

Emergence of Shared Behaviour in Distributed Scheduling Systems for Domestic Appliances

Alessandro Facchini, Cristina Rottondi^{*}
Dalle Molle Inst. for Artificial Intelligence (IDSIA)
Univ. of Lugano (USI) - Univ. of Applied Science
and Arts of Southern Switzerland (SUPSI)
{alessandro.facchini,
cristina.rottondi}@supsi.ch

Giacomo Verticale
Dept. of Electronics, Information and
Bioengineering (DEIB)
Politecnico di Milano
giacomo.verticale@polimi.it

ABSTRACT

When energy prices change during the day, users will schedule their appliances with the aim of minimizing their bill. If the variable price component depends on the peak demand during each given hour, users will distribute their consumption more evenly during the day, resulting in lower peak consumption. The process can be automated by means of an Energy Management System that chooses the best schedule that satisfies the user's delay tolerance threshold. In turn, delay tolerance thresholds may slowly vary over time. In fact, users may be willing to change their threshold to match the threshold of their social group, especially if there is evidence that friends with a more flexible approach have paid a lower bill. We show that social interaction can increase the flexibility of users and lower the peak power, resulting in a more smooth usage of energy throughout the day.

Keywords

Smart Grid; Demand Side Management; Agent-Based Modelling; Social Norm

1. INTRODUCTION

The application of Demand Side Management (DSM) approaches to the smart grid ecosystem has recently gained popularity and several frameworks aimed at shaping the aggregated power load curve of groups of customers [21] (e.g. to reduce/shift consumption peaks [27]), avoiding outages and improving power quality [11], or maximising the usage of Renewable Energy Sources (RESes) [13] have been proposed.

In DSM, different strategies may be adopted to motivate users to alter their energy usage patterns. Historically, stakeholders have focused on price-based policies: dynamic pricing schemes exhibiting hourly variations and reflecting

the costs incurred by the smart grid system to satisfy the customers' demand have proven to be effective when the objective is the minimization of the users' bill [7, 12]. To this aim, customers may opt for coordinated optimization schemes to avoid the drawbacks of uncoordinated shifts in their energy usage schedules (e.g. excessive consumption peaks during low-price periods). Coordinated solutions include centralized and distributed DSM frameworks: the former typically maximize a shared utility function [5], whereas in the latter each consumer locally defines her energy plan according to her personal preferences (e.g. bill minimization or comfort maximization).

However, several recent studies have investigated the effectiveness of non-monetary strategies in shaping/reducing consumption by stimulating long-term changes in beliefs and norms [10, 3, 20]. Indeed, consumers do not live in isolation: they can interact with each others and with public institutions, and therefore being influenced in their own attitudes, preferences and possible actions. This approach is consistent with the sociological paradigm of "Homo Socialis" [14], according to which agents' actions are not only determined by the desire to maximize their utility but also driven by shared norms, roles, and relationships.

The main objective of our work is to take into account both the role of price policies and the influence mechanisms of norms on energy consumption behaviors. To this aim, we propose a distributed game-theoretic DSM framework which relies on an agent-based modeling approach. The framework includes a model of the social structures and interaction models which define the reciprocal influences of socially-connected agents. These models make it possible to study the impact of social interaction on the user tolerance of a starting delay of appliances with and without knowledge of the electricity bill of other users. In turn, the impact of delay tolerance on the electricity bill is modeled by using the a load scheduling game for distributed demand side management, where rational agents run a distributed protocol to minimize the users' bills. The main contributions of this paper are: (1) a description of the interaction mechanisms aimed at modeling the influences of society on individual delay tolerance preferences; (2) an evaluation of how individual delay tolerance preferences may be changed by social interactions, which in turn affects the aggregated energy consumption curve obtained at the end of the execution of the load scheduling game.

The remainder of the paper is structured as follows: Section 2 provides a short overview of the related literature,

^{*} Author Names are in alphabetic order.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Greenmetrics '16 Antibes, France

© 2016 ACM. ISBN xxx...\$15.00

DOI: xxx

whereas Section 3 describes the structure of the agent-based model. The performance assessment of our proposed model and the discussion of the experimental results are provided in Section 4. Conclusions are drawn in the final Section.

2. RELATED WORK

Agent-Based Models (ABMs) have raised interest in the smart grid research community as a promising approach to capture the complex interdependencies in the behaviour of electricity users. Several recent studies propose frameworks incorporating multi-agent systems to collaboratively detect and react to grid outages [23], to improve the voltage profile by means of active/reactive power load control [1], or to develop energy market control strategies [8].

