Demand-Response: let the devices take our decisions

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Abstract: The hierarchical, centrally controlled energy grid is ill-suited to the third digital revolution. The electric power industry is undergoing rapid change. The energy transition move from the current energy system using non-renewable resources to a smart grid, including distributed resources and home automation. Now, the demand is flexible and can be managed, it is called Demand-Side-Management (DSM). It encompasses different domains of reducing consumption, it can be both a physical standpoint than digital. In this paper, after a quick state of an art on DSM, we will focus on the digital way. The main idea is to create consumption's schemes, thanks to home automation in order to find the best way to consume.

1 Introduction

The creation of the Smart Grid has been posed as one of the greatest challenges of this century, as countries face dwindling non-renewable energy sources and the adverse effects of climate change due to carbon emissions [1].

The vision of a Smart Grid includes technologies that enable the efficient integration of new sources of energy. It will smooth demand by allowing consumers to better manage how electricity is used, stored, and delivered. However, the balance between demand and production is not an easy task. Both supply and demand levels can change rapidly due to outages, sudden load change or volatile renewable energy sources.

The term Demand-Side Management, introduced in 80s by the Electric Power Research Institute, refers to all strategies that can reduce the consumption and peak demand (e.g., in (Ruiz et al., 2009; Centolella, 2010)). The trend started in the 70s, and became rapidly a government project.

The DSM encompasses all means possible in reducing energy in a house or a building: a top wall insulation prevents heat dissipation, so a thermal energy loss; light sensors avoid waste lighting; smart devices reduce power consumption; photo-voltaic panels on the roof produce electricity for a home.

One of recent industrial developments concern the concept of the smart meter which aims to manage the devices in the home to minimise inefficiencies in usage and maximise the user's savings. Smart meters also aim to interact with the grid in order to help reduce peaks in demand and keep up with variable energy generators or batteries [2]. This approach has been shown to be effective for small pool sizes of industrial and commercial consumers (Hammerstrom et al., 2007).

While such DSM techniques have been shown to bring about significant improvements on a small number of houses, it is unclear how such technologies will scale when smart meters with millions of homes or buildings nationwide. In particular, the centralized management of even thousands of smart meters is likely to be a complex task that may require intruding upon user's privacy to cater for all homes.

The fact that increasingly more and more features of the home are likely to be electrified in the future (Galvin and Power, 2009), means that more significant peaks may be created due to the reactive behavior of the smart devices. Nonetheless, without some form of coordination, the population of smart grid entities may end up with overly-homogeneous optimized consumption patterns that may generate significant peaks in demand in the grid.

In a collaborative system such as the smart grid, fairness and stability is important when taking a decision. If, for example, a number of devices can shed

[1] US DOE, Grid 2030: A national vision for electricity's second 100 years, 2003

[2] DECC Smarter Grids report, The Opportunity,December 2009

their load, and already one of them shedding is sufficient, it might always be the quickest that wins the monetary incentive. With communication, it can be arranged that all of them have their turn. Without communication, all of them react to grid problems in the same manner (Palensky and Dietrich, 2011). It is the perfect recipe for instabilities.

There is a need to deploy innovative models and algorithms that capture the following characteristics of the emerging smart grid: communication in a heterogeneous system, distributed operation, low-complexity distributed algorithms (Saad et al., 2012).

This paper provides a classification of DSM programs and a categorization of devices for home automation management. It also exposes a description of a model that would optimize the Demand-Response, a DSM programs which focuses on a digital aspect. This model is generic and is applicable to any network.

First of all, in section 2, we introduce the notion of Demand-Side Management, a classification about the intrinsic concepts. Then we expose a solution in section 3 about the management of smart devices through Demand-Response strategies. The section 4 describes how to build consumption's schemes, thanks to home automation and generic modeling. The section 5 shows a game theoretic approach to avoid peak demand and optimize each consumer's comfort.

