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Agent Based Social Interaction in Distributed Demand Side Management

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Ian Stewart,
Professor Stewart's Cabinet of Mathematical Curiosities

Abstract

In presence of time-variable energy tariffs, users will try to schedule the usage of their electrical appliances with the goal of minimizing their bill. If the variable price component depends on the peak aggregate demand during each given hour, users will be incentivized to distribute their consumption more evenly during the day, thus lowering the overall peak consumption. The process can be automated by means of an Energy Management System that chooses the best schedule while satisfying the user's constraints on the maximum tolerable delays. In turn, users' thresholds on delay tolerance may slowly change over time. In fact, users may be willing to modify 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. It will be interesting to study the social interaction effect in a set of users by means of evaluating the impact of the Agent based social interaction in distributed side management systems. We provide an algorithmic framework that models the effect of social interactions in a distributed Demand Side Management System and show that such interactions can increase the flexibility of users' schedules and lower the peak power, resulting in a smoother usage of energy throughout the day. Additionally, we provide an alternative description of the model by using Markov Chains and study the corresponding convergence times. We conclude that the users reach a steady state after a limited number of interactions.

Abstract (IT)

In un sistema in cui le tariffe elettriche variano in base alle fasce orarie di utilizzo, gli utenti cercheranno di programmare l'uso dei propri elettrodomestici allo scopo di ridurre al minimo la bolletta. Se la componente variabile del prezzo dell'energia dipende dai picchi nella domanda aggregata per ogni ora del giorno, gli utenti saranno incentivati a ripartire i propri consumi durante tutta la giornata, abbassando così il consumo di picco stesso. Questo processo può essere automatizzato per mezzo di un Sistema di Gestione dell'Energia in grado di scegliere l'orario ottimale, rispettando allo stesso tempo i limiti massimi di posticipo imposti dall'utente. A loro volta, questi limiti possono cambiare progressivamente nel tempo. Gli utenti, infatti, potrebbero voler modificare i propri parametri per farli coincidere con quelli del gruppo sociale di appartenenza, soprattutto qualora vengano a sapere che amici con un profilo più flessibile hanno risparmi concreti sulla bolletta. In questo contesto si rivela particolarmente interessante l'effetto delle interazioni sociali su un gruppo di utenti. In particolare, sarà oggetto di studio il modello ad agenti dell'interazione sociale nella gestione della domanda. In questo lavoro presentiamo un quadro algoritmico che riproduce l'effetto delle interazioni sociali in un Sistema di Gestione della Domanda e dimostriamo come le stesse possano aumentare la flessibilità dei consumi degli utenti ed abbassare la potenza di picco, portando ad un conseguente uso più omogeneo di energia nel corso della giornata. Il nostro studio fornirà, inoltre, una descrizione alternativa del modello per mezzo di processi markoviani ed analizzerà i relativi tempi di convergenza. In conclusione verrà constatato che gli utenti raggiungono l'equilibrio in seguito a un numero limitato di interazioni.

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List of Symbols / Abbreviations

DSM	Demand Side Management
RES	Renewable Energy Sources
DG	Distributed Generation
DLC	Direct Load Control
RTP	Real Time Pricing
CPP	Critical Peak Pricing
ESS	Energy Storage Systems
SP	Smart Pricing
PV	Photovoltaic
MILP	Mixed Integer Linear Program
ABM	Agent Based Model
VCG	Vickrey-Clarke-Grove
FIP	Finite Improvement Property
π	Contractual Limit

Chapter 1.

INTRODUCTION

The concept of Demand-Side Management (DSM) has been introduced in many fields, more specifically, it is widely studied for the electricity industry. It has been originally defined as the planning, implementation and monitoring of a set of programs and actions carried out by electric utilities, the distribution system operator, to influence energy demand in order to modify electric load curves in a way which is advantageous to the utilities. This concept gives customers a greater role in shifting their own demand of electricity during peak period, and reducing their overall consumption overall. Enabling customers to transfer their load during periods of high demand to off-peak periods can reduce the critical peak demand, 20 to 50 hours of greatest demand throughout the year, or change the daily peak demand, the maximum demand during a 24-hour period. Shifting the daily peak demand flattens the load curve, allowing more electricity to be provided by less expensive base load generation. Changes in load curves must decrease electric systems running costs, (both production and delivery costs), and also allow for deferring or even avoiding some investments in supply-side capacity expansion such as building new additional generation capacity to meet future critical peak demand. Thus, DSM has been driven by strict economic reasons.

On other hand, smart grid may have a large usage of DSM. Provided by this concept, smart grid will have better benefits and higher results towards accomplishing smart cities. Smart grids aim to provide more reliable, environmentally friendly and economically efficient power systems. In most of the countries interested in smart cities, the utility company that sells electricity to consumers has equipped their customers with smart meters. These smart meters exchange information between consumers and the utility company, and schedule the household energy consumption for consumers. The information gathered through smart meters can be used by the utility company to adjust the electricity prices. DSM is a key mechanism to make smart grids more efficient and cost-effective. DSM then refers to the programs adopted by utility companies to directly or indirectly influence the consumers' power consumption behavior in order to reduce the peak periods of the total load in the smart grid system. A higher peak period results in much higher operation costs and possibly outages of the system, while the application of DSM approaches to the smart grid ecosystem aims at shaping the aggregated power load curve of groups of customers, avoiding outages and improving power quality, or maximizing the usage of Renewable Energy Sources. DSM aims to incentivize consumers to shift their peak-time power consumption to off-peak times, thereby resulting in significant peak reductions in the power system thanks to the installation of smart meters.

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, since the latter is directly related to the amount of energy consumed and includes a price component that refers to the peak power. A typical energy bill is comprised of two main sections: the charges for the energy supply (kWh) and the charges from the local utility to deliver the energy. A building's peak demand (kW) for a period is usually the main driver for the utility to calculate the delivery charges. In many cases, demand charges exceed 50% of the total electric power bill. This makes DSM a very attractive option to reduce costs. 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, whereas in the latter each consumer locally defines her energy plan according to their 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. As a matter of fact, consumers do not live in isolation: they can interact with each other and with public institutions, and therefore can be influenced in their own attitudes, preferences and possible actions. This approach is consistent with the sociological paradigm, 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. In addition to that, society benefits from DSM by making it greener. Reduced or shifted energy usage can directly translate into less air pollution, less carbon emissions, and a way to lower the potential environmental threats associated with global warming. DSM programs are a promising alternative strategy to the increased concerns customers, utilities and government agencies have now regarding global warming and carbon emissions. Moreover, a properly designed DSM program can actually track the program impacts and measure the amount of carbon reduced or saved based on program activities. The domestic electricity consumption has been rising in the last years, being the residential and the transportation sectors the ones that increased their consumption the most. Furthermore, the percentage of metropolitan citizens has grown leading to a higher demand of the national electricity consumption. This increase is a consequence of several factors, such as the growth of electric equipment in the dwellings (e.g., audiovisuals, specially personal computers and air conditionings). However, such phenomenon may be a consequence of the number of customers and appliances which makes DSM an effective tool to achieve smart cities.

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 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 work are:

- A description of the interaction mechanisms aimed at modeling the influence of the society on individual delay tolerance preferences.
- An evaluation of how social interactions modify individual delay tolerance preferences, which, in turn, affects the aggregated energy consumption curve obtained at the end of the execution of the load scheduling game.
- A Markov-chain model of the interaction mechanisms and the evaluation of the time necessary to converge to the steady state.

1. Statement of the Problem

Historically, electricity peak demand is used to refer to a high point in the sales record at a certain period of time. In terms of energy use, peak demand describes a period where customer demand is at its highest. Peak demand, peak load or on-peak are terms used in energy demand management to describe a period in which electrical power is expected to be provided for a sustained period at a significantly higher than average supply level. Peak demand fluctuations may occur on daily, monthly, seasonal and yearly cycles. For an electric utility company, the actual point of peak demand is a single half-hour or hourly period which represents the highest point of customer consumption of electricity. The daily peak demand usually occurs around 5:30 pm (Pigenet, 2009). At this time there is a combination of office, domestic demand and at some times of the year, the fall of darkness, which induces more usage of lightning systems. It is a common practice that utilities charge customers based on their individual peak demand. The maximum demand dictates the size of generators, transmission lines, transformers and circuit breakers for utilities, even if that amount lasts just one hour per year. Natural gas fueled power generators must all have adequately sized pipelines. Power generation which is able to be rapidly ramped up for peak demand often uses more expensive fuels, is less efficient and has higher marginal carbon emissions. Peak demand may exceed the maximum supply levels that the electrical power industry can generate, resulting in power outages and load shedding. In order to avoid these consequences and ensure the quality of service that customers are promised, DSM may provide a feasible solution avoiding many big investments. The absence of new projects saves the customers an unwanted tariff in their bill based on the capex and operational costs. However, customers must apply to this new approach and schedule their load wisely avoiding peak hours.

Nonetheless, scheduling the load may not be so trivial and simple. In our study we used, beside DSM mechanism, an algorithm which can allocate the starting time of each appliance of the customer based on his prescheduled preferences. For each appliance of all the customers, a comfort level is defined on a daily basis. Using this type of approach, the algorithm can calculate the best solution in a neighborhood. The definition of our proposed solution to use a comfort threshold level assigned to each customer has not been experimented before, since DSM strategies were:

- Energy Efficiency: Reduce energy use overall.
- Peak Load Reduction: Reduce peak load consumption.
- Load Shifting: Move load to cheaper times.

- Load Building: Increase consumption to off-peak hours or increase overall consumption.

These stated strategies lacked the customer comfort level and threshold. In our study, we will be focusing on that to achieve results that might be useful for future studies and to reach the global goal of a cheaper bill and a smarter city.

2. Current Status of Art

The topic of DSM is widely spread and it has already many publications in several papers which describe it and use the same strategies listed above in order to reach and meet the requirements. Numerous agent based models tackle socio-behavioral aspects of the interactions among users and between users and utilities: Worm et al. in their paper (2015) 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 renewable energy sources (e.g. solar panels), and a long-term behavioral model, which defines how social interactions may alter users' attitudes towards comfort requirements, energy efficiency, usage of renewable energy sources 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. As a matter of fact, social interaction can provide benefits to diminishing peak demand, which is another aspect of our study where we will simulate the interaction based on two different scenarios. The results and observations will be discussed in the next section.

3. Proposed Solution and Objectives

The DSM solution requires many coordinated and interconnected strategies. The entity is a software agent that is installed at customers' premises. This entity will allow the customer to schedule and reschedule their appliances while considering their comfort threshold. The set of customers which are present in a neighborhood have to play all together to accomplish the objective of minimizing peak load demand at a certain hour. The mechanism that manages all the customers is adaptive to the customer's consumption. Based on that, in the study, using a distributed algorithm, the parameters are modelled in game theory. At this point, each player (customer) uses best response to achieve the best allocation. The best response is to avoid high demand hours and spam the unused or off-peak hours such as night hours. After the allocation of each appliance of each customer, the scheme iterates between them, until the bill is accepted by every player, and none of the players is willing to change their schedule since all comfort levels were respected and thresholds meet the allocation. At convergence, local max is reached and the solution is given by the predicted market prices of the next day. After the implementation of this scheme, the load profile for the neighborhood is flatter. A smoother load profile will imply many benefits, such as less gas emissions, more social interaction and mainly lower bill. The objectives reached aim to help the electric utilities in accomplishing more smart grids and less expensive rates of electricity.

