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The economic potential of Demand Response in liberalised electricity markets: a quantitative assessment for the French power system

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Présentée par
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THE ECONOMIC POTENTIAL OF DEMAND RESPONSE IN LIBERALISED ELECTRICITY MARKETS – A QUANTITATIVE ASSESSMENT FOR THE FRENCH POWER SYSTEM

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Proverbe créole.

ABSTRACT

In liberalised power industries the lack of responsiveness of electricity end-users to bulk power system conditions has often been pointed out as a primal source of inefficiency. Stemming from technological, political and sociological obstacles, the inability of consumers to adapt their demand in accordance to wholesale market prices is however increasingly challenged. Nowadays, technical progress within the smart grid industry as well as behavioural changes constitute indeed promising changes for the integration of active end-users into the power system. In addition, empirical evidence emerging from pilot projects generally show a high degree of end-users acceptance towards these technologies as well as efficient responses to financial incentives based on wholesale market prices. Demand Response (DR) has also been encouraged at the political level, in particular by the European Commission. Despite these favourable trends, economic viability remains a barrier to overcome if DR is to be deployed on a large scale.

This PhD thesis tackles this issue by assessing the economic value of large scale DR. Our contribution is twofold. First we simultaneously address (i) the feedback of DR on market prices, (ii) the effect of power system uncertainty on the value of DR, and (iii) the modelling of DR with the help of a storage approach, allowing to represent behavioural and technical constraints among different groups of end-users. Second, we perform a case study providing a quantification of the DR economic potential in France. The dissertation consists of three parts.

Part one provides general understandings about the evolution of DR from the start of liberalisation until today. We especially highlight the importance of smart grid technologies as well as the growing role of private aggregators. Aggregators are pivotal facilitators contracting with end-users in order to provide DR to wholesale markets. Furthermore, in order to get insights on consumer behaviour and acceptance of smart grid technologies, we focus on empirical lessons drawn from demonstration projects. These empirical evidence are then used in next parts of the thesis as parameters defining the contract terms proposed by the aggregator.

Part two describes the modelling framework built in order to quantify DR economic value. We implement an economic dispatch optimisation model under uncertainty, wherein DR is represented as a storage unit. The model is formulated as a multistage stochastic linear problem. To deal with tractability issues due to the potentially high number of DR technologies in the model, we resort to Stochastic Dual Dynamic Programming (SDDP) as a solving method. Economically, the model can be seen as a wholesale energy-only market on which the aggregator activates DR events on behalf of its customers.

Part three analyses the economic potential of DR in France by a business case of DR aggregators. The aggregator benefits are quantified from numerical simulations of the model calibrated on the French power system. Our results suggest that in France, the capacity value of DR is much higher than the energy value. Profitable DR segments are (i) load-shedding in the industrial sector and (ii) load-shifting in the industries of Cement, Paper, and pulp. In the residential and tertiary sectors, load-shifting of electric heaters is not profitable. To challenge these conclusions, two effects are tested: (i) an additional capacity remuneration and (ii) the reluctance of consumers to contract with the aggregator. Although the additional capacity remuneration increase benefits of all DR technologies they do not change the former conclusions. Furthermore, the reluctance of consumers has two opposite influences for the aggregator: the decrease of benefits due to reduced volume of DR can be offset by higher market prices due to more frequent periods of scarcity. Overall, results show that DR is beginning to become economically attractive in a number of industrial sectors, but that fixed costs of smart grid technologies still need to come down further to fully develop its potential.

Key words: Demand Response; Aggregator business case; Electricity markets; Uncertainty; Stochastic Dual Dynamic Programming

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INTRODUCTION

The demand-side of electricity markets

The deregulation of the electric power industry made every effort to creating competition at the production level, which resulted in electricity markets characterised by a competitive supply side while the demand side has remained the same (Kirschen 2003). Consequently, electricity markets have inherited a demand for electricity endowed with two flaws: the "failure of customers to respond to relevant price fluctuation", and "the customer's ability to take power from the grid without a contract" (Stoft 2002). This resulted in a power demand largely unresponsive to wholesale market prices. Economists might consider this situation as a market failure, in the sense that the market cannot provide an efficient allocation of the commodity "electricity", neither in the short-term with issues regarding the system balance under circumstances of demand peaks, nor in the long-term in terms of optimal investments in the energy mix (Finon, Defeuilley, and Marty 2011). Because electricity cannot be stored at reasonable costs and flows over a network which has to be balanced in real-time, this market failure may manifest in spectacular ways, as happened in California between 2000 and 2001. At the time, this American state was struck by giant black-outs after the exercise of market power by some producers, creating an artificial scarcity of generation capacities. On the newly implemented wholesale markets, prices skyrocketed but consumers did not respond accordingly, creating a mismatch between supply and demand and a collapse of the entire network. The "California crisis" outlined that electricity markets where consumers cannot respond to wholesale markets prices are not sustainable (Joskow 2001).

Before deregulation, power system balancing was managed by a single operator vertically integrated along the entire value chain of electricity: the public-owned utility. Within this institutional model, power system reliability is supported by the peak-load pricing theory developed by Boiteux (1960). Peak-load pricing theory assumes that some consumers would reduce their own demand due to a higher tariff accompanying peaks of demand. Under this marginal pricing mechanism, when the network was jeopardised by unforeseen events such as a power plant shutdown or an extremely high demand level, rolling black-outs could be used as a last resort. In practice though, only a few electricity consumers were incentivised by a peak-load pricing (principally large industrial consumers), the rest of them being largely disconnected from the fluctuations of electricity generation costs. Moreover, rolling black-outs are a rough way to balance the system since it does not discriminate among consumers who might assign different values over the reliability level of the electricity supply. To deal with this issue, Chao and Wilson (1987) developed an appealing theoretical framework whereby consumers self-reveal their preferences over different levels of reliability. Nevertheless they insist on the need of an appropriate communication infrastructure that was not available before liberalisation reforms. In line with Boiteux (1960) and Chao and Wilson (1987),

Schweppe et al. (1988) then proposed their spot-pricing of electricity theory, fitting well with the market reforms occurring at the time. Nevertheless, it has never been put in practice because of the lack of enabling communication systems, and also probably because it was too complex to be understood by consumers.

Power system reliability has not been the only reason to desire a flexible demand-side. Following an academic trend in energy economics called integrated least-cost planning, public-owned utilities launched in the 80s a set of measures named demand-side management (DSM) programmes (Ruff 2002). This academic movement was initiated by the Energy Policy Project of the Ford Foundation (Ford Foundation Energy Policy 1974), and subsequent series of works by Lovins (1974). DSM measures aimed to induce end-users of electricity to re-shaping their load (MW) or consumption (MWh) patterns, which would in turn provide a more efficient operation and use of power plants. In this case, economic efficiency was the purpose: in the short-run, savings in production costs were expected by a higher capacity factor of existing power plants, and investments in additional generation and network capacities were avoided in the long-run. DSM is actually an extension of peak-load pricing which can be seen as a particular DSM tool. As for peak-load pricing, only a small share of consumers used to take part of DSM programmes.

This quick overview over the structural characteristics of the electricity demand raises one conclusion: although the electricity demand is acknowledged to being reactive to some extent to energy prices, the supply-side has remained the favourite option for operating the power system. Indeed, this “supply must follow the load” paradigm has subsisted despite market reforms, mainly because the fixed retail rates inherited from the time of public utilities are still charged to the vast majority of consumers (Chao 2011). Yet it has been increasingly stressed out by industrials, politicians, academics and other stakeholders that the power system’s need for flexibility is strengthening. Flexibility needs are especially growing in the European Union, where member states have already installed substantial amounts of solar and wind generation capacities in order to comply with the policies defined by the EU commission. It has also been widely recognised that this flexibility could come from the active participation of electricity consumers, which is nowadays referred to as *Demand Response* (DR). The potential of DR in providing flexibility to the European electricity markets has been fostered at the political (European parliament 2012, European Commission 2013), industrial (SEDC 2017), and academic levels (He et al. 2013). Nevertheless, the penetration rate of DR remains rather low in Europe (Torriti, Hassan, and Leach 2010) compared with the existing potential. A legitimate question we should ask ourselves is then: why the potential of flexibility arising from the demand-side has not been exploited on a larger scale, especially in regions like Europe?

Barriers to unlocking Demand Response potentials in power systems

DR potentials can be broken down into four different categories: the theoretical, the technical, the economic, and the achievable potential. Throughout this dissertation we will assess the economic potential of DR while including some barriers characterising the achievable potential.

The *theoretical potential* encompasses all electric loads (facilities, devices, appliances, industrials processes) suitable for DR (Gils 2014). A load is suitable for DR if its normal consumption pattern can be modified with reasonable disturbance for the end-user. One can think of hospitals, public transports, elevators, and lighting infrastructures as facilities that are not suitable for DR. At the opposite, electric heaters, cooling and ventilation facilities, electric vehicles, and many industrial processes present storability features that fit well with the concept of DR. Among these different usages of electricity, neither the technical method nor the cost of actually changing their usual consumption are the same. The *technical potential* refers to the aforementioned electric loads whose consumption can be technically altered, regardless of its costs. Technical capability requires a so-called *enabling infrastructure*. Information and communication technologies, such as smart meters, are modern instances of this DR enabling infrastructure[1] (Clastres 2011; Joskow 2012; Haney, Jamasb, and Pollitt 2009). A first subset of the technical potential is the *economic potential*, which considers loads that can be technically operated in a cost efficient way. Indeed, activating DR comes at a cost which is twofold: (i) a variable cost endured by the consumer who might find inconvenient to alter his normal consumption, and (ii) a fixed cost arising from the investment in the enabling infrastructure. Obviously, DR also provides value to the different agents of the power industry. Fundamentally, the value of DR lies in the discrepancy between consumers' utility and producers' marginal costs. Another independent subset of the technical potential takes account of sociological and regulatory barriers. Taking into account these barriers leads to the definition of the *achievable*, or *practical potential* (Gils 2014). We can distinguish two degrees of sociological barriers: (i) consumers' acceptance, and (ii) consumers' performance. The key question pertaining to this is: are electricity consumers able and willing to change their usual consumption patterns in order to provide the electric power system a new cost-effective option to balance supply and demand? Some people might not be willing at all to change their habits when it comes to the consumption of electricity. Their reluctance may bear no relation to economic factors. For instance, aversion to consumption change can arise from concerns about privacy or a lack of understanding about DR modalities. Once this first obstacle has been overcome, it is not straightforward to know how the set of incentives proposed to the consumer will perform, i.e. how people will actually respond in terms of change in their consumption patterns. Consumers' acceptance and performance are crucial; this is why they have been an increasingly research topic for a few years.

[1] These can also be quite old, as a simple phone call. For instance, some system operators used to call energy-intensive industrial sites in order to ask them to shut their processes down in case of highly stressed situations on the power network. Recently, innovation linked to smart grid technologies has created new and more sophisticated tools enabling DR to spread out over a larger range of consumers, in particular small and medium ones on the residential and tertiary sectors.

An appropriate regulatory framework is a prerequisite to the deployment of DR. In Europe, some countries such as Belgium, Finland, France, Ireland, Great Britain, and Switzerland have set market rules adapted to DR; whereas in other countries like Estonia, Italy, Portugal, and Spain, DR is not allowed to participate in wholesale electricity markets (SEDC 2017). These regulatory barriers can however be relieved by a DR aggregator, a market intermediary enabling the end-user to provide flexibility to the power system (Eid et al. 2015).

Looking at these definitions, we can derive four types of barriers impeding a larger deployment of DR in the power system: technical, economical, consumer-based, and regulatory barriers. However, there is nowadays little doubts regarding the technical ability of smart grid technologies to support an extension of DR to all classes of electricity consumers. While only large industrial consumers have been used to provide DR capacities so far, smaller consumers like households and tertiary buildings represent a large potential which could be tapped thanks to the roll-out of smart grid technologies. The debate about DR has thus logically moved to the economic question of the investment in these technologies, which is organised around two key issues: (i) should we invest, and (ii) who should invest? This breaking-down is absolutely essential because "smart grids are not exclusively designed to facilitate balancing of supply and demand" (Clastres 2011). In other words, many actors with different purposes have interests in the deployment of smart girds[2]. There is then a typical free-riding issue since the value of smart grids is split-up between many stakeholders (IEA 2003). According to Koliou (2016), the brunt of investment in smart grids lies on distribution system operators (DSO), which is indeed the path followed by Enedis in France with the deployment of its smart meter "Linky". In this context, a public intervention might be claimed to foster the full roll-out of smart grid technologies, but then a "chicken-and-egg problem" arises: "without the infrastructure, smart appliances and DR cannot be used to their expected potential and without DR through smart appliances, the limited benefits of the enabling infrastructure do not justify the costs of its roll-out" (He et al. 2013). In Europe, the lack of concrete measures from policy makers can be explained by the difficulty to properly assess the economic value of DR. This is a view shared by Strbac (2008) for whom the assessment of benefits is a challenge to overcome. In fact, this assessment is complex because of the lack of knowledge regarding acceptance and performance of consumers. This is why many pilots and demonstration projects involving smart grid technologies have been set up around the world for a few years. Although empirical lessons drawn from these field studies have regularly come up with encouraging conclusions, it seems that they have not brought enough confidence. Uncertainties around the results and how they would transpose at the large scale remain an obstacle.

[2] For instance, consumers would benefit from an energy bill reduction by providing DR, while the distribution system operator would gain from savings in meters reading and maintenance costs.

Purpose and motivation

One major challenge for DR is to demonstrate the economic viability of a rolling out smart grid technologies on a large scale, based on a sound and trustworthy estimation of its economic benefits. The aim of this thesis is to provide such a quantification framework and to propose a case study for the French power system. As highlighted in the previous section, assessing the achievable potential requires to take into account sociological barriers, thus to get insights from smart grid demonstration projects and field studies, whose analyses rely on sample of consumers. In this dissertation, we will outline the fact that field studies insights cannot be extended to a broader population. Moreover, because the value of DR is diffuse throughout the entire power system, it makes sense to assess it with power system fundamental modelling. This approach enables to simulate a large scale integration of DR the system. Power system modelling uses optimisation tools which are quite opposite to the statistical analyses and behavioural research processes used in field studies. The disconnection in these two methodological approaches constitutes a knowledge gap that motivates our research. Our methodology consists in using a power system model including some sociological barriers identified within field studies. They are translated into the model as consumer-based constraints and encompass consumers' acceptance and performance. The two other key features of our model are the endogenous electricity market price and power system uncertainty stemming from the demand and the renewable energy generation. The impact of DR on the market price has to be consider if we assume a large scale deployment. Taking uncertainty into account is primordial because it is a structural characteristic of power systems, and also because a deterministic setting would overestimate the value of DR. The contribution of the approach developed in this thesis is to consider these three key aspects (consumer-based constraints, impact of DR on market prices, and uncertainty) that have not been treated together so far.

Research question

The aim of this thesis is to quantify the economic value of large scale DR in liberalised electricity markets. More precisely, we will tackle this issue with a quantification for the French power system, where private DR providers such as load aggregators have started to emerge. This brings us to formulate our research question as follow:

What is the economic value of Demand Response?
Is there a business opportunity for aggregators in France?

Thesis structure

The dissertation is divided in seven chapters embedded in three parts. PART I justifies our methodological choice. Chapter 1 introduces key notions regarding DR and makes the case for the

growing role of DR aggregators. Chapter 2 gives an overview on empirical lessons drawn from the most robust field studies conducted in the U.S., Europe, and France.

PART II describes our methodological approach. Chapter 3 is a literature review of DR modelling. Chapter 4 presents an electricity market model that is used to quantify the economic value of DR. The model is a wholesale energy-only market under uncertainty whose solving is handled by *Stochastic Dual Dynamic Programming (SDDP)*. Chapter 5 uses a didactic model illustration in order to highlight some of the main outputs of the model. In particular, a focus is made on the marginal cost function of DR in a stochastic environment.

PART III is a business case of DR aggregators based on the quantitative results of the model. Chapter 6 presents the business case. Results are obtained from a calibration of the model on the French power system. Chapter 7 analyses the impact of a capacity remuneration on the aggregator business case. Another impact is tested with a sensitivity analysis on the reluctance of consumers to enter into contract with the aggregator.

A general conclusion and a summary in French conclude this dissertation.

PART I – FROM THE NOTION OF DEMAND RESPONSE TO ITS ACTIVATION ON ELECTRICITY MARKETS

CHAPTER 1 DEMAND RESPONSE: THEORY AND PRACTICES

1.1 Introduction

A lot of DR programmes exist worldwide in liberalised electricity markets. This variety has led to a multi-faceted conception of what DR is. This diversity stems from the different purposes of each programmes as well as the various inducements to elicit consumers' response. Some authors even pointed out the need to clearly distinguish DR from *dynamic-pricing*, arguing that the current way of integrating DR in electricity markets is a second-best that would crowd out the first-best option represented by a *price-responsive demand* (Bushnell, Hobbs, and Wolak 2009). This is illustrative of the difficulty to put DR into one single harmonised notion. In essence though, all concepts derived from the notion of DR refer to the consumer's participation in electricity markets. Modifying consumer's demand entails to look at the multiple end-uses of electricity that lie behind DR, adding another source of diversity in the way DR behaves: power demand from end-uses can either be shifted or shed. We will refer to this as *load-shifting* and *load-shedding*. Furthermore, the category of consumer matters when it comes to the practical activation of DR. Large industrial, small residential, medium tertiary and medium industrial consumers have different characteristics that one needs to take into account. More importantly, unlocking the potential of small and medium sized consumers might require the help of (i) *enabling technologies* and (ii) a third-party making the link with wholesale electricity markets. Enabling technologies correspond to *information and communication technologies (ICTs)* whose ongoing improvements have made them increasingly available within power industry. The third-party can be any kind of agent in the power industry. However one particular role has been especially highlighted for a few years: the *Demand Response aggregator*. DR aggregators and ICTs have brought promising avenues to unlock a DR potential that is far from being fully exploited.

The purpose of this chapter is to set up the framework into which DR will be studied throughout this dissertation. To do so we need to explore the aforementioned diversities and to assess what might evolve further to the penetration of new ICTs and the emergence of DR aggregators, which are both steadily observed trends in the electricity markets. The rest of the chapter is organised as follow. In section 1.2, commonly used definitions of DR are reported as well as the various programmes that have been implemented in practice. Section 1.3 gives an overview over the various conceptions of DR, making the distinction between price-responsive demand and the technological view of DR. Section 1.4 focuses on the demand side resources suitable to DR, that is to say end-uses of electricity whose normal consumption patterns can be altered. In Section 1.5 empowerment of small and medium-sized consumers by a DR aggregator is examined along with the role of new ICTs, and section 1.6 concludes.

1.2 Definition and scope of Demand Response

The term "Demand Response" fits in with a market context. Indeed DR refers "to bring the demand-side of the electricity market back into the price-setting process" (IEA 2003). This is a refinement of the notion of demand-side management which does not specify any particular institutional framework and which was used before market reforms.

1.2.1 Definitions

The most general definitions of DR are proposed by the three following institutions:

- Department of Energy: DR represents "changes in electric 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" (US DOE 2006).

- European commission: "Demand response is to be understood as voluntary changes by end-consumers of their usual electricity use patterns - in response to market signals (such as time-variable electricity prices or incentive payments) or following the acceptance of consumers' bids (on their own or through aggregation) to sell in organised energy electricity markets their will to change their demand for electricity" (European Commission 2013).

- International Energy Agency: "Demand response refers to a set of strategies which can be used in competitive electricity markets to increase the participation of the demand-side, or end-use customers, in setting prices and clearing the market" (IEA 2003).

In all definitions the underlying idea is the involvement of electricity end-users such that they can somehow participate in the wholesale electricity markets. However they do not stipulate that the end-user be a direct participant of the market. Given the current hybrid electricity markets structure characterised by the co-existence of wholesale and retail markets, small and medium consumers cannot be direct participants of wholesale energy markets. However a third party can empower them to participate in wholesale markets. Be it a participation whereby the electric load is controlled by a third party or directly self-managed, the above definitions emphasise on the need to have end-users aware of the overall process such that changes in consumption are efficient for both the consumer and the power system.

1.2.2 Demand Response programmes

When it comes to the actual implementation of DR, the term *programme* is added. *Demand Response programmes* set up the frame in which the consumer is incentivised to modify its demand, the result of

the programme being a *Demand Response resource* for the power system or a *price-responsive demand* on the wholesale energy market. Different DR programmes have been implemented worldwide. For instance t*ime-of-use (TOU) pricing* was established for large customers in California in the 1990. In the UK and in France, TOU tariffs are widely implemented in a form of day/night tariffs. *Critical peak pricing (CPP)*, which implies very high tariff during critical peak periods on the system, has been proposed in France to some medium and residential consumers. *Interruptible programmes* are also very common since they provide the system operator with a reliable tool to balance supply and demand. In Europe for instance, system operators have used this type of programmes with large industrial consumers (Torriti, Hassan, and Leach 2010). *Direct load control* are programmes where a third party directly takes over the consumption of a specific appliance on the end-user's premises (Dupont 2015). They target more specifically small residential and commercial consumers (Albadi and El-Saadany 2008). The aforementioned programmes are a legacy of DSM measures: they were launched by the public utilities before liberalisation reforms. Although they do not fit well with the DR definitions that are in use nowadays, they are still viewed as DR programmes. Since then, a set of more market-oriented programmes has been deployed, as shown by **Table 1.1**, which gives an overview of existing DR programmes based on (Albadi and El-Saadany 2008).

Table 1.1 – Segmentation of existing Demand Response programmes

	Non-dispatchable Demand Response[3]	Dispatchable Demand Response[4]
Price-based programmes	Time-of-use pricing	
	Critical peak pricing	
	Real-time pricing	
System-based programmes		Direct load control
		Interruptible/Curtailable programmes
		Demand bidding
		Emergency Demand Response
		Capacity market
		Ancillary services market

DR programmes are split along two dimensions. Price-based are to be distinguished from system-based programmes. In addition to this we can separate those according to the dispatchability versus

[3] These programmes provide consumers with financial incentives to modify their energy consumption. The incentive is then expressed in € per MWh and come into effect only when the consumption is actually modified.

[4] To make DR dispatchable, these programmes also remunerate consumers for the availability of capacity. For instance, the Transmission System Operator (TSO) may remunerate consumers on a € per MW basis to make sure that the capacity will be provided when needed. This contractual arrangement with the TSO thus provides participating consumers with a remuneration even though no DR events are triggered. However, consumers are committed to respond (if they do not, they bear a financial penalty) unlike with price-based programmes whose consumption changes are let at the consumers' discretion.

non-dispachability nature of the resulting DR resource. System-based programmes are logically dispatchable since they aim at providing the power system with a reliable demand-side resource. In principle these programmes allow to know the amount of load reduction or increase with certainty. Price-based programmes focus on encouraging the electricity consumer to change its demand with time-varying tariffs. The response is then let at the consumer's discretion. Therefore they cannot be considered as dispatchable. In **Table 1.1**, programmes highlighted in grey are programmes that are market-oriented. *Demand bidding, emergency Demand Response, capacity market* and *ancillary services market* are designed to remunerate demand-side resources with the corresponding wholesale market price. *Real-time pricing (RTP)* is the direct pass through of wholesale energy market prices on consumer tariffs. Logically, we could also break down DR programmes according to a third criteria that would be whether the programme is market-oriented or not. But if we follow the definitions proposed above, we would end up considering only these latter programmes as being a DR programme, since these definitions all emphasise on the market dimension of DR. However another document published by the IEA explains that "Demand response includes time-of-use and dynamic rates or pricing, reliability programmes such as direct load control of devices and instantaneous interruptible load, and other market options for demand changes, such as demand side bidding" (IEA 2009).

The term DR was created following the power industry liberalisation. Naturally we ended up to use it to define practices occurring before market reforms. The lack of harmonisation regarding DR programmes stems from the co-existence of several institutional environments. Thereof co-exist different demand-side practices that we all refer to as DR. It might be the case that some programmes become one day obsolete, others would be coupled together, and others would remain even in a non-market context, leading to a more harmonised vision of DR. The following examples support this analysis:

- RTP can be implemented in a non-market context. As an example, in the USA, Georgia Power Company has implemented RTP tariffs since the late 1980's, although there have been no liberalisation reforms in this state.

- Interruptible programmes can be seen as RTP with very "blunt prices", in the sense that "the price offered is usually pre-determined and does not vary with the tightness of supply" (Borenstein, Jaske, and Rosenfeld 2002). According to the same authors, in a world with a widespread application of RTP, the resulting price-responsive demand would cut the needed amount of interruptible contracts substantially.

- CPP can be viewed as a restricted RTP over the frequency of activation and/or the tariff level. Thus CPP could be set up based on real-time wholesale market prices.

- Direct load control could be coupled with dynamic-pricing. Consumers would be incentivised by a dynamic tariff rather than by an upfront payment disconnected from the market prices.

This overview over DR definitions and programmes draws one particular conclusion: in its understanding and its application DR is a body of concepts rather than a single well unified notion. Depending on the institutional framework in which it is deployed and whether it is system-based or focused on charging consumers with dynamic-pricing, one can end up with different conceptions of DR that we develop in the next section.

1.3 Two broad conceptions of Demand Response

Economics of electricity markets can sometime conflict with the engineering-based operations of power systems. While economists would support DR programmes promoting a price-responsive demand on wholesale energy markets, grid operators would prefer programmes ensuring that they "have resources they can call on with near-certainty to increase supply or reduce demand" (Borenstein, Jaske, and Rosenfeld 2002). The practical issue arising when considering DR as resources is the need to have recourse to a *customer baseline.* The customer baseline is a reference load profile used to measure the actual demand reduction/increase. Broadly speaking, the baseline defines what would have been the consumption absent any DR activations. As observed by Bushnell, Hobbs, and Wolak (2009) the customer baseline is a "counterfactual consumption level that is impossible to observe". Thereof result three theoretical issues that have been studied in particular by Chao (2010), Crampes and Léautier (2010), and Ruff (2002), namely the double payment problem, the moral hazard problem and the adverse selection problem. Because of the baseline problem, some economists consider price-responsive demand as a more efficient approach. Note however that the problem with considering DR as a resource does not lie in the fact to see DR as a resource. The problem comes from the confusion created after calling DR a resource. One can indeed end up to ignore the baseline issue, because traditional supply-side resources, that is to say power plants, are not concerned with it. This confusion actually led to "inefficient DR policies such as paying twice for the same thing" (Ruff 2002). For instance, in the US, the Federal Energy Regulatory Commission had been supportive to a poorly conceived vision of DR resources, resulting in inefficient DR programmes (Bushnell, Hobbs, and Wolak 2009). A similar debate happened in France between the regulator and a DR provider. Finally, given the reality of power system operations and the actual design of power markets, the resource approach could be an option as valuable as the price responsive demand approach, as long as it is set properly.