2 Demand Side Management

DSM is a fuzzy concept which has various definitions. DSM programs usually refer to one or both of the following design objectives: reducing consumption and shifting consumption. DSM can be as well an energy reduction by using insulating materials for the home, or using devices controlled numerically.

2.1 Introduction to DSM

In (Saad et al., 2012), a survey about DSM programs, the authors define DSM as programs that attempt to make the users more energy-efficient on a longer time-scale. They also define the term Demand-Response as programs that utility companies use to encourage the grid users to dynamically change their electricity load so as to have a short-term reduction in energy consumption.

In other words, the goal of the DSM is to encourage the consumer to use less energy during peak hours, or to move the time of energy use to off-peak times such as nighttime. Peak demand management does not necessarily decrease total energy consumption, but could be expected to reduce the need for investments in networks and/or power plants for meeting peak demands.

First DSM programs are based on energy efficiency measures. They include all permanent changes on equipment or improvements in the physical properties of the system (Boshell and Veloza, 2008).

Numeric DSM programs are based on two schemes: direct load control and smart pricing. They focused on the interactions between producers and each individual end-user. Direct control enables to control the appliances inside a building, smart pricing provides monetary incentives for the users.

The definition varies, but in all cases, the benefits of DSM programs are for all actors. An overall electricity price reduction is expected because of a more efficient using of the infrastructure. The smart grid favors using local renewable energies or batteries than to activate coal plants. Moreover, DSM programs can increase short-term capacity using market-based programs, which in turn, results in an avoided or deferred capacity costs.

The generation cost increases exponentially near maximum generation capacity. A small reduction in demand will result in a big reduction in generation cost and, in turn, a reduction in electricity price, that affect all market participants. All of the avoided or deferred costs will be reflected in the price of electricity for all electricity consumers.

By having a well-designed DSM program, users also have the opportunity to help in reducing the risk of outages. Simultaneously and as a consequence, they reduce their own risk of being exposed to forced outages and electricity interruption. On the other hand, the operator will have more options and resources to maintain system reliability, thus reducing forced outages and their consequences (Goel et al., 2006).

Rather, a bad DSM program creates a rebound effect (or payback), is typically not saved and maybe even a new peak is generated. In this figure, EE means Energy Efficiency and DR means Demand-Response. We will define those two terms in the following subsection.

2.2 Classification

This section is dedicated to classifying some programs by a set containing similar programs. The Figure 1 shows the classification.

We usually use devices or appliances at work and at home. Thus, social behaviors have a big impact on consumption. The Change Management (CM) is a