4. Relevance of the Project

The game theory approach is based on the set of customers that a neighborhood may present. Each player have many appliances: some are fixed, where the schedule cannot be modified or changed, and some are shiftable, where the starting time of each one of them is set based on a comfort threshold that each player sets. The incentive here is to have the lowest bill while having a comfort threshold that is acceptable. The importance and the additive structure to most of previous DSM study is the comfort threshold and the ability to change it based on the interaction among players.

Chapter 2.

RELATED WORK

DMS strategies may vary depending on the customers. The most popular existing approaches are the Direct Load Control (DLC) and the Smart Pricing (SP), which assign to each hour of the day a different price based on the amount of power being injected to the gird, for implementing DSM.

DLC refers to the program in which the utility company can remotely manage a fraction of consumers' appliances to shift their peak-time power usage to off-peak times (Linqi Song, 2014). Alternatively, SP provides an economic incentive for consumers to voluntarily manage their power usage. Examples are Real-Time Pricing (RTP), Time-Of-Use Pricing (TOU), Critical Peak Pricing (CPP) (J. Jhi-Young, 2007) and many others. However, the stated works do not consider the consumers' comfort level which is induced by altering their power consumption patterns.

In order to explain better the price incentives and tariff structures, in (Esmap, 2012), the electricity utilities explore all their aspects. The structure of the electricity tariffs can greatly influence the power demand and electricity use on mini-grids, an aspect which is critical for the economic sustainability of the whole system. Mainly, the commonly used tariff structures on mini-grids can be categorized into two major schemes (Glania, 2011): capacity-based (or power-based) and consumption-based (or energy-based).

The first category implies the customers to pay based on the maximum power that they are allowed to use. This scheme is often applied on mini-grids in which it may offer many other different levels of power allowance having the objective to meet the needs of all the existing customers in it. The basic allocation could be determined based on the customer's willingness to pay or by the permissible number of lights or type of appliances. These agreements are enforced through a contract, usually written, or implied by the use of current limiters. Capacity-based tariffs can make billing much easier, since all the parties have set their agreements in advance, however it might be faced with some difficulties to enforce the agreement itself. On the other side, current limiters are often subject to tampering and fraud, where many attempts of customers has been recorded. This type of tariffs has gained popularity on micro-hydro and other power-limited micro-grids, as they inherently limit and distribute the power equitably at any given instant. Additionally, some forms of capacity-based tariff or the current limiter may be used in conjunction with an energy based tariff on other types of mini-grids.

The second type of tariffs, the consumption-based, charges customers based on their metered energy consumption and can ultimately lead or encourage energy conservation. This features the ability to encourage conservation makes consumption-based tariffs appropriate for mini-grids that are energy-limited, such as solar and wind mini-grids. Nevertheless, micro-hydro mini-grids are not vulnerable to excessive power consumption since they are power-limited, so they usually do not require metering. The appropriateness of metering based on a biomass or diesel grid depends on the intermittency of the generation, the cost of fuel, and the efficiency curve of the generator. In other cases, where the system is independent from a battery bank and the fuel consumption of the generator, the variation is very small according to the generator since the cost of fuel is negligible, so capacity-based tariff would be more convenient since energy conservation is not critical. While energy conservation can be achieved through metering alone, for isolated mini-grids the peak demand must also be limited to prevent system overloads.

The structure of a consumption-based tariff has several options. Electrical utilities in industrialized nations are increasingly implementing dynamic electricity rates, such as real time pricing to limit demand during peak periods and encourage energy conservation for grid connected customers. In addition to these sophisticated rate structures, simpler ones that have been in wide use for central grid customers in industrialized countries, such as time of use or inverted block (or tiered) rates, can be applied to mini-grids in both developed and developing countries. Time of use rates can, in some cases, be applied to mini-grids but they are often only used by large commercial customers who can afford a more expensive meter or whose consumption is easily monitored. Other researchers investigating tariffs for rural utilities argue that use of an inverted block rate can be regressive within a given block, may be confusing to the consumer and can penalize consumers with connections shared by multiple households. Based on economic theory, these researchers suggest to use a flat-rate tariff equal to the unsubsidized marginal cost of the service in combination with a lump sum return to ensure that low income households can meet their essential needs. In addition to that, on some mini-grids, electricity rate may be highly subsidized so that they no longer provide the necessary price signals to encourage conservation. Pelland et al. (2012) found that mini-grid customers in Canada were using inefficient electric baseboard heaters and suggested that adding an inverted block rate would encourage conservation behavior on the diesel mini-grid. Nowadays, there are some new advanced metering systems offering additional variations on the consumption-based tariff that are particularly suited for the constraints of an isolated, energy limited grid. Some of these metering systems charge a tariff based on a predetermined daily or weekly energy allocation or rate of available energy.

Some recent works considered consumers' load scheduling strategies and aimed to jointly minimize the consumers' billing while changing their starting time. These works can be classified into two categories, depending on the deployed consumer model. The first category assumed that the consumers are price-taking, i.e., they do not consider how their consumption will affect the prices. As a result of this assumption, the decision making of a single foresighted consumer is formulated as a stochastic control problem aiming to minimize their long-term total cost in. Alternatively, in another model, consumers aim to minimize their current total costs and their decisions are formulated as static optimization problems among cooperative users for which distributed algorithms are proposed to find the optimal prices. The second category assumed that the consumers are responsible for their load since the bill will be affected by their consumption. In this case, each consumer's power usage affects the other consumers' billing costs. This type of work is modeled as the interactions emergence among second category consumers in which one-shot game of theory is modeled, the latter is the main subject of our study.

However, in our model, the consumers interact with each other repeatedly, as per the principle of social interaction, and are foresighted, thereby engaging in a repeated game.

Nevertheless, all the existing works considering multiple consumers assumed that the consumers belong to the first category and try to minimize their current costs. The optimal DSM strategies in these works are stationary, i.e., all consumers adopt fixed daily/weekly power consumption patterns as long as the system parameters (e.g., the consumers' desired power consumption patterns) do not change (Wayland, 210).

Numerous ABMs tackle socio-behavioral aspects of the interactions among users and between users and utilities. Ramchurn et al. (2011) describe a decentralized 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 minimizing peaks in the aggregated consumption within a neighborhood, 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. The solution we proposed 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. (2015) and Chavali et al. (2014), residential user agents are modelled as rational entities who solve a Mixed Integer Linear Program (MILP) to minimize 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 (C. Rottondi, 2016) that such game is a generalized ordinal potential game which converge in a few steps to a pure Nash Equilibrium. In this study, we adopt the same assumptions and build upon the theoretical results therein discussed. However, in this work 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. (D. Helbing, 2014) 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 behavior of others. In Contagion of habitual behavior in social networks, Klein et al.

(2012) 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 the influence and diffusions mechanism in residential use water consumption. Rixon et al. (2006) propose an ABM within a memetic framework capturing imitation of water use behavior. Agents are assumed to be characterized 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 behavior), and to consume water according to them. Memes are thence spread based on social interaction.

The model proposed by Athanasiadis et al. in (2005) 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 work, we adopt a similar characterization of the social attitudes of the users.

To minimize the total cost, some consumers are required to shift their peak-time power usage to the off-peak times while the remaining consumers can use energy when desired. By deploying this optimal strategy, the consumers who shift their peak-time consumption incur discomfort costs, but this leads to a reduction of the peak-time price and of the billing cost of all the consumers. More importantly, the nonstationary DSM strategy we propose can achieve the optimal total cost while ensuring fairness among consumers by recommending different subsets of consumers (referred to as the active set) to shift their peak time consumption each day. The active set is determined by the consumers' preferences and the past selection of active sets.

Moreover, another DSM system proposed by the literature is based on energy tariffs that are currently used and data forecasts for DG and power demand (e.g., photovoltaic power generation, devices future usage), defining a mechanism. The latter is able to schedule, in an automatic and optimal way, the home devices activities for future periods and to define the overall energy plan of users (i.e., when to buy and sell energy to the grid). The main goal of these solutions is to minimize the electricity costs while guaranteeing the users' comfort. This can be achieved through the execution of methods based on optimization models (Le), or heuristics, such as Genetic Algorithms and customized Evolutionary Algorithms (Florian Allerding, 2012), which are used to solve more complex formulations of the demand management problem. Since RESs diffusion is rapidly increasing, several works include renewable plants into DSM frameworks which are needed for management. In these cases, devices are scheduled also based on the availability of an intermittent electricity source (e.g., PV plants) and the users' profits from selling renewable electricity to the energy market are taken into account.

The uncertainty of RESs generation forecasts is tackled through stochastic approaches, such as stochastic dynamic programming. The latter is a very suitable tool to address the decision-making process of energy management systems in presence of uncertainty, as the case of the one related to the electricity produced from weather-dependent generation sources. The efficiency of demand management solutions can be notably improved by including storage systems that can increase the DSM flexibility in optimizing the usage of electric resources.

Specifically, batteries can be used to harvest the renewable generation in excess for later use or to charge the ESS (Energy Storage Systems) when the electricity price is low, with the goal of minimizing the users' electricity bill which represents another possible solution to our management framework. These proposed solutions are based on a single-user approach in which the energy plans of residential customers are individually and locally optimized. However, in order to achieve relevant results from a system-wide perspective, the energy management problem could be applied to groups of users (e.g., a neighborhood or micro-grids) – in our study a neighborhood – instead of single users.

For this reason, some preliminary solutions have been proposed in the literature to manage energy resources of groups of customers. In "House energy demand optimization in single and multi-user scenarios" (A. Barbato A. C., 2011), for example, the energy bill minimization problem is applied to a group of cooperative residential users equipped with PV panels and storage devices (i.e., electric vehicle batteries). A global scale optimization method is also proposed, in which an algorithm is defined to control domestic electricity and heat demand, as well as the generation and storage of heat and electricity of a group of houses. These multi-user solutions require some sort of centralized coordination system run by the operator in order to collect all energy requests and find the optimal solution.

To this end, a large flow of data must be transmitted through the Smart Grid network, thus introducing scalability constraints and requiring the definition of high-performance communication protocols.

Furthermore, the coordination system should also verify that all customers comply with the optimal task schedule, since the operator has no guarantee that any user can gain by deviating unilaterally from the optimal solution. Therefore, the collection of users' metering data and the enforcing of the optimal appliance schedule can introduce novel threats to customers' security and privacy. For these reasons, some distributed DSM methods have been proposed in which decisions are taken locally, directly by the end consumer. In this case, Game Theory represents the ideal framework to design DSM solutions. Specifically, A. Mohsenian-Rad et al. (2011) describe a distributed DSM system among users, where the users' energy consumption scheduling problem is formulated as a game: the players are the users, and their strategies are the daily schedules of their household appliances and loads. The authors considered a pricing mechanism based on a convex and an increasing cost function making their work a reference for DSM techniques. An alternative technique known as Vickrey-Clarke-Grove mechanism is proposed in (P. Samadi, 2012). Its aim is to achieve efficiency, nonnegative transfer (i.e. from utility to user) and truthfulness among users. The pricing mechanism presented is based on convex, increasing and differentiable cost function. The proposed VCG model encourages user to shift their load from peak hours to off-peak hours. Besides from obtaining a social welfare, the utility also gain benefits by having a reduced average load shape curve. The goal of the game is to either reduce the peak demand or the energy bill of users. Moreover, a game theoretical approach is also used in (C. Ibars, 2010), in which a distributed load management is defined to control the power demand of users through dynamic pricing strategies. However, these works use a very simplified mathematical description to model customers, which does not correspond to real use cases.