1.3.1 Price-responsive demand

For many reasons mentioned in the introductive chapter, such as fixed retail rates, electricity demand is usually fixed to a given amount of power affected only by the cycle of consumers' activities (Callaway and Hiskens 2011). No matter what the wholesale market price is, if not incentivised by more time-varying tariffs, consumers will not change their power withdrawals, resulting in an unresponsive demand on the market. When the purpose of a DR programme is to promote the deployment of dynamic-pricing based on the real-time wholesale market prices, the result is a price-responsive demand on this market. Price-responsive demand is the outcome of a price-based DR programmes (see **Table 1.1**) at the exception of TOU programmes, because TOU programmes poorly reflect the evolution of market prices since the pricing structure is settled in advance once for all. It then remains fixed regardless of the evolution of the power system conditions. In that sense, TOU pricing is time-varying but is not considered as dynamic. Still according to the categorisation of **Table 1.1**, price responsive demand cannot be qualified as dispatchable, in the sense that consumers would commit to provide a certain amount of energy to the market. Consumers simply decide of how much quantity of energy they consume at each moment according to the market price. The price-responsive demand approach is thus best-suited to energy markets like the day-ahead energy market. However price-responsive demand fits poorly with wholesale markets for reliability such as balancing markets or ancillary services markets, since the system operator needs to know with certainty that the proposed amount of power will be reduced/increased. This does not mean that DR cannot participate on reliability markets; it means that DR, conceived as a price-responsive demand, is not on its own sufficient for these markets. The fact that the price-responsive demand approach implicitly recognises that consumers will alter their demand on a continuous basis can be problematic. Let us assume that real-time pricing is offered to a consumer: on the one hand it might be very disruptive and uncomfortable to change on an hourly basis its consumption; on the other hand, to not react to real-time prices would possibly lead to very expansive electricity bills. To overcome this issue, some risk-hedging contracts can be proposed to consumers, reducing perhaps the reach of real-time pricing but increasing its acceptance.

1.3.2 Demand Response as a resource: the technological view

DR can be compared to several types of generating technologies. In the two next subsections we first address the following question: is the value of lost load (VoLL) an appropriate concept to understand what DR is? Then we move to analogies with generating technologies.

1.3.2.1 Value of lost load

Power systems economics introduces the notion of *value of lost load (VoLL)* as the cost that would endure consumers following an unexpected interruption of the electricity service. To some extent, the VoLL expresses how much a consumer is willing to pay for electricity. It does so however in the

particular case where the total generation capacity of the system has been reach. In a competitive market context, assuming consumers can respond to prices, VoLL is the highest price, capturing what is called a *scarcity rent* as illustrated in **Figure 1.1**:

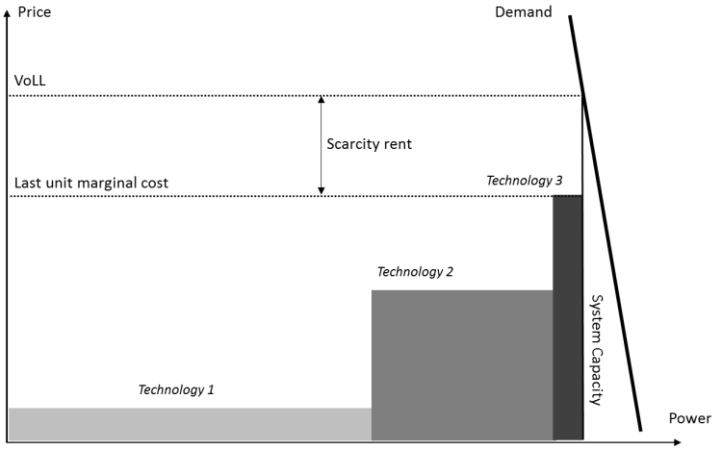

Figure 1.1 – VoLL in a competitive electricity market

Electricity market theory states that in a perfectly competitive market, scarcity rents enable all producers to recover their fixed costs**,** leading to optimal investments in generation capacity in the long-run. VoLL is thus fundamental to the efficiency of the market, because without VoLL setting the market price during extremely tight situations, producers cannot recover their fixed costs, meaning the market is flawed (see the missing money issue studied by Joskow (2006)). In terms of optimal investment in generation technologies, this leads to admit the existence of a technology with no-fixed costs and a marginal cost equal to the VoLL. As mentioned by O'Connell et al. (2014), "the most obvious form of Demand Response is systematic load-shedding, a last resort to avoid system blackout", which is the exact underlying role of this technology. DR can thus be seen as this technology. **Figure 1.2** represents screening curves (traditionally used to solve the optimal investment generation mix problem) in order to illustrate DR as a VoLL-based technology:

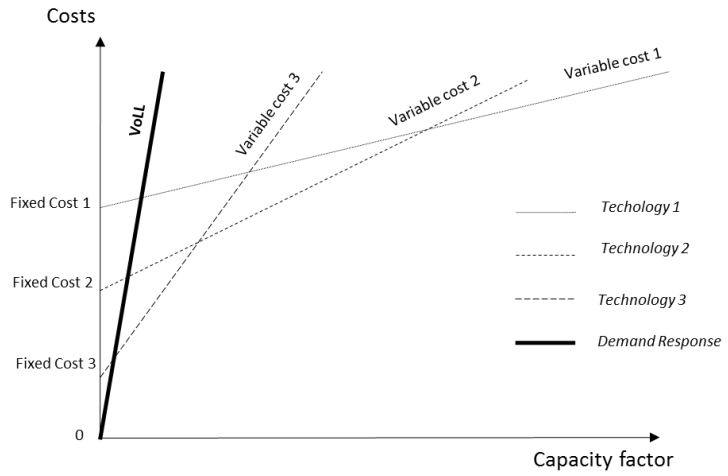

Figure 1.2 – Demand Response on screening curves

Flaws of the VoLL approach

This view only deals with situations of extreme tension on the system. VoLL therefore captures the value attached by consumers to adequacy. As illustrated in section 1.3.1, consumers might be willing to change their demand even under normal conditions, that is to say whenever the energy price is above their marginal willingness to pay. In other words, demand-side costs might not be as high as VoLL. In practice this approach implies mandatory curtailments handled by the system operator such as rolling black-outs. In this case, bundles of consumers are cut off, among those certainly have different willingness to pay for electricity service. TSO would certainly avoid to cut off hospitals or public transports in the first place. But the cost associated to the curtailment would be at a VoLL representing an average value over curtailed consumers. "It makes no distinction between those who need power the most and those who need it least" (Stoft 2002). To sum up, the VoLL approach represents an extreme sort of DR that will be used only at very last resort. Compared with the price-responsive demand, it is incomplete. Moreover it does not fit well with the way DR is envisioned today. Definitions of DR insist indeed on the active role and participation of the end-user in clearing the market price. Nevertheless the VoLL approach outlines that DR can be viewed as a resource for the system. In order to complete this approach, more refined DR technological views that fully capture DR capabilities need to be proposed.

1.3.2.2 Analogy with other generation technologies

As the price-responsive demand approach suggests, DR can be triggered on a continuous basis, not only when the system is strained. Unlike the price-responsive view which treats DR as pure changes in the level of demand, DR can be viewed as an additional type of generation technology available for the power system. Indeed, from the system point of view, to not withdraw a given amount of power is equivalent to inject the same amount of power. Therefore DR can be compared to a generation technology which can be dispatched in the same fashion as other conventional producing technologies.

Figure 1.3 shows how DR integrates in a classic merit-order (note that the demand function is fixed here since DR is represented in the supply-side).

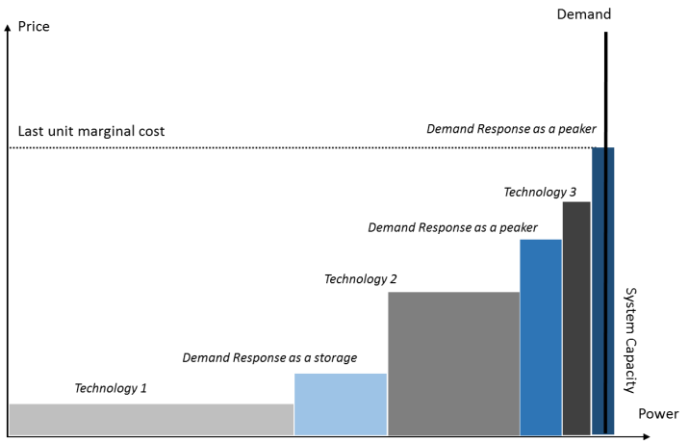

Figure 1.3 – Demand Response viewed as technologies in the merit-order

Like suggest (Vincent Rious, Perez, and Roques 2012), the most natural analogy is to be made with a peaking power plant. The comparison is primarily driven by the variable cost of shedding the load, which has the order of magnitude than a peaking power plant variable cost. Observe that load-shedding is not necessarily the most expansive technology in terms of marginal cost. The cost of shedding the load depends on the end-use which is curtailed. DR can also be assimilated to a storage facility. Indeed some electric loads have intrinsically some storage features, as well as some particular end-uses or processes whose consumption can be easily deferred or anticipated (Kirschen 2003; He et al. 2013). In this case the variable cost of shifting the load is quite low, since in this case, unlike load-shedding, the end user consumes the same amount of energy.

1.4 Processes and type of loads enabling Demand Response

Electric loads and processes suitable for DR are ubiquitous across all consumer classes. However they are not homogenous since the consumer load mix is made of a wide range of end-uses. He et al. (2013) proposes a categorisation which is reproduced in **Table 1.2**, with a few examples.

Table 1.2 – Categorisation of electric loads according to He et al. (2013)

Storable load	Non-storable load		
	Shiftable load	Non-shiftable load	
		Curtailable load	Non-curtailable load
Electric vehicles *Cooling*	*Laundry* *Cement mills*	*Lighting* *Steelmaking*	*Lighting* *Television*

Suggestion of simplification

First of all, since our interest are loads suitable for DR, we remove the non-curtailable loads to distinguish storable from shiftable loads. The nuance is subtle though since the result of changing the consumption of those loads is the same, that is to say, their electricity consumption is shifted over time. The difference lies behind the storability of end-uses, as the following examples illustrate. For electric vehicles, the battery is actually a storage of electricity, and for cooling there is a storage of thermal energy through the thermal inertia of the building. When it comes to shiftable loads, the storage is more subtle. Doing a laundry can wait until tomorrow, because clothes are stored in a laundry basket. When the clinker gets out of the cement kiln to go into the cement mill that will eventually grind it into cement, the cement mill can be shut down for a while without harming the entire production line, because the clinker can be stored in between the two processes. We see that no matter the sort of storage lying behind the end-use, the result is a shift of the load consumption over time. Regarding the integration of DR in electricity markets, this distinction is not necessary. Also we will prefer the term load-shedding instead of curtailable loads and we add a second axe of categorisation which is the consumer class. We eventually end up with the classification presented in **Table 1.3**, accompanied by a few examples.

Table 1.3 – Classification of end-uses suitable for Demand Response

	Load-shifting	Load-shedding
Residential consumers	*Heating* *Cooling* *Laundry*	/
Tertiary consumers	*Heating* *Cooling*	*Lighting*
Industrial consumers	*Cement mills*	*Steelmaking*

1.4.1 Load-shedding

When we refer to load-shedding we consider usages whose electricity consumption will never be recovered. Therefore, load-shedding implies a net energy cut for the consumer. This also means that load-shedding is disruptive, be it because of a loss of comfort when it concerns tertiary and residential consumers, or a loss in the production output for industrial consumers. To compensate these losses, a high remuneration has to be given to end-users. Put another way, consumers would decide to shed these usages when the market price is very high. Adopting the technological view, it means that load-shedding has a very high variable cost. Up to now, only industrial consumers have been used to provide load-shedding on a voluntary basis. Previous DSM programmes and current DR practices have implemented load-shedding among industries essentially because these programmes were reliability oriented, necessitating large customers. Here are some examples provided by Gils (2014):

- Electrolytic primary aluminium
- Electrolytic refinement of copper
- Electrolytic production of zinc
- Steelmaking in electric arc furnaces
- Chloralkali process

The extent to which tertiary and residential consumers can technically or are willing to provide load-shedding is unknown. Nevertheless field studies such as pilot and demonstration projects are bringing more and more knowledge about the ability of residential and tertiary consumers to shed their load. One example can be cited: in California some DR programmes enabled to slightly reduce lighting consumption in commercial buildings (Borenstein, Jaske, and Rosenfeld 2002). Still we believe that load-shedding within these sectors are not a priority, given the substantial potential to be exploited with regard to load-shifting. Moreover the study about the theoretical DR potential in Europe carried out by Gils (2014) shows no potential for load-shedding neither in the tertiary nor in the residential sector.

1.4.2 Load-shifting

With load-shifting, consumption is either anticipated or postponed. Theoretically there is no loss of energy and every usage curtailed at one moment should be recovered. Although it could be inconvenient for a household to change its habits or for an industrial company to change its original production plan, load-shifting is supposed to be not disruptive. Thus load-shifting is activated at a low variable cost. As this appellation suggests, load-shifting aims at smoothing out the load curve, following a very simple strategy which is to stop consuming when the market price is high in order to recover this consumption on a low market price. This price arbitrage is beneficial for both the consumer and the system as long as the prices difference is higher than the variable cost of shifting the load.

End-uses suitable for load-shifting are ubiquitous. We can distinguish thermal loads from deferrable loads. *Thermal loads* provide a temperature level desired by the end-user. Shifting of thermal loads makes use of the thermal inertia of buildings or of appliances such that the end user comfort is not affected. Examples are heating and air conditioning in all sectors, cooling food manufacturing in the industrial sector, cold storages in the tertiary sector, electric storage water and refrigerators in the residential sector, etc. Thermal loads are probably the best suited loads to DR since they can be easily automatically interrupted, and providing that the thermal inertia is good, with almost no disturbance. *Deferrable loads* involve more consumer participation and awareness since they concern end-uses of which initial planned consumption has to be redo. In the residential sector they include for instance washing machines or tumble driers. Some industrial processes fall into this

category as well, like paper machines, wood pulp production and cement mills. Still in the industrial sector, but with no link to any production process, are the cross-technologies. An example of cross-technology is ventilation. A summary of electric loads suitable for DR with cost level indicators is proposed below:

Table 1.4 – Classification of end-uses suitable for Demand Response with cost level indicators

	Load-shifting	Variable cost	Load-shedding	Variable cost
Residential consumers	Thermal loads Deferrable loads	+ ++	/	
Tertiary consumers	Thermal loads Deferrable loads	+ ++	/	
Industrial consumers	Deferrable industrial processes Cross-technologies	++ ++	"Sheddable" industrial processes	+++

1.5 The role of aggregators and information and control technologies

Until now electricity consumers have been missing two essential technological supports to respond to energy market prices: *enabling infrastructures* and *enabling technologies*. Innovation in the information and communications technology (ICT) industry has lowered the cost of this new technological support, often refer to as *smart grids*. Smart grids can be defined as "electricity networks that can intelligently integrate the behaviour and actions of all users connected to it – generators, consumers and those that do both – in order to efficiently deliver sustainable, economic and secure electricity supplies"[5]. A direct and simple observation following this definition is that smart grids serve multiple purposes. As pointed out by Clastres (2011), "European countries have set targets for smart grids deployment" but "each country has its own view as to which market segment would gain most from smart grid". The splitting of smart grid value along the electricity value chain raises the question of whether a single actor may invest in such technologies. This is precisely the research question of this thesis to determine whether electricity markets provide enough value to DR in order to incentivise one single actor to invest in some smart grid technologies enabling DR. In principle this actor could be any agent on the demand-side, like the consumer himself or the retail supplier. However, it turned out that in many countries, *aggregators* have been playing a growing role. In the rest of this section we detail smart grid-based technologies enabling DR, that is to say enabling infrastructures and enabling technologies. We then briefly explain some issues faced by consumers regarding the adoption of these technologies, highlighting the growing role of DR aggregators.

[5] Definition given by the European Technology Platform for smart grids.

1.5.1 Enabling infrastructure and technologies

Enabling infrastructure

The activation of DR requires two essential functionalities which are (i) to communicate prices information to consumers and (ii) to measure electricity consumption at the same time granularity as prices variations. The enabling infrastructure providing these functionalities is often refer to as *advanced metering infrastructure (AMI)*. AMI covers "the entire infrastructure of meters, communication networks and data management systems required for advanced information to be measured, collected and subsequently used" (Haney, Jamasb, and Pollitt 2009). Several generations of AMI exist; the most advanced form of AMI is commonly called smart meter. AMI are thus the key component of every DR programmes because they are "indispensable to implementing time-varying pricing" (Batlle López and Rodilla Rodríguez 2009) and billing consumers consequently. In the US, DOE has been funding demand-side pilot projects where AMI are the central common element of all projects (DOE 2012). Regarding DR deployment, smart meters make the link between retail consumers and wholesale electricity markets. One can imagine a frame whereby consumers install a smart meter on their premise and adapt manually their electricity demand according to the dynamic-pricing tariff (reflecting wholesale market prices) they have opted for. A major issue arising with this scheme is disruptiveness for consumers because they have to manually modify their demand on a frequent basis (unless dynamic-pricing tariff does not vary often, but in this case we lost the opportunity to capture wholesale market prices variations). A way to mitigate this disruptiveness issue is brought by DR enabling technologies.

Enabling technologies

Enabling technologies cover a broad range of tools that mainly provide information, control and automation. An example of information technologies is in-home displays. Their role is for instance to inform consumers of a DR event, to display the current applicable tariff, etc. Any other communication channel informing consumers, such as web portals, text messages, or twitter feeds, is an information technology. Although smart meters enable as well to transmit the same information, they do not do it in a user-friendly manner (people are more used to checking their cell phones rather than their electrical meters). In summary information technologies are conceived to bring the AMI information to the consumer's attention. Control technologies are load control devices designed to automatically modify the consumption of the corresponding appliance. Examples are programmable communicating thermostats (PCT) designed to control thermal loads, and energy management systems controlling for instance the charging of electric vehicles batteries. Control technologies directly and automatically manage appliances consumption. Although possibly intrusive, they provide comfort to consumers engaged in a DR programme since they do not have to respond manually by themselves to

price signals. Besides, consumers can still override the control technology decision. Consumers' acceptance of control technologies is a challenge which must be opposed to disruptiveness of manually responding. Moreover, once the control technology has been set up (e.g. the temperature set point for PCT), it might cut off the corresponding appliance too frequently or too long if system conditions are very strained, ending in consumers overriding. Therefore it is crucial for the direct load control to also consider some sort of consumer's preferences. As outlined by Callaway and Hiskens (2011) "load control schemes must meet the dual goals of being fully responsive and non-disruptive". For a few years now, this challenge has been addressed by a new market entrant called an aggregator.

1.5.2 Demand Response aggregators

Definitions

Today in some American markets over 80% of DR volumes are provided by *independent aggregators* and similar numbers are observed in New Zealand, Western Australia and Ireland (SEDC 2017). As of 2017, DR aggregators are also commercially active in Europe, for example in Austria, Belgium, France, Germany, the Netherlands, and in the UK. They can be defined as follow: "An aggregator is a service provider who operates – directly or indirectly – a set of demand facilities in order to sell the flexibility available from pools of electric loads as single units in electricity markets. The aggregator – a service provider who may or may not be a retailer of electricity – represents a new role within European electricity markets" (SEDC 2017). In this definition, aggregation relates to a service that any agent could take up, especially the retailer, although in practice the role has been endorsed by new market entrants called independent aggregators. Interactions between the aggregator and the retail supplier should be settled with care, because the aggregator affects the volume of energy consumed by end-users under contract with the retailer. Since the consumer objective when participating in a DR programme is to lower down its electricity bills, DR aggregator and retailer businesses compete. This conflict only arises if the retail market is regulated, more precisely if supply retailers have the possibility to charge consumers a retail rate which will cover their wholesale market expenditure no matter what. Indeed in a competitive retail market, suppliers would seek to minimise their wholesale market expenditure in order to offer to consumers the most competitive retail rate. Therefore a competitive retail market incentivises suppliers to propose DR programmes to their customers, since load management is a way to reduce wholesale market expenditure.

Regardless of the question of who should take up the aggregator roles which is beyond the scope of this thesis (for analysis of those questions see for instance (Koliou 2016; Abdul Muhaimin 2015)), we must wonder how an aggregator could practically foster the integration and participation of end-users in today's electricity markets. Let us give another definition of the aggregator: an aggregator is "a kind of agent who collects and distributes necessary data and information from other market participants, especially consumers, acts as an intermediate between consumers and grid operators

(and/or suppliers) as well as provides DR capacity through contracts with consumers" (Prüggler 2013). The contractual approach thus seems an interesting option to explore.

Contract between the aggregator and consumers

The practical frame through which a DR aggregator may empower consumers is thus based on contracts. A general representation is proposed by **Figure 1.4**. The aggregator offers a range of N different types of contract. Each contract corresponds to a particular consumer class.

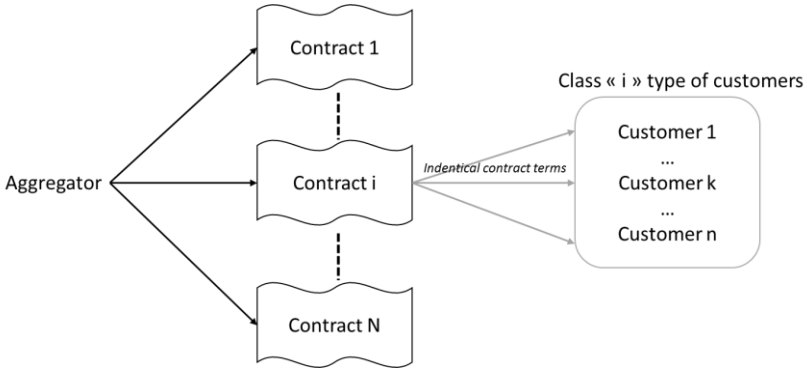

Figure 1.4 – Contract between consumers and the aggregator

Consumers' preferences drive to what class they belong to: we assume that all consumers belonging to the class "i" have homogenous preferences and similar consumption patterns. For every class the same high general contract terms are proposed (see **Table 1.5**). Taking consumers' preferences into account is highly important to empower them in a DR programme. It is in the interest of every stakeholder of the power industry that consumers' participation DR programmes be sustainable. A regularly observed effect in pilot demonstration projects is the phenomenon of attrition, or response fatigue (Cappers et al. 2013) which refers to recruited consumers deciding to leave the programme possibly because it has become too disruptive. Assuming the contract is well designed and respect consumers' preferences, DR activations are likely to be non-disruptive, resulting in a steady participation of consumers over time.

With respect to empowering end-users, the aggregator is a facilitator for DR. But it still has to meet the challenge of integrating DR into actual electricity markets. We claim that the aggregator facilitates this integration for at least three reasons:

- it opens the access to small consumers to wholesale markets,
- it releases the barrier associated with fixed retail rates,
- and, it invests in the enabling infrastructure and technology.

Table 1.5 – Contract terms between consumers and the aggregator

Contract terms	Units	Description
Load capacity	kW	Amount of power subscribed for DR
Price incentive (energy-based)	€/kWh	Financial compensation (for the aggregator: cost of activation)
Price incentive (capacity-based)	€/kW	Financial compensation (for the aggregator: penalty cost)
Duration of DR event	h	How long the end-use will be curtailed
Number of activations	n per period	DR activations allowed over a period, usually over a year
Time notice	h	Time period to notify the customer of an upcoming DR event
Time recovery	h	Maximum time to recover the amount of energy curtailed
Repetition	x per period	DR events allowed to be repeated over a short period, usually a few days or a week
Technology	-	What kind of enabling technology is installed on customer's premises

Access to wholesale markets

Wholesale electricity markets are made of different market places associated with different constraints for participants that hinder DR to be integrated in (Eid et al. 2015). These barriers are schematically represented in **Figure 1.5**:

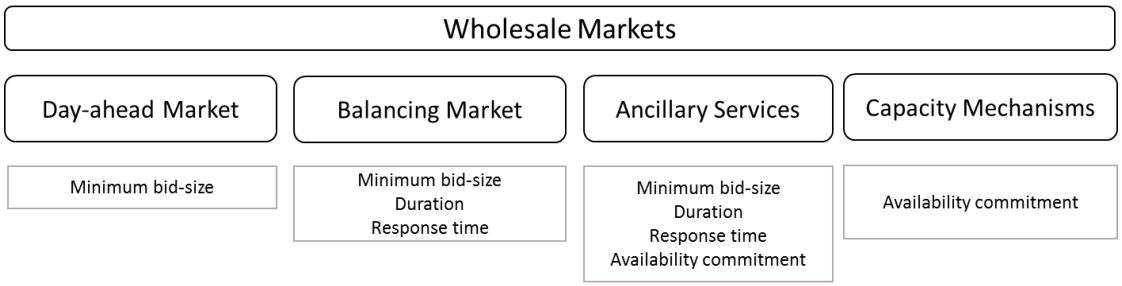

Figure 1.5 – Requirements for the participation in wholesale electricity markets

Balancing and ancillary services markets designs usually impose constraints such as minimum power capacity requirement, duration over which the capacity needs to be provide and fast response time. Through aggregation of loads, capacity and duration constraints can be satisfied since the aggregator provides a DR capacity and ensures that the demand reductions/increases last as long as required. Moreover if the aggregator has installed a control technology on consumers' premises, it can directly control the load activation on short notice. Therefore aggregation enables a reliable DR activation, opening DR to markets concerned with system reliability. Finally, as a business company, the aggregator's goal is to make of DR a sustainable and valuable product. Therefore it has interest in and

devotes time to look for valuation opportunities on every different market places, unlike small consumers who might not be interested in or capable of undertaking such an activity.

Retail rates barrier

As already mentioned, fixed regulated rates are seen as a major barrier to a price-responsive demand. Especially in the residential sector, implementation of RTP faces strong political aversion. No matter what the retail rate is, an aggregator can propose a remuneration scheme according to which its customers are financially compensated every time a DR event is triggered. Since the aggregator's business is to make benefits through wholesale market revenues, the activation of DR events are based on the wholesale market prices although consumers are not directly incentivised by dynamic-pricing.

Investment in the enabling infrastructure and technology

As outlined in section 1.5.1 an essential component needed to make load control non-disruptive for consumers are control technologies. Thus the DR aggregator should at least invest in this type of enabling technology, raising the question of the economic viability of such a product. The issue regarding the investment in the enabling infrastructure is broader since many other stakeholders have interest in smart meters deployment. Moreover metering infrastructure is owned by network operators. Metering can thus be a regulated activity, although two models co-exist in Europe: a regulated model and a liberalised model whereby metering activities are open to competition (Haney, Jamasb, and Pollitt 2009). Since DR cannot be properly deployed without an enabling infrastructure, the current status over metering activities leads us with two possibilities:

- either metering activities are opened to competition: the aggregator should then assess whether it is worth investing in smart meter, in addition to control technologies,

- or metering activities are regulated; the aggregator business would then depend on the Distribution System Operator (DSO) decision to install the enabling infrastructure; in this case data ownership and sharing issues have to be addressed.

