model. Published data (reports and surveys) and studies of general SNs and *Social Networking Sites* (SNSs) [26]–[28] are used as to provide a frame of reference based on the assumption that these results could apply to special purpose SNs and SNSs such as SGSNs, as little is known about SGSNs nor about user behaviour in SGSN sites. This hypothesis needs further investigation (e.g., with data collected from CIVIS test sites) in the next phases of the project.

1) Ratio of People that are SNS Users: Data shows that SNSs (mainly popular SNSs) are widely used over many demographic situations with the numbers of users increasing steadily [29]–[34]. For example, in Europe this ratio was at around .41 in 2013 and estimated to reach around .5 by 2017 [32]; online social networking is increasingly popular in the UK with around .5 of adults, in 2012, being recent users [33].

In the SGSN simulation model, the user ratio (r_u) at initialization is configurable between .01 and .2 ($r'_u \in [.01, .2]$). The value of $\hat{r}_u$ defines the maximum user ratio in the simulation (a stopping rule). It is configurable between r'_u and .5 ($\hat{r}_u \in [r'_u, .5]$).

2) Usage Frequencies of SNS Users: How often do people indeed make use of the SNSs they join? Data shows that usage frequencies have notable variation from user to user as well as from platform to platform [26], [29]–[31], [34]–[36]. For example, in 2010 some 52% US Facebook users and 33% Twitter users engaged with the platforms daily (these numbers are higher in a 2013 survey [34], 63% and 46% respectively), while only 7% MySpace users and 6% LinkedIn users did the same [29]; over 1/3 of Europeans used SNSs regularly in 2010; almost 20% used them on a daily or almost daily basis; however, a majority of Europeans (44%) never used SNSs [30].

Why are some SNSs more popular (or successful) than others? Some study supports the hypothesis that this might be associated with a specific positive affective state experienced by users when they use the SNSs [37]. Some study reports inconsistent findings in stress and quality of life in relation to SNS usage, which can likely be partially explained by the nature of the information that is shared on the SNSs [38].

As mentioned in Sect. II.-A., five categories are used in the simulation model to represent different SGSN usage frequencies (TABLE I). The model can be configured to

TABLE I.   DEFINITIONS OF SGSN USAGE CATEGORIES AND THE ASSOCIATED PROBABILITIES OF USAGE ON A DAY

Categories	4	3	2	1	0
Usage Frequencies	Daily	Three days per week	One day per week	One day per two weeks	Never
Probabilities of Usage on a day	1	3/7	1/7	1/14	0
Percentage Users at initialization	50%	15%	10%	10%	15%

initialize the SGSN usage categories in four ways: SGSN users ($\mathfrak{p}_j | u_j = true$) are assigned (i) with categories according to the initialization percentage defined in TABLE I, (ii) randomly with categories 1 to 4, (iii) only with category 2, or (iv) only with category 3; i.e., $\mathfrak{C} \in [1, 4]$. During a simulation run, a new user is assigned a SGSN usage category. The choice of category is assigned (i) randomly with categories 1 to 4, (ii) with category 2, or (iii) with category 3; i.e., $\mathcal{C} \in [1, 3]$.

3) User Activity Frequencies on SNSs: When a user is online using a SNS, how often does the user perform activities such as sending messages or comments? A few literature reviews data on SNS user activities [29], [35], [36]. For example, a survey in 2010 [29] shows that 15% US Facebook users updated their status at least once a day; 12% 3∼5 days a week, 17% 1∼2 days a week, 40% less often; 16% have never updated their status. Facebook reported in 2012 that its average user contributed 90 pieces of content per month [36].

In the SGSN simulation model, the activity frequency of an online user ($\mathfrak{p}_j | o_j = true$) is represented by a probability (ratio) of user activity per day ($r_{act,j}$). Its value is randomly assigned between 0 and $\hat{p}_{act}/100$ at model initialization. The value of max activity percentage $\hat{p}_{act}$ is configurable between 0 and 20 ($\hat{p}_{act} \in [0, 20] \in \mathbb{N}$). For example, if $\hat{p}_{act} = 5$, then a user can have $r_{act,j} \in \{0, .01, .02, .03, .04, .05\}$ with equal chance. This means that about 1/6 of SGSN users at initialization are assigned with each of the 6 values.