Chapter 3.

FRAMEWORK

In the framework of our study, we consider a distributed DSM method, which is able, within a group of residential users, to reduce the peak demand. The framework is modelled and studied using a game of theory. In our vision, the energy retailer fixes the energy price dynamically, based on the total power demand of customers; as a result, appliances autonomously decide their schedule, reaching an efficient equilibrium point.

1. Design

Our model proposes a power scheduling system designed to manage all electrical appliances of a group of residential users, $\boldsymbol{U}$. The used system will schedule the energy plan for the whole set of users, who previously allocated their power demand, over a 24-hour time period divided into a set, $\boldsymbol{T}$, of time slots duration, with the final goal of improving the efficiency of the whole power grid by reducing the peak demand of electricity, while still complying with users' needs and preferences. Each user $\boldsymbol{u} \in \boldsymbol{U}$, owns a set of non-interruptible electric appliance, or fixed appliance, $\boldsymbol{A_u}$, that must run once a day. In particular, the load profile of each appliance is modeled as an ordered sequence of time slots, in which a certain amount of power is consumed. The load profile of each appliance $\boldsymbol{a} \in \boldsymbol{A_u}$ lasts $\boldsymbol{N_{au}}$ time slots and its value in the *n*th time slot is given by $\boldsymbol{l^u}_{\boldsymbol{an}}$ with $n \in \boldsymbol{N_{au}} = \{\mathbf{1}, \mathbf{2} \ldots, \boldsymbol{N_{au}}\}$. For the sake of easiness, we assume that $\boldsymbol{l^u}_{\boldsymbol{an}}$ is constant for the whole duration of the *n*th time slot. Each appliance $\boldsymbol{a} \in \boldsymbol{A_u}$ is also associated with a set of parameters $\boldsymbol{c^t}_{\boldsymbol{au}} \in [0, 1]$ which define the comfort level perceived by user $\boldsymbol{u}$ in starting appliance $\boldsymbol{a}$ at time slot $\boldsymbol{t} \in \boldsymbol{T}$.

The rationale behind the definition of such comfort level is the following: each user decides a preferred time slot for the starting time of their appliances. However, in case of deferrable appliances, they may 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 $\boldsymbol{u}$ for starting appliance $\boldsymbol{a}$ at time slot $\boldsymbol{t}$ is, the lower $\boldsymbol{c^t}_{\boldsymbol{au}}$ is. In the extreme case of $\boldsymbol{c^t}_{\boldsymbol{au}} = \mathbf{0}$, user $\boldsymbol{u}$ specifies a threshold $\boldsymbol{Y_{au}} \in (0, 1]$ indicating the minimum acceptable delay tolerance level for appliance $\boldsymbol{a}$, which defines the degree of flexibility of the user in scheduling their appliances: the lower $\boldsymbol{Y_{au}}$ is, the more tolerant to delaying their starting time the user will be.

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

$$\boldsymbol{c^t}_{\boldsymbol{au}} = \begin{Bmatrix} 1 \; if \; t = t_{au} \\ 0 \; else \end{Bmatrix}$$

which guarantees that fixed devices have only one allowed starting time and that the system is forced to start them at time $\boldsymbol{t_{au}}$.

Conversely, *shiftable appliances* (e.g., washing machine, dishwasher…), represented by the subset $\boldsymbol{A^S}_{\boldsymbol{u}} \subseteq \boldsymbol{A_w}$ are controllable devices and their starting time is an output of a scheduling algorithm. For these appliances $\boldsymbol{c^t}_{\boldsymbol{au}}$ may assume non-zero values in multiple slots, providing that there exists at least one time slot $\boldsymbol{t}$ such that $\boldsymbol{c^t}_{\boldsymbol{au}} = \boldsymbol{1}$ (i.e., $\boldsymbol{t}$ is $\boldsymbol{u}$'s preferred starting time for appliance $\boldsymbol{a}$).

The scheduling strategy $\boldsymbol{i_u}$ of player $\boldsymbol{u}$ is described by a set of binary decision variables:

$$\boldsymbol{x^t}_{\boldsymbol{au}} = \begin{Bmatrix} 1 \; if \; appliance \; \boldsymbol{a} \; of \; user \; \boldsymbol{u} \; is \; started \; at \; time \; \boldsymbol{t} \\ 0 \; otherwise \end{Bmatrix}$$

We considered two different types of devices are:

Shiftable appliances (e.g., washing machine, dishwasher): they are manageable devices that must be scheduled and executed during the day. In particular, for each shiftable device $\boldsymbol{a} \in \boldsymbol{A_u}$ of the users $\boldsymbol{u} \in \boldsymbol{U}$, the minimum starting time and the maximum ending time are limited and bounded. Thus, our goal will be the optimization of scheduling their starting time.

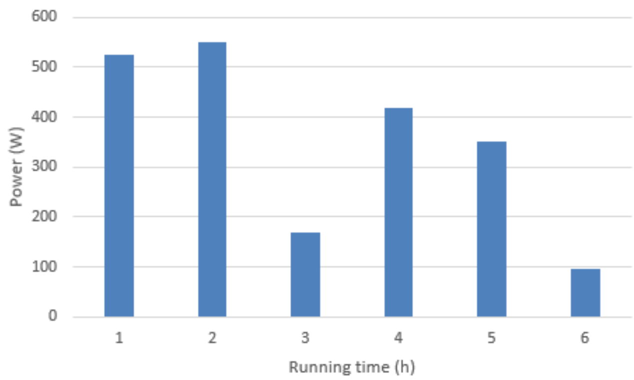


Figure 1: Example of a load profile of a washing machine.

Fixed appliances (e.g., light, TV): they are non-manageable devices, for which the starting and ending times are prescheduled and fixed, in other words they cannot be used in the optimization process. More specifically, for each fixed device $\boldsymbol{a} \in \boldsymbol{A_u}$ of the users $\boldsymbol{u} \in \boldsymbol{U}$, the minimum starting time and the maximum ending time are fixed into a well-known time frame.

Table 1: Table of Symbols

Notation	Description
$\boldsymbol{U}, \boldsymbol{T}$	Set of users, time slots within the optimization horizon
$\boldsymbol{A_u} = \boldsymbol{A^F}_{\boldsymbol{u}} \cup \boldsymbol{A^S}_{\boldsymbol{u}}$	Set of appliances of user $\boldsymbol{u} \in \boldsymbol{U}$, including non shiftable and shiftable appliances
$\boldsymbol{N_{au}}$	Load profile duration of appliance $\boldsymbol{a} \in \boldsymbol{A_u}$ owned by user $\boldsymbol{u} \in \boldsymbol{U}$
$\boldsymbol{c^t}_{\boldsymbol{au}}$	Comfort profile of appliance $\boldsymbol{a} \in \boldsymbol{A_u}$ owned by $\boldsymbol{u} \in \boldsymbol{U}$ during each time slot $\boldsymbol{t}$
$\boldsymbol{C_u}$	Comfort threshold of user $\boldsymbol{u} \in \boldsymbol{U}$
$\boldsymbol{l^u}_{\boldsymbol{an}}$	Power consumption of appliance $\boldsymbol{a} \in \boldsymbol{A_u}$ owned by user $\boldsymbol{u} \in \boldsymbol{U}$ during $\boldsymbol{n} \in \{\boldsymbol{1}, \boldsymbol{2}.., \boldsymbol{N_{au}}\}$
$\boldsymbol{\pi}$	Maximum user energy consumption
$\boldsymbol{y^t}_{\boldsymbol{au}}$	Energy consumption of user $\boldsymbol{u} \in \boldsymbol{U}$ during time $\boldsymbol{t} \in \boldsymbol{T}$

$\boldsymbol{p^l}_{\boldsymbol{u}}$	Aggregated energy consumption of users $\boldsymbol{U} / \{\boldsymbol{u}\}$ during time $\boldsymbol{t} \in \boldsymbol{T}$
$\boldsymbol{x^t}_{\boldsymbol{au}}$	Binary variable set to $\mathbf{1}$ if the start time of appliance $\boldsymbol{a}$ of user $\boldsymbol{u}$

2. Strategies and Constraints

The set of all strategies of $\boldsymbol{u}$ is denoted by $\boldsymbol{I_u}$. This set of strategies is modelled as the main constraints of our game theory optimization problem. The feasibility of the strategies is related to the satisfaction of their corresponding constraints. We say that the strategy $\boldsymbol{i_u}$ is feasible if it satisfies the following constraints:

$$(1) \qquad \sum_{\boldsymbol{a} \in \boldsymbol{A^F}_{\boldsymbol{u}}} \boldsymbol{c^t}_{\boldsymbol{au}} \boldsymbol{x^t}_{\boldsymbol{au}} \geq \left| \boldsymbol{A^F}_{\boldsymbol{u}} \right|$$

$$(2) \qquad \sum_{\boldsymbol{t} \in \boldsymbol{T}} \boldsymbol{c^t}_{\boldsymbol{au}} \boldsymbol{x^t}_{\boldsymbol{au}} \geq \boldsymbol{Y}_{\boldsymbol{au}} \quad \forall\, \boldsymbol{a} \in \boldsymbol{A^S}_{\boldsymbol{u}}$$

$$(3) \qquad \sum_{\boldsymbol{t} \in \boldsymbol{T}} \boldsymbol{x^t}_{\boldsymbol{au}} = \mathbf{1} \quad \forall\, \boldsymbol{a} \in \boldsymbol{A}_{\boldsymbol{u}}$$

Each of the previous constraint implies and verifies the conditions of our model. Constraints (1)-(2) ensure that the starting time of every appliance $\boldsymbol{a}$ provides a comfort level higher than the acceptability threshold $\boldsymbol{Y_{au}}$. Constraints (3) impose that each appliance is executed exactly once per day. Such condition can be easily generalized to include an upper bound on the number of usages of an appliance.