1.6 Conclusion

Following the liberalisation of power industry, DR has referred to the result of engaging the end-use consumer in the electricity markets. Because of the various ways of practically implementing DR, multiple conceptions have emerged. This trend is outlined throughout DR dualities (price-based vs system-based, dispatchable vs non-dispatchable) that might no longer stand if we consider the emergence of ICTs along with DR aggregators. Enabled by smart technologies, the couple "aggregator-consumers" can provide DR either on a continuous basis on the wholesale energy market

or dispatch reliable demand-side resources on balancing, ancillary services and capacity markets. The extent to which this DR scheme performs is limited by the contractual arrangements between the aggregator and consumers. Based on consumers' preferences, these contracts are however crucial in order to durably engage end-users in DR programmes. Enabling technologies make the load control non-disruptive for consumers. The aggregator ensures DR to be fully responsive. The contract increases consumers' acceptance and durability. In the rest of this dissertation, DR will be studied throughout the DR aggregator framework just described. Note also that the scope of our study excludes any forms of back-up generation at the demand-side such as diesel generators. Two important questions need to be addressed:

- the acceptance of consumers regarding contracts and,
- the business viability of aggregators.

The first issue is quickly tackled in chapter 2 while the aggregator business case is in-depth analysed throughout the following chapters.

CHAPTER 2 DEMAND RESPONSE: EMPIRICAL EVIDENCE

2.1 Introduction

In Europe and in the United States (US), policy makers are supporting smart grid deployment by co-funding smart grid demonstration and R&D projects. In the US, the American Recovery and Reinvestment Act of 2009 has allocated around $3.5 billion to the Smart Grid Investment Grant programme (SGIG) intended for smart grid pilot projects across the country (Cappers et al. 2012; DOE 2017). In Europe, the European Commission supports the coordination platform "Smart Grid European Technology Platform" renamed "Smart Grids Forum" as of 2009, with the objective to provide funding to smart grid demonstration projects. Up to now the European Union has injected nearly €1.2 billion in smart grid projects over a total of €5 billion invested on the continent (Gangale et al. 2017). The reason of launching those small-scale pilot experiments instead of directly supporting a full roll-out of smart grid technologies is the uncertainty about the benefits resulting from a wide deployment. Consequently, field studies usually accompany those pilot projects in order to build up knowledge about how smart grid technologies should be implemented and to what extent their use could bring benefits to the different stakeholders of the electricity system.

One particular interest of smart grid demonstration projects is the understanding of how consumers use and value electricity. For instance under the SGIG, Department of Energy (DOE) has launched ninety-nine projects deploying smart grid technologies among which sixty-two investigate consumers' response and behaviours (DOE 2012). In Europe the trend is primarily to launch network-oriented and consumer-oriented pilots. Consumer studies have received increasing attention among academics and industries given the new opportunities offered by smart grid technologies. Their purpose is to better understand how electricity end-users would respond if they are provided with DR enabling infrastructure and technologies as defined in chapter 1 (AMI, feedback and control technologies). Within the overall landscape of smart grid pilots, these type of field studies are often called *consumer behaviour studies (CBS).*

Today, CBS face one important challenge: the lack of coordination and harmonisation between the different field trials conducted around the world, leading to misunderstandings results. Because they are often narrowly focused on very local issues, CBS have proliferated without any possibilities of results comparison and conclusions extension. As a result, global knowledge about how consumers use and value electricity is quite small compared with the number of demonstration projects that have been implemented. However, as illustrates the DOE's SGIG programme, efforts have been made for a few years in order to move forward the "collective understanding of how customers respond to electricity prices and how new control and information technology might enable

customers to obtain greater value from their energy services" (EPRI 2014). The Electric Power Research Institute carried out a synthesis work in order to state where our current knowledge stands and insists on the need to use homogenous methodologies and transparent reporting when a CBS is undertaken (EPRI 2012).

This chapter builds essentially on papers and reports published within the SGIG framework to explain in greater details what practical issues can actually lead to misleading results and conclusions. Along with the recommendations they advocate for we present an overview of the main findings gathered in "properly" implemented pilot projects. Our purpose is to shed light on DR empirical evidence we can rely on in order to take them into account in the evaluation of the DR aggregator business case. Recall the aggregator framework discussed in the Conclusion of chapter 1: we need to get insights about consumers' preferences if they are to participate in a DR programme in cooperation with an aggregator. By contracting with the aggregator, consumers' preferences translate into consumer-based constraints for the aggregator. CBS can help gathering useful information to construct these consumer-based constraints. Ideally we would get insights about:

- how electricity end-users respond to different type of dynamic-pricing,
- whether control technologies improve the response performance,
- whether end-users accept these new technologies, and
- non-price factors such as the maximum number of activations determine their participation and response.

In the next section we propose a quick overview over the behavioural research process applied to electricity consumers by detailing the working steps of a CBS, from the participants' recruitment to the results publication. Then we precise in section 2.3 what practical issues may compromise the robustness and reliability of results and what conditions are necessary to tackle these issues. Section 2.4 outlines DR empirical evidence arising from reliable CBS, with a focus on those conducted in the US, in Europe, and in France.

2.2 A brief introduction to behavioural research applied to the electricity consumer[6]

CBS aim at improving the understanding of electricity consumers' behaviour. They rely upon field trials, or pilots, which are projects into which some electricity consumers, called *participants*, are enrolled and subjected to a set of inducements designed to modify their electricity demand. These incentives are called *treatments*. Although they are not exclusively targeted to households, CBS have primarily focused on small residential consumers. CBS are led according to three critical stages:

[6] This section is largely based on (Cappers et al. 2013), an article presenting analysis protocols for measuring the effects of different treatments on consumers' usage of electricity.

- the experimental stage,
- the analysis stage,
- The reporting stage.

Figure 2.1 schematises the global process.

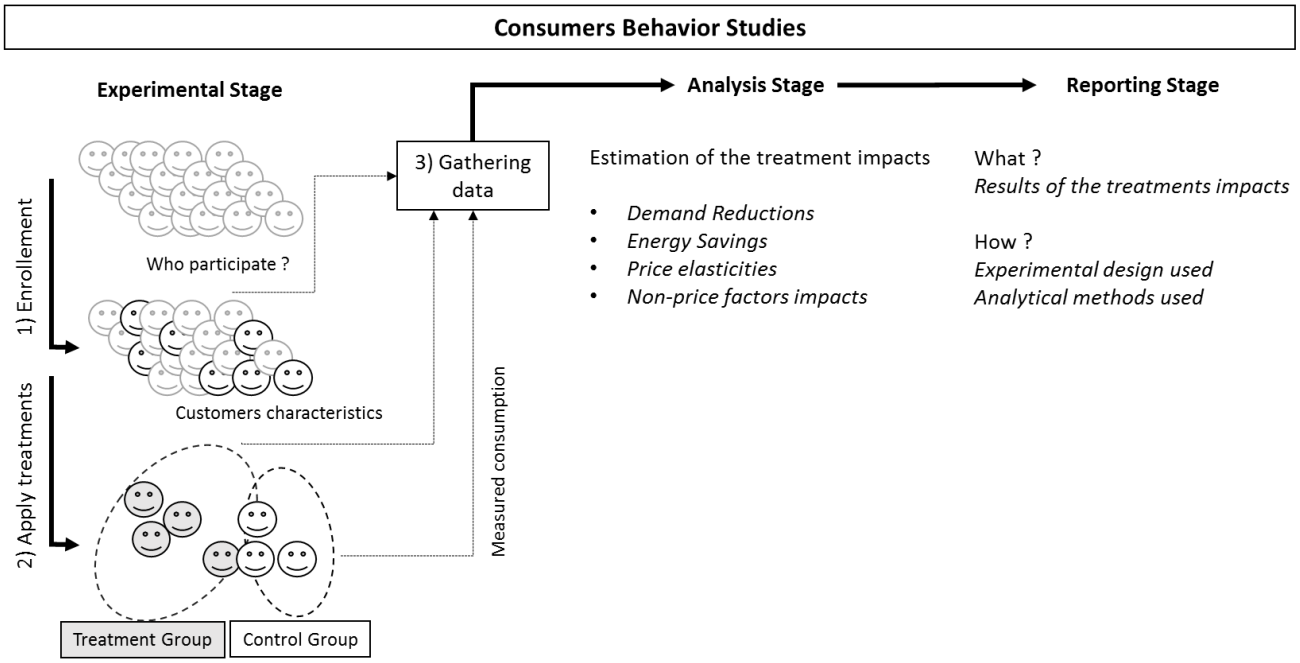

Figure 2.1 – A schematic description of behavioural research process

2.2.1 Experimental stage

The experimental stage can be broken down into three sub-stages: enrolment of participants, choice and application of treatments on participants, and data collecting. In order to build the sampling that will be used all along the study, electricity consumers are randomly offered to participate into the pilot through different sort of recruitment campaigns. Since the recruitment is rarely, if never, mandatory, two options can be proposed: *opt-in* or *opt-out* enrolment. With the opt-in approach, consumers volunteer to join the field trial, while opt-out means they are enrolled by default, but with the option to leave the project afterwards. The choice of opt-in versus opt-out involves policy and consumers' acceptance issues (DOE 2013). Recruited consumers are then randomly assigned to two different groups: the *treatment group* and the *control group*. Participants within the treatment group will be incentivised with different sort of inducements while participants within the control group will not. Electricity consumption measured on the control group participants serves to build the *reference load* which is counterfactual, i.e. an estimation of what the usage would have been absent any treatments. The way participants are recruited and assigned to the groups determines how samplings that will

serve for the entire study are built. Recruitment process, group assignment and sampling define what we call the *experimental design*. The experimental design is crucial in order to ensure the scientific validity of the study. We will go back to this point in section 2.3. Three types of treatments are usually tested: time-based rates, feedback mechanisms and enabling technologies. **Figure 2.2** gives some examples for each sort of treatment.

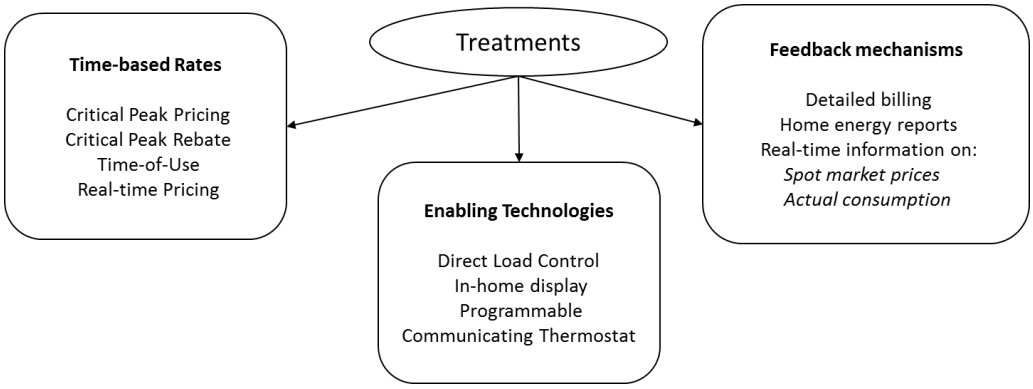

Figure 2.2 – Typology of treatments applied to the treatment group

In addition to this, *non-price factors* can be associated to time-based rates, including the following: duration of events, number of activations, advance notice, frequency, repetition, etc. Note that they represent the contract terms between the aggregator and its customers proposed in section 1.5.2 of chapter 1. In a last step, data are gathered. Data include consumption levels but also sociological information regarding who participate and other characteristics such as premises type and dimension.

2.2.2 Analysis stage

In the analysis stage, gathered data is used to evaluate the global field trial impact. A complete evaluation of a trial should include three levels of analysis (EPRI 2012). The first level deals with *participation*: who decide to participate, what is the recruitment rate? The second level is related to *performance*: how do participants respond once they are on the trial, what is the impact of treatments on electricity usages? The third level analyses *persistence*: how do participation and performance change over time, is there an attrition phenomenon?

Different metrics are used to tackle these questions. For instance, to answer the question of the time-based rate impact on electricity consumption, two metrics are usually employed: *load impacts* and *price-elasticities*. To answer the question of the control technology impact on a consumers response, loads impacts and/or price-elasticities can be compared between participants who do not have the technology with those who have it. To get knowledge about consumers' acceptance of enabling technologies, *recruitment rates* can be compared between offers including a technology with offers free of technology. Load impact measures the load reduction percentage following the application of a treatment or a combination of treatments. Two types of price-elasticities exists: *own-*

price elasticity and *elasticity of substitution*. Own-price elasticity is defined as "the percentage change in electricity usage during some period of time that results from a 1% change in the price of electricity during that same period of time" (Cappers et al. 2013). Elasticity of substitution "quantifies load shifting between time periods within a day; it is defined as the percentage change in ratio of the peak to off-peak electricity usage resulting from a 1% change in the ratio of off-peak to peak electricity price" (Cappers et al. 2013). Recruitment rate is defined as the percentage of requested people who eventually decided to participate in the pilot.

2.2.3 Reporting stage

The reporting stage communicates the results willing to be presented by the different stakeholders of the project, along with the methodologies used to estimate the different impacts, as well as the experimental design of the trial.

2.3 Challenges identified in consumers behaviour studies[7]

Most of field studies have come up with positive results regarding their performance, claiming for instance that electricity consumers do respond to time-based rates, that price-elasticities are significantly different from zero, that control technologies improve the response, etc. These studies however show a wide range of values leading to a lack of confidence in the results simply because the reader has no clue on what value to rely on. As mentioned in the introduction, this proliferation of misleading field studies does not help in building a sound knowledge about how consumers use and value electricity. In this section we outline what specific challenges CBS must overcome in order to provide reliable results and conclusions.

2.3.1 Bad experimental designs

The choice of the experimental design is essential: it guarantees the validity of the study. An *internally valid* study ensures that "the estimated impacts were caused by the treatment being evaluated". An *externally valid* study means that "the findings can confidently be extrapolated to a larger population of interest". To guarantee the external and internal validity of a study, there is only one possible experimental design: the *pure randomised control trial (pure RCT).* The first step of a pure RCT is to randomly select consumers from the population of interest. The second step is to randomly affect them either to the control or the treatment group, with no possibility to refuse, to drop or to opt-out the trial. With such an experimental design there is no selection bias, and reference loads are constructed in a way which enables "direct comparisons of differences in outcomes across treatment and control groups and the estimated treatment effects are unbiased". Unbiased estimated treatment effects ensure the internal validity of the study. No bias selection provides its external validity. Nevertheless, such a

[7] This section is largely based on (EPRI 2012) and (Cappers et al. 2013).

mandatory approach is never used. Alternatives is then to resort to *randomised control trials (RCT)* and *randomised encouragement design (RED).* RCT encourage consumers from the population of interest to sign up for the trial, then some of them decide to participate and others refuse: at this moment there is a selection bias. Because the estimated impacts are assessed only on a group of volunteers, we cannot extend the conclusions of the study to the entire population of interest: there is no external validity. Nevertheless the internal validity is preserved. Regarding RED, the same conclusions apply. The difference with RCT is that the selection bias occurs later on the recruitment process: consumers are first randomly assigned to one of the groups; they are then informed of the process and left with the choice to either stay in or drop out the trial. Any other kind of experimental designs would very likely produce a biased estimation of the effects being tested, meaning the study has no internal validity.

2.3.2 Implementation issues

Once the pilot has begun many problems can impede the rest of the study. These issues include for instance: too few participants leaving the project with sample size too small to be statistically relevant, equipment problems (e.g. smart meters not being delivered on time), loss of or insufficient data, not properly collected data, etc.

2.3.3 Lack of transparency in the reporting

Confidence in reported results crucially depends on whether the entire process that has led to these results is publicly available. In some studies the methodology can be missing. Experimental designs and other methodologies that were used should be reported in detail. **Figure 2.3** sums up the challenges presented above.

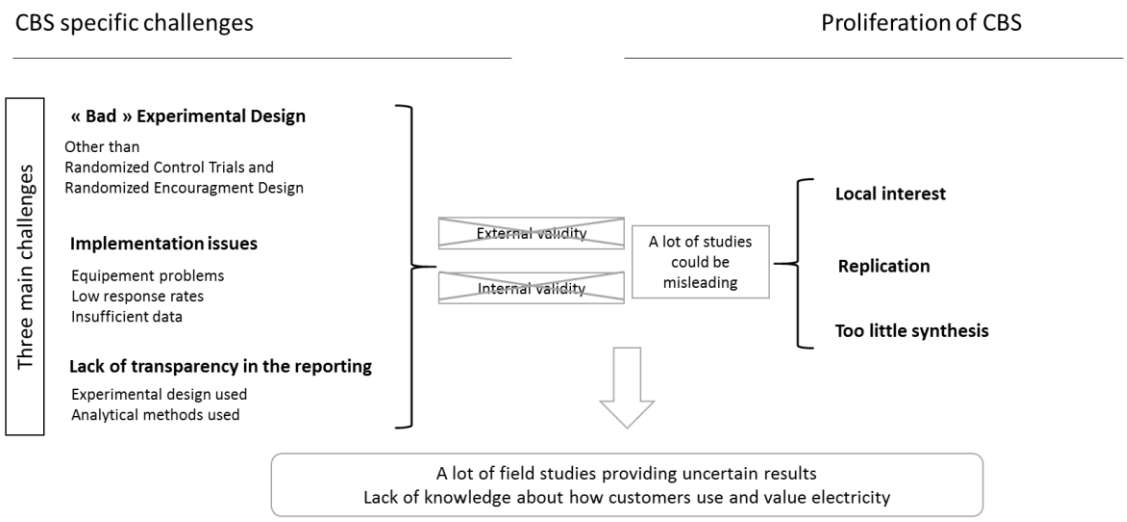

Figure 2.3 – Challenges of consumer behaviour studies

In order to take up these challenges and avoid the duplication of misleading field studies, the EPRI (2012) suggests 6 criteria that any CBS should met:

- Involve new ICTs
- Involve a substantial scale and scope
- Employ a rigorous experimental design
- Analyse non-price factors
- Provide detailed information about the design, implementation and evaluation in publicly available reports
- Report comprehensive metrics

In the next section, we present results and conclusions from CBS that meet the aforementioned criteria.

2.4 Demand Response empirical evidence from consumer behaviour studies

Within the scope of SGIG programme, the EPRI has published reports highlighting quantitative empirical evidences from reliable CBS (see for instance (EPRI 2012) and its updated version (EPRI 2014)). Projects presented in these reports were field trials implemented mainly in the US, but also in Europe (one in the UK and one in Ireland). It is worth noting that in France, as far as we know, there have been no demonstration projects that publically delivered such detailed quantitative results. It is also hard to find information about the experimental design used and the treatments tested. The CityOpt project, a pilot implemented in Nice, has produced an extensive report explaining the process of recruitment as well as the analysis protocols, but neither comprehensive metrics such as peak load reduction or elasticities, nor very great details about the treatments used are provided. Likewise, other pilots completed in France thus far, such as ENR-Pool, GreenLys, Modelec, Nice Grid, RéFLexE, Smart Electric Lyon, and TBH Alliance only came up with high-level qualitative conclusions (in terms of public deliverables). This is mainly due to confidentiality issues required by private stakeholders involved in the projects.

The following paragraphs aim at presenting key findings of the two EPRI reports. In addition to this, although French field trials have not published results with an equivalent level of details, we will include findings from studies carried out in France whenever it is possible. To do so we essentially rely on the ADEME[8] report (Berthollon, Kerouedan, and Regner 2016) but we also include information gathered in dedicated pilot projects websites.

[8] Agence de l'Environnement et de la Maîtrise de l'Energie

2.4.1 Impact of time-based rates

To illustrate this impact, we selected three American pilots, one British and one Irish, all of them being focused on the residential sector. Elasticities and peak load reductions are shown in **Table 2.1** for different time-based rates. For further information, refer to (EPRI 2012). CA-SPP and CL&P projects also included commercial and industrial consumers in their studies (**Table 2.2**). Note that the values for commercial and industrial consumers are smaller than for residential ones. EPRI outlines that we "clearly need more studies before we know what drive these types of customers to respond to dynamic-pricing". In France, the Smart Electric Lyon pilot reports peak load reductions ranging between -5% to -30% for residential consumers (Berthollon, Kerouedan, and Regner 2016), which is consistent with American studies notwithstanding the large range of values. All pilots show that consumers respond to time-varying pricing. The bigger effect arises from CPP although peak time rebates (PTR)[9] have similar level performance. TOU impact is lower, especially in terms of peak load reduction.

Table 2.1 – Elasticities and load reduction for three types of time-based rates in the residential sector (EPRI 2012)

Project name and location	*Own price elasticity*[10]			*Elasticity of substitution*[11]			*Peak load reduction (%)*		
	CPP	PTR	TOU	CPP	PTR	TOU	CPP	PTR	TOU
BG&E (US)	-0.04	/	/	0.10	0.10	/	-20	-20	/
CA-SPP (US)	-0.03	/	/	0.09	/	/	-13	/	/
CL&P (US)	-0.03	-0.03	0	0.08	0.05	0.05	-16	-11	-3
SSE (UK)	/	/	/	/	/	/	/	/	[-1.5;-2.5]
Nation-wide (Ireland)	/	/	-0.07	/	/	/	/	/	-8.8

If we take the example of the BG&E project, the application of CPP leads to a diminution of 20% of the peak demand. And if the CPP tariff is raised of 1%, the demand falls of 0.04% during the same CPP event (own-price elasticity). This value is quite low compared with the elasticity of substitution. This means that residential consumers are more disposed to anticipate and postpone their consumption rather than react to the current tariff raise.

[9] Peak time rebates reward consumers with lower rates if they reduce their demand during a peak event.
[10] Short-term own price elasticity, as defined in section 2.2.2.
[11] Elasticity of substitution between different hours (generally peak and off-peak), as defined in section 2.2.2.

Table 2.2 – Elasticities and load reduction for three types of time-based rates in the tertiary and industrial sectors (EPRI 2012)

Project name and location	*Own price elasticity*			*Elasticity of substitution*			*Peak load reduction (%)*		
	CPP	PTR	TOU	CPP	PTR	TOU	CPP	PTR	TOU
CA-SPP (US)	/	/	/	[0.03; 0.06]	/	/	[-5;-7]	/	/
CL&P (US)	/	/	/	0.02	0.00	0.00	-3	0	0

2.4.2 Impact of control technologies

To assess the impact of enabling technologies such as control technologies, we compare the elasticities and load reductions with and without technologies. As shown in **Table 2.3**, technologies always improve the response level of consumers, except for TOU. In many French trials, a general qualitative conclusion regarding this topic is that control technologies and/or direct load control appeared to be a key factor of success for the activation of DR.

Table 2.3 – Impact of control technologies on price elasticities and load reduction in the residential sector (EPRI 2012)

Project name and location		*Own price elasticity*			*Elasticity of substitution*			*Peak load reduction (%)*		
		CPP	PTR	TOU	CPP	PTR	TOU	CPP	PTR	TOU
BG&E Res (US)		-0.04	/	/	0.10	0.10	/	-20	-20	/
	with tech	/	/	/	0.18	/	/	-33	-31	/
CA-SPP Res (US)		-0.03	/	/	0.09	/	/	-13	/	/
	with tech	/	/	/	/	/	/	/	/	/
CL&P Res (US)		-0.03	-0.03	0	0.08	0.05	0.05	-16	-11	-3
	with tech	/	/	/	0.13	0.10	0.05	-23	-18	-3

Table 2.4 – Impact of control technologies on price elasticities and load reduction in the industrial and commercial sectors

Project Name and Location		*Own price elasticity*			*Elasticity of substitution*			*Peak load reduction (%)*		
		CPP	PTR	TOU	CPP	PTR	TOU	CPP	PTR	TOU
CA-SPP C&Indus (US)		/	/	/	[0.03; 0.06]	/	/	[-5;-7]	/	/
	with tech	/	/	/	[0.08; 0.09]	/	/	[-13;-10]	/	/
CL&P C&Indus (US)		/	/	/	0.02	0.00	0.00	-3	0	0
	with tech	/	/	/	0.04	0.03	0.00	-7	-4	0

Consumers' acceptance of control technologies

In all CBS reviewed by the EPRI, control technologies improve consumers' response. If they were perceived as intrusive by participants, direct load control would have been overridden. Therefore it seems that consumers accept control technologies once installed. Moreover, many pilots in France (Modelec, GreenLys and Nice Grid) show that only 5% of residential participants override a DR event when directly activated by control technology. Nevertheless we cannot drawn definitive conclusions at this point. In the US, FirstEnergy's pilot exhibit an acceptance rate of only 10.3% for control technology (EPRI 2014), underlying an ex-ante aversion regarding these technologies.

2.4.3 Impact of non-price factors

Non-price factors are features accompanying a DR event, like time notification, duration, frequency and maximum number of DR activations. We do not know much about how these non-price factors might affect consumers' willingness to participate in a DR programme and their willingness to respond. Some observations can be done though.

Time notification, duration, and maximum number of events

In France, Smart Electric Lyon observes that advising consumers of a DR event in advance increases the acceptability of the programme**.** The same pilot estimates that a 2 hours cut-off of electric heating system implies a 1°C decrease in the temperature room, while a 1 hour cut-off produces only a 0.2°C decrease which is imperceptible in terms of loss of comfort. Nevertheless we do not have any precision about the level of premises insulation so we cannot infer whether a 1 hour interruption would always produce such an insensitive drop of temperature. The pilot "RéFLexE" tested interruptions of 30 minutes, 2 hours, and 4 hours on the tertiary sector, but no significant conclusions have been drawn about participants' satisfaction. Still in France, ENR-Pool activated DR events lasting between 30

minutes and 3 hours to industrial consumers. When it comes to the maximum number of events, no evidence can be emphasised. Usually, numbers tested are 10, 20, 40 or even more per year. For instance in France, the ENR-Pool pilot proposed 10 activations per year at maximum, for industrial consumers. The American pilot OG&E Positive Energy Together applied 46 critical events on residential participants and 60 on commercial participants over one year (EPRI 2014).

2.5 Conclusion

The goal of this chapter was to challenge with empirical evidence the DR aggregator framework established in chapter 1. Empirical evidence supports relatively well our proposed DR aggregator framework, especially regarding consumers response to dynamic-pricing and performance of control technologies. First, most field trials implemented worldwide have concluded that consumers actually respond positively to any kind of price or financial incentives the aggregator may offer to them. Second, empirical evidence shows that control technologies improve substantially the response of consumers. Moreover once installed on consumers' premises it seems that they are well accepted and used. However we do not know much about the ex-ante acceptance of these technologies. It seems that only a small part of end-users are willing to install a control technology on their premises. Improving the acceptability of such technologies might thus be a concern for the aggregator. A third important point concerned non-price factors. Non-price factors represent other consumers' preferences which are included in the contract terms. Therefore, it was of our interest to get from field studies what these preferences are. However this knowledge remains relatively weak and CBS have not drawn satisfying conclusions regarding this topic. Nevertheless, we still have a range of value for duration and maximum number of activations that are usually tested in field studies. We can use those as parameters in the model developed to quantify the economic value of DR. This modelling framework will now be described in details in the following chapters.