Numerous ABMs tackle socio-behavioural aspects of the interactions among users and between users and utilities: Worm *et al.* [28] propose a two-layered framework including a short-term choice model which captures the effects of energy price variations on the users' consumption patterns, depending on their comfort needs and on the presence of local RESes (e.g. solar panels), and a long-term behavioural model which defines how social interactions may alter users' attitudes towards comfort requirements, energy efficiency, usage of RESes, and price policies. Similarly, in this work we study the effects of social pressure on a user-defined delay tolerance threshold, taking into account the users' personal price-delay trade-off.

Ramchurn *et al.* [24] describe a decentralised DSM framework which allows autonomous software agents installed at the customers' premises to collaboratively schedule the usage of domestic controllable appliances with the aim of minimising peaks in the aggregated consumption within a neighbourhood, assuming the usage of dynamic pricing. The framework includes an adaptive mechanism which models the learning process adopted by the users to modify the deferral time of their controllable loads based on predicted market prices for the next day. Our proposed solution is also aimed at peak shaving and adopts a similar learning approach to update the users' delay tolerance threshold.

In the distributed DSM systems proposed by Barbato *et al.* [6] and Chavali *et al.* [9], residential user agents are modelled as rational entities who solve a Mixed Integer Linear Program (MILP) to minimise their energy bill. Under this assumption (i.e., each user applies a best response strategy), the users can be considered as players in a non-cooperative game theoretical framework: it has been proved in [26] that such game is a generalised ordinal potential game which converge in a few steps to a pure Nash Equilibrium. In this paper we adopt the same assumptions and build upon the theoretical results therein discussed. However, in this paper the MILP formulation therein provided has been modified to take into account delay tolerance thresholds based on the users' attitudes.

Among the ABMs investigating influence and imitation mechanisms between agents, Helbing *et al.* [15] propose a model of norm formation in scenarios where agents exhibit incompatible preferences, and where rewards or punishment mechanisms are adopted to encourage conformity to the behaviour of others. In [16], Klein *et al.* introduce a computational model for habit contagion and change in a social network, in which cognitive processes are combined with interaction mechanisms.

Two models have been recently proposed to study in-

fluence and diffusions mechanism in residential use water consumption. Rixon *et al.* [25] propose an ABM within a memetic framework capturing imitation of water use behaviour. Agents are assumed to be characterised by a degree of belief in water saving encoded in memes (some which are explicit water saving memes and some which are not and suggest indifferent behaviour), and to consume water according to them. Memes are thence spread based on social interaction.

The model proposed by Athanasiadis *et al.* in [2] aims at estimating water consumption under different scenarios of pricing policies, taking into account the propagation of water conservation signals among individual consumers, and responsiveness to water conservation policies. In particular, users are classified depending on their capability to influence others and to understand influence signals sent by others. In our paper, we adopt a similar characterisation of the social attitudes of the users.

3. THE ABM FRAMEWORK

3.1 Architecture

We consider a set of residential users, \mathcal{U} , who allocate their power demand over a 24-hour time period divided into a set, \mathcal{T} , of time slots of duration T . Each user $u \in \mathcal{U}$ owns a set of non-interruptible electric appliances, \mathcal{A}_u , that must run once a day. The load profile of each appliance $a \in \mathcal{A}_u$ lasts N_{au} time slots and its value in the n th time slot is given by l_{an}^u (with $n \in \mathcal{N}_{au} = \{1, 2, \dots, N_{au}\}$). For the sake of easiness, we assume that l_{an}^u is constant for the whole duration of the n th time slot. Each appliance $a \in \mathcal{A}_u$ is also associated to a set of parameters $c_{au}^t \in [0, 1]$ which define the comfort level perceived by user u in starting appliance a at time slot $t \in \mathcal{T}$. The rationale behind the definition of such comfort level is the following: each user decides a preferred time slot for the starting time of her appliances. However, in case of deferrable appliances, she can tolerate to delay the starting time up to a certain number of time slots. Intuitively, the higher the delay is, the less comfortable such schedule is perceived by the user. It follows that the less pronounced the preference of user u for starting appliance a at time slot t is, the lower c_{au}^t is. In the extreme case of $c_{au}^t = 0$, user u will never turn on appliance a at slot t . In addition, user u specifies a threshold $\gamma_{au} \in (0, 1]$ indicating the minimum acceptable delay tolerance level for appliance a , which defines the degree of flexibility of the user in scheduling her appliances: the lower γ_{au} is, the more tolerant to delaying their starting time the user will be.