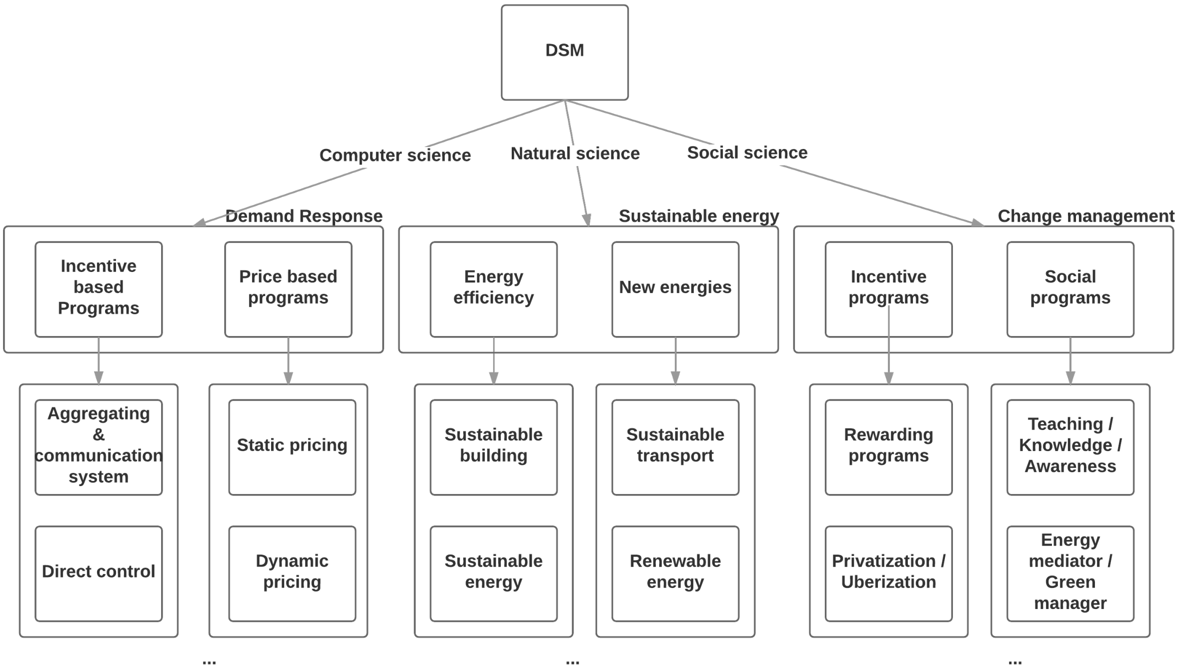

Figure 1: Classification of DSM types.

set of incentive programs and social programs in order to create responsible behaviors, like sorting the wastes in the late 90s. People need some information, knowledge and teaching about home automation, sustainable energy, energy management's dashboard or any other current of future technologies which will interact in the smart grid. By the way, CM has to give awareness about the two other edges of DSM: Sustainable Energy (SE) and Demand-Response (DR).

The SE includes all permanent changes in equipment or improvements in the physical properties of the system (Boshell and Veloza, 2008). By definition, Energy Efficiency (EE) is the goal to reduce the amount of energy required to provide products and services. Using less power to perform the same tasks.

In simple words, SE involves a permanent reduction of demand by using more efficient load-intensive appliances such as water heaters, refrigerators, or washing machines. For example, insulating a home allows a building to use less heating and cooling energy to achieve and maintain a comfortable temperature. Installing fluorescent lights, LED lights or natural skylights reduces the amount of energy required to attain the same level of illumination compared with using traditional incandescent light bulbs.

Improvements in the SE are generally achieved by adopting a more efficient technology or production process or by application of commonly accepted methods to reduce energy losses.

The last but not least edge of DSM is the DR, it allows to know how electricity consumers can be responsive. DR programs follows, including classical incentive programs, new market-based and dynamic pricing scenarios, besides potential cost savings and benefits related to different market components, it performs digital control of consumption.

2.3 About Demand-Response

According to the Federal Energy Regulatory Commission, DR is defined as:

> The changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.

To resume, DR includes all intentional modifications to consumption patterns of electricity to induce customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption (Albadi and El-Saadany, 2007).

We notice two categories of devices that you can apply DSM: those that includes DR programs and those that don't. Examples of the latter include lighting, entertainment devices, phone charging and computer usage. Those devices interact with the grid through automatic process thanks to sensors or integrated circuit. This kind of process cannot be qualified as "smart", i.e. not flexible and not adaptive.

DR programs can be classified into two main categories: Incentive-Based Programs (IBP) and Price-Based Programs (PBP) (Albadi and El-Saadany, 2008; Cappers et al., 2010).

In IBP, participating customers receive participation payments, usually as a bill credit or discount rate. Those following programs are part of IBP: direct load control, curtaible rates, emergency demand response, capacity market program, demand bidding program (Ramchurn et al., 2011).

PBP programs are based on dynamic pricing rates in which electricity tariffs are not flat; the rates fluctuate following the real time cost of electricity. These rates include the Time of Use (TOU) rate, Critical Peak Pricing (CPP), Extreme Day Pricing and Real Time Pricing (RTP) (Rahman et al., 1993; Ramchurn et al., 2011). Many studies on PBP programs offer an overview of the rebound effect.