PART II – MODELLING FRAMEWORK

CHAPTER 3 DEMAND RESPONSE MODELLING APPROACHES: A LITERATURE REVIEW

3.1 Introduction

The analysis of DR performance is tackled by a rich literature featuring several modelling approaches. In most academic papers, DR is generally integrated as a module into a broader modelling framework developed for the purpose of the study. For instance, unit commitment models with an inclusion of DR as a key component have been used to estimate the role of DR on power system reserves requirement. While the global model DR is included in often determines the resulting DR modelling approach, different DR representations can be found in models aimed at addressing similar issues. Conversely, identical DR representations can be used across models built for different purposes. Whatever the modelling choice, one has always to find a compromise between the degree of accuracy of the chosen representation and the tractability of the model. In this thesis, we have developed an optimisation model minimising the operating cost of generation units, among which DR technologies are represented as storage facilities. The model is linear, stochastic and features several time periods, such that it is formulated as a multistage stochastic linear problem. Before going to the model presentation in chapter 4, we provide here a literature review which justifies our approach.

In the literature, three categories of modelling techniques for DR are commonly found: (i) *physical models*, (ii) *demand function models*, and (iii) *negative generation models*. Physical models are focused on the demand-side of the power system. They are thus the most detailed and accurate models in terms of load behaviours representativeness. However they fail to assess the mutual feedbacks between DR and the supply-side of the power system, and when they attempt to do so, the resulting *integrated model* become costly to solve. On the contrary, demand function and negative generation models are included into power system models such that interactions between demand and supply are accounted for. A drawback of demand function models is the lack of representation of technical constraints inherent to the activation of DR. Negative generation models tackles such a technical representation, which is why we have opted for this approach. Negative generation models exploit the similarities between DR and the behaviours of electric storages. Therefore, we have raised our attention on stochastic models, since a sound and realistic assessment of storages value necessitates to account for uncertainty sources inherent to power systems. Otherwise, in a deterministic setting, storages are overvalued (Mokrian and Stephen 2006).

We should note that Bruninx et al. (2013) provide a literature review comparable to the one presented in this chapter. However their attention is eventually held by the need for integrated models while we raise the importance of stochastic models. The interested reader can also refer to

Papavasiliou and Oren (2014) for a literature review with a focus on DR integration in unit commitment models, and to De Jonghe, Hobbs, and Belmans (2011) for a review of long-term planning models incorporating DR.

3.2 Physical models focused on the demand-side of power systems

3.2.1 Principle and scope

Physical models are used to analyse the effects of a DR programme on a particular end-use of electricity or on a demand-side technology. The scope of physical models is the demand-side technology of which a very precise level of representation is proposed. For instance, consumers' behaviour, temperature evolution inside dwellings, effects of weather conditions, etc., are usually endogenously modelled through equations that dictate the physics of the electric load. The purpose of physical models is often to demonstrate whether the demand-side technology/end-use is a good candidate to provide DR or not. The model can test the reaction of a given demand-side technology to an exogenous dynamic-pricing incentive while accounting for all constraints related to the level of service (of the modelled end-uses) commensurate with consumers expectations.

3.2.2 Articles

Stadler (2008) evaluates the technical potential in Germany of thermal electric and deferrable loads suitable for DR by simulations of temperatures evolution. Thermal loads encompass storage heating, ventilation systems, refrigeration, water heating systems, CHP, and heat pumps with thermal storage. Chassin and Fuller (2011) model the load behaviour of thermostatic heating devices in order to understand the impact of the load diversity on the efficiency of a set of DR programmes. Ali et al. (2014) model a house thermal behaviour to optimise the response of direct electric space heating and partial thermal storage with regard to pre-determined dynamic prices. Mathieu et al. (2013) evaluate the wholesale market prices arbitrage value of aggregated residential thermal loads. The authors assume that the resulting DR is small enough to not affect market prices: the optimisation problem thus minimises the cost of buying electricity on the wholesale market assuming exogenous prices. Everett and Philpott (2004) study the industrial sector and determine the optimal scheduling of mechanical pulp production with regards to uncertain exogenous electricity prices. Materassi et al. 2014) analyse the optimal response of an individual consumer with deferrable demand to exogenous stochastic prices.

3.2.3 Computational challenge

Due to computational complexity, it is challenging to connect physical models with a power system model. For this reason all of the aforementioned models assume exogenous market prices. Interactions between supply and demand are thus not captured. Nevertheless a number of studies have performed integrated simulations taking into account feedbacks between supply and demand at the

power system level. Let us mention Bruninx et al. (2013) who propose an integrated approach combining both a physical model of electric heating systems and its feedback onto power system operations through a unit commitment and economic dispatch model.

Integrated models could have been an appealing option with regards to the scope and the purpose of our thesis, since they enable to identify the effects of integrating DR in electricity markets. Yet, our research questions led us to dismiss this solution. Firstly, we intend to study the integration of large scale DR, which means that the scope of our thesis covers an extended range of DR technologies. We would not have been able to develop as many physical models as required to cover all DR technologies. Secondly, an economic assessment of DR as realistic as possible requires to take into account uncertainties that are inherent to all power systems. This involves the formulation of stochastic optimisation problems that are already computationally demanding to solve, even with more simplified DR representations. Therefore we eventually choose to restrict our modelling options on either the demand function approach or the technological representation (DR as negative generation) that are presented in the next section.

3.3 Demand function models

This section describes a first stream of modelling options allowing to easily integrate DR in a power system model. These papers assume that a certain share of electricity consumers is price-responsive. They build a linear demand function around price elasticities values. As mentioned in chapter 2 section 2.2.2, two types of elasticity exist: own-price and cross-price elasticities.

3.3.1 Own-price elasticity studies

The demand function approach with single own-price elasticities is well suited to study the effect of switching from flat tariffs to dynamic-pricing structures. Such a question is for instance analysed by Borenstein and Holland (2003), Joskow and Tirole (2006) and Joskow and Tirole (2007). Furthermore, Léautier (2014) builds on the same approach to derive optimal share of smart meters and real-time pricing deployment in the French power system. Demand functions are also used by Madaeni and Sioshansi (2011) but with different motivations: the authors use a stochastic unit commitment and economic dispatch model to analyse the potential of DR in mitigating wind power uncertain generation.

3.3.2 Cross-price elasticity studies

Considering only own-price elasticities neglects the shifting potential characterising certain electricity consumption tasks. Load-shifting can be represented by an elasticity matrix as it considers cross-price elasticities. Within an elasticity matrix, columns and lines represent time periods (e.g. hours), and the value situated on line i and column j is the cross-elasticity associated to the shift of demand from hour

i to hour j. Values on the diagonal represent own-price elasticities, that is to say the pure demand decrease (or increase) resulting from the price level at a given moment. Aalami, Moghaddam, and Yousefi 2010) and Moghaddam, Abdollahi, and Rashidinejad (2011) make use of elasticity matrixes to analyse the performance of various DR programmes. De Jonghe, Hobbs, and Belmans (2011) develop a long-term investment model with the inclusion of a DR representation through an elasticity matrix.

3.3.3 Lack of accuracy to represent Demand Response technical constraints

Although elasticity matrixes improve the DR representation by integrating cross-price elasticities, it remains a too simplistic way to model DR accurately since technical characterisation is absent. As examples of shortcomings of this approach, let us mention that elasticity matrixes cannot capture the fact that some DR processes or appliances have capacity and energy related constraints, stating that only a limited amount of power can be curtailed during a limited amount of time. Moreover, elastic demand functions ignore the effect of external factors such as outdoor temperature on the availability of DR capacity. O'Connell et al. (2014) insist on this point: "Demand Response is very poorly represented in the form of an elasticity matrix and more detailed modelling is required to achieve a realistic representation of its capabilities". A solution towards this more realistic representation is brought by assuming that DR behaves like a system resource with negative output, which is the point developed in the next section.

3.4 Negative generation units models

3.4.1 Principle

A second stream of studies assumes that decreasing the power demand is equivalent to increasing the power generation. From the system operator point of view, DR can thus be viewed as a virtual generator with negative output, as explained in section 1.3.2.2 of chapter 1. The logical ensuing question is about the appropriate representation to use. Papavasiliou and Oren (2014) argue that "many flexible consumptions tasks are best characterised as deferrable, in the sense that consumers need a certain amount of energy within a certain time window. As such deferrable demand behaves much like a hydro or storage resource from the view point of the system operator". In essence, load-shifting thus mimics the behaviour of a storage facility. Regarding load-shedding, a direct comparison can be done with a peak power plant. Nevertheless this approach disregards the energy constraint associated with load-shedding, which stipulates that the usage cannot be shut off beyond a certain time period. Given this constraint, load-shedding is more appropriately represented by a hydro power plant with a single reservoir. Modelling DR as a storage makes it easy to integrate it in an optimisation model minimising system-level costs. As outlined in the following articles presentation, the model can be linear, non-linear, deterministic or stochastic, depending on the purpose of the study.

3.4.2 Articles

Papavasiliou and Oren (2014) develop this modelling approach for load-shifting within a stochastic unit commitment and economic dispatch model. The model is a two-stage optimisation problem whereby first-stage decisions are conventional generators and DR commitments, while second-stage decisions concern the economic dispatch. The economic dispatch is done for one day with an hourly resolution. The model is used to compare the performance between different DR control paradigms (centralised vs decentralised RTP; centralised vs coupling with renewables). Zerrahn and Schill (2015) propose a similar DR representation, yet more refined than Papavasiliou and Oren (2014) within a dispatch and investment model. A cost minimisation is performed over a full year with 8760 hours. The model is used to evaluate storages and DR requirements in the context of large scale deployment of renewable energy. A case study on Germany is provided. Unlike Papavasiliou and Oren (2014), the model features a deterministic setting. Steurer et al. (2015) use the fundamental model E2M2s, standing for "European Electricity Market Model stochastic version", in order to evaluate the economic potential of DR in Germany. DR is modelled as a storage with negative output as explained in Steurer et al. (2014). The scope of DR technologies is wider than in Zerrahn and Schill (2015), since the study covers specifically all DR technologies across industrial, commercial and residential sectors, whereas Zerrahn and Schill (2015) only distinguish generic DR processes through their duration (i.e. the maximum consecutive number of hours a process can be shifted or curtailed). Segmentation used by Steurer et al. (2015) enables to include a temporal availability constraint for each process technology (i.e. when the DR capacity is available). This exhaustive DR representation is integrated into the stochastic optimisation model E2M2s which captures unit commitment, economic dispatch and long term planning. The optimisation is executed with an hourly resolution over a one-year period. To tackle such a computational challenging programme, the optimisation is myopic. Myopic optimisation models consist in decomposing the problem horizon "to a sequential decision making process with a moving time window" (Poncelet et al. 2016). Formally, the model employed here is thus not stated as a multistage stochastic problem that would have more accurately represented the decision making process regarding for instance, DR activations over the entire year. Indeed, a multistage formulation ensures that all decisions made across the horizon problem are inter-related. More concretely a multistage formulation suggests that the decision to dispatch a DR technology at a given time step affects the possibility to use the same DR technology afterwards. Instead, the authors have chosen to consider reserve commitment, dispatch, and investment decisions in their model formulation. A model capturing such a complete view in terms of DR valuation opportunities would have probably be intractable if implemented as a multistage stochastic programme. Papavasiliou, Cambier, and Scieur (2015) study the large scale integration of DR within such a stochastic multistage problem. The model is an economic dispatch under uncertainty. They examine the possible benefits to

use the DR potential in Germany for balancing the variability and uncertainty of renewable energy production. The paper also analyses and compares performance of different DR programmes (RTP, TOU and interruptible service). To solve the model, they use the *Stochastic Dual Dynamic Programming (SDDP)* method developed by Pereira and Pinto (1991). As explained by the authors, SDDP is an algorithm "originally developed for solving the monthly hydrothermal planning problem" and the model they propose is "the short-term analogue (daily horizon with hourly time steps) of the medium-term planning model proposed by Pereira (annual horizon with monthly time steps)".

3.4.3 Importance of stochastic models

Among the four reviewed models, three feature a stochastic setting. Since DR is therein modelled as a storage (for load-shifting) and as a hydro power plant with a single reservoir (for load-shedding), taking into account the uncertainty arising for instance from the wholesale residual demand is of high importance. Indeed, the optimal bidding strategies of storages and water releases from reservoirs are easy to determine within a deterministic setting. Under perfect foresight the value of a storage is thus an upper bound on its real value. (Mokrian and Stephen 2006) provide a comparison between the valuation of electricity storages assuming perfect foresight and under uncertainty. Any models that address the valuation of DR under perfect foresight should thus be seen as a benchmark of its real value. Therefore, a realistic assessment of DR value should be tackled within a power system model under uncertainty.

3.5 Conclusion

This chapter reviewed three general trends regarding the modelling of DR. The first set of models, denominated as physical models, provides the most subtle representation of DR in terms of load behaviours and consumers constraints. An important challenge is to couple these models with a power system model, such that the mutual effects between end-users and wholesale system conditions are accounted for. So-called integrated models take up this challenge but their tractability becomes an issue as the number of DR technologies in the model increases. Since the objective of this thesis is to address large scale integration of DR within power systems, with an exhaustive scope covering many technologies, we had to dismiss the aforementioned approaches.

A second set of models represents DR through elastic demand functions. This approach is well suited, for instance, to study how dynamic-pricing impacts the wholesale electricity markets. This modelling scheme is however quite unrealistic because it does not capture some inter-temporal constraints related to the dynamics of DR technologies. Moreover demand functions represent the behaviour of aggregated consumers, thus they do not allow to easily distinguish between categories of consumers and, within a given category, between electricity end-uses. To address our research question, we rely on a framework which assumes that an aggregator attempts to unlock the economic potential of DR by investing in the appropriate infrastructure and by enabling all electricity consumers

to participate in the wholesale energy market. To carry out this aggregator business case, our setting has to reflect how the aggregator controls its customers' appliances/processes, whose technical constraints should be explicitly taken into account. Since these constraints depend on consumer classes as well as on end-uses, our modelling approach should also enable to make this segmentation.

The third set of models reviewed (negative generation models) is much more adapted to our needs. The principle of this modelling technique is to view DR as a storage (for load-shifting) and as a hydro power plant with a single reservoir (for load-shedding). This approach enables to include DR directly into the set of supply resources of a power system model. DR technical constraints can be easily integrated as well as a consumer/end-use segmentation. Among studies following this modelling approach, Papavasiliou, Cambier, and Scieur (2015) and Steurer et al. (2015) present the most similarities with the frame we have developed in this thesis. Firstly, they include DR into a stochastic model. Secondly, the scope their study includes a large range of DR technologies. Although done over a full year with an hourly resolution, the optimisation in Steurer et al. (2015) is myopic, which is somehow detrimental to an accurate representation of inter-temporal constraints linked to DR activations. A more proper formulation would be to formulate the optimisation problem as a multistage stochastic problem, which is done by Papavasiliou, Cambier, and Scieur (2015). However, they provide a case study with a one-day optimisation. Because the optimisation is myopic in (Steurer et al. 2015), and because the time horizon is of twenty-four hours in Papavasiliou, Cambier, and Scieur (2015), none of these papers include the annual energy constraint related to the maximum number of DR activations allowed by the consumer when contracting with an aggregator (see chapter 1, section 1.5.2). As far as we know, this annual contractual limit has not been explicitly treated in the literature within a model featuring uncertainty, although it might be a key element driving both the value of DR and consumers acceptance.

The contribution of our work is thus to use a multistage stochastic problem setting with a time horizon of one year, and an hourly resolution, in order to explicitly account for the annual contractual limit. Implications of this annual contractual limit, especially on DR marginal costs, will be explained in the next chapter, while chapter 5 provides numerical results regarding this topic. The next chapter describes in details how DR has been modelled and integrated within the electricity market model formulated as a linear multistage stochastic problem. The solving method, namely SDDP, is briefly introduced as well. Another contribution of this thesis is to perform case studies on the French power system, while the geographical scope of Steurer et al. (2015) and Papavasiliou, Cambier, and Scieur (2015) is Germany. These case studies are presented in the last part of this dissertation, chapters 6 and 7.

CHAPTER 4 THE MODEL: WHOLESALE ENERGY-ONLY MARKETS UNDER UNCERTAINTY

4.1 Introduction

The economic value of DR can be computed as the market benefits made by a DR aggregator. An important output of the electricity market model described in this chapter are thus market prices, which have to be endogenous in order to account for their mutual feedbacks with DR activations. To make our assessment realistic, two other effects have to be taken into account: (i) power system uncertainty and (ii) intertemporal influence of the aggregator decisions on each other. Indeed, the literature review of chapter 3 outlined the similarities between DR and electricity storage. In this context, it is key to address the issue of DR valuation by considering power system uncertainties, because deterministic settings lead to storage management decisions which tend to overestimate the resulting value compared with decisions made in an uncertain environment. Furthermore, when the aggregator decides to activate a DR event at a given moment, it has an influence on the possibility to use the same DR technology afterwards. Given a limited DR stock, using a DR technology in a particular moment entails future costs. The aggregator's decisions are thus efficient only if these underlying future costs are considered.

This chapter develops the modelling framework where all these requirements are embedded. Section 4.2 emphasis on DR representation as a storage unit. Section 4.3 then describes the wholesale energy-only market model into which DR is integrated. The model mathematical formulation of the underlying optimisation problem is detailed and we briefly introduce its solving method, namely the stochastic dual dynamic programming algorithm.

4.2 Demand Response modelling

4.2.1 Hydro storage representation of Demand Response

Technically, activation of DR on wholesale markets results from the modification of electric loads consumption patterns which comes in two main forms: consumption can either be purely shed or shifted away from one time period to another, depending on process and appliance. Load-shedding is mainly available in industries, while load-shifting can be found in industries like cement, paper and pulp sectors, but also in residential and tertiary sectors with thermal loads (for more examples of process and appliances fitting with both load-shedding and load-shifting, refer to section 1.4). In terms of modelling, we follow the approach of Papavasiliou and Oren (2014) who argue that "many flexible consumptions tasks are best characterised as deferrable, in the sense that consumers need a certain

amount of energy within a certain time window. As such deferrable demand behaves much like a hydro or storage resource from the view point of the system operator". In order to cover every sectors, we propose a modelling approach including both load-shedding and load-shifting. The principle is the following:

- In the first place, we use a hydro storage representation of DR with a distinction between load-shedding and load-shifting. Load-shedding behaviours is mimicked by a hydroelectric plant with a *single upstream reservoir* while load-shifting is represented by a hydroelectric *pumped-storage* with upstream and downstream reservoirs. The integration of technical characteristics like the duration of a DR event is straightforward: this is done by sizing the reservoir volume appropriately.

- Secondly, we improve the hydro storage representation in order to take into account other key features of DR, such as the maximum number of activations authorised by consumers over a given period.

Our modelling approach of DR is outlined by **Figure 4.1**. The next section describes how the modelling of DR is precisely formalised.

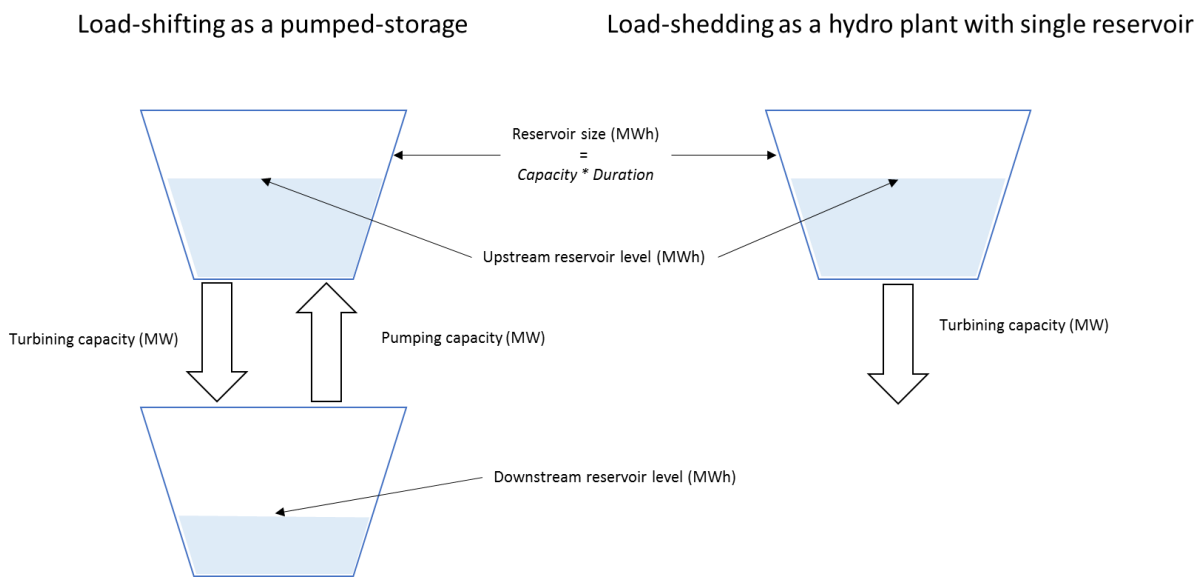

Figure 4.1 – Drawing of our Demand Response modelling approach

4.2.2 Formalisation

Let *dr* denote the reservoir associated to a given DR technology. Load-shedding facilities are made of one reservoir while load-shifting needs to be represented by two reservoirs linked with each other (upstream and downstream reservoirs). Within the model, the connection between the upstream and

the downstream reservoir is ensured by a mapping[12] between elements of the reservoir set. We associate to reservoir *dr* the key following elements and notation (**Table 4.1**):

Table 4.1 – Key elements of Demand Response modelling

Notation	Description	Unit	Mathematical element
x^{dr}	Reservoir level	MWh	State variable
$turb^{dr}$	Turbined water	MWh	Decision variable
$pump^{dr}$	Pumped water	MWh	Decision variable
$InstCap^{dr}$	Installed capacity	MW	Parameter
$Duration^{dr}$	Number of hours consumption can be shed/shifted	h	Parameter

First of all, we assume that the installed capacity $InstCap^{dr}$ is the same for downstream and upstream reservoirs.[13] For each reservoir *dr*, *state variable* x^{dr} tracks the level of available energy. If we keep the analogy with hydro storages, x^{dr} would be the water level in the reservoir. The evolution of x^{dr} is dictated by *decision variables* $turb^{dr}$ and $pump^{dr}$. They are similar to water release and pumping decisions related to the operation of real hydroelectric storages. The following equivalence should be kept in mind:

Turbine water ⇔ Curtail the energy consumption

Pump water ⇔ Recover the energy consumption

The duration parameter determines the size of each reservoir, which is an upper bound of x^{dr}. Besides, the reservoir level should be positive. We thus have:

$$0 \leq x^{dr} \leq Duration^{dr} * InstCap^{dr} \qquad \text{Eq. 4.1}$$

Equation 4.1 ensures that the DR event does not last more than a maximum amount of time. To make sure that water flows correctly, we impose the two following inequalities over the turbined water and pumped water variables,

$$0 \leq turb^{dr} \leq MaxTurbining * BlockDuration \qquad \text{Eq. 4.2}$$

$$0 \leq pump^{dr} \leq MaxPumping * BlockDuration \qquad \text{Eq. 4.3}$$

[12] In the mathematical sense, i.e. association of elements.

[13] Determining the value of the installed capacity requires the introduction of load profiles corresponding to a given DR application. We will introduce load profiles and the way installed capacities are computed further down in the chapter.

where *MaxPumping* and *MaxTurbining* are parameters set in the inputs files as follow :

$$MaxTurbining = \begin{cases} InstCap & for\ upstream\ reservoirs \\ 0 & for\ downstream\ reservoirs \end{cases}$$

$$MaxPumping = \begin{cases} 0 & for\ upstream\ reservoirs \\ InstCap & for\ downstream\ reservoirs \end{cases}$$

and *BlockDuration* is the length of the hour blocks structuring the time decomposition of our optimisation problem (in practise, all hour blocks will last one hour in our case studies).

Eq. 4.2 and Eq. 4.3 ensure that no energy can be produced (resp. consumed) by downstream reservoirs (resp. upstream reservoirs). Finally, a water balance equation is added in order to keep track of the evolution of reservoir levels x^{dr}. This water balance will be made explicit further down in the chapter because it requires additional set definitions and also because it is common to all type of reservoirs, including real hydro power plants reservoirs.

Now, the analogy with hydro storage facilities should be amended in order to include additional constraints inherent to electricity consumers. These constraints actually stem from the contract terms between consumers and the aggregator. Let us remind here the contract terms shown in the first chapter, **Table 1.5**:

Contract terms	**Units**	**Description**
Load capacity	kW	Amount of power subscribed for DR
Price incentive (energy-based)	€/kWh	Financial compensation (for the aggregator: cost of activation)
Price incentive (capacity-based)	€/kW	Financial compensation (for the aggregator: penalty cost)
Duration of DR event	h	How long the end-use will be curtailed
Number of activations	n per period	DR activations allowed over a period, usually over a year
Time notice	h	Time period to notify the customer of an upcoming DR event
Time recovery	h	Maximum time to recover the amount of energy curtailed
Repetition	x per period	DR events allowed to be repeated over a short period, usually a few days or a week
Technology	-	What kind of enabling technology is installed on customer's premises

So far, our model only integrates the *load capacity* and the *duration* contract terms. An accurate representation of DR should integrate additional elements of the contract that we will refer to as consumer-based constraints.

4.2.3 Consumer-based constraints

Consumer-based constraints arise from the contract established between the aggregator and consumers. Among contract terms of **Table 1.5**, the following are integrated within our DR model[14]:

- Load capacity (MW)
- Duration (h)
- Price incentive (€/MWh)
- Number of activations (x per period)

Moreover, a *time availability* constraint has also been included in order to account for the fact that DR capacities are only available if consumers have actually switched their appliance on. More precisely, the availability of DR capacities are restricted over time by end-users' *load profiles*. *Price incentive* can be seen as the *activation cost* of curtailing one unit of energy on consumers' premises. It is analogous to the variable cost of power plants. *Number of activations* restricts the use of DR technologies over a given time period. Concretely, this contract term limits the number of times any given DR reservoirs can be fully used. To that extent, the *number of activations* parameter represents a *contractual limitation* for the aggregator. The higher the number of activations, the higher the possibilities of market bids for the aggregator. The following paragraphs detail how we have added these constraints to the hydro storage representation.

4.2.3.1 Time availability: the need for load profiles

The way consumers use their electrical appliances and operate their industrial production line entails load profiles which reflect time-varying constraints over the availability of DR capacity. For instance, DR events from air conditioning cannot be triggered during winter because these appliances are not plugged to the grid at this specific period. In order to model the time availability constraint, Eq. 4.2 and Eq. 4.3 are amended by multiplying the right-hand side by a turbining and pumping *availability factor*, noted respectively $A\_TURB_t^{dr}$ and $A\_PUMP_t^{dr}$. These factors are scalar numbers whose values are comprised between 0 and 1. The t index represents the model time steps. For any time steps t, we have:

$$turb_t^{dr} \leq MaxTurbining * BlockDuration * A\_TURB_t^{dr} \qquad \text{Eq. 4.4}$$

$$pump_t^{dr} \leq MaxPumping * BlockDuration * A\_PUMP_t^{dr} \qquad \text{Eq. 4.5}$$

[14] Time notice, time recovery and repetition have not been modelled.