Each user $u \in \mathcal{U}$ may own two different types of appliances. *Fixed* appliances (e.g., lights, TV), represented by the subset $\mathcal{A}_u^F \subseteq \mathcal{A}_u$, are non-shiftable and their starting time is predefined. Such constraint is imposed by assuming that there exists exactly one time slot $\bar{t}_{au} \in \mathcal{T}$ such that:

$$c_{au}^t = \begin{cases} 1 & \text{if } t = \bar{t}_{au} \\ 0 & \text{else} \end{cases}$$

which guarantees that fixed devices have only one allowed starting time and that the system is forced to start them at time \bar{t}_{au} . Conversely, *shiftable* appliances (e.g., washing machine, dishwasher), represented by the subset $\mathcal{A}_u^S \subseteq \mathcal{A}_u$, are controllable devices and their starting time is an output of a scheduling algorithm. For these appliances, c_{au}^t may as-

sume non-zero values in multiple slots, providing that there exists at least one time slot t such that $c_{au}^t = 1$ (i.e., t is u 's preferred starting time for appliance a).

The scheduling strategy i_u of player u is described by a set of binary decision variables:

$$x_{au}^t = \begin{cases} 1 & \text{if appliance } a \text{ of user } u \text{ is started at time } t \\ 0 & \text{otherwise} \end{cases}$$

The set of all strategies of u is denoted by \mathcal{I}_u .

We say that the strategy i_u is *feasible* if it satisfies the following constraints:

$$\sum_{a \in \mathcal{A}_u^F} c_{au}^t x_{au}^t \geq |\mathcal{A}_u^F| \quad (1)$$

$$\sum_{t \in \mathcal{T}} c_{au}^t x_{au}^t \geq \gamma_{au} \quad \forall a \in \mathcal{A}_u^S \quad (2)$$

$$\sum_{t \in \mathcal{T}} x_{au}^t = 1 \quad \forall a \in \mathcal{A}_u \quad (3)$$

Constraints (1)-(2) ensure that the starting time of every appliance a provides a comfort level higher than the acceptability threshold γ_{au} . Constraints (3) impose that each appliance is executed exactly once per day.¹

The pair $(\{c_{au}^t \mid t \in \mathcal{T}, a \in \mathcal{A}_u\}, \{\gamma_{au}^t \mid a \in \mathcal{A}_u\})$ is called the *comfort characteristic* of user u . Moreover, a comfort characteristic $C_u := (\{c_{au}^t \mid t \in \mathcal{T}, a \in \mathcal{A}_u\}, \{\gamma_{au}^t \mid a \in \mathcal{A}_u\})$ of user u is said to be *consistent* with the contractual limit π_u on the amount of purchasable energy per time slot if there exists a strategy i_u such that:

$$\sum_{a \in \mathcal{A}_u} \sum_{\substack{n \in \mathcal{N}_{au}: \\ n \leq t}} l_{an}^u \cdot x_{au}^{t-n+1} \leq \pi_u \quad \forall t \in \mathcal{T} \quad (4)$$

Constraints (4) determine the overall consumption of the appliances in each time slot and bound the amount of purchasable energy in order not to exceed the contractual limit, π_u . Such consumption depends on the scheduling strategy: the energy required by each device a in every time slot t is equal to the energy consumption indicated by the n th sample (with $n \in \mathcal{N}_{au} = \{1, 2, \dots, N_{au}\}$) of the load profile, l_{an}^u , executed at time t . Note that the energy amount indicated by the n th sample of the appliance load profile is consumed during slot t only in case the appliance is started at time $t - n + 1$, thus if $x_{au}^{t-n+1} = 1$.

The non empty set of feasible scheduling strategies consistent with π_u is denoted by \mathcal{I}_u^C . We also say that \mathcal{I}_u^C is determined by (C_u, π_u) .

We model the price of electricity at time $t \in \mathcal{T}$, $b_t(\cdot)$ as an increasing function of the total energy demand of the group of users \mathcal{U} at time t [22]. Under this assumption, prices will increase during peak consumption periods. Therefore, an energy utility may impose such a price function with the goal of inducing peak shaving. For this reason, due to the conflicting goals of the users, the load scheduling problem cannot be solved with a centralised approach. Therefore, we adopt the distributed game-theoretic framework proposed in [26], which models the problem as a game $\mathcal{G} = \{\mathcal{U}, \mathcal{I}, \mathcal{P}\}$, defined by: *i*) the *players* representing the users in the set \mathcal{U} , each one associated to a comfort characteristic C_u and

a contractual limit π_u on the purchasable energy per time slot; *ii*) the *strategy* set $\mathcal{I} \triangleq \prod_{u \in \mathcal{U}} \mathcal{I}_u^{C_u}$, where $\mathcal{I}_u^{C_u}$ indicates the strategy set of player u corresponding to her feasible load schedules determined by (C_u, π_u) (we assume here that such set is not empty); *iii*) the *payoff function* set $\mathcal{P} \triangleq \{P_u\}_{u \in \mathcal{U}}$, where P_u is the payoff function of user u , which coincides with her daily electricity bill.