The pair ($\{\boldsymbol{c^t}_{au} \mid \boldsymbol{t} \in \boldsymbol{T}, \boldsymbol{a} \in \boldsymbol{A_u}\}$,$\{\boldsymbol{Y^t}_{au} \mid \boldsymbol{a} \in \boldsymbol{A_u}\}$) is defined and called the *comfort characteristic* of user $\boldsymbol{u}$. Moreover, a comfort characteristic $\boldsymbol{C_u}$ = ($\{\boldsymbol{c^t}_{au} \mid \boldsymbol{t} \in \boldsymbol{T}, \boldsymbol{a} \in \boldsymbol{A_u}\}$,$\{\boldsymbol{Y^t}_{au} \mid \boldsymbol{a} \in \boldsymbol{A_u}\}$) of user $\boldsymbol{u}$ is said to be *consistent* with the contractual limit $\boldsymbol{\pi_u}$ on the amount of purchasable energy per time slot if there exists a strategy $\boldsymbol{i_u}$ such that:

$$(4) \quad \sum_{\boldsymbol{a} \in \boldsymbol{A_u}} \sum_{\boldsymbol{n} \in \boldsymbol{N_u}: \boldsymbol{n} \leq \boldsymbol{t}} \boldsymbol{l^u}_{an} \, . \, \boldsymbol{c^{t-n+1}}_{au} \leq \boldsymbol{\pi_u} \quad \forall \, \boldsymbol{t} \in \boldsymbol{T}$$

This 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, $\boldsymbol{\pi_u}$. Such consumption depends on the scheduling strategy: the energy required by each device $\boldsymbol{a}$ in every time slot $\boldsymbol{t}$ is equal to the energy consumption indicated by the *n*th sample (with $\boldsymbol{n} \in \boldsymbol{N_{au}} = \{\boldsymbol{1}, \boldsymbol{2}.., \boldsymbol{N_{au}}\}$) of the load profile, $\boldsymbol{l^u}_{an}$, executed at time $\boldsymbol{t}$. Note that the energy amount indicated by the *n*th sample of the appliance load profile is consumed during slot $\boldsymbol{t}$ only in case the appliance is started at time $\boldsymbol{t} - \boldsymbol{n} + \boldsymbol{1}$, thus if $\boldsymbol{x^{t-n+1}}_{au} = \boldsymbol{1}$.

3. Pricing

We model the price of electricity at time $\boldsymbol{t} \in \boldsymbol{T}$, $\boldsymbol{b_t}(.)$ as an increasing function of the total energy demand of the group of users $\boldsymbol{U}$ at time $\boldsymbol{t}$ (V. Wong, 2010). 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. As a result, due to the conflicting goals of the users, the load scheduling problem cannot be solved with a centralized approach. For this reason, we adopt the distributed game-theoretic framework proposed in (G. Verticale, 2016), which models the problem as a game $\boldsymbol{G} = \{\boldsymbol{U}, \boldsymbol{I}, \boldsymbol{P}\}$, defined by:

i. The *players* representing the users in the set $\boldsymbol{U}$, each one associated to a comfort characteristic $\boldsymbol{C_u}$ and a contractual limit $\boldsymbol{\pi_u}$ on the purchasable energy per time slot.
ii. The *strategy* set $\boldsymbol{I} \triangleq \prod_{\boldsymbol{u} \in \boldsymbol{U}} \boldsymbol{I^{Cu}}_{\boldsymbol{u}}$ where $\boldsymbol{I^{Cu}}_{\boldsymbol{u}}$ indicates the strategy set of player $\boldsymbol{u}$ corresponding to its feasible load schedules determined by $(\boldsymbol{C_u}, \boldsymbol{\pi_u})$ (we assume here that such set is not empty).
iii. The *payoff function* set $\boldsymbol{P} \triangleq \{\boldsymbol{P_u}\}_{\boldsymbol{u} \in \boldsymbol{U}}$, where $\boldsymbol{P_u}$ is the payoff function of user $\boldsymbol{u}$, which coincides with their daily electricity bill.

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

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

where

$$\boldsymbol{y_{ut}} = \sum_{\boldsymbol{a} \in \boldsymbol{A_u}} \sum_{\boldsymbol{n} \in \boldsymbol{N_{au}}:\boldsymbol{n} \leq \boldsymbol{t}} \boldsymbol{l^u}_{\boldsymbol{an}} \cdot \boldsymbol{x^{t-n+1}}_{\boldsymbol{au}}$$

is the energy demand of user $\boldsymbol{u}$ at time $\boldsymbol{t}$ and $\boldsymbol{b_t(y_t)}$ is the price of electricity at time $\boldsymbol{t}$ defined a as linear function of $\boldsymbol{y_t} = \sum_{\boldsymbol{u} \in \boldsymbol{U}} \boldsymbol{y_{ut}}$, which represents the total electricity demand of the players at time $\boldsymbol{t}$. It has been proved that such function is a regular pricing function. It thence follows that $\boldsymbol{G}$ is a generalized ordinal potential game, with $\boldsymbol{P(I)}$ 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 (Kukushkin, 2004). As proposed in (C. Rottondi, 2016), we assume that the best response method is implemented in an iterative way as follows. Users in $\boldsymbol{U}$ are listed in a predefined order. The first user initiates the algorithm by choosing their optimal load schedule assuming flat tariffs. Then, the user communicates their 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 process ends when none of the users alters their 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:

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

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

4. The Interaction Model

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

The social interaction is mediated by an automated mechanism that collects delay tolerance thresholds and the energy price paid by the user's friends and that adjusts the user's thresholds according to some filtering rule. For example, a user might be willing to adjust their thresholds towards the thresholds of similar users who pay a lower price. However, users may not interact with their friends on a 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 $\boldsymbol{p^l}_{\boldsymbol{u}}$which is set to $\mathbf{1}$ if user $\boldsymbol{u}$ is willing to compare (and possibly revise) their delay tolerance thresholds on day $\boldsymbol{l} \in \boldsymbol{L}$, to $\mathbf{0}$ otherwise. Moreover, let $\boldsymbol{R}[\boldsymbol{u}]$ be the list of $\boldsymbol{u}$'s social neighbors. Similarly to the approach proposed in (Bloustein, 2005), in order to capture the users' capability to make rational decisions about whom to imitate (and up to which extent), for each appliance $\boldsymbol{a} \in \boldsymbol{A^S}_{\boldsymbol{u}}$ we consider a two-dimensional attitude space (see Figure 2). This assumption also enables the users to redefine the sets $\boldsymbol{A^F}_{\boldsymbol{u}}, \boldsymbol{A^S}_{\boldsymbol{u}}$ before each game execution, e.g. in case some appliances are not regularly used on daily basis.

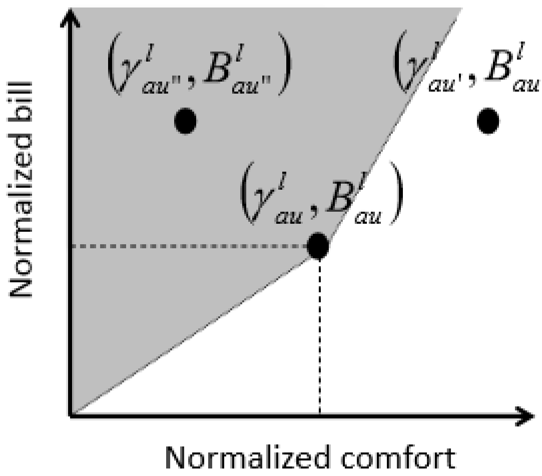


Figure 2: Users' attitude space

where each user locates themselves and their neighbors based on their current delay tolerance threshold $\boldsymbol{y^l}_{\boldsymbol{au}}$ and normalized daily energy bill per appliance $\boldsymbol{B^l}_{\boldsymbol{au}}$ defined as:

$$\boldsymbol{B^l}_{\boldsymbol{au}} = \frac{\sum_{t \in T} \boldsymbol{b_t}(\boldsymbol{y_{ut}}) \sum_{n \in N_{au}: n \leq t} \boldsymbol{l^u}_{\boldsymbol{an}} \cdot \boldsymbol{x^{t-n+1}}_{\boldsymbol{au}}}{\sum_{t \in T} \boldsymbol{b_t}(\boldsymbol{y_{ut}}) \cdot \boldsymbol{y_{ut}}}$$

Based on their position, user $\boldsymbol{u}$ defines an area of interest $\boldsymbol{A^l}_{\boldsymbol{u}}$ (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 theirs, though their bill is - even significantly- higher than theirs, whereas they would never imitate users with a lower delay tolerance threshold, even if their daily expense is lower than their own) and may be revised at each game execution $\boldsymbol{l}$.

The interaction protocol executed by user $\boldsymbol{u}$ at day $\boldsymbol{l} \in \boldsymbol{L}$ proceeds as follows. User $\boldsymbol{u}$ defines a Boolean parameter $ή_{\boldsymbol{u}'}$ computed as:

$$ή_{\boldsymbol{u}'} = \begin{cases} 1 \ if \ \left(\boldsymbol{y^l}_{\boldsymbol{au}'}, \boldsymbol{B^l}_{\boldsymbol{au}}\right) \in \boldsymbol{A^l}_{\boldsymbol{u}} \\ 0 \ else \end{cases}$$

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

$$(7) \qquad \boldsymbol{y^{l+1}}_{\boldsymbol{au}} = \begin{cases} \boldsymbol{y^l}_{\boldsymbol{au}} + \dfrac{\sum_{ή_{\boldsymbol{u}'} \wedge \boldsymbol{p^l}_{\boldsymbol{u}} \boldsymbol{p^l}_{\boldsymbol{u}'} = 1} \boldsymbol{h_a}(\boldsymbol{u}, \boldsymbol{u}')(\boldsymbol{y^l}_{\boldsymbol{au}'} - \boldsymbol{y^l}_{\boldsymbol{au}})}{|\ \boldsymbol{R}[\boldsymbol{u}]\ |} \\ \boldsymbol{y^l}_{\boldsymbol{au}} \ else \end{cases}$$

where $\boldsymbol{h_a}(\boldsymbol{u}, \boldsymbol{u}')$ is the similarity between the comfort profiles of users $\boldsymbol{u}$ and $\boldsymbol{u}'$ with respect to appliance $\boldsymbol{a}$. In this paper we will define similarity as half the number of time slots where $\boldsymbol{c^t}_{\boldsymbol{au}}$ and $\boldsymbol{c^t}_{\boldsymbol{au}'}$ are both non-zero. The condition of constraints (7) is

$$\boldsymbol{y^{l}}_{\boldsymbol{au}} + \frac{\sum_{\acute{\eta}_{\boldsymbol{u'}} \wedge \boldsymbol{p^{l}}_{\boldsymbol{u}}\boldsymbol{p^{l}}_{\boldsymbol{u'}}=\mathbf{1}} \boldsymbol{h_a}(\boldsymbol{u},\boldsymbol{u'})(\boldsymbol{y^{l}}_{\boldsymbol{au'}} - \boldsymbol{y^{l}}_{\boldsymbol{au}})}{|\, \boldsymbol{R}[\boldsymbol{u}] \,|} > 0$$

User $\boldsymbol{u}$ will then use the updated delay tolerance threshold $\boldsymbol{y^{l+1}}_{\boldsymbol{au}}$ in the next day for the execution of the load scheduling game.