$A\_TURB_t^{dr}$ and $A\_PUMP_t^{dr}$ are computed after load profiles which are made of three elements: a maximum level, a minimum level, and the load profile per se. Maximum and minimum levels bound the power consumption. In between evolves the load profile which is the actual end-users consumption, as shown by **Figure 4.2**:

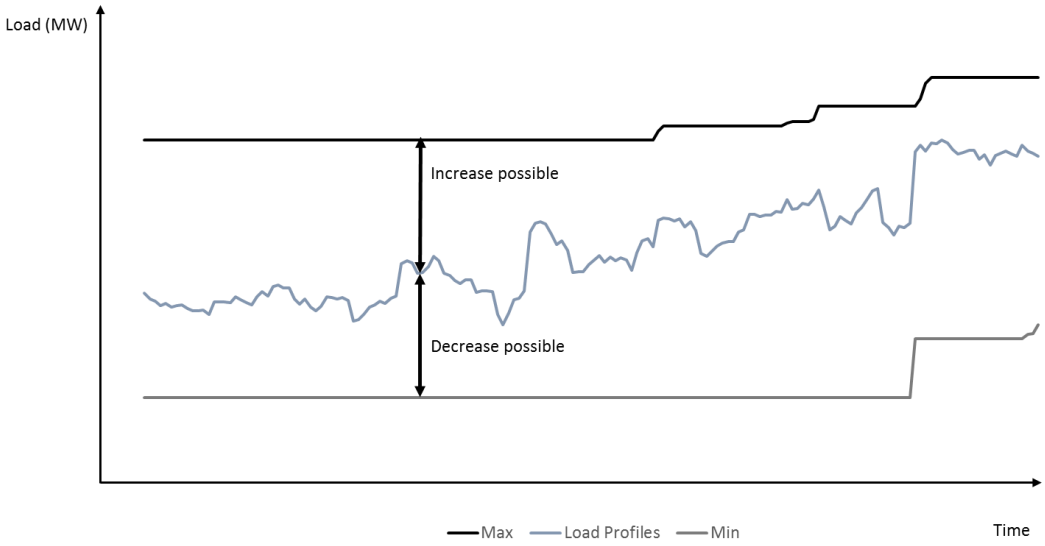

Figure 4.2 – Load profile example

As shown by the figure, these maximum and minimum levels can be time-varying as well, according to end-users' behaviours. If we take the example of a household, it can be assumed that children are students getting back home only for week-ends, raising consequently the maximum theoretical level of power consumption at that time. The difference *load profile – minimum level* determines a *possible decrease* of power consumption, that is to say the available capacity of turbining. Similarly, the difference *maximum level – load profile* is a *possible increase* which in turns reflects the available pumping capacity. Possible increases and decreases are computed for every time steps *t*. The installed capacity is defined by Eq. 4.6:

$$InstCap^{dr} = \max_t possible\ decrease_t \qquad \text{Eq. 4.6}$$

The availability factors are computed as follow:

$$A\_TURB_t^{dr} = \frac{possible\ decrease}{\max_t possible\ decrease_t} \qquad \text{Eq. 4. 7}$$

$$A\_PUMP_t^{dr} = \frac{possible\ increase}{\max_t possible\ increase_t} \qquad \text{Eq. 4.8}$$

4.2.3.2 Price incentive: the activation cost

Activation cost is the variable cost of shedding or shifting the load. Its level depends on the end-user category and the type of appliance[15]. For instance, it will be rather high for load-shedding in the industry (e.g. around or above 100 €/MWh), and rather low for load-shifting (roughly below 20 €/MWh). Activation cost reflects the minimum value for which consumers are willing to modify their usage of electricity. Thus, this is the price incentive the aggregator should at least propose to them. Every MWh of energy curtailed will be compensated by this financial reward. For load-shedding, activation cost is high because there is a net loss of the consumed energy. For instance, industrial consumers face an opportunity cost to interrupt their process because they would endure a decrease of their sales due to a smaller production (Gruber, Biedermann, and von Roon 2014). For load-shifting, the disturbance is lower because the amount of electricity consumed remains unchanged, thus low activation costs: this is the non-disruptiveness principle claimed by Callaway and Hiskens (2011) in order to foster participation of small consumers in DR programmes. If we let AC^{dr} denote the activation cost of DR technology dr, then the cost of turbining water from upper reservoirs[16] is given by:

$$cost\ of\ turbining^{dr} = AC^{dr} * turb^{dr}$$

4.2.3.3 Number of activations: the contractual reservoir

To model the number of activations, we created a *contractual reservoir* associated to each DR technology. This contractual reservoir has the following features:

- It has the same turbining capacity than its corresponding DR technology.
- Its size is equal to the physical reservoir size multiplied by $Number\ of\ Activations$:

$$Contractual\ reservoir\ size^{dr} = InstCap^{dr} * Duration^{dr} * Number\ of\ Activations^{dr} \qquad \text{Eq. 4. 9}$$

- It is not connected to the power network, i.e. it does not provide any energy to the system, as opposed to the "physical" reservoirs.
- Its activation cost equals 0 €/MWh.

[15] The activation is not the marginal of using a DR reservoir. DR marginal cost functions will be treated in chapter 5. We will see that the activation is just a component of the marginal cost.

[16] Note that the activation cost only concerns turbining decisions: within our modelling approach, we assume that pumping water comes with no activation cost. The cost of pumping water only results from consuming energy at the market price.

Figure 4.3 depicts our approach with the example of load-shifting:

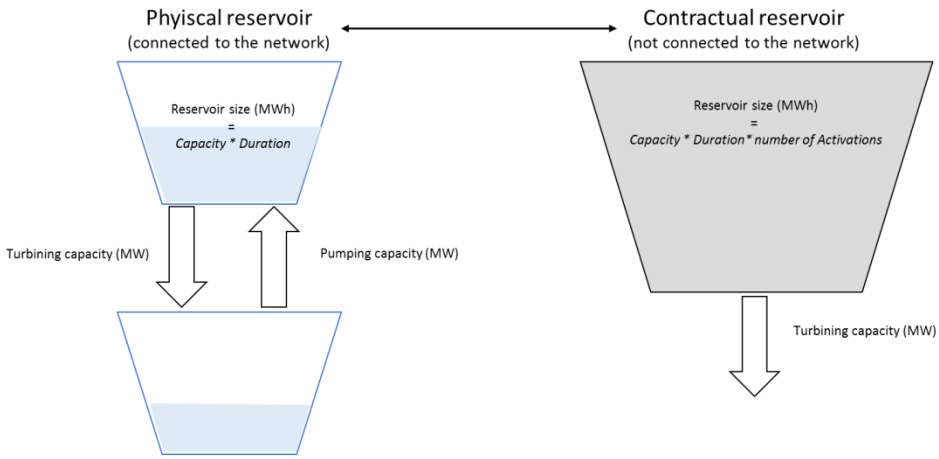

Figure 4.3 – The contractual reservoir

The link between contractual and physical reservoirs is ensured by a mapping. To ensure that physical reservoirs produce and consume (in the case of load-shifting) electricity, they are associated to a power system zone, unlike contractual reservoirs which are not. This is illustrated by **Table 4.2** where no electricity zone "FR" (abbreviation for France) is assigned to contractual reservoirs. Reservoirs with an electricity zone define a sub-set among the reservoirs set. As we will see later on, only reservoirs belonging to this sub-set are included in the electricity balance equation (Eq. 4. 14).

Table 4.2 – Contractual reservoir disconnection to the electricity zone

Reservoir name	Electricity zone
Load-shifting_1_upstream	FR
Load-shifting_1_downstream	FR
Load-shifting_1_contract	
Load-shedding_1	FR
Load-shedding_1_contract	
Load-shifting_2_upstream	FR
Load-shifting_2_downstream	FR
Load-shifting_2_contract	

The use of contractual reservoirs follows exactly the use of the associated physical reservoir, in terms of turbining decisions. This is imposed by Eq. 4.10:

$$turb_t^{dr\_contract} = turb_t^{dr} \qquad \text{Eq. 4.10}$$

However, since the contractual reservoir is made of only one reservoir, there is no possibility to fill it again by pumping water up. Therefore, every time a given amount of energy is released from the physical reservoir, the same amount is restricted from the contractual reservoir; thus, as the physical reservoir is used, the contractual reservoir level irremediably falls. Once the contractual reservoir has been emptied there is no more possibility to use the physical reservoir.

Important remarks

First, this approach is obviously a proxy of actually counting the number of DR events which have been triggered. In practice, the number of activations counts how many times consumers allow at most the aggregator to operate their appliances. But this counting implies integer variables that we voluntarily exclude from our model in order to keep the optimisation problem convex. Second, coupling physical with contractual reservoirs is well suited for the operation of load-shifting, because water can go up and down. However this coupling is unnecessary for load-shedding because the physical reservoir cannot be filled again once it has been emptied. We thus do not add any contractual reservoir for load-shedding. Instead, we consider one physical reservoir whose size is equal to: $Capacity^{dr} * Duration^{dr} * Number\ of\ Activation^{dr}$. The problem is that the duration constraint is rendered somehow obsolete, because a DR event can last more than the recommended duration, given that the reservoir size has been extended.

Economic implication

A direct consequence of the *Number of activations* constraint is the apparition of an opportunity cost. To not have any contractual limitation means that the aggregator is allowed to trigger an unlimited number of DR events. If the use of physical DR technologies is limited by the contract term *Number of activations*, the aggregator should arbitrate between activating DR now or wait for better market valuation opportunities. The wholesale energy-only market that we developed in this thesis builds upon a class of mathematical optimisation problems accounting for this effect. This topic will be formally treated in chapter 5, section 5.3.

4.3 Wholesale energy-only electricity market model

4.3.1 Economic dispatch under uncertainty

The electricity market model is an *economic dispatch under uncertainty*, whereby a random residual power demand has to be satisfied by an exogenous mix of generating technologies[17]. In essence, the model simulates a Transmission System Operator (TSO) seeking to minimise the operating cost of

[17] In the model setting, the uncertainty stems from the level of power demand and production of non-dispatchable renewable energy sources.

meeting the power demand. Nevertheless, as we will explain further down, our model can also be seen as a *competitive wholesale energy-only market*.

The model is set up around a multistage timeframe. Each time period (or time step) is then decomposed into different hour blocks (or sub-time periods/steps) whose length are set up according to users need. If we let D denote the power demand, t the time period and h the hour block, D has to be indexed as follow: $D \rightarrow D_{t,h}$. One can decide to run the model with one time step accounting for one day, with hour blocks of different length: the only constraint being that the sum over all hour blocks equals 24 hours. To fit our purpose, we run the model with hour blocks all equal to 1 hour. Indeed, an hourly granularity is essential in order to capture the chronological operating constraints related to DR. With that regard, our model is then comparable to a *wholesale hourly spot market*.

Mathematically, the model is formulated as a cost minimisation problem. Moreover it belongs to the class of multistage stochastic linear problems.

4.3.1.1 Economic interpretation: hourly spot market

The economic dispatch model can be seen as a wholesale energy-only market, where market agents are electricity producers and electricity retailers (or consumers having a direct access to the wholesale market). They respectively supply and buy electricity on the market for each hour.

Among retailers, one particular agent is the DR aggregator. His role is to operate a stock of flexible end-uses in order to generate the highest benefits by making either intertemporal price arbitrage (load-shifting) or bidding pure load reduction (load-shedding). The aggregator makes his bidding decisions under constraints stemming from the contract he has signed with consumers. Those constraints have been detailed in section 4.2. We assume that the aggregator is the unique agent able to provide DR on the market. All other retailers or consumers are supposed to take their decision regardless of the market price: their demand is inelastic. Consequently, part of the electricity demand on the market is subject to hazard. This leads to random prices as well, rendering the aggregator bidding decisions not straightforward. When bidding decisions are repeated over many time periods, the aggregator would like to maximise his *current* and his *future* benefits. At a given period, current decisions will necessarily come at a cost, because they affect the set of his future possibilities. For instance, if the aggregator is allowed to trigger only ten DR events over the course of the year, he will be willing to seek for the ten periods of highest price levels (or price spreads). Even if the current market price is high enough to generate benefits, the aggregator might wait until later periods if he knows that prices will be even higher at those periods. In other words the aggregator faces an opportunity cost. This opportunity cost exists as long as the aggregator problem is embedded in a multistage setting. However, under the assumption of perfect foresight, the aggregator decision is straightforward because he knows what will be the ten periods of highest prices. Decisions making under uncertainty is more complicated because the aggregator has to decide in the face of expected realisations of stochastic prices.

4.3.1.2 The pure and perfect competition assumption

We assume that the market is perfectly competitive such that all agents are price-takers and propose their full available generating capacity at short-run marginal costs. This assumption ensures that the market equilibrium corresponds to a welfare maximisation handled by a social planner. The equivalence between perfectly competitive markets and planning model for a social planner is argued by Samuelson (1952) in a static single period optimisation setting. This result is used by De Jonghe, Hobbs, and Belmans (2011) in the case of resource planning in the electricity sector. Furthermore, this result still holds in the case of multistage stochastic optimisation problems if we assume that (i) agents are risk-neutral and (ii) they all share the same beliefs about the evolution of uncertainty (Philpott, Ferris, and Wets 2013a; Papavasiliou, Cambier, and Scieur 2015; Papavasiliou and Smeers 2015). Moreover, if the economic dispatch problem maximising total welfare is convex, then (i) shadow prices associated to the demand satisfaction equation can be interpreted as the competitive market prices, and (ii) shadow prices associated to state transition equations represent the *value of water*[18], i.e. the marginal value of releasing water from one particular reservoir (Papavasiliou, Cambier, and Scieur 2015; Philpott 2017). To sum up, if we assume (i) pure and perfect competition, (ii) risk-neutrality, (iii) that all agents share a common knowledge about uncertainty, the energy-only hourly spot market equilibrium can be characterised by the outcome of the economic dispatch problem under uncertainty. Moreover the convexity of the problem ensures that market prices can be computed from the problem shadow prices. In the following section, we detail our economic dispatch problem under uncertainty and precise as we write it as a multistage stochastic linear problem.

4.3.2 Mathematical formulation

4.3.2.1 Notation

Sets and indices

t	Time periods
h	Hour blocks
dr	Set of DR reservoirs
hp	Set of hydro power plants reservoirs
tp	Set of thermal power plants
ω_t	Set of scenarios at time step t

Exogenous parameters

$D_{t,h}^{\omega_t}$	Power demand associated to the realisation of scenario ω_t	MW
$BlockDuration_{t,h}$	Block duration of hour block h at time step t	h
AC^{dr}	Activation cost of DR reservoir dr	€/MWh
VC^{hp}	Variable cost of hydro power plant hp	€/MWh
VC^{tp}	Variable cost of thermal power plant tp	€/MWh
PC	Variable cost of non-served demand; equivalently, the market price cap	€/MWh

[18] The marginal value of water notion will be used later on in order to compute the marginal costs of DR.

Eff^{hp}	Efficiency of hydro power plant hp	MWh/Mm^3
$InstCap^{dr}$	Installed capacity of DR reservoir dr	MW
$InstCap^{hp}$	Installed capacity of hydro reservoir hp	MW
$InstCap^{tp}$	Installed capacity of thermal power plant tp	MW
$Duration^{dr}$	Duration of a DR event associated to DR reservoir dr	h
$Number\ of\ Activations^{dr}$	Maximum number of times a physical reservoir dr can be fully used	
$Reservoir\ size^{hp}$	Size of hydro reservoir hp	MWh
$A\_TURB_{t,h}^{dr}$	Turbining availability factor of DR reservoir dr at time step t and hour block h	
$A\_PUMP_{t,h}^{dr}$	Pumping availability factor of DR reservoir dr at time step t and hour block h	
$A\_GEN_{t,h}^{tp}$	Generating availability factor of thermal power plant tp at time step t and hour block h	
	Endogenous variables	
$x_{t,h}^{dr}$	Level of DR reservoir dr at time step t and hour h (state variable)	MWh
$x_{t,h}^{hp}$	Level of hydro power plant reservoir hp at time step t and hour h (state variable)	Mm^3
$turb_{t,h}^{dr}$	Water turbining decision from DR reservoir dr	MWh
$pump_{t,h}^{dr}$	Water pumping decision from DR reservoir dr	MWh
$turb_{t,h}^{hp}$	Water turbining decision from hydro reservoir hp	Mm^3
$pump_{t,h}^{hp}$	Water turbining decision from hydro reservoir hp	Mm^3
$gen_{t,h}^{tp}$	Generating capacity decision of thermal power plant tp	MW
$slack_{t,h}^{+}$	Mandatory decision of power generation curtailment	MW
$slack_{t,h}^{-}$	Mandatory decision of power demand curtailment	MW

4.3.2.2 Variables

First of all, let us precise that all variables are positive. Second, we can distinguish between *decision* and *state* variables. State variables are reservoir levels $x_{t,h}$ of DR and hydro power plant technologies. Decision variables are power generation decisions from the set of generating technologies (DR, hydro power plant and thermal power plant). In addition, slack variables are artificially introduced to make the optimisation problem always feasible at every time steps: when there is not enough power available, the demand is curtailed according to $slack_{t,h}^{-}$ at the highest variable cost in the model, which is the market price cap PC. Similarly if there is too much power available the generated electricity is stopped following $slack_{t,h}^{+}$.

4.3.2.3 Objective function

Objective function consists of (i) the immediate cost of producing electricity from the set of generating technologies plus (ii) future costs. Immediate costs are variable costs of generating electricity from DR, hydroelectric power plants, and thermal power plants plus mandatory curtailment costs. Since we assume that pumping water is free, the cost of pumping water up is not included in the objective function. Thus, for any time step t,

$$\begin{aligned} Immediate\ cost_t \\ = \\ \sum_{dr}\sum_{h} AC^{dr} * turb_{t,h}^{dr} \\ + \sum_{hp}\sum_{h} VC^{hp} * Eff^{hp} * turb_{t,h}^{hp} \\ + \sum_{tp}\sum_{h} VC^{tp} * BlockDuration_{t,h} * gen_{t,h}^{tp} \\ + \sum_{h} PC * BlockDuration_h * (slack_{t,h}^{+} + slack_{t,h}^{-}) \end{aligned} \qquad \text{Eq. 4. 11}$$

Future costs arise from the use of DR and hydro reservoirs. Current decisions have an impact on future reservoir levels that affect the range of feasible decisions. For example, if all water present in reservoirs is used at the beginning of the problem, there might be a shortfall of capacity in subsequent periods coming at a very high cost. These future costs should then be taken into account in the objective function, and they depend on reservoir levels x_t. Future costs will be noted as follow:

$$Future\ cost_t \ \widehat{=}\ \alpha_t(x_t^{dr}, x_t^{hp}) \qquad \text{Eq. 4. 12}$$

Finally, for any time step *t* the objective function of the optimisation problem can be formulated as:

$$Objective\ Function_t \ \widehat{=}\ Immediate\ cost_t + \alpha_t(x_t^{dr}, x_t^{hp}) \qquad \text{Eq. 4. 13}$$

4.3.2.4 Constraint set

First of all, the classic balance equation of demand satisfaction is:

$$D_{t,h}^{\omega_t} \leq \frac{turb_{t,h}^{dr} - pump_{t,h}^{dr} + Eff^{hp}\left(turb_{t,h}^{hp} - pump_{t,h}^{hp}\right)}{BlockDuration_{t,h}} + gen_{t,h}^{tp} + slack_{t,h}^{-} - slack_{t,h}^{+} \qquad \text{Eq. 4. 14}$$

The state transition equation tracking reservoir levels from one time period to the next one is accounting for by the *water balance* equation. Here the water balance equation is written down for DR reservoirs, but it is exactly the same for hydro reservoirs:

$$x_{t,h}^{dr} = x_{t,h-1}^{dr} + turb_{t,h}^{dr} - pump_{t,h}^{dr} + \sum_{dr' \in upstream} turb_{t,h}^{dr'} + \sum_{dr'' \in downstream} pump_{t,h}^{dr''} \qquad \text{Eq. 4. 15}$$

Eventually, generating technologies are operated under technical constraints which are detailed hereafter, distinguished by set of technologies:

Demand Response

$$turb_{t,h}^{dr} \leq MaxTurbining^{dr} * BlockDuration_{t,h} * A\_TURB_{t,h}^{dr}$$
$$pump_{t,h}^{dr} \leq MaxPumping^{dr} * BlockDuration_{t,h} * A\_PUMP_{t,h}^{dr}$$
$$turb_{t,h}^{dr\_contract} = turb_{t,h}^{dr}$$

with

$$MaxTurbining^{dr} = \begin{cases} InstCap^{dr} & for\ upstream\ reservoirs \\ 0 & for\ downstream\ reservoirs \end{cases}$$
$$MaxPumping^{dr} = \begin{cases} 0 & for\ upstream\ reservoirs \\ InstCap^{\ dr} & for\ downstream\ reservoirs \end{cases}$$

$$0 \leq x_{t,h}^{dr} \leq \begin{cases} InstCap^{dr} * Duration^{dr}\ for\ physical\ reservoirs \\ InstCap^{dr} * Duration^{dr} * Number\ of\ Activations^{dr}\ for\ contractual\ reservoirs \end{cases}$$

Hydro power plants

$$turb_{t,h}^{hp} * Eff^{hp} \leq MaxTurbining^{hp} * BlockDuration_{t,h} \qquad \text{Eq. 4. 16}$$

with

$$MaxTurbining^{hp} = \begin{cases} InstCap^{hp} & for\ upstream\ reservoirs \\ 0 & for\ downstream\ reservoirs \end{cases}$$

$$pump_{t,h}^{hp} * Eff^{hp} \leq MaxPumping^{hp} * BlockDuration_{t,h} \qquad \text{Eq. 4. 17}$$

with

$$MaxPumping^{hp} = \begin{cases} 0 & for\ upstream\ reservoirs \\ InstCap^{\ hp} & for\ downstream\ reservoirs \end{cases}$$

$$0 \leq x_{t,h}^{hp} \leq Reservoir\ size^{hp} \qquad \text{Eq. 4. 18}$$

Thermal power plants

$$gen_{t,h}^{tp} \leq InstCap^{tp} * A\_GEN_{t,h}^{tp} \qquad \text{Eq. 4. 19}$$

4.3.2.5 Multistage stochastic linear problem

For sake of clarity, let us take the compacted following notation[19]:

- ω_t is the hazard at stage t associated with a strictly positive probability
- $U_t\left(x_{t,h}, D_{t,h}^{\omega_t}\right)$ denotes the set of constraints defined in the previous section: this is the range of potential decisions at time step t given system state $x_{t,h}$ and demand realisation $D_{t,h}^{\omega_t}$.
- x_t is the vector of state variables at time step t, i.e. $x_t = (x_{t,h}^{dr}, x_{t,h}^{hp})$.
- u_t is the vector of decision variables at time step t:

$$u_t = (turb_{t,h}^{dr}, pump_{t,h}^{dr}, turb_{t,h}^{hp}, pump_{t,h}^{hp}, gen_{t,h}^{tp}, slack_{t,h}^{-}, slack_{t,h}^{+})$$

- c_t is the vector of unit costs:

$$c_t = (AC^{dr}, VC^{hp} * Eff^{hp}, VC^{tp} * BlockDuration_{t,h}, PC * BlockDuration_{t,h})$$

- F the transition function, such that $x_t = F(x_{t-1}, u_{t-1})$
- T the time horizon of the problem: $t \in \{1, \dots, T\}$

The purpose is to minimise the objective function explicated in section 4.3.2.3 over the entire time horizon while satisfying all constraints. At a given period, we thus minimise the sum of current decision cost and of the expected future decision cost. Note that the set of feasible decision U_t is a linear and convex set of constraints. Moreover, we assume that the outcomes ω_t are stagewise independent. We can thus write our economic dispatch problem under uncertainty as a multistage stochastic linear problem where the objective function to minimise is:

$$\mathbb{E}_{\omega_1}\left\{\min_{u_1 \in U_1(x_1, D_1^{\omega_1})}\left\{c_1 u_1 + \mathbb{E}_{\omega_2}\left\{\min_{\substack{u_2 \in U_2(x_2, D_2^{\omega_2}) \\ x_2 = F(x_1, u_1)}}\left\{c_2 u_2 + \cdots + \mathbb{E}_{\omega_T}\left\{\min_{\substack{u_T \in U_T(x_T, D_T^{\omega_T}) \\ x_T = F(x_{T-1}, u_{T-1})}} c_T u_T\right\}\right\}\right\}\right\}\right\}$$

Problem 4.1

4.4 Solving method: Stochastic Dual Dynamic Programming

Solving the optimisation problem formulated above is computationally challenging when the number of demand scenarios, time steps, and state variables becomes significant.

4.4.1 Stochastic programming

In theory, *stochastic programming* is the most obvious way to solve the problem formulated above. It consists in discretising the random power demand in a scenario tree and solving the *equivalent*

[19] In this notations, hours *h* are voluntary removed for sake of clarity. In the next sections, we will reason with time periods.

deterministic problem. The equivalent deterministic problem can be written as one big single-stage linear problem:

$$\begin{array}{c} \min \\ u_1^{\omega_1} \in U_1\left(x_1, D_1^{\omega_1}\right) \forall \omega_1 \\ x_2 = F\left(x_1, u_1^{\omega_1}\right) \forall \omega_1 \\ \vdots \\ x_T = F\left(x_{T-1}, u_{T-1}^{\omega_{T-1}}\right) \forall \omega_{T-1} \\ u_T^{\omega_T} \in U_T\left(x_T, D_T^{\omega_T}\right) \forall \omega_T \end{array} \quad \mathbb{E}_{\omega_1,\ldots,\omega_T}\left\{c_1 u_1^{\omega_1} + c_2 u_2^{\omega_1,\omega_2} + \cdots + c_T u_T^{\omega_1,\ldots,\omega_T}\right\}$$

Problem 4.2

If we let K represent the number of possible power demand realisation, then there are K decision variables associated at each stage. Within our setting, K is constant over time. **Figure 4.4** illustrates the scenario tree, with K corresponding to the number of branches at each stage.