The payoff function of each player, P_u , is defined as a function of \mathcal{I} as follows:

$$P_u(\mathcal{I}) = \sum_{t \in \mathcal{T}} y_{ut} b_t(y_t) \quad (5)$$

where

$$y_{ut} = \sum_{a \in \mathcal{A}_u} \sum_{n \in \mathcal{N}_{au}: n \leq t} l_{an}^u \cdot x_{au}^{t-n+1}$$

is the energy demand of user u at time t and $b_t(y_t)$ is the price of electricity at time t defined as a linear function of $y_t = \sum_{u \in \mathcal{U}} y_{ut}$, which represents the total electricity demand of the players at time t . In [26], it has been proved that such function is a regular pricing function. It thence follows that \mathcal{G} is a generalised ordinal potential game, with $P(\mathcal{I})$ being the potential function. Potential games admit at least one pure Nash Equilibrium which can be obtained by applying the Finite Improvement Property (FIP). Such propriety guarantees that any sequence of asynchronous improvement steps is finite and converges to a pure Nash equilibrium. In particular, a succession of best response updates converges to a pure equilibrium [17]. As proposed in [26], we assume that the best response method is implemented in an iterative way as follows. Users in \mathcal{U} are listed in a predefined order. The first user initiates the algorithm by choosing his/her optimal load schedule assuming flat tariffs. Then, the user communicates her scheduled energy profile to the next user in the list, who executes the same operations but considering the hourly energy prices calculated from the expected hourly load obtained by summing the schedules of all the users in the list. At every iteration energy prices are updated and, as a consequence, other users can decide to modify their schedules. The procedure stops when none of the users alters her schedule in an iteration, meaning that convergence is reached.

In order to find the optimal schedule, each user solves the following Mixed Integer Non-linear Programming Model:

$$\min \sum_{t \in \mathcal{T}} y_{ut} \cdot b_t \quad (6)$$

subject to constraints (1)-(4), where $b_t = b^{Anc} + s(y_{ut} + p_{ut})$, being p_{ut} the total energy demand of the players of the set $\mathcal{U} \setminus \{u\}$ received by user u at the current game iteration, b^{Anc} the cost of ancillary services (e.g., electricity transport, distribution and dispatching, frequency regulation, power balance) and s the slope of the cost function, respectively.

3.2 The Interaction Scenario

We consider a time span of \mathcal{L} days. During each day, users socially interact with the aim of influencing each other's delay tolerance thresholds γ_{au} . As a consequence of such interactions, user u may modify the values of γ_{au} to be used in the next execution of the load scheduling game (i.e., during the next optimisation time horizon).

The social interaction is mediated by an automated mechanism that collects delay tolerance thresholds and the en-

¹Such a condition can be easily generalised to include an upper bound on the number of usages of an appliance.

ergy price paid by the user's friends and adjusts the user's thresholds according to some filtering rule. For example a user might be willing to adjust her thresholds towards the thresholds of similar users that pay a lower price. However, users may not interact with their friends on regular daily basis (e.g. they may decide to communicate their delay tolerance thresholds only occasionally). Therefore, we assume that each user is characterized by a parameter p_u^ℓ which is set to 1 if user u is willing to compare (and possibly revise) her delay tolerance thresholds on day $\ell \in \mathcal{L}$, to 0 otherwise. Moreover, let $R[u]$ be the list of u 's social neighbours. Similarly to the approach proposed in [8], in order to capture the users' capability to make rational decisions about whom to imitate (and up to which extent), for each appliance $a \in \mathcal{A}_u^S$ we consider a two-dimensional attitude space² (see Figure 1) where each user locates herself and her neighbours based on their current delay tolerance threshold γ_{au}^ℓ and normalised daily energy bill per appliance B_{au}^ℓ defined as:

$$B_{au}^\ell = \frac{\sum_{t \in \mathcal{T}} b_t(y_{ut}) \sum_{n \in \mathcal{N}_{au}: n \leq t} l_{an}^u \cdot x_{au}^{t-n+1}}{\sum_{t \in \mathcal{T}} b_t(y_{ut}) \cdot y_{ut}}$$

Based on her position, user u defines an area of interest A_u^ℓ (see shaded area in Figure 1) representing acceptable bill-comfort pairs. The criteria for the definition of such area depend on the personal attitude of the user (e.g., a user with a strong hedonistic attitude would be willing to imitate users with a higher delay tolerance threshold than hers, though their bill is -even significantly- higher than hers, whereas she would never imitate users with a lower delay tolerance threshold, even if their daily expense is lower than hers) and may be revised at each game execution ℓ .