The TOU pricing simply biases the real price of electricity in order to incentive users who typically aim to maximize their savings, to shift their loads to off-peak periods (i.e., when aggregate demand is lower). However, where the price of electricity at night is cheaper than during the day, the TOU pricing has been observed to create significant additional peaks in demand as soon as the off-peak period is reached (Ramchurn et al., 2011; Strbac, 2008).

There exists a lot of alternatives, hybrid programs such as Smart Pricing, where users are encouraged to individually and voluntarily manage their loads, e.g., by reducing their consumption at peak hours (Centolella, 2010; Herter, 2007). Some scheduling programs using CPP, TOU pricing, and RTP are among the popular options.

DR includes automatic process and decision making process. In this paper, we present a decision making model to manage home automation in response to an RTP based on produced energy price, not on a supply/demand energy market price.

3 Process of our model

A smart grid must allow customers to make informed decisions about their energy consumption, adjusting both the timing and quantity of their electricity use. The process of our model is as follows:

Step 1, Data Update: at the beginning of a new iteration, sensors and automata update data.

Step 2, Consumption's schemes (Figure 2): through a knapsack problem and thanks to automaton, consumption's schemes are built (Section 4). They represent all the consumption possibilities in a smart house.

Step 3, Game for Demand-Response (Figure 3): a game between each consumer and producer is created. Strategies depend on consumption's schemes and producers' response. The best economic choice in the game is chosen (Section 5).

Step 4, Decision: following to the previous decision, the smart grid computes how energy is routed across the grid. In function of the result, the final decision is taken or a feedback adjusts the game.

The process of the whole model is presented in (Ahat et al., 2013). This paper improves the local and microgrid management.

4 Consumption's strategies

Technologies are available, and more are under development, to automate the process of DR. Such technologies detect the need for load shedding, communicate the demand to participating users, schedule load shedding, and verify compliance with demand-response programs. GridWise and EnergyWeb are two major federal initiatives in the United States to develop these technologies. Universities and private industry are also doing research and development in this field.

In this section, we provide our approach through automation and a set of consumption's schemes. Each prosumer build its set on each possibility of consumption of the local devices. Then, the set is sent to the microgrid. In function of how the grid will react, the best strategy is chosen for each prosumer through a game. Figures 2 and 3 show an overview of the process, see references in section 3 for more information about the process.

4.1 DR programs

Let us remind you the definition of DR programs. They include all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption (Albadi and El-Saadany, 2008).

There are four general actions by which a customer response can be achieved (QDR, 2006; Sezgen et al., 2007; Valero et al., 2007):

Reducing Power: customers can reduce their electricity usage during critical peak periods when

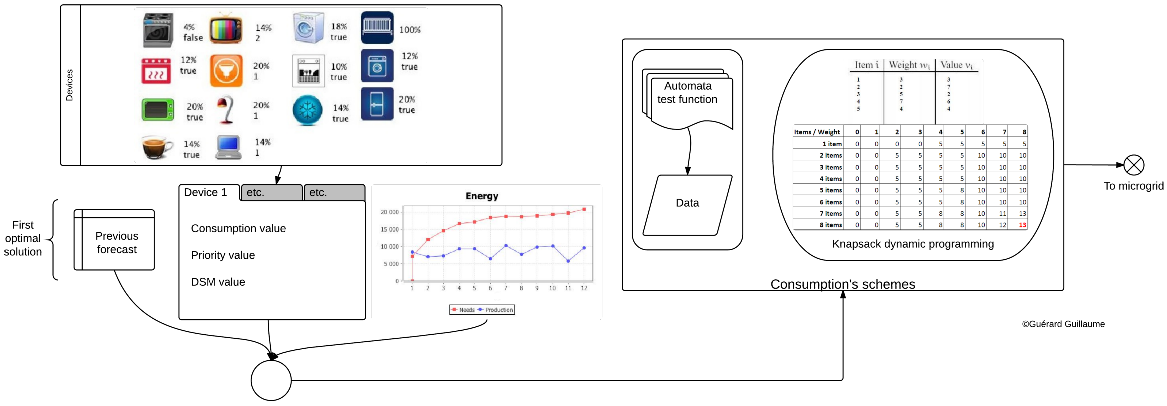

Figure 2: From devices to consumption's schemes.