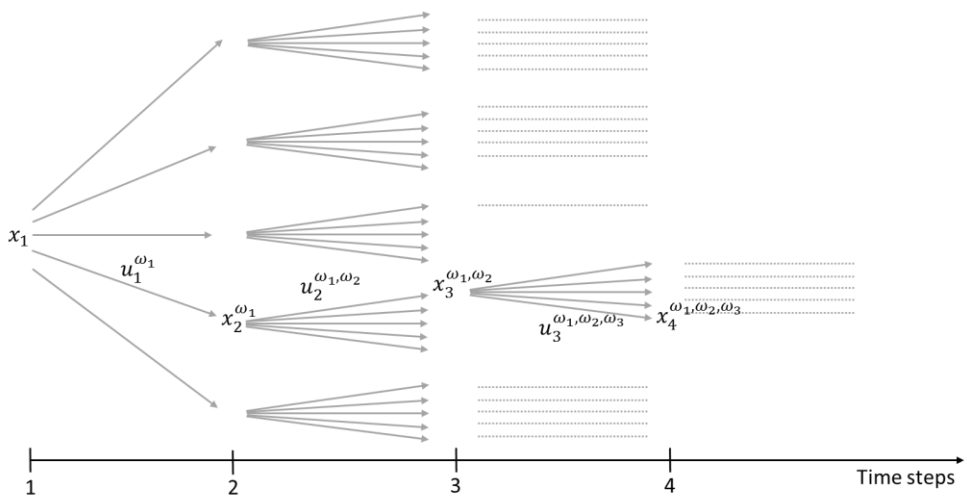

Figure 4.4 – Scenario tree

One can easily see that this method requires to deal with a number of decision variables which is proportional to K^T, T being the number of time steps. Since the case study presented in the 3rd Part of this dissertation involves 52 time steps and 20 demand scenarios, thus 20^{52} variables to handle, stochastic programming turns out to be inappropriate to tackle our optimisation problem.

4.4.2 Dynamic programming

An alternative option would be to have recourse to dynamic programming, a method introduced by R. Bellman in 1957, whose book was recently reedited (Bellman 2013). Dynamic programming consists in breaking down the multistage problem into a series of two-stage sub problems. Dynamic programming principle relies on the dynamic programming equation:

$$\alpha_t(x_t) = \min_{u_t \epsilon U_t\left(x_t, D_t^{\omega_t}\right)} c_t u_t + \mathbb{E}_{\omega_{t+1}}\{\alpha_{t+1}(x_{t+1})\} \qquad \text{Eq. 4. 19}$$

$\alpha_t(x_t)$ is called the *value function*. Within our model, this is the future cost function defined by Eq. 4. 12. By assigning no value to the future cost function at last time step of the problem, the last stage sub-problem simplifies as,

$$\min_{u_T \in U_T(x_T, D_T^{\omega_T})} c_T u_T$$

Problem 4.3

and can be solved. The value function at time step T-1 is then known according to Eq. 4. 19, so that we can solve the T-2 sub-problem, giving the value function of time step T-3, etc. Going backwards in time, dynamic programming enables to derive the value functions for every time steps. The multistage problem can then be solved step by step, following the process shown in **Figure 4.5**:

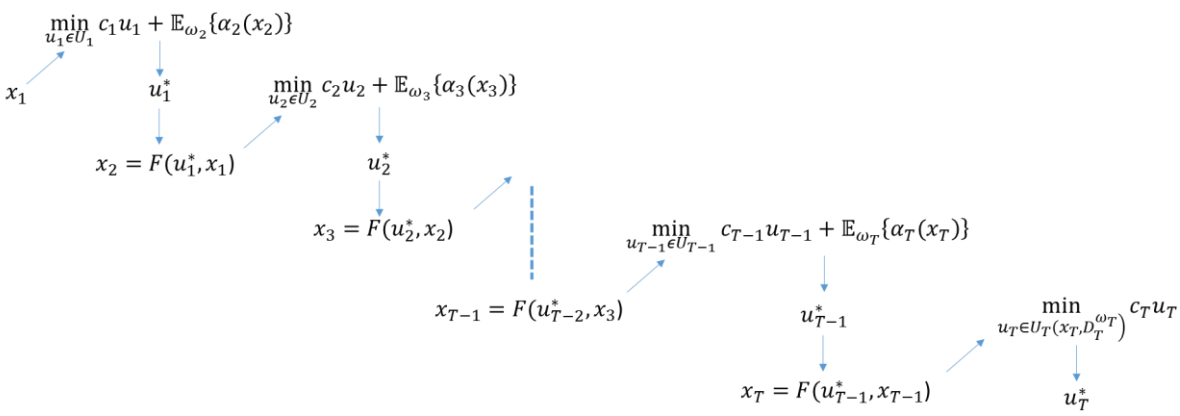

Figure 4.5 – Dynamic programming solving process

The issue of this approach was coined by Richard E. Bellman as the "curse of dimensionality" which refers in the context of dynamic programming to the difficulty to compute the value function. Indeed, in the present case, α_t is a function of x_t which cannot be calculated in a closed form. We thus need to discretise the state space into a set of trial values $\{x_t^i,\ i = 1, \dots, n\}$, and to calculate the value function for each x_t^i: $\alpha_t(x_t^i)$. The value function can then be accurately represented by interpolation. We see that the state space discretisation requires to solve as many sub-problems as they are discretisation points. When the number of state variable increases, computation time explodes because the number of sub-problems to solve is proportional to $card(I)^{card(X)}$ if we let $card(I)$ be the number of discretisation points and $card(X)$ the number of state variables. In case studies of part III we work

with 10 discretisation points and 20 reservoirs at minimum, i.e. 20 state variables. The number of problems to solve is then proportional to 10^{20}.

4.4.3 Stochastic Dual Dynamic Programming

Stochastic Dual Dynamic Programming (SDDP) is a well-known algorithm which tackles the tractability issue inherent to both stochastic and dynamic programming. Initially introduced by Pereira and Pinto (1991), SDDP is fit for an extensive use of our model since it can handle big-size problems while ensuring a solution closed to optimality.

SDDP first principle is to approximate the value function α_t by a *piecewise linear function*, instead of building it by discretisation of the state space, as in the dynamic programming approach. The piecewise linear approximated value function is obtained by solving *dual problems*. To illustrate this, let us consider a simpler version of our economic dispatch **Problem 4.1** with only two stages and in a deterministic setting:

$$\min_{\substack{A_1 u_1 \geq b_1 \\ E_1 u_1 + A_2 u_2 \geq b_2}} c_1 u_1 + c_2 u_2$$

Problem 4.4 – Two-stage deterministic problem

Given a feasible solution $\hat{u}_1$ of **Problem 4.4**, the value function is defined as the solution of the following problem:

$$\alpha_2(\hat{u}_1) = \min_{A_2 u_2 \geq b_2 - E_1 \hat{u}_1} c_2 u_2$$

Problem 4.5 – Primal problem

Problem 4.5 is called *primal* and its dual is given by:

$$\max_{\pi A_2 \leq c_2} \pi(b_2 - E_1 \hat{u}_1)$$

Problem 4.6 – Dual problem

where π is the vector of lagrangian multipliers. In linear programming, primal and dual problems have the same optimal solution. The value function can thus be derived from the dual problem **Problem 4.6**:

$$\alpha_2(\hat{u}_1) = \max_{\pi A_2 \leq c_2} \pi(b_2 - E_1 \hat{u}_1)$$

The interest of using the dual problem is that the constraint set $\{\pi/\pi A_2 \leq c_2\}$ does not depend on first stage solution $\hat{u}_1$. Possible solutions are thus only characterised by second stage parameters A_2 and c_2. Moreover the set of solution corresponds to one of the vertices of the constraint set $\{\pi/\pi A_2 \leq c_2\}$. If we let $\{\pi^1, \dots, \pi^v\}$ be the set of possible solutions, then there is a $\pi^i \in \{\pi^1, \dots, \pi^v\}$ such that:

$$\alpha_2(\hat{u}_1) = \pi^i(b_2 - E_1\hat{u}_1)$$

The value function is then characterised as a piecewise linear function of the first stage variable u_1 which is, from the second stage view point, a state variable. An illustration of the value function approximation is provided by **Figure 4.6**.

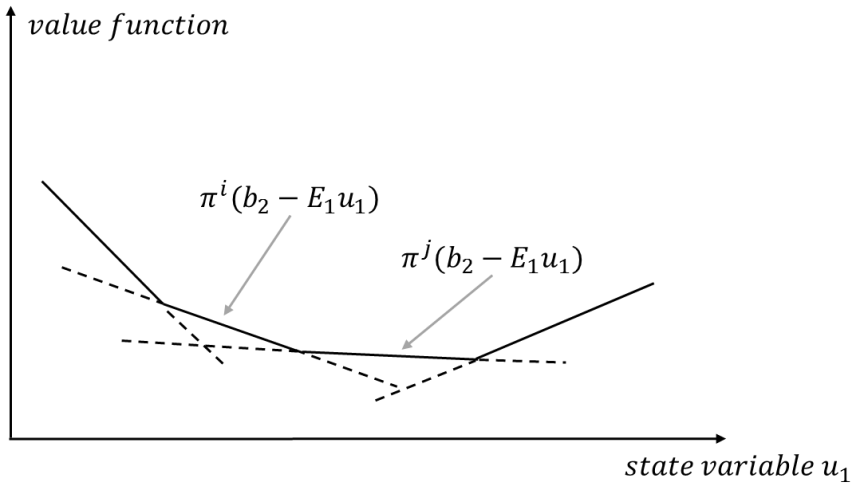

Figure 4.6 – Piecewise linear approximation of the value function in SDDP

Instead of building the value function around a set of discretised values of the state space, the SDDP algorithm computes *hyperplanes* $\pi^i(b_2 - E_1\hat{u}_1)$ by getting the π^i around possible values of the state variable. The π^i, which give us the slope of the value function, can be interpreted as the *marginal costs* of the constraint implying $\hat{u}_1$. In other words, SDDP key outputs are the marginal costs associated to the release of an incremental quantity of water in a given reservoir.[20] The algorithm, easily extendable to multistage problems, works as follow:

- In a first forward simulation, the multistage problem is solved without taking any future costs into account, i.e. each one-step sub problem is solved. This gives us a feasible solution $(\hat{u}_1, \hat{u}_2, \dots, \hat{u}_T)$. This solution is obviously sub-optimal because no future costs are

[20] This topic will be addressed in more details in chapter 5.

considered. The obtained solution is then greater than the optimal solution: forward simulations thus provide an *upper bound* of the optimal objective function.

- In a backward recursion**,** value functions are approximated around feasible states $(\hat{u}_1, \hat{u}_2, \dots, \hat{u}_T)$ provided by the first forward simulation. The process starts at the last time step and goes backward in time, as in the dynamic programming approach. Hyperplanes are computed based on the process described above, giving us future costs. Here, only a subset of existing hyperplanes is calculated. Therefore, the approximated value functions are a lower bound to the real future costs.

- Then a new forward phase is run, taking into account the formerly approximated value functions. This gives another feasible solutions, over which a new backward phase is run, providing a more refined approximation of future costs.

- Many forward and backward phases are iterated until lower and upper bounds are close enough.

4.5 Conclusion

We presented the generic model developed for this thesis in order to assess the value that a DR aggregator would get from an energy-only electricity market. Our modelling approach views DR as storage units integrated in the power system. Their optimal management takes into account both uncertainty and future costs. Therefore, a formulation of the electricity market model as a stochastic multistage problem is relevant. Our research questions necessitate to perform calibrated case studies, thus an extensive use of our model. We then had to have recourse to SDDP as a solving method. In the next chapter, a didactic model illustration is proposed in order to highlight the main outcomes we can get from the model. In part III of this dissertation, a case study calibrated on the French power system will be presented.

CHAPTER 5 ECONOMIC VALUE AND MARGINAL COST OF DEMAND RESPONSE IN A STOCHASTIC ENVIRONMENT

5.1 Introduction

In chapter 4 has been presented an electricity market model based on SDDP that can be used to quantify the economic value of DR in an uncertain environment. As outlined in chapter 4, taking into account uncertainty is of high importance when assessing the value of DR, since assuming perfect foresight of the future necessarily leads to an overestimation. In this chapter we show this point by analysing how DR marginal costs are computed in a stochastic environment. In particular we demonstrate that opportunity costs associated to the activation of a DR technology can significantly raise the marginal cost. We also intend to provide additional insights regarding:

- the relation between market prices and DR marginal costs,
- the market price cap effect on DR marginal costs,
- and the competition between DR technologies with an emphasis on the effect of reducing the contract size[21] of one particular DR technology on other DR technologies.

Finally we calculate the social and private values of DR. The social value is computed as the social welfare impact of DR while the private value is computed as the DR aggregator benefits. Social welfare is the difference between consumers surplus and total system costs, while the aggregator benefit is the difference between market revenues and production costs of DR.

In PART III of this dissertation, chapters 6 and 7, we will use the model for an empirical case study calibrated on the French power system in order to estimate the economic potential of DR in France. The analysis of the case study results requires understandings about the interactions and mechanics that lie behind the optimisation process of the model, which is precisely what we intend to do in this chapter. But since it is not an easy task to go in details into the model outputs when important data sets are used, we start with a simplified data set. Analyses proposed therein rely on this illustrative model for didactic purposes.

The rest of the chapter is organised as follow. Section 5.2 presents the model setting. Section 5.3 provides an explicit mathematical formulation of DR marginal costs and illustrates how those marginal costs set the market price. Furthermore we investigate the price cap impact on marginal costs and analyse how DR technologies compete with each other's. In section 5.4 we quantify the

[21] Contract size is the size of the contractual reservoir, which is determined by the annual number of DR activations.

economic value of DR by proposing a calculation of its social and private values. Section 5.5 concludes by summarising the findings.

5.2 Didactic model presentation

The didactic model has 4 time steps or periods denoted by t that we can interpret as the four seasons of year. Periods are denominated as winter, spring, summer and autumn: $t \in \{winter; spring; summer; autumn\}$. Typical winter, spring, summer and autumn weeks are represented: the length of each period is thus one week. Although working with a single day might have been more adapted to this didactic model context, we chose to consider a week rather than a day in order to account for week-ends patterns of the power demand of electricity.

5.2.1 Power demand

Power demand is decomposed on an hourly basis. Therefore there are 168 values of power demand inside each week, as shown by **Figure 5.1**. If we let D be the power demand, we must index it as follow: $D_{t,h}$ where $h \in \{1; 2; \dots; 168\}$.

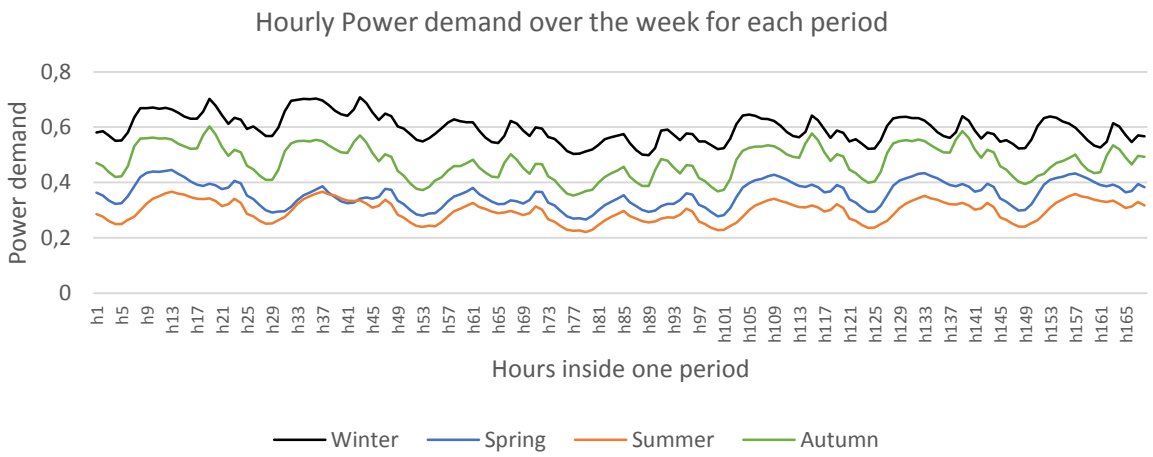

Figure 5.1 – Power demand representation for each time step

5.2.2 Uncertainty

In the model, a random variable ω_t is used to represent uncertainty arising from the power demand. One specific realisation of variable ω_t comes with the realisation of a power demand scenario $D_{t,h}^{\omega_t}$. For each time step t the model has to deal with 5 scenarios occurring on equal probability; but as soon as the model has opted for a scenario in period t the optimisation is performed under perfect foresight over the h hours inside the week.

Let us place ourselves at the beginning of the optimisation problem, that is to say for $t = winter$. Just before winter starts, the model only knows the 5 equally probable values of $D_{t,h}^{\omega_t}$. Once

the winter power demand scenario has realised, the optimisation inside the winter week is done under perfect foresight: we know exactly what will be the next 168 power demand levels inside this winter week. Then winter ends and spring begins: there again we only know the 5 power demand possibilities of spring, occurring again on equal probabilities. Right after the scenario for spring is chosen, the optimisation inside this spring week is performed under perfect foresight, etc. The process is repeated up to the end of the optimisation horizon. A representation of power demand scenarios and the way uncertainty strikes the system is illustrated by **Figure 5.2**.

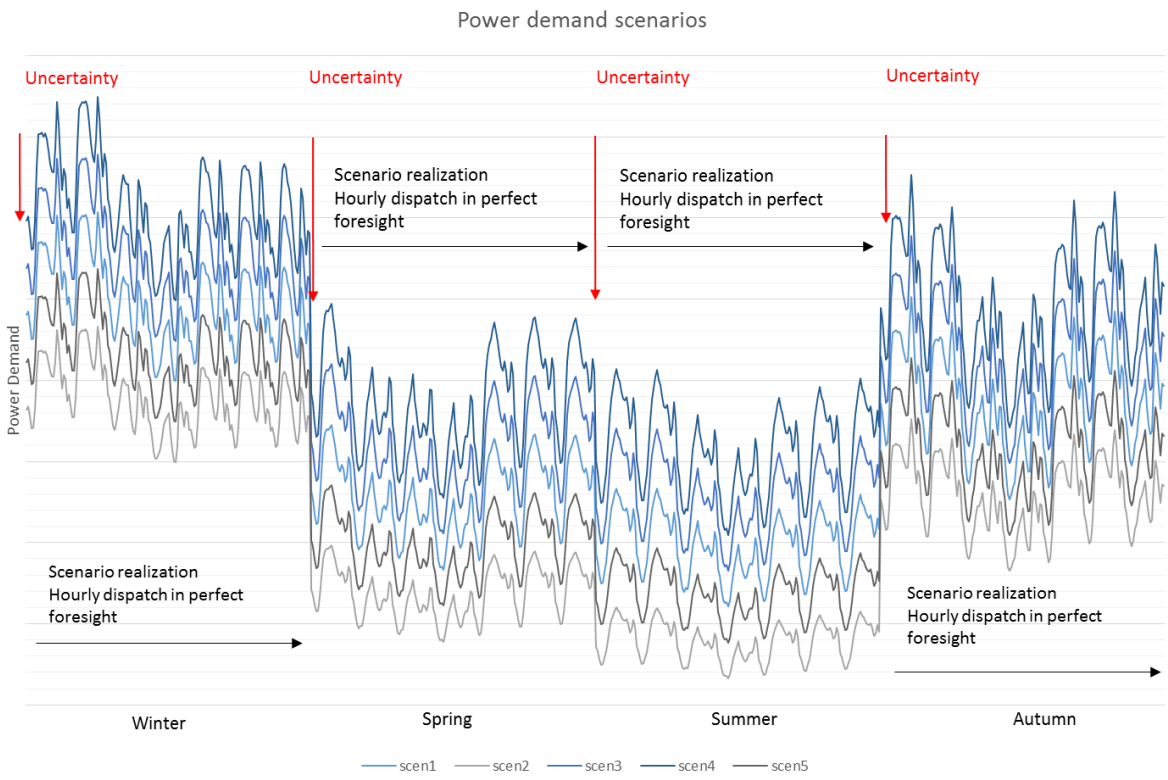

Figure 5.2 – Power demand scenarios and how the uncertainty hits the system

5.2.3 Generation mix

At each time step, the model optimises the dispatch of generating units to meet the demand for power at least cost. Set of generators is made of conventional thermal power plants and DR technologies. To make the optimisation problem feasible, a slack variable is introduced. The slack variable is activated at very last resort if the demand cannot be satisfied by generating technologies. Its variable cost is thus the highest in the generation mix. The slack variable can be interpreted as a mandatory curtailment operated by the system operator. Thus it is not limited in capacity. Moreover, the variable cost of this slack "unit" can be seen as the price cap on the wholesale market. **Table 5.1** introduces key parameters of each technology in the generation mix. Load-shedding_low, load-shedding_high, and load-shifting provide illustrative examples of DR technologies. Load-shedding_low has a variable cost comprised between the semi-peaker and the peaker variables costs while load-shedding_high is the most

expensive technology in the generation mix. We created this two categories of load-shedding, because as we will see further down, the mechanics of their marginal cost setting is not the same.

Table 5.1 – Generation mix of the didactic model

	Generating unit name	Capacity (MW)	Variable cost (€/MWh)
Conventional thermal power plants	Base load	60	20
	Semi-peaker	30	100
	Peaker	10	500
Demand Response	Load-shifting	10	10
	Load-shedding_low	10	200
	Load-shedding_high	10	1,000
Mandatory curtailment	Slack	∞	Price cap: 3,000

Compared with conventional power plants, DR have additional features that are detailed in **Table 5.2** (refer to chapter 4 for explanations regarding how DR is modelled).

Table 5.2 – Demand Response parameters in the didactic model

	Reservoir name	Duration (h)	Number of activations	Reservoir size (MWh)
Load-shifting	Load-shifting upstream	1	/	10
	Load-shifting downstream	1	/	10
	Load-shifting contract	/	50	500
Load-shedding_low	Load-shedding_low	6	/	60
	Load-shedding_low contract	/	20	1200
Load-shedding_high	Load-shedding_high	6	/	60
	Load-shedding_high contract	/	20	1200

Remind that DR technologies are made of two types of reservoirs. One reservoir (or two if we consider the downstream reservoir of load-shifting) physically connected to the grid which produces energy, and one corresponding contractual reservoir which does not produce any MWh of electricity. Contractual reservoirs are added to take into account the *number of activations* parameter which represents the maximum DR events that the DR aggregator is allowed to trigger. Practically the contractual reservoir constrains the use of the physically grid-connected reservoir through the number of activations: once the contractual reservoir has been emptied, the corresponding DR technology can no longer provide energy to the system (refer to chapter 4 for more explanations). Note that there is no other type of electricity storage in the generation mix. Although hydroelectric power plants with a

single reservoir and hydro pumped storage are natural competitors to DR, we chose to abstract from them in order to restrain our analysis on the competition between DR technologies.

5.3 The marginal cost function of Demand Response

5.3.1 Formulation

DR marginal cost is made of two components: the activation cost and the opportunity cost. For all DR technologies we have, at a given time step t:

$$Marginal\ cost_t = Activation\ cost + Opportunity\ cost_t \qquad \text{Eq. 5. 1}$$

As mentioned in previous chapters, activation cost is the variable cost of shedding or shifting the load (refer to sections 1.4 and 4.2.3.2) and opportunity cost is derived from the future cost function, also called the value function (refer to section 4.4.3). Let us consider dr as being a specific DR technology and let us denote by x_t^{dr} the reservoir level of DR technology dr at the beginning of time step t. Regarding the reservoir level, the activation cost is a constant whereas the opportunity cost is a function of x_t^{dr}. We thus have:

$$Marginal\ cost_t(x_t^{dr}) = Activation\ cost + Opportunity\ cost_t(x_t^{dr}) \qquad \text{Eq. 5. 2}$$

The opportunity cost is the opposite of the partial derivative of the value function α_t with regards to x_t^{dr}. The value function is defined by equation Eq. 4. 12 and it is obtained by SDDP (refer to section 4.4). The value function is defined on all state variables (one reservoir level accounting for one state variable). Therefore opportunity cost of DR technology dr is also determined by the level of all other reservoirs present in the system, that we note $\bar{x_t}$. The opportunity cost is then:

$$Opportunity\ cost_t(x_t^{dr}, \bar{x_t}) = -\frac{\partial \alpha_t(x_t^{dr}, \bar{x_t})}{\partial x_t^{dr}} \qquad \text{Eq. 5. 3}$$

Remember that the real value function is not actually known. SDDP builds instead an approximated value function (see chapter 4, section 4.4.3). Therefore, opportunity costs computed in our model are approximations of real opportunity costs.

$$\widetilde{Opportunity}\ cost_t(x_t^{dr}, \bar{x_t}) = -\frac{\partial \widetilde{\alpha_t}(x_t^{dr}, \bar{x_t})}{\partial x_t^{dr}} \qquad \text{Eq. 5. 4}$$

$$where\ \widetilde{\alpha_t}\ is\ the\ approximated\ value\ function\ built\ by\ SDDP$$

At this point, we should precise that mathematically, as a function of x_t^{dr}, the opportunity cost is not defined for all value of x_t^{dr}, because the value function α_t is a piece-wise linear function, thus non-differentiable everywhere on the definition set. On non-differentiable points (where the approximated value function has a break, see figure **Figure 4.6**), the marginal cost is not defined. Nevertheless, this definition issue will not be problematic for our analysis, since we will focus on marginal cost functions. For sake of simplicity we will call marginal cost the cost computed from the approximated opportunity cost obtained from SDDP:

$$Marginal\ cost_t \mathrel{\widehat{=}} Activation\ cost + \widetilde{Opportunity}\ cost_t \qquad \text{Eq. 5.5}$$

We can now calculate the marginal cost for every DR technology as follow:

- we select one DR technology dr,
- we fix other state variables x_t at a specific value $\overline{x_t}$,
- the model then builds the approximated value function $\widetilde{\alpha_t}$ in order to get $\widetilde{Opportunity}\ cost_t(x_t^{dr}, \overline{x_t})$,
- and we add up the activation cost to the approximated opportunity cost.

5.3.2 Marginal cost function of Demand Response

Figure 5.3 shows the value function and the marginal cost function associated to load-shedding_low in winter, where all other state variables $\overline{x_t}$ are set at their average levels over all scenarios and all time steps. When the slope of the value function changes, the marginal cost changes in conformity with Eq. 5. 3. When the opportunity cost is equal to zero, that is to say when the slope of the value function is equal to zero, the marginal cost is equal to the activation cost, that is to say 200 €/MWh in this example. When the energy available in the reservoir gets more scare, the value of the remaining energy inside the reservoir increases, hence a higher opportunity cost as the reservoir level decreases. Thus, the lower the reservoir level the higher the marginal cost. Similarly, **Figure 5.4** and **Figure 5.5** respectively show the marginal cost function of load-shedding_high and load-shifting.