The interaction protocol executed by user u at day $\ell \in \mathcal{L}$ proceeds as follows. User u defines a boolean parameter η_u^ℓ computed as:

$$\eta_u^\ell = \begin{cases} 1 & \text{if } (\gamma_{au}^\ell, B_{au}^\ell) \in A_u^\ell \\ 0 & \text{otherwise} \end{cases}$$

For each neighbour $u' \in R[u]$, user u updates the delay tolerance threshold γ_{au}^ℓ of each appliance $a: a \in \mathcal{A}_u^S \wedge a \in \mathcal{A}_{u'}^S$, as follows:

$$\gamma_{au}^{\ell+1} = \begin{cases} \gamma_{au}^\ell + \frac{\sum_{u' \in R[u]: \eta_{u'}^\ell \wedge p_u^\ell p_{u'}^\ell = 1} h_a(u, u') (\gamma_{au'}^\ell - \gamma_{au}^\ell)}{|R[u]|} & \text{if } (\clubsuit) \text{ holds} \\ \gamma_{au}^\ell & \text{otherwise} \end{cases} \quad (7)$$

where $h_a(u, u')$ is the similarity between the comfort profiles of users u and u' with respect to appliance a . In this paper we will define similarity as half the number of time slots where c_{au}^t and $c_{au'}^t$ are both non-zero. The condition (\clubsuit) is

$$\gamma_{au}^\ell + \frac{\sum_{u' \in R[u]: \eta_{u'}^\ell = 1 \wedge p_u^\ell p_{u'}^\ell = 1} h_a(u, u') (\gamma_{au'}^\ell - \gamma_{au}^\ell)}{|R[u]|} > 0.$$

User u will then use the updated delay tolerance thresholds $\gamma_{au}^{\ell+1}$ in the next day for the execution of the load scheduling game.

²This assumption also enables the users to redefine the sets $\mathcal{A}_u^F, \mathcal{A}_u^S$ before each game execution, e.g. in case some appliances are not regularly used on daily basis.

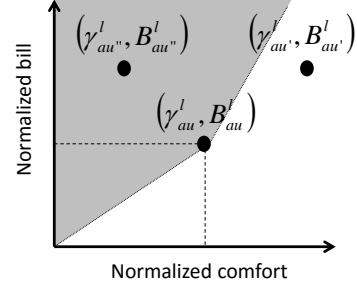


Figure 1: Users' attitude space

4. NUMERICAL ASSESSMENT

In our tests, the 24-hour time horizon is represented by a set \mathcal{T} of 24 time slots of $T = 1$ hour each. We consider $\mathcal{L} = 30$ consecutive executions of the load scheduling game presented in Section 3 and simulate social interactions at the end of each execution. The parameters of the electricity tariff, b_t , are defined based on the real-time pricing currently used in Italy for large consumers. Specifically, $b^{Anc} = 0.05 \text{ €/MWh}$ and $s = 2.3 \times 10^{-4} \text{ €/MWh}^2$.

We consider a scenario with $\mathcal{U} = 50$ users. The set $R[u]$ of each user's neighbours is computed based on the topology of a random scale-free network graph generated according to the Barabasi-Albert model, which is a popular generative model for based social networks and online communities [4].

Each user u has a contractual limit, π , of 3 kW and owns 4 shiftable appliances (i.e., $\mathcal{A}_u^S = \{\text{washing machine, dishwasher, boiler, recharge of robotic vacuum cleaner}\}$) and 7 fixed ones (i.e., $\mathcal{A}_u^F = \{\text{refrigerator, purifier, lights, microwave oven, oven, TV, iron}\}$). The operation of shiftable appliances is assumed to be controllable and fully automatized (i.e. by means of a home energy management system such as the one described in [18]). The energy consumption patterns of each appliance have been extracted from a real dataset [19]. On average, the energy consumption due to deferrable appliances accounts for 55% of the total daily consumption. For each appliance, the comfort curve c_{au}^t assumes a right-angled triangular shape of 4 slots duration randomly placed within the 24-hours scheduling horizon, with values $[1, 0.75, 0.5, 0.25]$ (i.e., we assume that the preferred starting time is the slot t such that $c_{au}^t = 1$ and that users' satisfaction decreases linearly with delay). The initial values of the appliance delay tolerance thresholds γ_{au}^1 are randomly chosen with uniform distribution in the range $[0, 0.75]$. For the sake of easiness, we always assume that $p_u^\ell = 1$.