4) Other Parameter Configuration: As explained earlier, the model is exploratory rather than predictive at this stage. High degrees of freedom in parameter configuration allow model users to experiment with different input combinations. Besides the ones mentioned above, other input variables and their value domains are: $m \in [100, 1000]$ the number of households; $\hat{v} \in [1, 10]$ the max value of a message; $\hat{p}_{aw}, \hat{k}_{ls}, \hat{k}_{er} \in [5, 20]$ the thresholds for awareness points, load-shifting and energy-reduction knowledge; $\hat{p}_\wedge \in [5, 10], \hat{p}_\vee \in [\hat{p}_\wedge, 30]$ the min and max values of the upper threshold for SN points, i.e., $\hat{p}_{sn} \in [\hat{p}_\wedge, \hat{p}_\vee]$; $\check{p}_{sn} \in [-10, -1]$ the lower threshold for SN points; $\hat{c}_{quit} \in [1, 3]$ the max number a user can quit (or join) the SGSN; $\hat{c}_{inact} \in [10, 30], \hat{c}_{idle} \in [5, 15]$ the thresholds for inactive and idle counters.

III.   SIMULATION EXPERIMENTS

Seven parameter sweeping experiments are performed, TABLE II, (incomplete factorial experimental design [39]) to explore the parameter space of the SGSN model. In each experiment, the number of varying parameters and the possible values are depicted. In the current launch phase of SGSN, the

TABLE II. PARAMETER CONFIGURATION FOR THE SIMULATION EXPERIMENTS

#	r'_u	$\hat{p}_{act}$	$\hat{k}_{ls}$	$\mathcal{C}$	m	$\hat{p}_\wedge$	$\hat{p}_\vee$	$\hat{p}_{aw}$	$\hat{c}_{idle}$	$\hat{v}$	$\mathfrak{C}$	$\check{p}_{sn}$	$\hat{c}_{inact}$	$\hat{r}_u$	$\hat{k}_{er}$	$\hat{c}_{quit}$
1	.02,.06,.1,.14,.18	4,8,12,16,20	10	3	1000	5	19	10	30	5	1	-7	10	.35	10	2
2	.02,.04,.06,.08,.1	4,6,8,10	10	3	1000	5	19	10	30	5	1	-7	10	.35	10	2
3	.04	4,8,12,16,20	10	3	1000	5	19	10	30	5	1,2,3,4	-7	10	.35	10	2
4	.02,.06,.1,.14,.18	8	10	3	1000	5	19	10	30	5	1,2,3,4	-7	10	.35	10	2
5	.04	4,8,12,16,20	10	3	1000	5	19	6,10,14,18,22	30	5	1	-7	10	.35	10	2
6	.04	8	10	3	1000	5	10,14,18,22,26	6,10,14,18,22	30	5	1	-7	10	.35	10	2
7	.04	8	10	3	1000	5	10,14,18,22,26	10	30	5	1	-9,-7,-5,-3,-1	10	.35	10	2
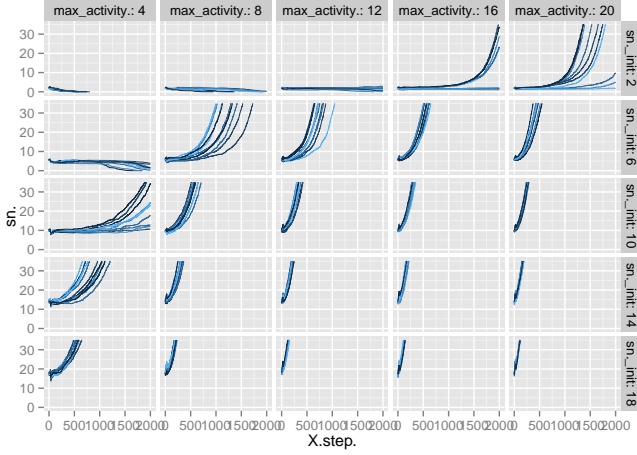
Fig. 2. Exp. 1: $\hat{p}_{act} \in \{4, 8, 12, 16, 20\} \sim r'_u \in \{.02, .06, .1, .14, .18\}$

focus is on small values. Each configuration is run with 10 replications.

The *BehaviorSpace* tool in *NetLogo*[4] is used to perform parameter sweeping: given a number of parameters each with a set of values, running each parameter combination with replications. Exp. 1, e.g., has two input variables, r'_u and $\hat{p}_{act}$; each has five values, $\{.02, .06, .1, .14, .18\}$ and $\{4, 8, 12, 16, 20\}$ respectively. The other parameters remain constant. Thus, Exp. 1 has 25 input parameter combinations. As each model configuration is simulated with 10 replications, there are 250 runs in total. The simulation terminates when $r_u = .35$ or when the simulation step $t = 2000$ (5+ years). In principle, any model state can be rendered as model output. The variables to be recorded as output are: the percentage of SGSN users, the percentage of online users, the number of messages shared, etc. For simplicity, only the percentage of SGSN users is presented, i.e., $p_u = r_u * 100$ (a key indicator of the SGSN evolution), in the output plots where replications are colored in different shades of blue.