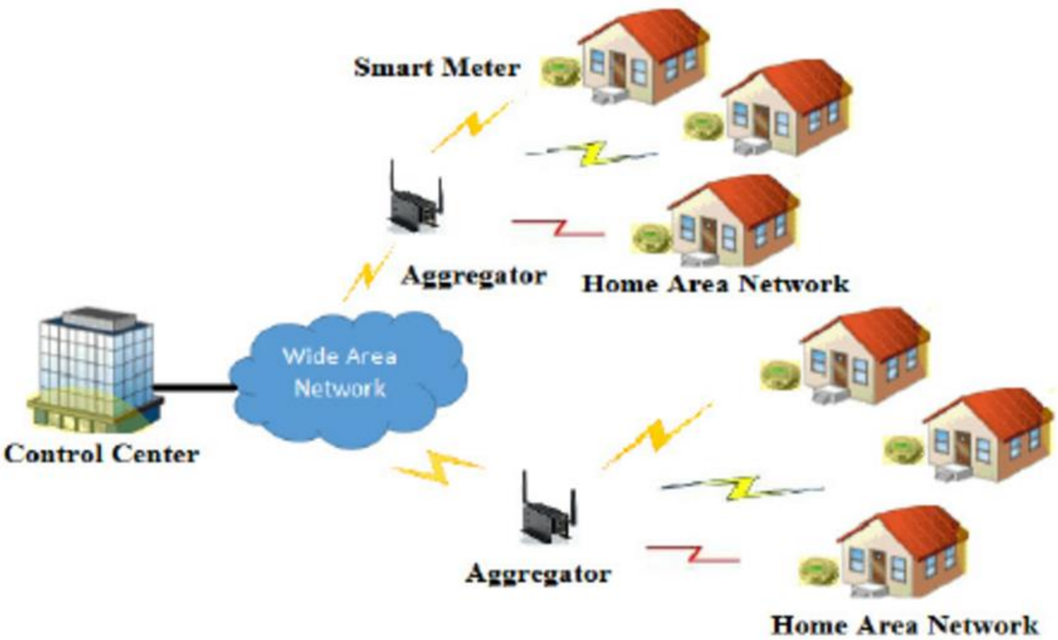


Figure 3: Home users sending their preferences (comfort level, appliance scheduling) to the aggregator

To sum the potential social interaction and evaluate the effects of uses' social interactions, we define the following two scenarios:

On day 1, we assume that no interaction occurs among the users. This assumption is considered as the benchmark of our study into the game of theory.

- Scenario I assumes that users can influence the comfort threshold $\boldsymbol{C_u}$ of their neighbors.
- Scenario II assumes that users can influence both the comfort threshold $\boldsymbol{C_u}$ and the comfort parameter $\boldsymbol{c^t}_{\boldsymbol{au}}$ of their neighbors.

In the following section we will provide the details of the social mechanisms which characterize the two latter scenarios.

i. Scenario I

In order to characterize the social attitudes of the users (i.e. their ability to promote or comprehend price signals and sensibility to the mechanism), we allocate to each user $\boldsymbol{u}$ of the neighborhood:

- An influence probability $\boldsymbol{p^u}_{\boldsymbol{au}}$
- An imitation coefficient $\boldsymbol{h_u}$

The probability $\boldsymbol{p^{u}}_{\boldsymbol{au}}$ characterizes the strength of the influence of user $\boldsymbol{u}$ on their neighbors (the higher is $\boldsymbol{p^{u}}_{\boldsymbol{au'}}$ the more likely user $\boldsymbol{u}$ will be successful in convincing the neighbors about the interaction to alter their preferences). The imitation coefficient measures the extent up to which user $\boldsymbol{u}$ is disposed to imitate the preferences of their neighbors.

In this scenario we assume that users exchange only comfort signals, i.e. they socially interact with the aim of influencing each other's comfort threshold $\boldsymbol{C_u}$. We also assume that the social interactions occur after the execution of the load scheduling game which will be described in the next scenario. As a consequence of the interactions with their neighbors, user $\boldsymbol{u}$ may modify the value of $\boldsymbol{C_u}$ to be used in the next execution of the load scheduling game (i.e., during the next optimization time horizon).

User $\boldsymbol{u}$ will use the updated comfort threshold in the next iteration of the load scheduling game. Note that the updating mechanism defined in Eq. 7 is purely imitative and does not assume any critical attitude of the users towards the type of social messages provided by their neighbors, i.e. user $\boldsymbol{u}$ will be equally likely to imitate each of their neighbors $\boldsymbol{u'}$, regardless to the value of their comfort threshold $\boldsymbol{C_u}$. However in real scenarios, users could show higher propulsion towards the imitation of hedonistic (or non-hedonistic) behaviors.

Therefore, in the next scenario we refine our social interaction mechanism to model the users as rational decision makers.

ii. Scenario II

Similarly to the approach proposed previously, in order to capture the users' capability to make rational decisions about whom to imitate (and to which extent), we consider the same attitude space adopted in Figure 1, where all users locate themselves and their neighbors based on their current comfort threshold $\boldsymbol{c^l}_{\boldsymbol{u}}$ and daily energy bill $\boldsymbol{P_u}$. Based on their position, user $\boldsymbol{u}$ defines an area of interest $\boldsymbol{A^l}_{\boldsymbol{u}}$ (the shaded area in Figure 1) representing acceptable bill-comfort pairs. The criteria for definition of such depend on the personal attitude of the user (e.g., users with a strong hedonistic attitude would be willing to imitate users which a higher comfort threshold than theirs, though their bill is –even significantly- higher that their own, whereas they would never imitate users with lower comfort threshold, even if their daily expenses is lower that their own) and may be revised and executed at each game execution $\boldsymbol{l}$.

5. Implementation

The most peculiar property of potential game theories is that they have at least one pure Nash equilibrium, namely the strategy that minimizes $\boldsymbol{P(I)}$. Furthermore, in such games, best response dynamics always converge to a Nash equilibrium although it might not coincide with the optimal equilibrium of the issue. It is a sort of a local maximum which guarantees the solution for all the users in the neighborhood.

Hereafter, we describe a simple implementation of best response dynamics, which allows each user $\boldsymbol{u}$ (namely each appliance $\boldsymbol{a}$) to improve its cost function in the proposed power scheduling game. Such algorithm is the best response strategy for a player $\boldsymbol{u}$ minimizing objective function Eq. 6, assuming other appliances are not changing their strategies. Specifically, each appliance, in an iterative fashion, defines its optimal power scheduling strategy based on electricity tariffs (calculated according to other players' strategies) and broadcasts its energy plan (i.e., its daily power demand profile) to the group. At every iteration, energy prices are updated according to the last strategy profile and, as a consequence, other appliances can decide to modify their consumption scheduling by changing their strategy according to the new tariffs. The iterative process is repeated until convergence is reached. Once converged, the appliances power scheduling and the energy prices are fixed as well as the energy bill charged to each user $\boldsymbol{u}$, which is simply the sum of all his appliances prices

The best response mechanism is executed by solving, in an iterative way, an optimization model. Specifically, at every iteration and based on the energy demands of other appliances, this model is used to optimally decide the power plan of the appliance in charge of defining its energy demand at this step of the iterative process, with the goal of minimizing the electricity bill. We will show in the Numerical Results section that our proposed algorithm converges, in few iterations, to a Nash equilibrium.

Note that the best response dynamics here proposed is only used to identify and study the efficiency of the Nash Equilibrium of the game. While the transmission of the power profile to other users may raise security and privacy concerns, we observe that each appliance needs only the aggregated power profile of other appliances for the real implementation of the DSM algorithm. Therefore, we can envisage a system in which appliances communicate only with the operator that broadcasts the aggregated information after collecting all appliances' schedules.

Chapter 4.

NUMERICAL RESULTS

In our model we used the software Matlab, in order to create the algorithm and all the functions necessary to build the program. We implemented many and different solutions trying to figure out what would be the most convenient to our case study. The results are obtained after many simulation and the numerical data used are described in the section below.

1. Numerical Assessment

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

We consider a scenario with $\boldsymbol{U} = \mathbf{50}$ users. The set $\boldsymbol{R}[\boldsymbol{u}]$ of each user's neighbors is computed based on the topology of a random scale-free network graph generated according to the Barabasi-Albert model with mean degree $\boldsymbol{d}$, which is a popular generative model for based social networks and online communities (Albert, 1999). If not differently stated, we assume $\boldsymbol{d} = \mathbf{6}$.

Each user $\boldsymbol{u}$ has a contractual limit, $\boldsymbol{\pi}$, of $\mathbf{3kW}$ and owns 4 shiftable appliances (i.e., $\boldsymbol{A^S}_{\boldsymbol{u}}$ = { washing machine, dishwasher, boiler a recharge of robotic vacuum cleaner}) and other 7 fixed ones (i.e., $\boldsymbol{A^F}_{\boldsymbol{u}}$ = {refrigerator, purifier, lights, microwave, 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 (D. m. Han, 2010)). The energy consumption patterns of each appliance have been extracted from a real dataset (MICENE, 2015). On average, the energy consumption due to deferrable appliances accounts for 55% of the total daily consumption. For each appliance, the comfort curve $\boldsymbol{c^t}_{\boldsymbol{au}}$ 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 $\boldsymbol{t}$ such that $\boldsymbol{c^{t}_{au}} = \mathbf{1}$ (see figure 3), and that users' satisfaction decreases linearly with delay).

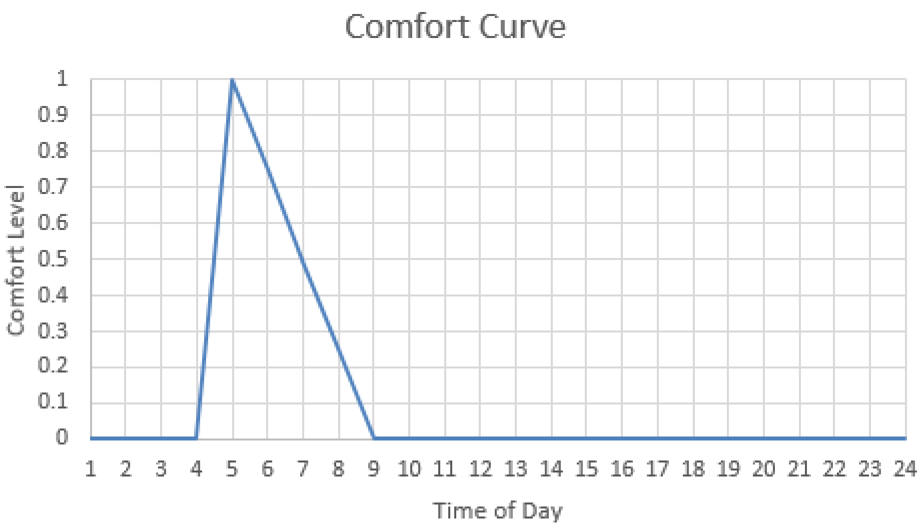


Figure 4: Comfort curve of an appliance

The initial values of the appliance delay tolerance thresholds $\boldsymbol{y^{l}_{au}}$ are randomly chosen with uniform distribution in the range [0, 0.75]. If not differently stated, we assume that $\boldsymbol{p^{l}_{u}} = \mathbf{0.85}$. In order to evaluate the performance of the proposed interaction mechanism we consider three scenarios. The first one assumes that the area of interest $\boldsymbol{A^{l}_{u}}$ of user $\boldsymbol{t}$ is defined as:

$$\boldsymbol{A^l}_{\boldsymbol{u}} = \{(\boldsymbol{y^l}_{\boldsymbol{au'}}, \boldsymbol{B^l}_{\boldsymbol{au'}}): \boldsymbol{B^l}_{\boldsymbol{au'}} < \boldsymbol{B^l}_{\boldsymbol{au}}\}$$

(i.e., users imitate neighbors whose daily bill is lower than theirs); in the second one we define $\boldsymbol{A^l}_{\boldsymbol{u}}$ as:

$$\boldsymbol{A^l}_{\boldsymbol{u}} = \{(\boldsymbol{y^l}_{\boldsymbol{au'}}, \boldsymbol{B^l}_{\boldsymbol{au'}}): \boldsymbol{y^l}_{\boldsymbol{au'}} < \boldsymbol{y^l}_{\boldsymbol{au}}\}$$

(i.e., users imitate neighbors who impose lower delay tolerance thresholds than theirs), whereas in the third one we set $\boldsymbol{A^l}_{\boldsymbol{u}}$ as:

$$\boldsymbol{A^l}_{\boldsymbol{u}} = \left\{(\boldsymbol{y^l}_{\boldsymbol{au'}}, \boldsymbol{B^l}_{\boldsymbol{au'}}): \boldsymbol{y^l}_{\boldsymbol{au'}} < \boldsymbol{y^l}_{\boldsymbol{au}} \wedge \boldsymbol{B^l}_{\boldsymbol{au'}} < \boldsymbol{B^l}_{\boldsymbol{au}}\right\}$$

(i.e., users imitate neighbors who have both lower daily bill and delay tolerance thresholds).