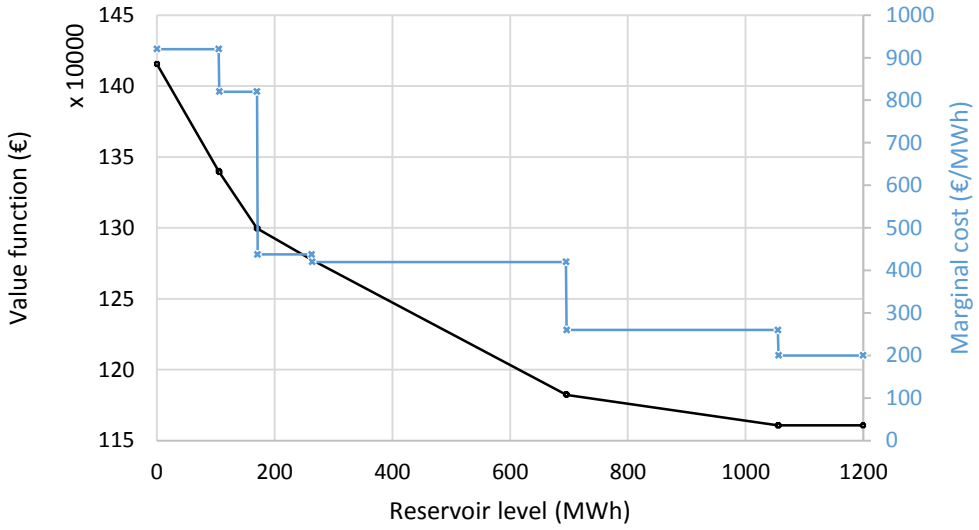

Figure 5.3 – Marginal cost function of load-shedding_low in winter

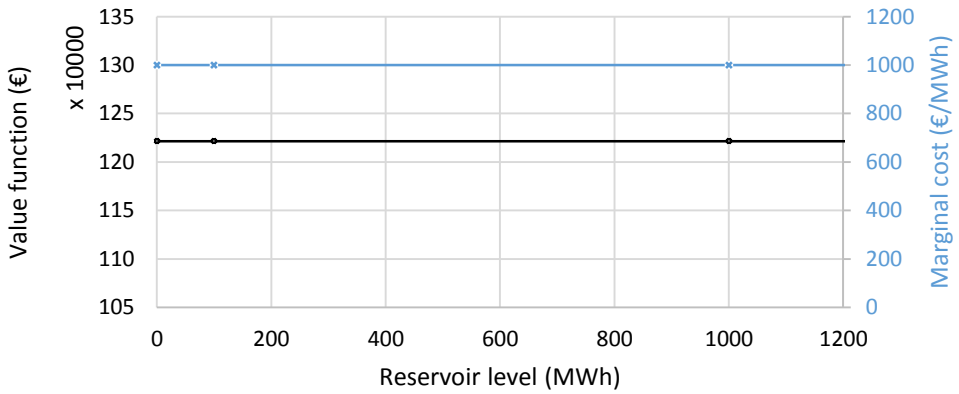

Figure 5.4 – Marginal cost function of load-shedding_high in winter

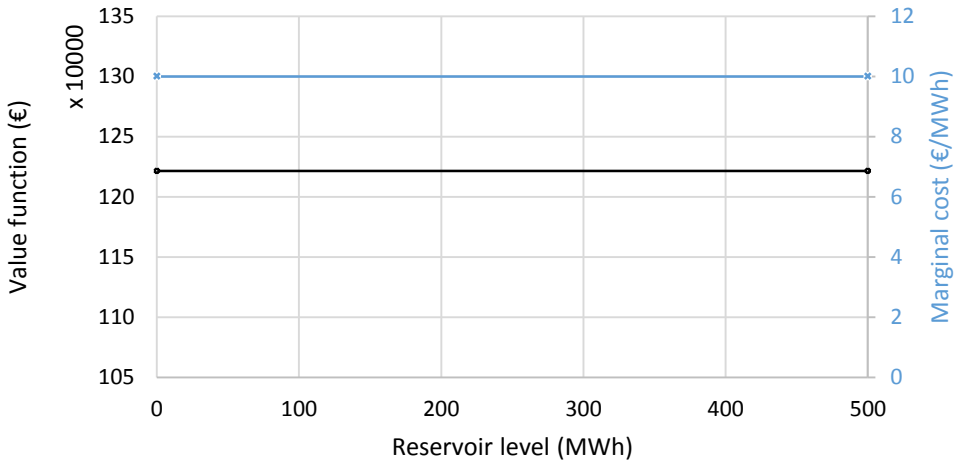

Figure 5.5 – Marginal cost function of load-shifting in winter

Load-shedding_high and load-shifting have similar marginal cost structures and both are quite different from the one of load-shedding_low. Unlike load-shedding_low whose marginal cost significantly raises as the reservoir level goes down, their opportunity cost is null for every reservoir level. This structural similarity should be interpreted differently though. For load-shifting opportunity cost is equal to zero because the contractual reservoir is big enough to capture all prices arbitrage opportunities in the system. Looking at load-shifting contractual reservoir confirms this results: in every scenarios the contractual reservoir is not fully emptied (**Figure 5.6**). It means that the energy constraint associated to the contract is not binding, that is to say the physical reservoir can be used without restrictions.

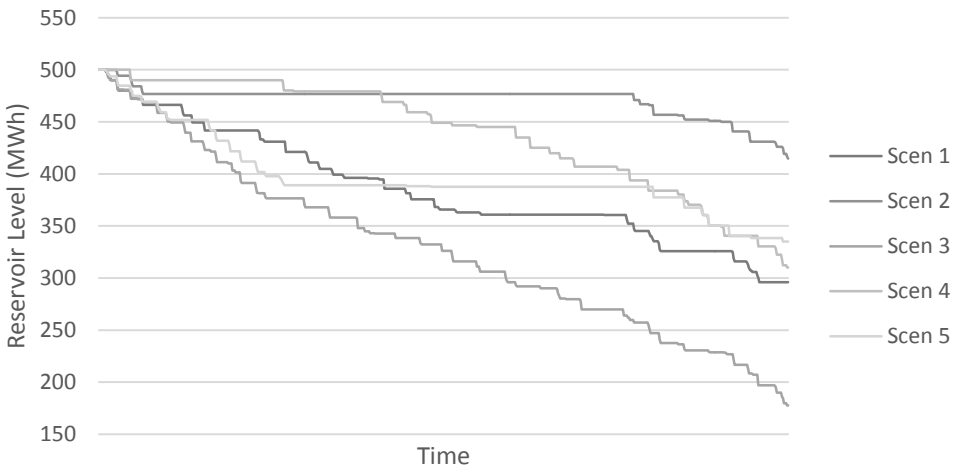

Figure 5.6 – Load-shifting contractual reservoir levels by scenario over time

Load-shedding_high opportunity cost is null because it is the most expensive generating technology in the system and no other technologies have a marginal cost above its activation cost, which is of 1,000 €/MWh. Indeed, the most expensive thermal power plant has a variable cost of 500 €/MWh, and even load-shedding_low marginal costs remain under 1,000 €/MWh, with a maximum at 920 €/MWh (see **Figure 5.3**). Thus, the strategy of using load-shedding_high is straightforward: it consist of waiting until the market price rises up to the price cap at 3,000 €/MWh. If this happens, load-shedding_high will benefit of a 2,000 €/MWh infra-marginal rent, and this is the only possible infra-marginal rent it could get because no other technologies in the merit-order have a marginal cost above its activation cost. On the contrary, load-shedding_low faces different valuation opportunities because it is inserted in between other technologies in the merit-order. Given its activation cost of 200 €/MWh, the infra-marginal rents levels load-shedding_low can get are:

- 500 €/MWh – 200 €/MWh = 300 €/MWh if the peaking power plant sets the market price
- 1,000 €/MWh – 200 €/MWh = 800 €/MWh if load-shedding_high sets the market price
- 3,000 €/MWh – 200 €/MWh = 2,80 0€/MWh if the demand cannot be satisfied and the price cap is reached

Here, given the uncertainty, the decision to dispatch load-shedding_low is not straightforward. Indeed, the aggregator has to decide when to trigger this DR technology on the market and at what price. If the market price is set by the peaker at 500 €/MWh, the aggregator would get a 300 €/MWh margin. But he could also wait for better rents opportunities, without being sure however that future states of the world will actually make this happen. In other words, the aggregator faces an infra-marginal rents trade-off that must be taken into account in his bidding decision. Similarly, from an optimised system point of view, activating load-shedding_low as soon as the market price is set higher than 200 €/MWh does not necessarily yield to the best outcome. Indeed, at some periods, the system operator could find out that it is more optimal to dispatch the peaker unit rather than load-shedding_low although the peaker variable cost is higher. For example, if a high demand scenario occurs at the end of the optimisation problem, it is worth having some remaining energy in the load-shedding_low reservoir in order to avoid a costly mandatory curtailment. Therefore an optimised system computes marginal costs by taking into account the energy constraints associated to each contractual reservoirs. Note that this analysis relies on well-known results regarding the optimisation of power systems with large penetration of hydroelectric energy. For more information, see among others (Philpott 2017; Philpott, Ferris, and Wets 2013).

5.3.3 Marginal costs and market prices

As explained in chapter 4 we know from microeconomics and the optimisation theory that under certain conditions, the optimal solution of our cost-minimisation problem coincides with a competitive market equilibrium. The competitive assumption ensures that market prices are set by the marginal cost of the last generating unit called to satisfy the demand. The purpose of this section is to focus on DR technologies and to understand to what extent they clear the market. **Figure 5.7** represents the set of market price values for all scenarios.

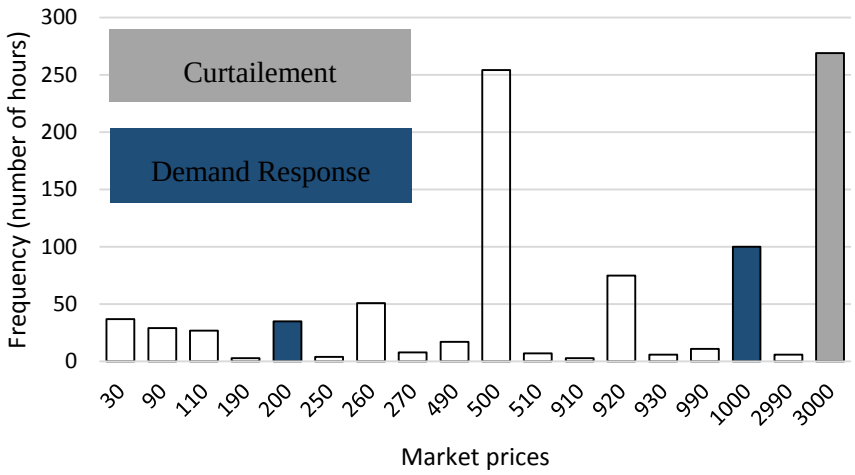

Figure 5.7 – Histogram of market prices in all scenarios

Coloured bars are easily understandable since they reflect situations where the market price is set at the variable cost of the corresponding generating unit. We see that load-shedding_low and load-shedding_high rarely clear the market, compared to thermal power plants[22]. Note also that during more than 200 hours, demand cannot be served and the market price reaches the price cap. To understand the other price values we need to look at DR marginal costs in this particular run of the model. Table 5.3 gives the set of marginal cost values for each DR technology.

Table 5.3 – Set of Demand Response marginal cost values

	Marginal costs		
Load-shifting	10		
Load-shedding_low	920	260	200
Load-shedding_high	1000		

On **Figure 5.7**, when the market price equals 920 €/MWh and 260 €/MWh it corresponds in fact to a value of load-shedding_low marginal costs. Observe now that load-shifting has only one marginal cost value, which is 10 €/MWh, and that the market price sometimes equals the variable cost of a generation unit, plus or minus 10 €/MWh. This occurs when load-shifting is used, either to produce energy from the upstream reservoir, or to consume energy by the downstream reservoir.

5.4 Impact of price cap, contract size, and competition between DR technologies

5.4.1 Price cap impact

In this section we illustrate the price cap impact on the DR marginal cost function. This is interesting policy-wise since it reflects the effect of additional capacity remuneration incentives for DR aggregators.[23]. For this purpose we perform a supplemental run where the price cap is set at 20,000 €/MWh. Recall that with a price cap of 3,000 €/MWh, the marginal cost function of

- load-shedding_low increases as the reservoir level decreases (**Figure 5.3**),
- load-shedding_high is constant, equal to the activation cost (1,000 €/MWh, **Figure 5.4**),
- load-shifting is constant, equal to the activation cost (10 €/MWh, **Figure 5.5**).

Load-shedding_low

On **Figure 5.8** we see that compared with a price cap of 3,000 €/MWh the value function and the marginal cost for load-shedding_low has changed. With a price cap of 20,000 €/MWh, the value function gets steeper at some point entailing a higher marginal cost, due to intertemporal adjustments. The value function represented on this graph is an evaluation of the expected future cost that the system may endure if load-shedding_low is used at winter instead of keeping it for later seaons.

[22] We took out some market prices that occurred too frequently for sake of readability. In the 5 scenarios, the price is indeed set at 20 €/MWh for 1,121 hours and at 100 €/MWh for 1,297 hours.

[23] We will discuss this topic in greater details in PART III, explaining that setting the price cap at greater values can simulate capacity remuneration from, for instance, a capacity market.

Moreover, remember that the price cap is the cost of non-served demand. Logically a higher price cap increases the expected future cost, since a bad decision regarding load-shedding_low activation at winter could then imply a power demand curtailment that would cost 20,000 € per unit of non-served demand instead of 3,000 €. The reasoning from the DR aggregator's view is the following: the higher the price cap the bigger the incentive to wait for higher revenues, hence a higher opportunity cost to activate DR.

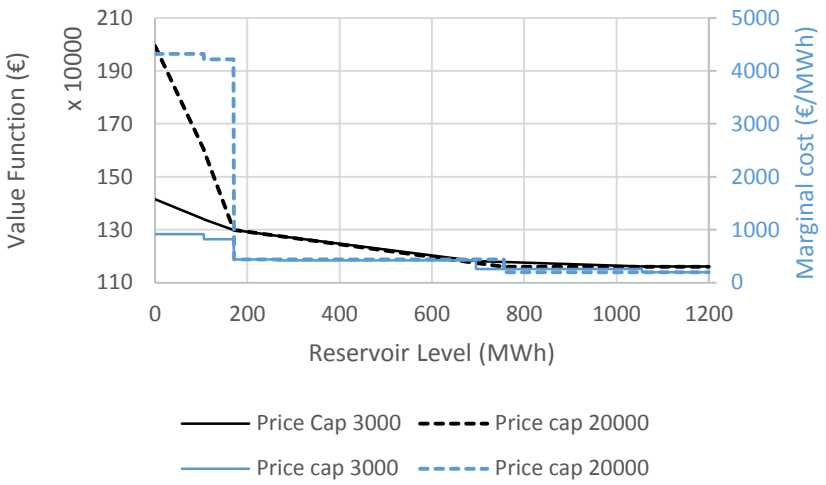

Figure 5.8 – Price cap impact on load-shedding_low marginal cost

Load-shedding_high

The rise of price cap has a repercussion on load-shedding_high as well. In section 5.1 we saw that this type of DR had an opportunity cost equal to zero because it is the most expensive technology in the generation mix. Herein, observe on **Figure 5.8** that when the reservoir level of load-shedding_low is smaller than 170 MWh, the marginal cost goes up to 4,320 €/MWh. This implies that load-shedding_high has now two opportunities of infra-marginal rents, since the market price can theoretically be cleared by load-shedding_low at 4,320 €/MWh. Thus the opportunity cost of load-shedding_high is no longer equal to zero and the value function is re-shaped with a steep part as illustrated on **Figure 5.9**.

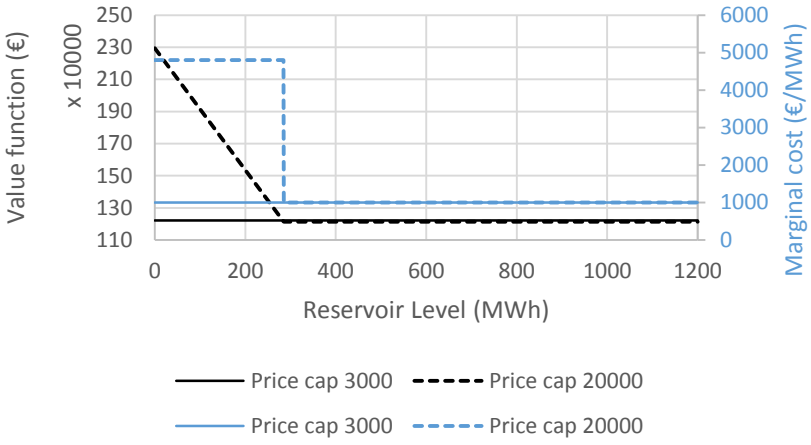

Figure 5.9 – Price cap impact on load-shedding_high marginal cost

Load-shifting

In this specific situation, increasing the price cap has no effect on load-shifting: the marginal cost remains zero for all reservoir levels no matter the price cap level. This is because the contractual reservoir is big enough to not constrain the use of the physical reservoir. This result should be taken carefully though since it depends on a particular situation where the amount of energy in the contractual reservoir is significant. In principle, the price cap level can modify load-shifting marginal costs, but the effect is ambiguous because it depends on whether changing the price cap creates new opportunities of price arbitrage or not. Let us illustrate this throughout a simple hypothetic example. Imagine a two-stage problem whereby the decision to take is to use a load-shifting DR technology, given some exogenous price profiles. For sake of simplicity, let us assume that the maximum number of activations allowed is 2, and that the activation cost is zero. We also suppose that the first step of the problem is deterministic such that we know what will be the price profile in this first step. At the second period, two price profiles can occur on equal probability: one profile with a spike equal to the price cap set at 3,000, and one flat profile (see **Figure 5.10**).

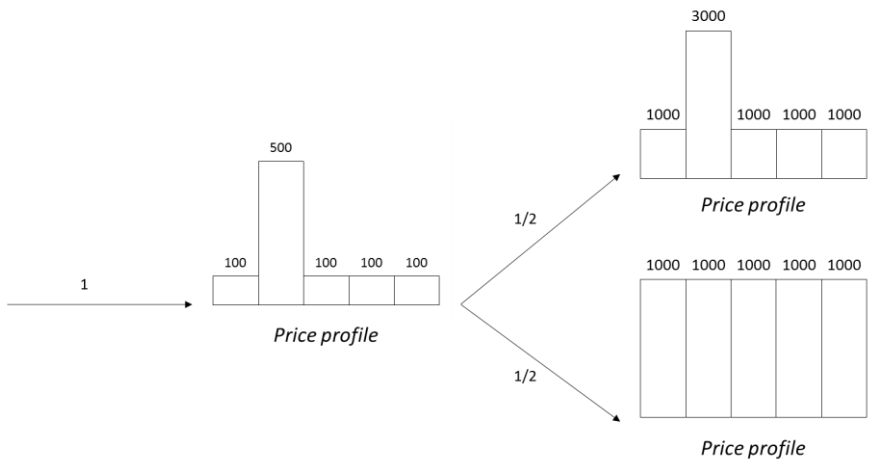

Figure 5.10 – A simple problem illustration for load-shifting activation (1)

With these price profiles, there is one possibility of price arbitrage at each time step, totalling two possibilities over the entire problem, which is as many as the number of allowed activations. Therefore, making one load-shifting activation in the first period will not prevent us to benefit from the high price differences in the second period: the opportunity cost is null. The optimal strategy is thus to activate load-shifting during the first period. The expected gain is:

$$Expected\ gain = (500 - 100) + \frac{1}{2} * (3{,}000 - 1{,}000) = 400 + 1{,}000 = 1{,}400.$$

The situation is different if we have only one possible activation. Then we have to choose between a certain gain of 400 in the first period and an expected gain of 1,000 in the second period. If we are risk-neutral we should decide to not activate load-shifting in the first period, because we prefer an expected gain of 1,000 to a certain gain of 400. Moreover, if we use this unique allowed activation in the first period, we would renounce an expected gain of 1,000 in exchange to a certain gain of 400: thus we face an opportunity cost of 600. The optimal decision is thus to not use the load-shifting at the first period, because the arbitrage value in this period is only of 400.

Let us now assume that the price cap is set at 20,000 and that we get again two allowed activations. If the shape of the price profiles remain the same (**Figure 5.11**), then the opportunity is still null as in the previous case, although our expected gain have raised significantly:

$$Expected\ gain = (500 - 100) + \frac{1}{2} * (20{,}000 - 1{,}000), = 400 + 9500 = 9{,}900.$$

For the same number of activations and the same price profile, a raise in the price cap does not change the opportunity cost. However, if once again we are left with only one load-shifting activation, we note that the opportunity cost has increased up to 9,500-400=9,100.

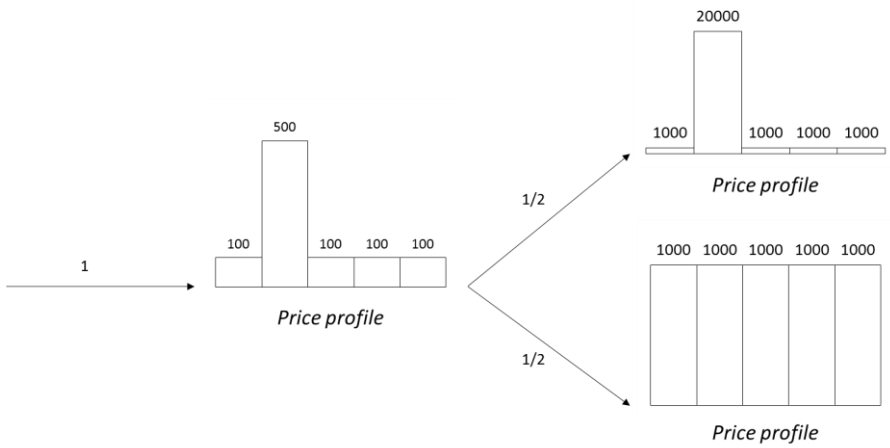

Figure 5.11 – A simple problem illustration for load-shifting activation (2)

Let us now assume that the price cap modifies the load profiles by creating more price arbitrage opportunities in the second time step (**Figure 5.12**). Then the opportunity cost increases. Indeed if we have two allowed activations, then using one of it in the first round gives us 400, but deprive us of an

eventual gain of ½*(20,000-1000)=9500: the opportunity cost is thus 9,500-400=9,100 while it was 0 with a price profile containing only one price spike.

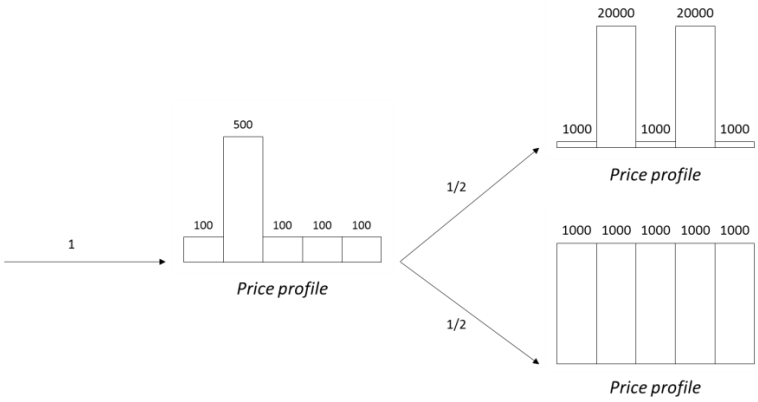

Figure 5.12 – A simple problem illustration for load-shifting activation (3)

On the contrary if the price cap smooths out the price profiles, the opportunity cost is reduced. Suppose again that the number of activation is 1. With price profiles of **Figure 5.12** we saw that the opportunity cost amounted to 9,100. With price profiles proposing less arbitrage opportunities such as those of **Figure 5.13**, the opportunity cost is equal to zero.

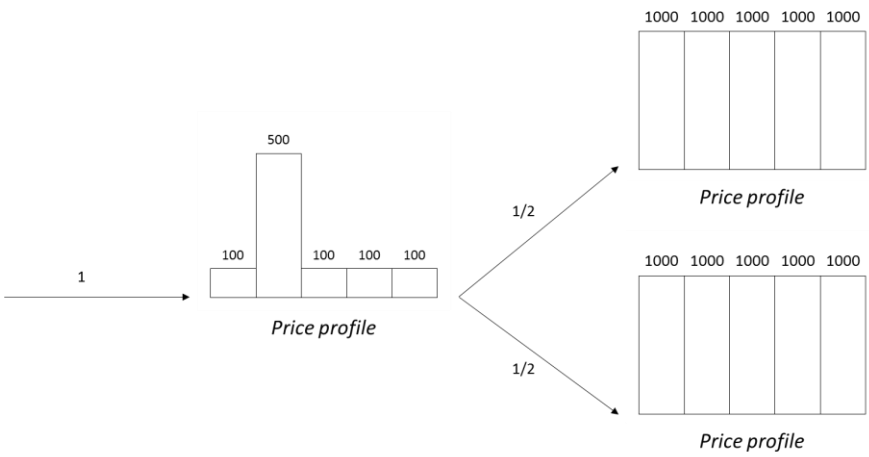

Figure 5.13 – A simple problem illustration for load-shifting activation (4)

This simple example however explores the variation of load-shifting marginal cost on limit conditions, i.e. when the number of activations is just equal to, just one more or just one less than the number of price arbitrage opportunities. This explains why the marginal cost suddenly varies from 0 to significant values. If we get back to our didactic model, marginal cost variations are likely to be smoother. If we want to observe these variations and determine the impact of changing the price cap on the marginal cost of load-shifting, we need to create a situation where the number of activations is lower than opportunities of price arbitrage. Remember that up to now, load-shifting was designed as follow:

- Capacity: 10 MW
- Duration: 1 hour
- Number of activations: 50

The contractual reservoir size the adds up to 500 MWh. Let us change those parameters in a way that the contractual reservoir size is reduced:

- Capacity: 10 MW
- Duration: 0.5 hour
- Number of activations: 20

The contractual reservoir size now adds up to 100 MWh. The influence of two different price caps can now be observed, because 100 MWh are not enough to capture all price arbitrage opportunities in the market. On **Figure 5.14** we see that load-shifting marginal costs are no longer equal to zero, and that a higher price cap leads to a lower marginal cost. Therefore, unlike for load-shedding technologies, the price cap does not increase the marginal cost. Nevertheless, as pointed out by the small example presented above, the effect of price cap on load-shifting marginal cost can be ambiguous.