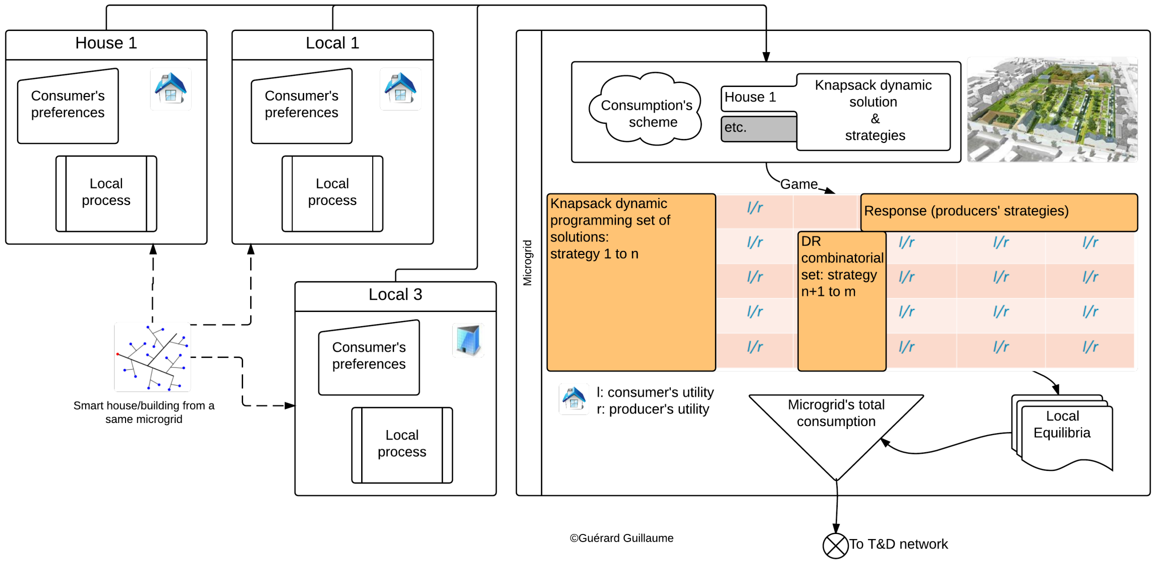

Figure 3: From consumption's schemes to a microgrid game.

prices are high without changing their consumption pattern during other periods.

Shifting: customers respond to high electricity prices by shifting some of their peak demand operations to off-peak periods.

Spinning Reserves: customers use local batteries and distributed generation combined with loads' management.

Emergency Cut: when the peak demand is still active even after the first three actions, an emergency cut is operated.

Reducing power involves turning down or off specific appliances. For example, heating may be turned down or air conditioning or refrigeration may be turned up, delaying slightly the draw until a peak in usage has passed (Sinitsyn et al., 2013). The success of such programs depends on a suitable pricing system for electricity.

In shifting load, the load is shed at the critical time and the process has to catch up later. For this, load models are needed. They predict how long devices can be turned off, how much it takes to fill the storage, and what it costs (Kupzog and Palensky, 2007). The strategies to manage loads are complex and need to communicate with the grid to establish a schedule.

Spinning reserve is done with batteries. It tries to support the traditional providers of ancillary services by imitating their behavior. Two implementations of this scheme are the Integral Resource Optimization Network (IRON) (Stadler et al., 2005) and the grid-friendly controller (Cantin et al., 1995). Both measures the frequency and react to it. The difference is that IRON has an additional communication interface that allows cooperative algorithms, i.e. a consensus among devices.