In order to evaluate the performance of the proposed interaction mechanism we consider two scenarios: the first one assumes that the area of interest A_u^ℓ of user u is defined as:

$$A_u^\ell = \{(\gamma_{au'}^\ell, B_{au'}^\ell) : B_{au'}^\ell < B_u^\ell\}$$

(i.e., users imitate neighbours whose daily bill is lower than theirs); in the second one we define A_u^ℓ as:

$$A_u^\ell = \{(\gamma_{au'}^\ell, B_{au'}^\ell) : \gamma_{au'}^\ell < \gamma_{au}^\ell\}$$

(i.e., users imitate neighbours who impose lower delay tolerance thresholds than theirs). The daily results obtained in the two scenarios are compared to the ones obtained during the first day (i.e. for $\ell = 1$), when no social interactions among the users have occurred. For the assessment, the following metrics are measured: *individual bill*, i.e. the

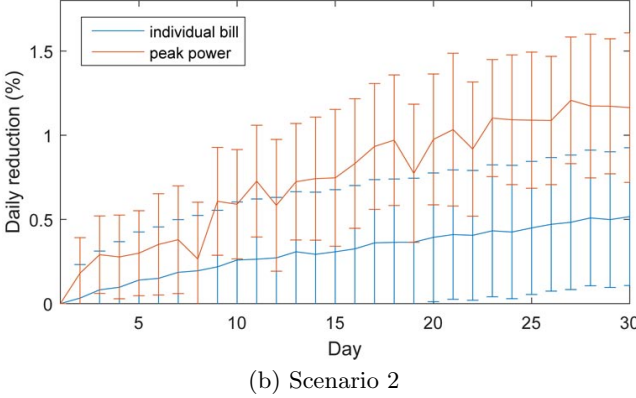
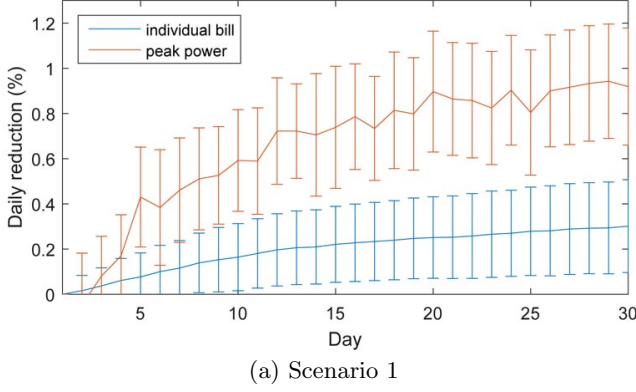


Figure 2: Percentual reduction of daily bill and peak energy consumption depending on the definition of the users' area of interest A_u^ℓ . 95% confidence intervals are plotted.

electricity bill of each user $u \in \mathcal{U}$, and *peak demand*, i.e. the peak of the aggregated energy demand of the group of users \mathcal{U} defined as $\max_t y_t$. Average results obtained over 50 instances of each scenario are reported in Figure 2, which shows that in both scenarios the imitation of virtuous behaviours lead to non negligible decreases of the individual daily bills and of the aggregate peak energy consumption. Such reductions are more consistent in scenario 2, i.e. when users imitate neighbours with lower delay tolerance thresholds, (0.5% bill reduction and more than 1% peak reduction after one month, versus 0.3% bill reduction and almost 1% peak reduction obtained in scenario 1). This is due to the fact that achieving a low bill does not necessarily imply a low delay tolerance threshold: users can indeed achieve low bills if their preferred appliance usage periods are very different from the ones of the other users (e.g. they span night hours), which would lead to lower values of the aggregate power consumption and, consequently, to lower energy prices. It follows that imitating users with low bills does not always lead to an increase of the flexibility of the individual schedules.