Exp. 1 tests model responses to the initial user ratio r'_u and the max activity percentage $\hat{p}_{act}$. The SGSN grows when the values increase. To study the effect small values, Exp. 2 has smaller value increments. The results show that while p_u is sensitive to both variables, r'_u is more critical than $\hat{p}_{act}$ when they both have small values. This can be explained to indicate that user presence is a necessary but not sufficient condition for user activity.
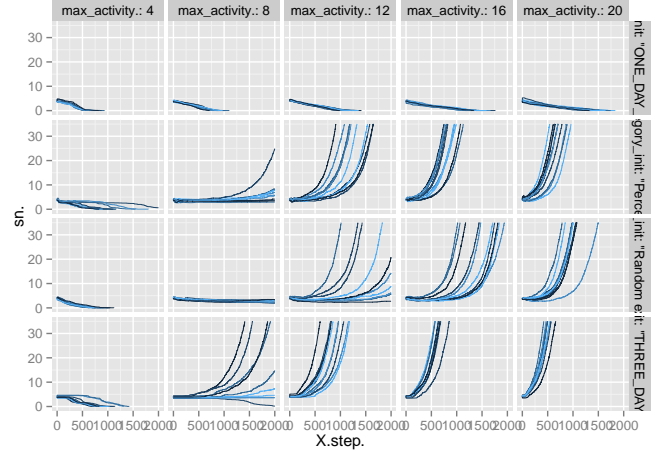
Fig. 3. Exp. 3: $\hat{p}_{act} \in \{4, 8, 12, 16, 20\} \sim \mathfrak{C} \in \{1, 2, 3, 4\}$
Exp. 4: $r'_u \in \{.02, .04, .06, .08, .1\} \sim \mathfrak{C} \in \{1, 2, 3, 4\}$

Result 1: A low level of user presence is more critical to SGSN growth than a low level of user activity.

In Exp. 3 and 4, the SGSN usage category initialization condition $\mathfrak{C}$ varies together with $\hat{p}_{act}$ or r'_u. In both cases, usage frequency of "one day per week" ($\mathfrak{C} = 3$) results in negative p_u growth. The "three days per week" initialization ($\mathfrak{C} = 4$) outperforms the "percentage" initialization ($\mathfrak{C} = 1$). This implies that a larger user base with an average frequent usage can yield faster p_u growth than a smaller user base using the SGSN more frequently.

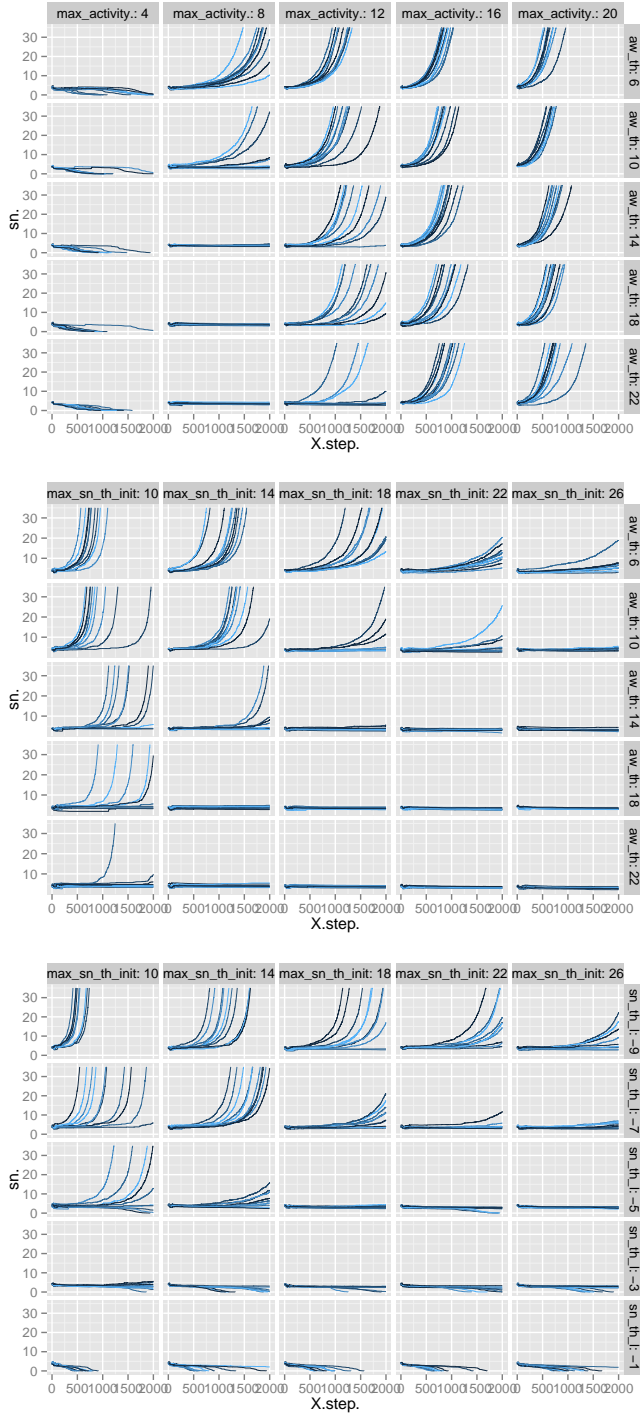Result 2: A large user community with members that are