The daily results obtained in the three scenarios are compared to the ones obtained during the first day (i.e. for $\boldsymbol{l} = \boldsymbol{1}$), when no social interactions among the users have occurred. For the assessment, the following metrics are measured: *inductive bill,* i.e. the electricity bill for each user $\boldsymbol{u} \in \boldsymbol{U}$, and *peak demand,* i.e. the peak of the aggregated energy demand of the group of users $\boldsymbol{U}$ define as max $\boldsymbol{y_t}$. This allows us to assess the peak power consumption before the optimization theory and after like in Figure 4.

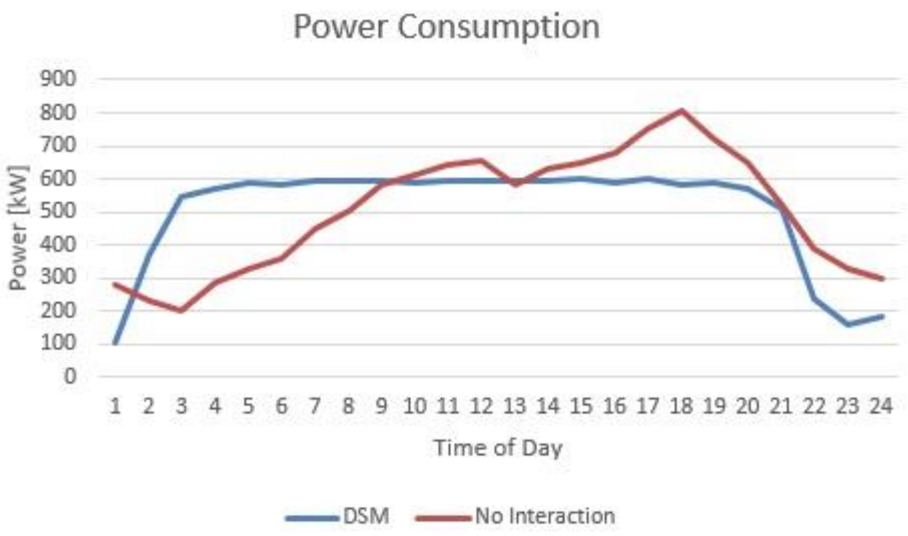


Figure 5: Power consumption

2. Numerical Results

Average results obtained over 50 instances of each scenario are reported in Figure 5 and 6, which show that in all scenarios the imitation of virtuous behaviors lead to non-negligible decreases of the individual daily bills and of the aggregate peak energy consumption. Bill reductions are more consistent in scenario 2, i.e. when users imitate neighbors with lower delay tolerance thresholds regardless to their bill (0.5% reduction versus 0.3% in scenario 1 and 0.4% in scenario 3). 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. In terms of aggregate peak reduction, simulation results make it possible to conclude that Scenario 1 leads to the least peak power reduction, which settles at about 0.9% less than the peak power obtained with no social interaction. Better performance is obtained in the other two scenarios, which provide similar peak power reductions.

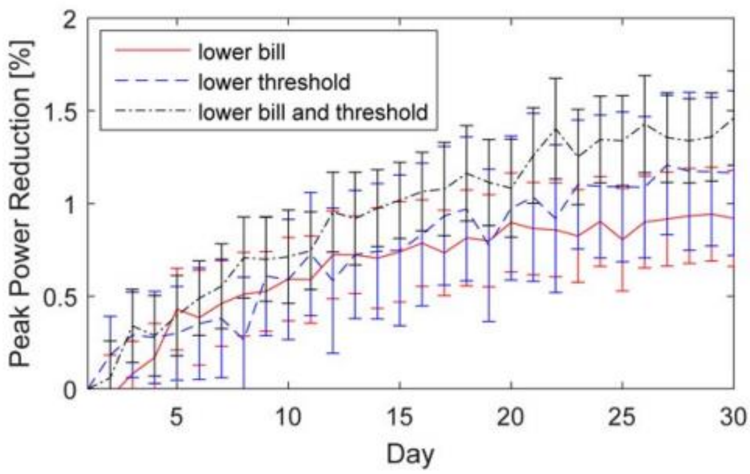


Figure 6: Percentual reduction of peak energy consumption

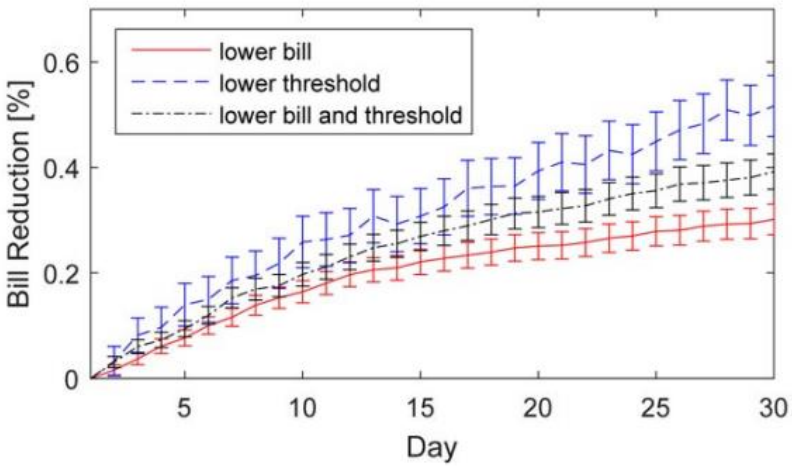
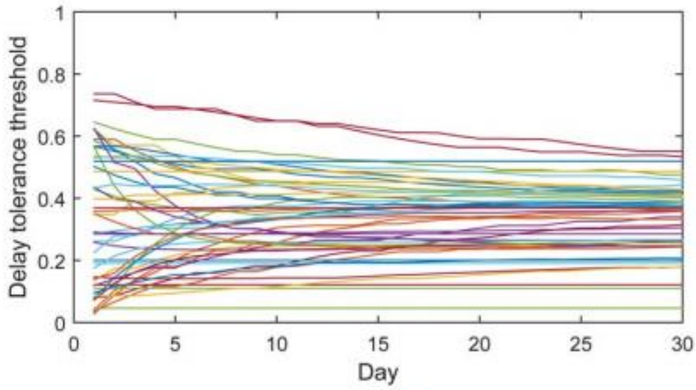
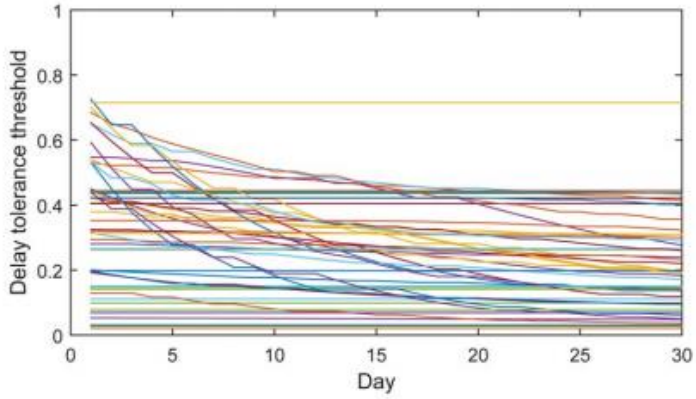


Figure 7: Percentual bill reduction

Figure 7 shows the evolution of the delay tolerance threshold $\boldsymbol{y}^{i}_{au}$ for usage of the washing machine for the whole population of users in a representative instance of the two scenarios.



(a) Scenario 1



(b) Scenario 2

Figure 8: Trend of the washing machine delay tolerance over time depending on the definition of the users' area of interest

As depicted in Figure 7a, in the first scenario the imitation of the neighbors with lower bills leads to a homogenization of the thresholds. Moreover, the average value of $\boldsymbol{y}^{i}_{\boldsymbol{au}}$ tends to decrease, due to the fact that people experiencing lower bills are more likely to have chosen low 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 neighbors ever experiences lower bill than theirs. Conversely, in scenario 2 the benefit of imitating neighbors with lower delay tolerance threshold clearly emerges: in this case, $\boldsymbol{y}'_{au}$ 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 their neighbors. Results obtained in scenario 3 show trends analogous to Scenario 2 and are thus not reported for the sake of conciseness.

We now further refine our assessment focusing on scenario 1 (i.e. the imitation of users experiencing lower bills). Figure 8 reports bill and peak power savings depending on the level of participations of the users to the social interactions. Intuitively, the more the users are willing to interact and revise their strategies based on the comparison of their bill to those of their neighbors, the higher are the obtained savings. Figure 8 shows that increasing the level of user activity from 50% to 100% doubles both the bill reduction and the peak power reduction achievable in one month

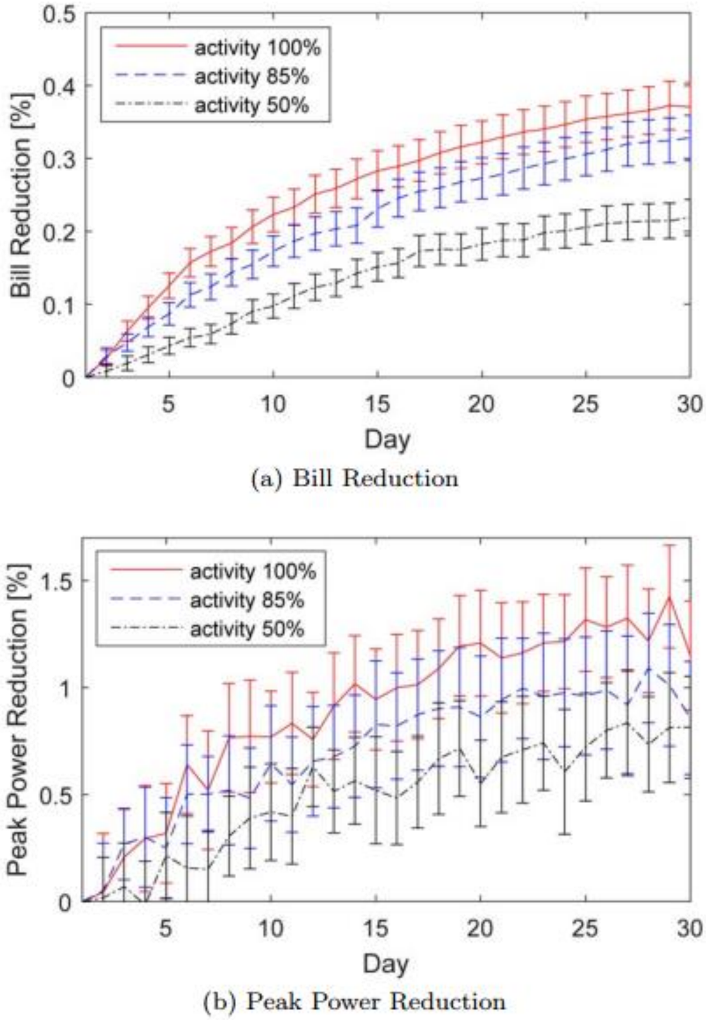


Figure 9: Percentual reduction of daily bill and peak energy consumption for different values of the parameter $p^l{}_u$. *95% confidence intervals are plotted.*

Moreover, we evaluate the impact of the mean degree of connectivity ***d*** of the social network. Figure 9 shows that increasing ***d*** from 3 (which corresponds to a user interacting with around 4% of the other users) to 6 (i.e. each user interacts on average with 10% of the other users) almost triplicates the bill reduction and doubles the peak power reduction. Further increasing ***d*** did not lead to noticeable additional savings.