Figure 3 shows the evolution of the delay tolerance threshold γ_{au}^ℓ for the usage of the washing machine for the whole population of users in a representative instance of the two scenarios. As depicted in Figure 3a, in the first scenario the imitation of the neighbours with lower bills leads to a homogenisation of the thresholds. Moreover, the average value of γ_{au}^ℓ tends to decrease, due to the fact that people experiencing lower bills are more likely to have chosen low

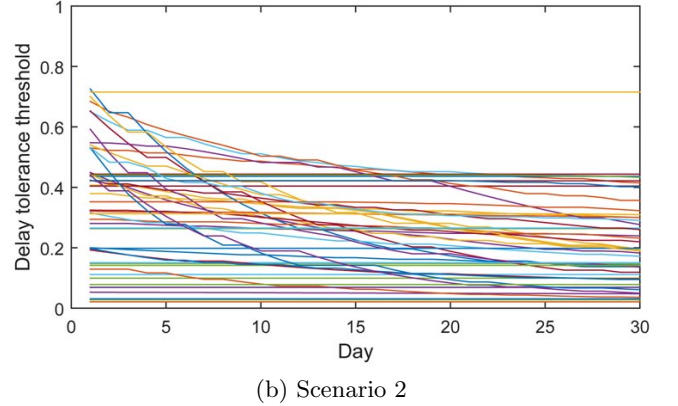
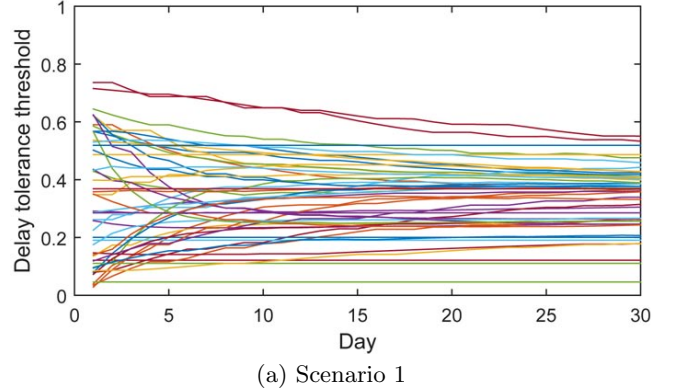


Figure 3: Trend of the washing machine delay tolerance threshold γ_{au}^ℓ over time depending on the definition of the users' area of interest A_u^ℓ .

delay tolerance thresholds. It follows that imitating them leads to more elasticity in the scheduling patterns. However, some users never alter their delay tolerance threshold: this happens when none of their neighbours ever experiences lower bill than theirs. Conversely, in scenario 2 the benefit of imitating neighbours with lower delay tolerance threshold clearly emerges: in this case, γ_{au}^ℓ never increases with time w.r.t. its initial value and remains constant only in case the delay tolerance threshold of a given user is always lower than the one of all her neighbours.

5. CONCLUSION

In this paper, we study the benefits that social interaction can have on peak power demand by users with deferrable appliances. One of the problems with demand side management is that user flexibility may vary over time depending on observed savings and social pressure. In this study we assume that users are willing to vary their delay tolerance thresholds over time by matching the ones of the users of their social group that have a lower energy bill. We show with simulations that this has a beneficial impact on the overall peak demand, reducing energy management costs.

The models and the findings of this paper can be used by utilities to study how much user awareness of other users' behavior can impact on the demand behavior. The simulations results in this paper show that the knowledge of the electricity bill or delay tolerance of similar users yields a peak power reduction in the long term. As future extension,

we plan to evaluate the effect of varying the initial characteristics of the population to capture different propensities to imitation of positive/negative behaviors depending on user's social attitude and delay tolerances, as well as the impact of different social network models.