Energy storage is expected to be a key component in smart homes, and, thus, it has a strong impact when used with home automation and local renewable energies. For example, a user may decide to store energy during off-peak hours and use this stored energy to schedule its appliances, instead of obtaining this energy directly from the substation during peak hours.

4.2 Devices classification

There are many ways to classify devices. Some classify devices according to their usefulness or inner workings (wet, cold, water heating, etc.) (Hamidi et al., 2009). We follow some simple rules in our classification (see Figure 4): can the device follow DR programs? which data are useful for a device? The classification is made in order to categorize all existing devices and the ones which will be created.

The No DR programs gather devices which cannot be controlled by a decision making process, but still can be managed by sensors. The devices may be Cyclic or Acyclic, and with Sensors.

Cyclic means the devices which have an operating cycle (i.e. boilers, coffee maker), they have a start, an operating time defined, and an end. These kind of devices cannot be controlled because their uses are unpredictable and immediate. So do the acyclic devices which encompass the most household machines (i.e. vacuum cleaner, blender, TV, radio, microwave, iron, modem, telephone, DVD player, printer, oven).

The third one includes devices controlled by sensors, it concerns more generally lighting. The lighting control is based on a brightness sensor assembly, which estimates the amount of light for a room according to the natural light received from the outside.

In this model, devices are controlled by automaton in order to optimize their own consumption. A device is defined by a set of four categories, it picks one element of each category:

1. the device is cyclic (i.e. washing machine) or acyclic (i.e freezer)
2. the device has or doesn't have batteries
3. which data are used: external (i.e. heater in the room) or internal (i.e internal temperature of the refrigerator)
4. the device consume, or produce, or both.

Then, a device gets a set of parameters. They are input values that determine how and when a device will consume or adjust its consumption following a DR program. The set includes:

Internal data : they correspond to internal data of the machine, collected by internal sensors (i.e. temperature inside the fridge).

External data : they correspond to external data of the machine, in its environment collected by sensors (i.e. the temperature data of a room).

Consumer's preference : these parameters are the most important. Because the user should not be hampered in his daily life, its preferences are the bounds that devices have to reach (i.e. which temperature the consumer prefers in its bedroom).

Price : consumers, as described in (Kirschen et al., 2000), consider both current prices and the prices of one step into the future. To perform shifting, devices have to know how to schedule their consumption. In our model, we use current prices, prices of one step into the future and price trend. The last two are calculated from derivative function, norms and a pricer.

5 Game theory and best Consumption's strategies

The authors in (Mohsenian-Rad et al., 2010) show that it is better to develop a DR approach that optimizes the properties of the aggregate load of the users. This is enabled by the deployment of communication technologies that allow the users to coordinate their energy usage, when this is beneficial.

The essence of DR revolves around the interactions between various entities with specific objectives which are reminiscent of the players' interactions in game theory. As Saad et al. said (Saad et al., 2012):

> Game theory provides a plethora of tools that can be applied for pricing and incentive mechanisms, scheduling of appliances, and efficient interconnection of heterogeneous nodes.

In our model, each smart meter sends all the consumption's schemes, defined by their automaton, of their devices. A strategy for a consumer is a combination of a possible scheme of consumption of each device. Thus, the number of strategies is a combinatorial set. For example, if the smart building has four devices with respectively 2, 3, 3, 4 schemes, the number of strategies is equal to 72.