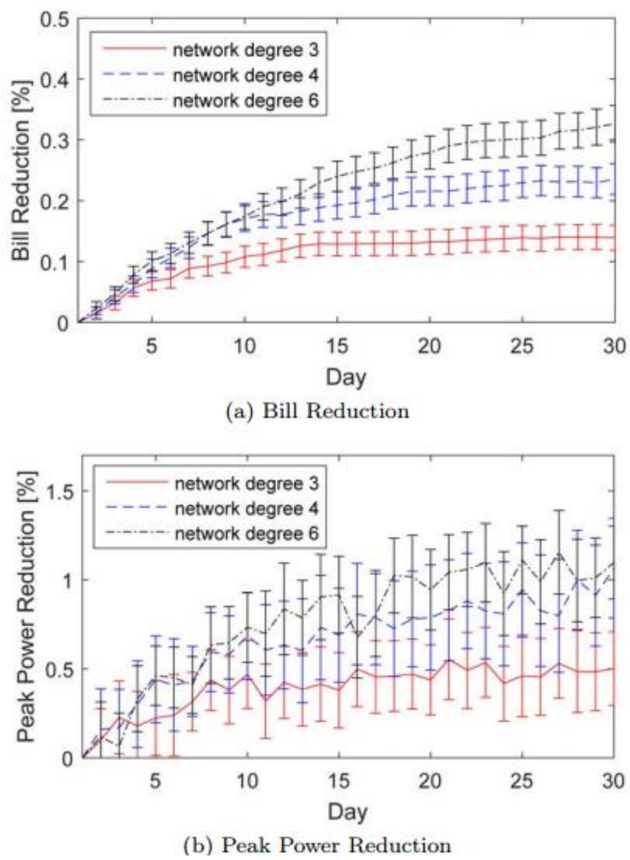
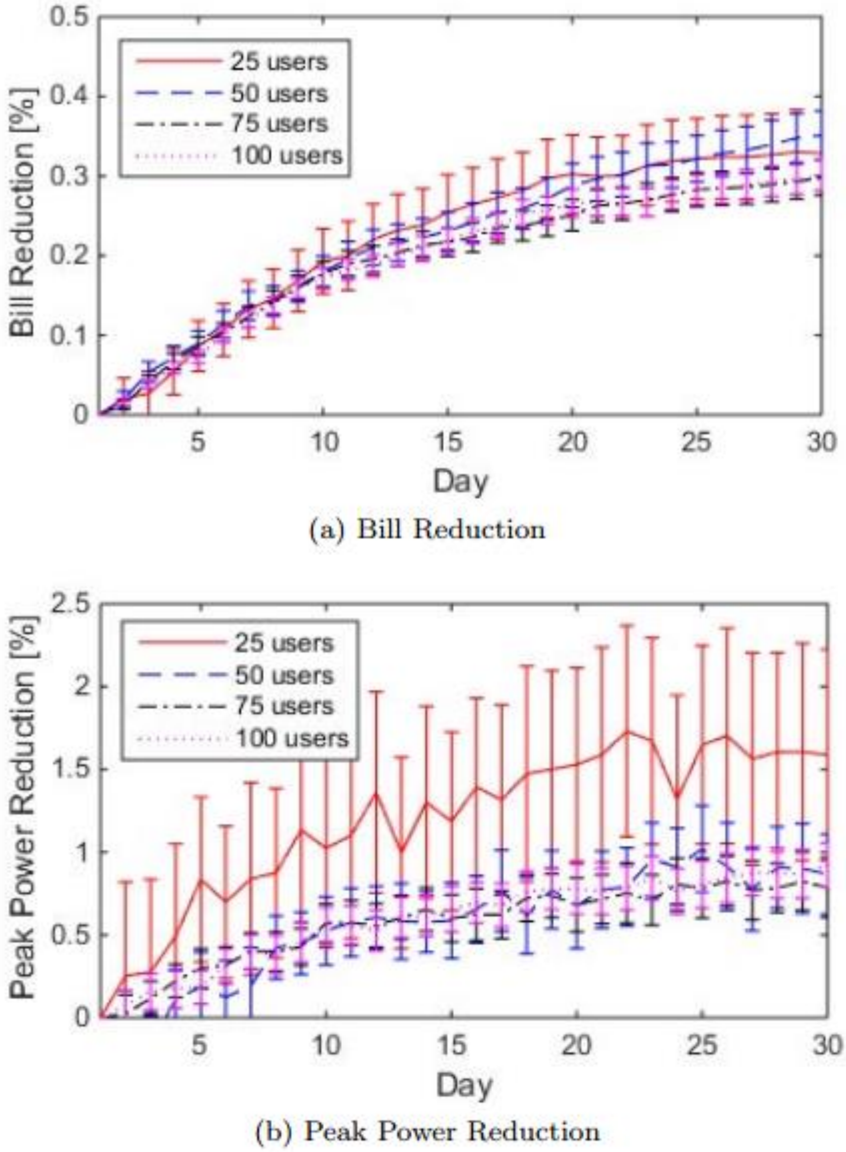


Figure 10: Percentual reduction of daily bill and peak energy consumption depending on the average connectivity degree of the social network. 95% confidence intervals are plotted.

Nevertheless, we investigate the impact of the total number of users participating to the DSM protocol. Interestingly, as shown in Figure 10, increasing the cardinality of the set of users does not lead to significant variations in the average bill reduction, whereas the peak power reduction is highest for very small groups (e.g. 25 users). In fact, when users are fewer, the impact of each user on the peak power is larger and it is sufficient that a single user lowers their delay tolerance threshold to have a beneficial effect on the peak power. As the number of users grows, it is necessary that many users improve their tolerance for having a significant effect.



(a) Bill Reduction

(b) Peak Power Reduction

Figure 11: Percentual reduction of daily bill and peak energy consumption depending on the total number of users. 95% confidence intervals are plotted.

Chapter 5.

STUDY OF CONVERGENCE

Until now, the majority of the studies conducted on probability has dealt with independent trials processes. These processes are the basis of classical probability theory and much of statistics. We have discussed the main theorem in which we will realize our model: the game theory. We have seen that when a sequence of chance experiments forms an independent trials process, the possible outcomes for each experiment are the same and occur with the same probability. Furthermore, knowledge of the outcomes of the previous experiments does not influence our predictions for the outcomes of the next experiment. The distribution of the outcomes of a single experiment is sufficient to construct a tree and a tree measure for a sequence of n experiments, and enabling us to answer any probability question about these experiments by using this tree measure. Modern probability theory studies chance processes for which the knowledge of previous outcomes influences predictions for future experiments. In principle, when we observe a sequence of chance experiments, all of the past outcomes could influence our predictions for the next experiment. For example, this should be the case in predicting the next possible state of a user $\boldsymbol{u}$ to arrive to another state or remain in the same position. But to allow this much generality would make it very difficult to prove general results. In 1907, A. A. Markov began the study of an important new type of chance process. In this process, the outcome of a given experiment can affect the outcome of the next experiment. It concerns about a sequence of random variables, which correspond to the states of a certain system, in such a way that the state at one time epoch depends only on the one in the previous time epoch. This type of process is called the Markov chain. We, in our study, will use the discrete Markov chain process, in order to study the convergence of our model.

1. Modelling the System Evolution with Markov Chains Model

The agent-based model described above can be analyzed with the help of a discrete-time Markov Chain. In order to do so, we need to make the following assumptions:

- The user delay tolerance threshold can only take values that are integer multiples of a fixed step $\Delta\gamma$. The total number of possible tolerance threshold levels is:

$$\mathbf{1} + \frac{1}{\Delta\gamma}$$

- The agent state is represented by its tolerance thresholds at any given time for each appliance.
- Each day is divided in iterations. At each iteration $\boldsymbol{i}$, a single agent interacts with another user and modifies its delay tolerance threshold. This is slightly different than the model in the section of the interaction scenario, which considers that the effects of multiple interactions are applied at the same time. This assumption will make the Markov matrix more sparse and, thus, more manageable.

On the other hand, the system will evolve more slowly.

Without loss of generality, we consider that each user has a single appliance. Since the thresholds for the various appliances evolve independently, the full state of each user can be described by a set of identical Markov Chains evolving independently

The full state at iteration $\boldsymbol{i}$ for appliance $\boldsymbol{a}$ is thus given by the tuple: ($\gamma^{t}{}_{\boldsymbol{a1}}, \gamma^{t}{}_{\boldsymbol{a2}}, \gamma^{t}{}_{\boldsymbol{a3}}, \ldots, \gamma^{t}{}_{\boldsymbol{aU}}$). Thus, the total number of states is $|\,\gamma\,|^{\mathbf{1+1}/\Delta\gamma}$, which grows exponentially fast as $\Delta\gamma$ become small. Therefore the model can be used only with a small number of levels.