6. REFERENCES

- [1] A. Aquino-Lugo, R. Klump, T. J. Overbye, et al. A control framework for the smart grid for voltage support using agent-based technologies. *Smart Grid, IEEE Transactions on*, 2(1):173–180, 2011.
- [2] I. N. Athanasiadis, A. K. Mentis, P. A. Mitkas, and Y. A. Mylopoulos. A hybrid agent-based model for estimating residential water demand. *Simulation*, 81(3):175–187, 2005.
- [3] I. Ayres, S. Raseman, and A. Shih. Evidence from two large field experiments that peer comparison feedback can reduce residential energy usage. Technical report, National Bureau of Economic Research, Working Paper 15386, 2009.
- [4] A.-L. Barabási and R. Albert. Emergence of scaling in random networks. *science*, 286(5439):509–512, 1999.
- [5] A. Barbato and A. Capone. Optimization models and methods for demand-side management of residential users: A survey. *Energies*, 7(9):5787–5824, 2014.
- [6] A. Barbato, A. Capone, L. Chen, F. Martignon, and S. Paris. A distributed demand-side management framework for the smart grid. *Computer Communications*, 57:13–24, 2015.
- [7] E. Bloustein. Assessment of customer response to real time pricing. *Rutgers-The State University of New Jersey, Tech. Rep.*, 2005.
- [8] E. F. Bompard and B. Han. Market-based control in emerging distribution system operation. *Power Delivery, IEEE Transactions on*, 28(4):2373–2382, 2013.
- [9] P. Chavali, P. Yang, and A. Nehorai. A distributed algorithm of appliance scheduling for home energy management system. *Smart Grid, IEEE Transactions on*, 5(1):282–290, Jan 2014.
- [10] R. Cialdini and W. Schultz. Understanding and motivating energy conservation via social norms. Technical report, William and Flora Hewlett Foundation, 2004.
- [11] M. Delfanti, D. Falabretti, M. Merlo, G. Monfredini, and V. Olivieri. Dispersed generation in mv networks: performance of anti-islanding protections. In *Harmonics and Quality of Power (ICHQP), 2010 14th International Conference on*, pages 1–6. IEEE, 2010.
- [12] A. Faruqui and S. Sergici. Household response to dynamic pricing of electricity: a survey of 15 experiments. *Journal of Regulatory Economics*, 38(2):193–225, 2010.
- [13] P. Finn, C. Fitzpatrick, D. Connolly, M. Leahy, and L. Relihan. Facilitation of renewable electricity using price based appliance control in ireland's electricity market. *Energy*, 36(5):2952–2960, 2011.
- [14] H. Gintis and D. Helbing. Homo socialis: An analytical core for sociological theory. *Review of Behavioral Economics*, 2(1-2):1–59, 2015.
- [15] D. Helbing, W. Yu, K.-D. Opp, and H. Rauhut. Conditions for the emergence of shared norms in populations with incompatible preferences. *PLoS ONE*, 9(8):e104207, 2014.
- [16] M. Klein, N. Mogles, J. Treur, and A. van Wissen. Contagion of habitual behaviour in social networks: An agent-based model. In *Privacy, Security, Risk and Trust (PASSAT), 2012 International Conference on and 2012 International Confernece on Social Computing (SocialCom)*, pages 538–545, Sept 2012.
- [17] N. S. Kukushkin. Best response dynamics in finite games with additive aggregation. *Games and Economic Behavior*, 48(1):94–110, 2004.
- [18] D. m. Han and J. h. Lim. Smart home energy management system using iee 802.15.4 and zigbee. *IEEE Transactions on Consumer Electronics*, 56(3):1403–1410, Aug 2010.
- [19] MICENE Project, Official web site (ITA). http://www.eerg.it/index.php?p=Progetti_MICENE, feb 2015.
- [20] D. L. Mitchell, M. Cubed, and T. W. Chesnutt. Evaluation of east bay municipal district's pilot of watersmart home water reports. Technical report, California Water Foundation and East Bay Municipal Utility District, 2013.
- [21] A.-H. Mohsenian-Rad and A. Leon-Garcia. Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE Transactions on Smart Grid*, 1(2):120–133, 2010.
- [22] A.-H. Mohsenian-Rad, V. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. *Smart Grid, IEEE Transactions on*, 1(3):320–331, Dec 2010.
- [23] M. Pipattanasomporn, H. Feroze, and S. Rahman. Multi-agent systems in a distributed smart grid: Design and implementation. In *Power Systems Conference and Exposition, 2009. PSCE'09. IEEE/PES*, pages 1–8. IEEE, 2009.
- [24] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. Jennings. Agent-based control for decentralised demand side management in the smart grid. In *The 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*, pages 5–12. International Foundation for Autonomous Agents and Multiagent Systems, 2011.
- [25] A. Rixon, M. Moglia, and S. Burn. Exploring water conservation behaviour through participatory agent-based modelling. *Topics on system analysis and integrated water resource management*, page 73, 2006.
- [26] C. Rottondi, A. Barbato, L. Chen, and G. Verticale. Enabling privacy in a distributed game-theoretical scheduling system for domestic appliances. *IEEE Transactions on Smart Grid*, PP(99):1–11, 2016.
- [27] G. Strbac. Demand side management: Benefits and challenges. *Energy Policy*, 36(12):4419–4426, 2008.
- [28] D. Worm, D. Langley, and J. Becker. Modeling interdependent socio-technical networks: The smart grid - an agent-based modeling approach. In *Simulation and Modeling Methodologies, Technologies and Applications*, pages 87–100. Springer, 2015.