Fig. 4.   Exp. 5: $\hat{p}_{act} \in \{4, 8, 12, 16, 20\} \sim \hat{p}_{aw} \in \{6, 10, 14, 18, 22\}$
Exp. 6: $\hat{p}_{\vee} \in \{10, 14, 18, 22, 26\} \sim \hat{p}_{aw} \in \{6, 10, 14, 18, 22\}$
Exp. 7: $\hat{p}_{\vee} \in \{10, 14, 18, 22, 26\} \sim \check{p}_{sn} \in \{-9, -7, -5, -3, -1\}$

occasionally active yields faster SGSN growth than a smaller community of very active users.

In Exp. 5 and 6, the awareness threshold $\hat{p}_{aw}$ with $\hat{p}_{act}$ or $\hat{p}_{\vee}$ which is the max value of $\hat{p}_{sn}$ (the upper threshold of p_{sn}) varies. The larger the value of $\hat{p}_{aw}$, the harder users can gain awareness through the SGSN. $\hat{p}_{\vee}$ is a variable that together with $\hat{p}_{\wedge}$ define the range of $\hat{p}_{sn}$, i.e., $\hat{p}_{sn} \in [\hat{p}_{\wedge}, \hat{p}_{\vee}]$. Thus, the

larger the value of $\hat{p}_{\vee}$ the larger the mean of $\hat{p}_{sn}$, the less easy users can become more engaged in the SGSN. The simulation results indeed indicate this trend. The results also show that $\hat{p}_{aw}$ is negatively correlated (i.e., user awareness is positively correlated) to p_u growth. Moreover, although user awareness is necessary for p_u growth, a low level of user awareness does not make the SGSN die out if there is sufficient user activity.

Result 3: A low level of user awareness does not decrease SGSN growth as long as there is sufficient user activity.

In Exp. 7 $\hat{p}_{\vee}$ and $\check{p}_{sn}$, the lower threshold of p_{sn} are varying parameters. The smaller the value of $\check{p}_{sn}$, the less easily users downgrade SGSN usage category or quit the SGSN. Hence, $\check{p}_{sn}$ has a negative correlation to p_u growth. The results show that the SGSN model is more sensitive to the lower threshold than the upper threshold of p_{sn}. This means that negative p_u growth is more easily triggered than positive p_u growth.

Result 4: Negative SGSN growth is more easily triggered (by negative SGSN experience) than positive growth (triggered by positive experience).

IV.   CONCLUSION

This paper introduces the concept of *Smart Grid Social Network*s (SGSNs). An agent-based model is used to simulate user interactions and to explore their impact on the evolution of the SGSN. Initial experiments show that in this context a large community with members that are occasionally active forms a better predictor for successful energy communities than a smaller community of very active users. In more detail, simulation results show that:

- A low level of user presence is more critical to SGSN growth than a low level of user activity.

- A larger user base with an average frequent usage yields faster SGSN growth than a smaller user base using the SGSN more frequently.

- A low level of user awareness does not decrease the SGSN growth as long as there is sufficient user activity.

- Negative SGSN growth is more easily triggered (by negative SGSN experience) than positive growth (triggered by positive experience).

Future research will refine and extend the model for further SGSN studies. Modeling user activities on the SGSN in this paper did not include the correlation among user activities where social ties influence activity patterns [28], [40]. This is a phenomenon in SNs that could be included in the SGSN model. A number of the SGSN model variables, e.g., load-shifting and energy reduction (knowledge) points, are indicators of user/household energy consumption behaviors. These indicators can be transformed into concrete energy consumption quantities, e.g., in kWh, once relevant data becomes available from the CIVIS project test sites. With the consumption and pricing quantities, model refinement and extension can be made to study community negotiation in trading and donating energy. The results are to be used to inform the design, development and experimentation of the CIVIS ICT platform.

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