The price signal to incentivise the agents may defer their demand. Even if an accurate price signal is provided, the adaptive and autonomous behaviour of the agents in the system is a key component that can

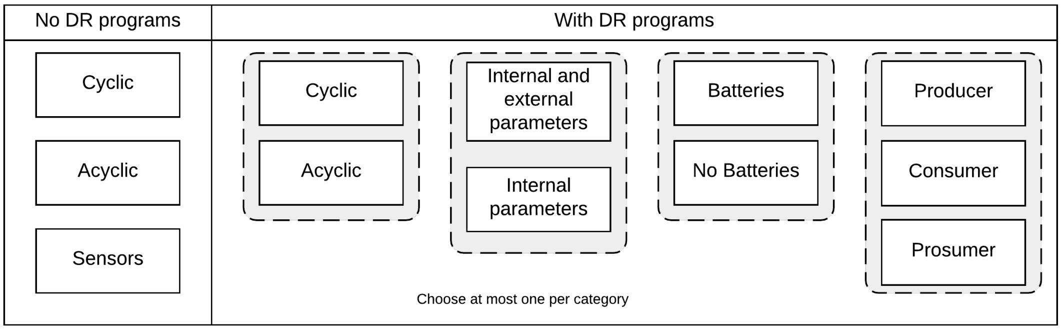

Figure 4: Characterization of a device.

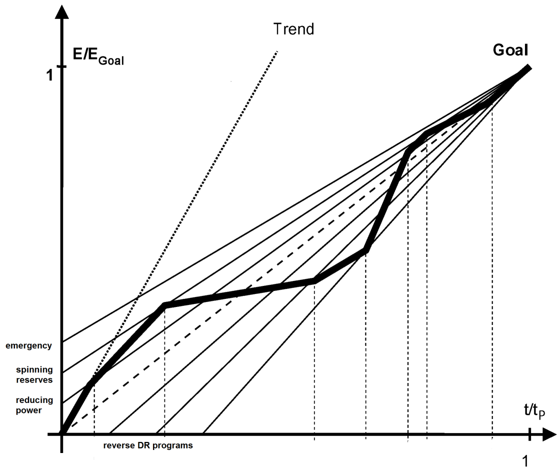

Figure 5: Lipschitz function that manages DR programs.

enable significant performance benefits in the smart grid. It's important to determine how comfort is more important to the user relative to price. This is done following the Palenksy et al.'s works (Palensky and Dietrich, 2011).

Both parameters depend on how much the current consumption's curve is far from an ideal consumption's curve as shown in Figure 5. DR programs like emergency programs or reducing programs depends on the value of the k-Lipschitz function.

If the computed load is larger than the previous one, a DR program is launched. In opposite case, if the curve is smaller than the previous one, more devices consume or return to a basic mode of consumption. Different emergency programs trigger depending to how much k in the Lipschitz function is large. In this way, the global consumption curve flattens over time.

With communication, the shed can be arranged by the game, i.e. in the same microgrid. Such coordination also contributes to stability. Imagine a community of autonomous, distributed controllers without communication. All of them reacting to grid problems increase instabilities. They will do it one after another to avoid a too strong reaction (Palensky and Dietrich, 2011).

We don't argue about the second player is this paper. This one represents producers, user's contract and some other properties that depend on government policies about DR. We don't present an utility function. It depends on the price's values, user's preference, and the feedback function (Guérard et al., 2015). Those works will be shown in a future paper with the feedback process.

Once a strategy is valid, i.e. can be routed from the producers to the microgrid, the last one send a signal to the smart building. This consensus is reached in the whole grid at the same time. Thus, every consumer and prosumer know how to adapt their behavior for the next step. All the generated data is useful to compute forecasts, future production scheme and to be used in data mining and machine learning (Guérard et al., 2015).

6 Conclusion

There is a need to deploy new models and algorithms that can capture the following characteristics of the emerging smart grid. It is a current and active field that will give birth to many innovations and technologies. The needs to build an efficient and flexible smart grid are known, and it becomes an urgent matter while population and technologies increase drastically.

The presented model provides some simple and useful tools for a generic model of smart grid. This decision making tool can be used to test existing or future technologies in a smart grid design. As any multi-agent system, this model can be set as wanted. Examples will be made on different sets of microgrid and a small smart grid.

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