At each time slot, an agent $\boldsymbol{u}$ uniformly at random interacts with another user $\boldsymbol{u'}$ uniformly at random and changes its delay threshold to:

$$\gamma^{\boldsymbol{t+1}}{}_{\boldsymbol{au}} = \gamma^{\boldsymbol{t}}{}_{\boldsymbol{au}} + \left\lfloor \frac{\boldsymbol{\delta}_{\boldsymbol{u,u'}}}{\Delta\gamma} \right\rfloor \Delta\gamma \; with\, probability \; \frac{\boldsymbol{\delta}_{\boldsymbol{u,u'}}}{\Delta\gamma} - \left\lfloor \frac{\boldsymbol{\delta}_{\boldsymbol{u,u'}}}{\Delta\gamma} \right\rfloor$$

Or

$$\gamma^{\boldsymbol{t+1}}{}_{\boldsymbol{au}} = \gamma^{\boldsymbol{t}}{}_{\boldsymbol{au}} + \left\lfloor \frac{\boldsymbol{\delta}_{\boldsymbol{u,u'}}}{\Delta\gamma} \right\rfloor \Delta\gamma \; with\, probability \left\lceil \frac{\boldsymbol{\delta}_{\boldsymbol{u,u'}}}{\Delta\gamma} \right\rceil - \frac{\boldsymbol{\delta}_{\boldsymbol{u,u'}}}{\Delta\gamma}$$

with

$$\boldsymbol{\delta}_{\boldsymbol{u,u'}} = \boldsymbol{h}_{\boldsymbol{a}}(\boldsymbol{u}, \boldsymbol{u'})(\gamma^{\boldsymbol{i}}{}_{\boldsymbol{au'}} - \gamma^{\boldsymbol{i}}{}_{\boldsymbol{au}})$$

It follows that the transition probability is as follows:

$$\Pr\left[(\ldots,\gamma_{au}^{\tau}+k\Delta\gamma,\ldots,\gamma_{au'}^{\tau+1},\ldots)|\right.$$
$$\left.(\ldots,\gamma_{au}^{\tau},\ldots,\gamma_{au'}^{\tau},\ldots)\right]=\frac{1}{|\mathcal{U}|(|\mathcal{U}|-1)}\times$$
$$\left[\left\|\left\{u':k=\frac{\delta_{u,u'}}{\Delta\gamma}\right\}\right\|+\sum_{u':\,k=\left\lfloor\frac{\delta_{u,u'}}{\Delta\gamma}\right\rfloor}\frac{\delta_{u,u'}}{\Delta\gamma}-\lfloor\frac{\delta}{\Delta\gamma}\rfloor+\right.$$
$$\left.\sum_{u':\,k=\left\lceil\frac{\delta_{u,u'}}{\Delta\gamma}\right\rceil}\left\lceil\frac{\delta_{u,u'}}{\Delta\gamma}\right\rceil-\frac{\delta_{u,u'}}{\Delta\gamma}\right]\quad(8)$$

For all integer $\boldsymbol{k}$ such that $\mathbf{0}\leq\boldsymbol{\gamma^{t}}_{\boldsymbol{au}}+\boldsymbol{k}\,\Delta\gamma\leq\mathbf{1}$, while it is equal to zero in all other cases.

We used Equation (8) to model an homogenous system with $\boldsymbol{h_a}(\boldsymbol{u},\boldsymbol{u'})=\mathbf{0.5}$ for all users $\boldsymbol{u},\boldsymbol{u'}$ and study the number of time slots to reach state. Figure 10 shows the average number of interactions after which the state probabilities change over time by less than 1%.

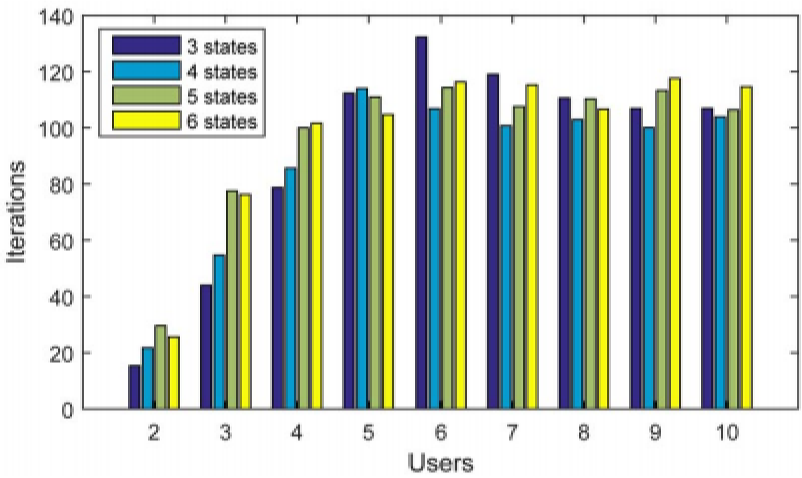


Figure 12: Number of iterations to a steady state, depending on the number of users and states per users.

The results are averaged over 100 Monte Carlo simulations with random initial conditions. Figure 11 shows that the number of discrete threshold levels has a limited impact on the convergence time, making it possible to study this important parameter with large discretization steps, resulting in smaller, more manageable chains. Additionally, we note that, for a very small number of users, the interactions to reach steady state grow as the number of users grows. Instead, for more than 5 users, the number of social interactions to reach equilibrium does not depend on the size of the social community. Consequently we can state that, for a large network, the number of users has a limited impact on the convergence time, whereas the important parameter is the frequency at which users interact. Frequent interactions with a large set of neighbors result in faster convergence.

2. Numerical Assessment of Markov Chain Model

In order to project the numerical assessment of our Markov chain model, we assigned the following set of variables the following parameters:

- We considered having a set of user, each having shiftable appliances.
- Each shiftable appliance is associated with a comfort level.
- Each user is associated with a comfort threshold level.

To be clearer a simple example is listed.

Let us consider a small neighborhood having only 2 users $\boldsymbol{u}$, where all users have only one shiftable appliance $\boldsymbol{a}$. The quantization step $\boldsymbol{f}$ is set to 4 steps, meaning that the approximation of the values will be based from [0, 1/3, 1/6, 1]. As shown in the example, this choice of numbers will very much impact the size of the matrix as well as the number of iterations in order to reach convergence. Note that the choice of number is taken for the sake of simplicity and clearness.

First, the Markov chain model implies building the state matrix. The quantization step will define the number of rows $\boldsymbol{r}$ of our matrix and the sum of the number of shiftable appliances of each user will set the number of columns.

We can define it as follow:

$$\boldsymbol{r} = \boldsymbol{f}^\wedge(\boldsymbol{u} * \boldsymbol{a})$$

We can notice that the size of the matrix grows exponentially with the size of its consistent elements. In our examples we will have a 16x2 matrix as which will allow to enumerate all the possible states of our problem.

After building the state matrix, we can start building the transition matrix which contains all the probabilities of moving from a current state to either changing or remaining in the current one. Moreover, we need to define the size of the matrix $\boldsymbol{c}$, which is described as the number of rows of the state matrix for the row and column. The size is as follows:

$$\boldsymbol{c} = \boldsymbol{r}$$

As expected, the size will be very huge and we might face some computational problems calculating neighborhood with large number of users or big number of shiftable appliances. Usually, the transition matrix is a sparse matrix, and the sum of probabilities of every transition of each state should be equal to **1.**

$$\sum_{i=1}^{c} \boldsymbol{p_i} = \mathbf{1}$$

In order to obtain the elements of the transition matrix, we need to assume some approximation. The probabilities of the states are calculated based on their distance from the corresponding step value as following:

$$\boldsymbol{p_1} = \left(\frac{\boldsymbol{d_1}}{\mathbf{D}}\right) * (\mathbf{u})^{-\mathbf{1}} * [(\mathbf{u} - \mathbf{1}) * \boldsymbol{a}]^{-\mathbf{1}}$$

$$\boldsymbol{p_2} = \left(\frac{\mathbf{D} - \boldsymbol{d_1}}{\mathbf{D}}\right) * (\mathbf{u})^{-\mathbf{1}} * [(\mathbf{u} - \mathbf{1}) * \boldsymbol{a}]^{-\mathbf{1}}$$

where

$\boldsymbol{d_1}$ is the position of the value that we want to approximate

D is the entire distance of the step

The choice of each probability is dependent on the approximation to the floor or ceiling of each value and element of the transition matrix. This procedure is made in order to increase the number of elements of the matrix since for each non integer element we would be able to calculate two elements in which the probability of the closest one is for $\frac{d_1}{\mathbf{D}}$ and the other is for $\frac{D-d_1}{\mathbf{D}}$. In this way the sparse matrix would have some more elements, which will be used for the study of the convergence.

Considering again our example, having two users each having one shiftable appliance, and after building the state matrix, the $\boldsymbol{transition}$ matrix will be as follows:

$$\begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 5/8 & 0 & 0 & 0 & 3/8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 4/8 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 1/8 & 0 & 0 & 0 & 3/8 & 0 & 0 & 0 & 0 \\
1/8 & 0 & 0 & 0 & 7/8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 5/8 & 0 & 0 & 0 & 3/8 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1/8 & 0 & 0 & 0 & 7/8 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5/8 & 0 & 0 & 0 & 3/8 \\
0 & 0 & 0 & 0 & 1/8 & 0 & 0 & 0 & 3/8 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 4/8 & 0 & 0 & 0 & 4/8 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1/8 & 0 & 0 & 0 & 7/8 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}$$

The transition matrix will be the key element in studying the convergence of our system. We will need the indexing vector $\boldsymbol{v}$ which has the same number of rows of both matrices.

The indexing vector is initialized as uniform distribution among all of its rows, this is only one case of choosing the vector, since any random vector would lead to convergence, but for the sake of simplicity and ensuring a more random environment, we chose a uniformly distributed vector, which is as follows

$$\begin{bmatrix} 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \\ 1/16 \end{bmatrix}$$

Furthermore, the average number of interactions after which the state probabilities change over time by less than 1%, at that point we can note convergence of our system and the number of iterations is registered. The error vector is calculated by the multiplication of the transition matrix by the indexing vector.

$$\boldsymbol{v'} = \boldsymbol{v} * \boldsymbol{transition}$$

Finally, we considered that each user has a set of 4 shiftable appliances, where users can interact with all others having the same set of shiftable appliances. In the first study conducted, we tried to highlight the difference between having the interaction based on the neighboring preferences or based on the comfort level of a neighboring user having a higher threshold of comfort. The convergence in Figure 13 shows the difference between having more preference in order to convergence since the transition matrix will be sparser, pointing more and bigger number of iteration to reach convergence.

Chapter 6.

CONCLUSIONS

Nowadays, electric utilities still have many reasons to be skeptical about the projections of DSM results. Since 1970s, they have tried to capture load shifting and load reduction benefits, with mixed results. These efforts, however, were limited in scope and relied on costly, proprietary technology solution. The good news is that there has been significant progress in areas vital to the success of DSM.

Electric Utilities are using federal stimulus funding opportunities to deploy statistically significant pilots to measure the impact of various DSM program designs. Also electric regulators are considering reforms that credit utilities for DSM reductions. Still much work at all levels remains to be done if the economic and social promise of DSM is to be fully realized in the next decade.

In this study, we assumed and proposed a very good aspect of DSM which aims at reducing the peak demand of a group of residential users. We have modeled our system into a game theoretical approach, where players are the customer's appliances, which decide autonomously when to execute. Also we were able to demonstrate that having the proposed parameters of our game theory, and it is a generalized ordinal potential one, and we proposed a best response dynamics mechanism which is guaranteed to converge in few steps to efficient Nash equilibrium solutions, which is the local maximum. Furthermore, we showed that our approach performs extremely close to a more complex setting where each customer must optimize the schedule of all their appliances, since it provides practically the same results in terms of minimizing their daily electricity bill. For this reason, due to its intrinsic simplicity, robustness and distributed architecture, we recommend the adoption of our proposed approach. The latter were able to show the benefits that social interaction can have on the 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 work show that the knowledge of the electricity bill or delay tolerance of similar users yields a peak power reduction in the long term. We also show that a limited number of interactions with a relatively small set of neighbors is sufficient to achieve a steady state condition.

Finally, the numerical results obtained using realistic load profiles and appliance models demonstrate that the proposed DSM system having interaction mechanisms helps at modeling the influence of the society on individual delay tolerance preferences which affects the aggregated energy consumption by the execution of the load scheduling game. It also, represents a promising and very effective solution to reduce the peak absorption of the entire system and the electricity bill of individual customers in applying social interaction mechanisms.

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