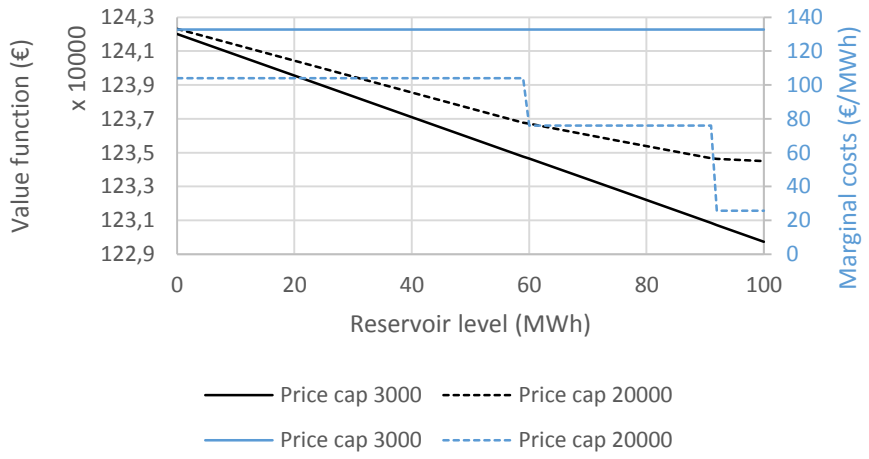

Figure 5.14 – Price cap impact on load-shifting marginal cost (winter)

Let us look at another time step. **Figure 5.15** represents the load-shifting marginal cost at spring. Unlike during winter a higher price cap does not yield to a lower marginal cost. Indeed when the price cap is set at 20,000 €/MWh, the marginal cost skyrockets for low levels of energy in the contractual reservoir, probably because if the reservoir level goes below this threshold, very valuable price arbitrage opportunities may be missed. However if the reservoir level remains above this threshold the marginal cost is lower than with a price cap of 3,000 €/MWh. More generally, we observe that the two marginal cost curves intersect at many points, highlighting the ambiguous effect of the price cap on load-shifting marginal costs.

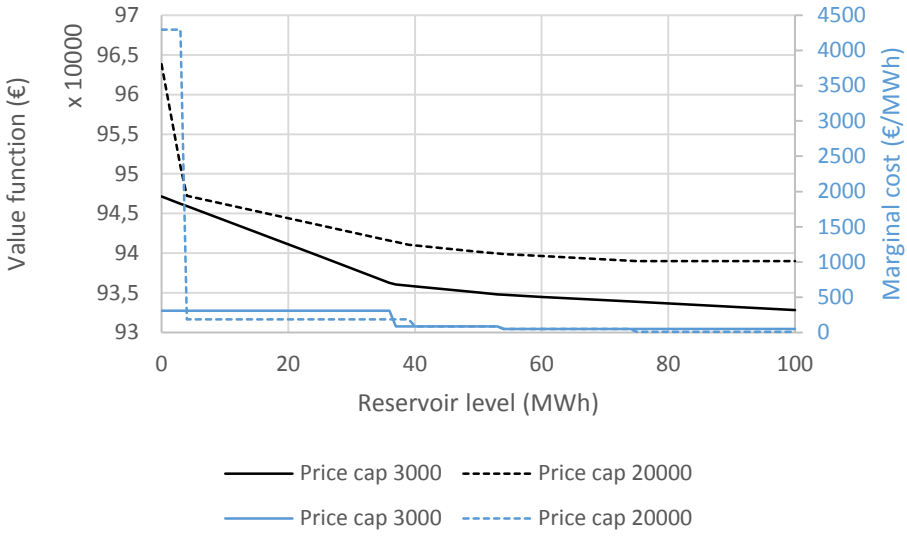

Figure 5.15 – Price cap impact on load-shifting marginal cost (spring)

Summary

To sum up, when it comes to load-shifting, the price cap impact is more difficult to analyse than in the case of load-shedding. Regarding load-shedding, a price cap increase is a direct incentive to wait for more valuable scarcity rents. Therefore the higher the price cap the higher the marginal cost. For load-shifting it depends on two situations:

- If number of activations > price arbitrage opportunities, then the price cap has no impact on the marginal cost.
- If number of activations < price arbitrage opportunities, the price cap has an ambiguous effect on the marginal cost.

5.4.2 Competition between Demand Response and contract size impact

Within power systems, DR theoretically competes with storage facilities because, just as for hydroelectric reservoirs or pumped hydroelectric storages for instance, they can produce energy over a limited time window. Moreover as explained in chapter 1, load-shedding is also a competitor of peaking power plants because they have similar level of variable costs. Eventually, DR technologies naturally compete with each other. However in this section, we restrain our analysis on the dynamics of competition between DR technologies. We do not address the competition with other storage facilities and peaking power plants for the following reasons:

- In practice, DR are non-competitive compared with storage facilities as hydroelectric reservoirs or pumped storage given the differences in capacities and reservoir sizes.

- Since thermal power plants have no energy limits their marginal cost is only driven by their variable cost.

On the contrary, competition between DR technologies requires a closer look in order to be well understood. The activation of a particular DR technology provides energy to the system, but then the total amount of energy available in the overall reservoirs has been reduced. This mechanically increases the value of all other storages. In previous section we already saw how decreasing the contractual reservoir size of load-shifting raised its own marginal cost: from 500 MWh to 100 MWh available in the contractual reservoir, the marginal cost raised from 10 €/MWh up to a maximum value of 4,296 €/MWh. This fact underlines predominance of opportunity costs over activation costs when the available energy in the reservoir gets scarce. However, remember that when the reservoir size of load-shifting is set at 500 MWh, load-shedding_high, which is the most costly DR, has an opportunity cost equal to zero no matter its reservoir level. The reason is that load-shedding_high is structurally the last unit in the merit-order in terms of variable cost. Therefore, unless marginal costs of other reservoirs are higher than its activation cost, its opportunity is null. In the light of these examples it becomes clear that dynamics of competition between DR facilities is not as straightforward as it looks at first sight: because of opportunity costs, marginal costs can converge in the same range of values although there is a significant gap between activation cost values. **Figure 5.16** shows this convergence, which occurs for low reservoir levels. Marginal costs curves shown on this graph are derived from a model run where the reservoir size of load-shifting has been reduced to 100 MWh.

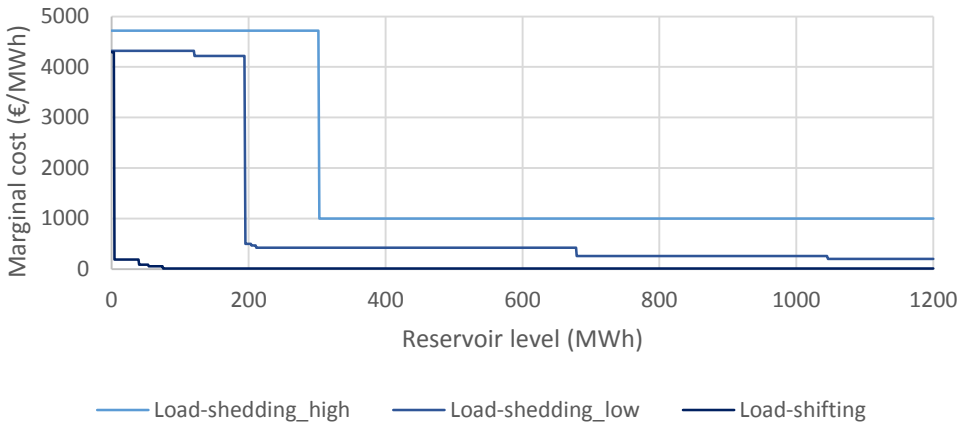

Figure 5.16 – Marginal costs convergence (PC at 20,000 €/MWh)

We already saw that the reduction of its own contractual reservoir size had a big impact on load-shifting marginal cost. We must now assess whether the contractual reservoir size of load-shifting also impacts the marginal cost of other DR. According to Eq. 5. 3, contractual reservoir levels of load-shifting theoretically impact other DR marginal costs. **Figure 5.17** and **Figure 5.18** show that the impact

is actually weak both on load-shedding_high and load-shedding_low: marginal costs remain roughly identic.

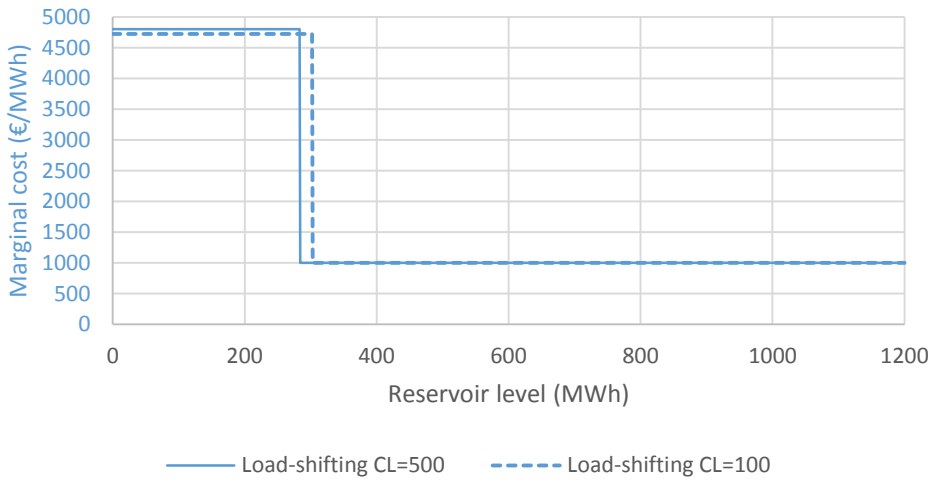

Figure 5.17 – Impact of load-shifting contract size on load-shedding-high marginal cost

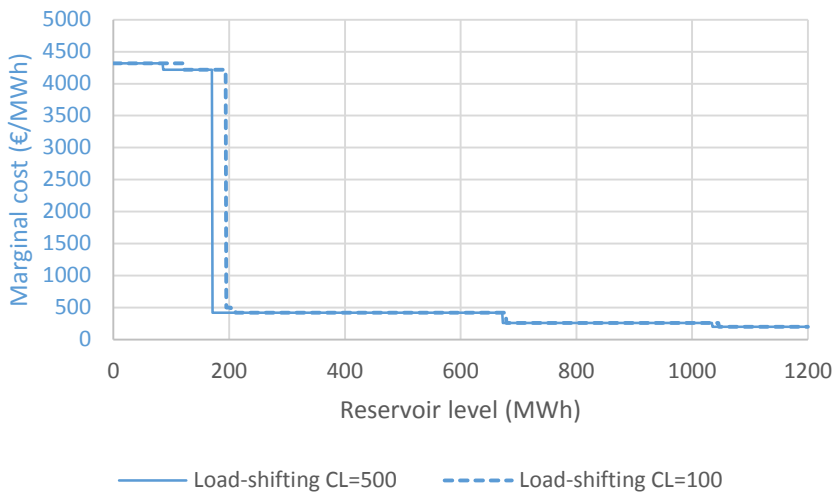

Figure 5.18 – Impact of load-shifting contract size on load-shedding_low marginal cost

5.5 Social and private value of Demand Response

5.5.1 Social welfare

As defined by the economic theory, social welfare can be computed as the utility derived by all consumers from the consumption of electricity (the consumer surplus) minus the total cost of producing this quantity of electricity, at market equilibrium.

$$Social\ welfare = Consumer\ surplus - Total\ cost$$

Calculation of the consumer surplus requires elastic demand functions that we have not considered in our model setting. In our framework, the consumer surplus is only represented by the set of power demand levels. Power demand levels are inputs independent of any other model parameters. In particular, power demand levels does not depend on the quantity of DR integrated in the model. Therefore, neither does the consumer surplus. We can thus assess the social welfare impact of DR by computing its variation when DR is present in the system and when DR is absent:

$$\begin{gathered} Social\ welfare\ impact \\ = \\ Social\ welfare_{with\ DR} - Social\ welfare_{without\ DR} \\ = \\ Consumer\ surplus - Total\ cost_{with\ DR} - (Consumer\ surplus - Total\ cost_{without\ DR}) \\ = \\ Total\ cost_{without\ DR} - Total\ cost_{with\ DR} \end{gathered}$$

Total costs of producing electricity are easily computable from the values of the objective function. Note however that the total cost of producing electricity is not the objective function, it is the objective function minus the value function. Table 5.4 presents the social welfare increase in percentage following an integration of DR in the system, with the inputs setting presented in section 5.2.3.

Table 5.4 – Social welfare impact of Demand Response by scenario

	Scenario 1	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**
SW increase	45%	2%	53%	37%	18%

The influence of DR on social welfare depends on the scenario at stake. For example, scenario 2 is characterised by low power demand levels. Therefore, DR technologies are barely used in this scenario compared with other scenarios where DR is activated more often. In particular, load-shedding_high is not used at all in scenario 2, and load-shedding_low produces only 16 MWh in the same scenario, while in scenario 3, which is a high demand scenario, they produce respectively 514 MWh and 1,200 MWh.

5.5.2 The aggregator's benefits

The aggregator's benefits are commonly computed as the difference between total market revenues and total production cost for each DR technology dr and each scenario:

$$Benefit^{dr,\omega} = \sum_t Market\ Revenue_t^{dr,\omega} - \sum_t Production\ cost_t^{dr,\omega}$$

At time step t the market revenue is the volume of energy produced $E_t^{dr,\omega}$ multiplied by the current market price $Price_t$:

$$Market\ Revenue_t^{dr,\omega} = E_t^{dr,\omega} * Price_t$$

Production cost calculation depends on the type of DR technology. For load-shedding, production cost is equal to the activation cost multiplied by the energy produced:

$$Production\ cost_t^{load-shedding,\omega} = AC^{load-sehdding} * E_t^{load-shedding,\omega}$$

For load-shifting, a term is added to the production cost: the cost of recovering the energy that has been shifted from time period t to time period t'. The cost of recovering the energy is equal to the energy recovered $Er_{t'}$ multiplied by the market price at period t':

$$Production\ cost_{t,t'}^{load-shifting,\omega} = AC^{load-shifting} * E_t^{load-shifting,\omega} + Price_{t'} * Er_{t'}^{load-shifting,\omega}$$

Figure 5.19 presents the distribution of benefits per MW made by each DR technology and sort by scenario (with a price cap set at 3,000 €/MWh and contractual reservoir size of load-shifting at 500 MWh).

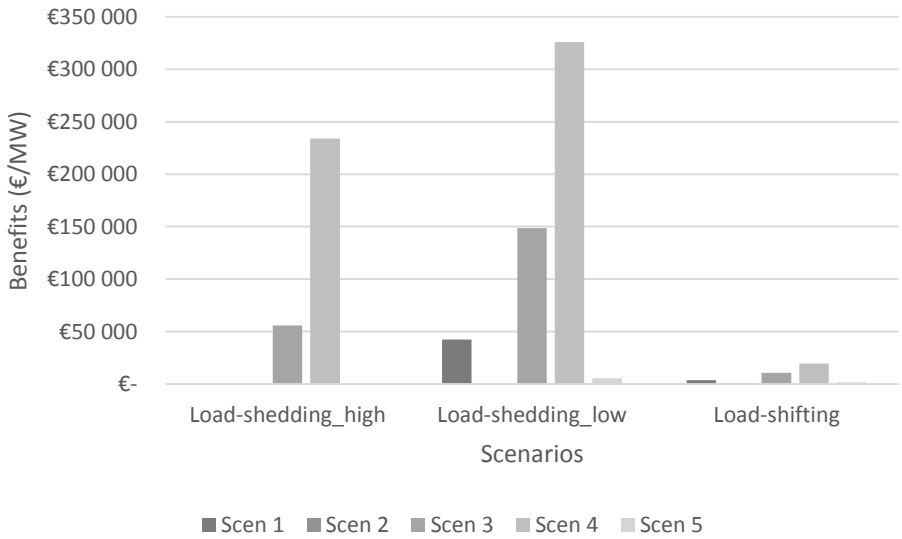

Figure 5.19 – Distribution of Demand Response benefits per capacity

Figure 5.20 proposes a zoom on load-shifting. Unlike load-shedding technologies, we note that load-shifting is used in all scenarios. Nevertheless load-shedding technologies makes much bigger benefits than load-shifting.

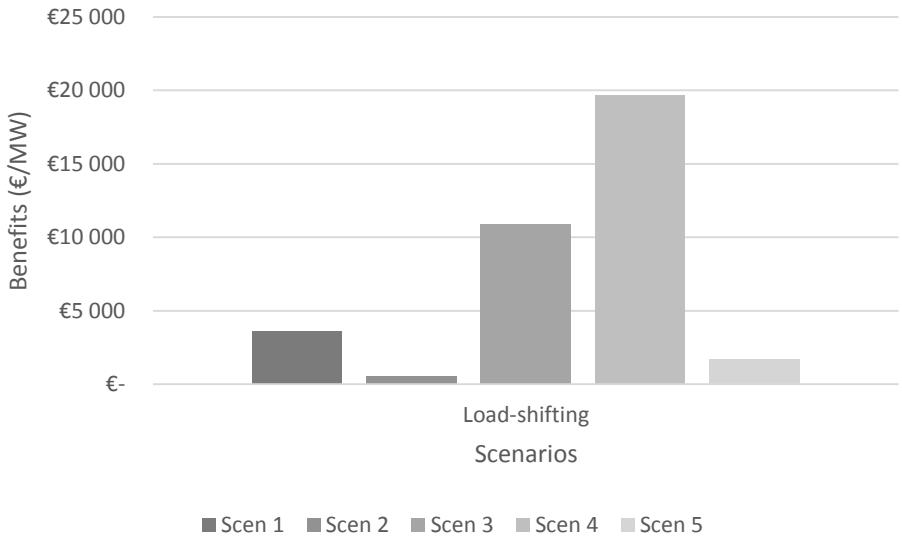

Figure 5.20 – Distribution of load-shifting benefits per capacity

In order assess the impact of changing the price cap and reducing the contractual reservoir size of load-shifting, we compare the benefits averaged over all scenarios in four situations (combination of two values for the price cap and two values for the contract size). In **Table 5.5** "CS" (for contract size) refers to the contractual reservoir size of load-shifting. We see that the price cap impact is positive for all DR technologies but with different intensities. For load-shedding_high, average benefits are multiplied by a factor of 10, which is greater than the price cap ratio (20,000/3,000≈6.667). For load-shedding_low, average benefits are almost 6.3 times greater while for load-shifting they are roughly 4.8 times higher. Reducing the contract size of load-shifting only reduces load-shifting benefits. For both price cap levels, benefits are reduced by roughly 30%. Benefits of load-shedding are slightly modified by the contract size.

Table 5.5 – Price cap and contract size effects on average benefits per capacity

Average benefits (€/MW)	**Price cap = 3,000**		**Price cap = 20,000**		**Benefits ratio**	
	CS=500	CS=100	CS=500	CS=100	CS=500	CS=100
Load-shedding_high	57,990	57,908	580,087	570,354	10	9.8
Load-shedding_low	104,455	105,474	658,769	649,897	6.3	6.1
Load-shifting	7,284	4,918	34,649	24,274	4.8	4.9

5.6 Conclusion

This didactic model illustration has provided us with several key insights regarding the marginal cost function of DR:

- Marginal cost is a decreasing function of the contractual reservoir level.

- Marginal cost function can be significantly affected due to changes in the intertemporal opportunity cost.

- For all DR technologies, the bigger the contractual reservoir, the lower the intertemporal opportunity cost. This effect can be significant on the concerned technology but has little impact on other DR technologies.

- For load-shedding, the higher the price cap the higher the marginal cost.

- For load-shifting, if the number of activations is greater than price arbitrage opportunities, the price cap has no impact. If the number of activations is lower than price arbitrage opportunities, the price cap effect is ambiguous.

Regarding social and private economic values of DR, we found out that:

- DR improves significantly the social welfare in average. Its impact varies according to the scenario. For low demand level scenario the impact is much smaller than for high demand scenarios.

- The aggregator's benefits are much more significant for load-shedding than for load-shifting.

- For all DR, a higher price cap leads to higher benefits. Moreover the higher the activation cost, the bigger the price cap impact.

- Decreasing the contractual reservoir size of one particular DR technology reduces benefits of this technology but does not impact other DR benefits.

Insights provided within this chapter intend to support the analysis of the case study results that will be presented in the two next chapters. Figures regarding DR economic values are no more than indicative because they depend on power systems conditions that are modelled. The generation mix modelled here is a simplistic copy of the current French power system characterised by high share of base load

capacity and a relatively low penetration of intermittent renewable energy sources. For instance, neither hydroelectric power nor intermittent renewable energy sources have been considered here. Nevertheless, these findings can be seen as a useful support in the view of our case study applied to France.

PART III – THE ECONOMIC VALUE OF DEMAND RESPONSE. A CASE STUDY ON THE BUSINESS OPPORTUNITY FOR AGGREGATORS IN FRANCE

Introduction

The two following chapters aim to assess the economic potential of DR in France. For a couple of years, the emergence of new DR capacities in France has been mainly taken on by DR aggregators, and it is likely that their role in empowering consumers, especially small and medium ones, will strengthen. To fit with this current trend, this third part provides an assessment of the economic potential of DR based on the business case of aggregators.

Our analysis relies on numerical simulations from the wholesale energy-only market model presented in Part II, which has been calibrated on the French power system. Because the model does not deal with investment decisions, we have integrated DR capacities exogenously in the energy mix. The analysis answers the following question: if DR technologies were integrated in the power system, what value would they derive given current conditions of electricity markets in France? We have thus assumed that a single DR aggregator owns contracts with different categories of electricity consumers representing different types of DR technologies. The approach is the same as in the didactic model presented in chapter 5. In this case study, the difference is that the representation of DR technologies covers a complete view of residential and tertiary end-uses of electricity, as well as industrial processes existing in France.

In chapter 6, we quantify the annual benefits that the DR aggregator would earn from the wholesale energy-only market. These benefits are distributed over the realisation of residual power demand scenarios representative of the uncertainty in the power system. Among the twenty residual power demand scenarios included in the model, our results show that most of the benefits earned by the aggregator are captured by one scenario. This particular scenario is characteristic of a *scarcity* situation, whereby generating capacity is missing to satisfy extreme peaks of demand. During these few hours of scarcity, market price reaches the price cap set at 3,000 €/MWh[24], ensuing *scarcity rents* for the aggregator. These scarcity rents reflect the capacity value of the system. We compare these *capacity revenues* with the *energy revenues* made during normal periods, that is to say when there is no scarcity in the system. We show that capacity revenues are much more significant than energy revenues. Furthermore, for some DR technologies, capacity revenues are not enough to cover the fixed cost of the enabling infrastructure, raising another question: what would be the impact of an additional capacity remuneration on the aggregator business case.

This is the issue tackled by chapter 7. Following the main conclusion of chapter 6, namely that the capacity value of DR is key for the economic viability of the aggregator, we have organised our analysis around the changes of parameters influencing the aggregator scarcity rents. In terms of benefits, the aggregator is better off if scarcity rents are *higher* or *more frequent*. A straightforward way to increase the amplitude of scarcity rents is to change the price cap level. In a first section, we

[24] In compliance with the price cap applicable by EPEX Spot in France.

then analyse how increasing the price cap from 3,000 €/MWh to 10,000€/MWh and 20,000 €/MWh[25] would change the aggregator benefits. The approach is motivated by the launch of the capacity market in France which organises a capacity remuneration for DR providers. In a second section, we test a parameter modifying the occurrence of scarcity rents: the *contract size* between the aggregator and consumers. The contract size is actually determined by the maximum number of DR activations per year consumers accept. In chapter 6, we have assumed a high number of DR activations per year, which we can consider as the highest degree of acceptability of consumers towards DR contracts[26]. The objective here is to test the *reluctance of electricity consumers* to engage with DR aggregators, by reducing the size of contracts. This issue is of high interest for the aggregator: if consumers accept less DR activations per year, does it come with lower benefits? We show that this is not necessarily the case. Indeed, from the system point of view, reduction of contract sizes comes with smaller amounts of energy provided by DR, thus possibly more periods of scarcity that the aggregator may take advantage of. The purpose of this section is precisely to determine whether reducing the energy volume of DR in the system can be offset by more opportunities of scarcity rents for the aggregator.

[25] Representing the level of the VoLL.

[26] Indeed, we rely on Gils' paper which is an assessment of the theoretical potential of DR in Europe. In terms of annual number of activations, values provided by Gils should thus be taken as a maximum theoretical benchmark, with no consideration over consumers acceptability of DR programmes.

CHAPTER 6 CASE STUDY: THE BUSINESS CASE OF A DEMAND RESPONSE AGGREGATOR IN FRANCE

6.1 Introduction

Supported by the Clean Energy package of the European Commission released in November 2016, the commercial activity of DR is progressively expanding within several European countries (SEDC 2017) but remains limited compared with the existing potential which can theoretically be tapped. Nowadays, DR aggregators are seen as private third-parties able to unlock wider DR capacities, provided that the regulatory framework ensures a level playing field for DR to compete with other traditional flexibility options. In France the access of DR to wholesale electricity markets has been prompted by a set of different legislative texts authorising demand-side resources to explicitly participate in wholesale markets, be it (i) the balancing mechanism (via the "NOME"[27] law), (ii) the energy-only day-ahead market (via the so-called "Brottes"[28] law) and (iii) the capacity market. Concretely, French regulatory framework now enables load aggregation to be remunerated through tailored market products, thus the emergence from a couple of years of independent DR aggregators. Voltalis, Energy Pool, and Actility are examples of such aggregators marketing respectively households, industrial consumers, and both. The existence of these new market entrants proves at least the technical feasibility to trigger successful DR events for both consumers and wholesale markets. Therefore, regulatory and technical barriers are no longer an issue for the commercial activity of DR in France. Nevertheless a pertaining issue to the business of DR is its economic viability in the long-term: will this commercial activity grow with years to come or rather remain steady? According to RTE[29] there is nowadays approximately 3.4 GW of active DR capacity in France (RTE 2015), meaning that the theoretical potential is far from being tapped. Indeed, if we add up the potential of electric heaters which are ubiquitous in the French power system to the potential estimated by Gils (2014), we end up with around 20 GW[30] of load capacity suitable for DR. We should thus wonder how much of this remaining capacity might be economically activated in the coming years.

[27] The NOME law, standing for « Nouvelle organisation du marché de l'électricité » establishes rules for the organisation of electricity markets in France. It stipulates that the TSO must implement DR capacities. Consequently RTE has contractualised DR capacities for system balancing purposes.

[28] This law released on 2013, the 15th of April led to the implementation of NEBEF mechanism by RTE, allowing DR providers to bid load reductions on the wholesale energy market.

[29] RTE – Réseau de Transport d'électricité – the French TSO.

[30] Gils' study estimates that around 11.5 GW of capacity for load reduction are potentially available in France (see Table 9 page 10). This number does not include electric heaters, so the 20 GW includes our own calculation of the potential stemming from electric heaters.

The case study presented in this chapter is a business case of DR aggregators in France. It relies on numerical results provided by simulations of the electricity market model described in chapter 4. The framework is similar to the didactic model of chapter 5: a single DR aggregator owns a set of DR technologies differentiated by class of consumers, process, and appliance, which are exogenously included in the generation mix. However, unlike the didactic model which is based on a generic representation of DR, we consider here the whole bunch of DR technologies potentially available in France. The model is calibrated on the French power system in order to reflect what would be the level of wholesale electricity prices in France further to a large scale penetration of DR[31]. From these market prices, which are a key outcome of our model, we compute the aggregator market revenues. The latter are distributed over the realisation of residual power demand scenarios. When a scenario of extreme peak of demand occurs, the aggregator can take advantage of scarcity rents, providing a *capacity value* to the power system. In the aggregator revenues, we thus distinguish the capacity value from the *energy value* which is provided under normal system conditions, that is to say when the demand can be met by the generating technologies. Furthermore, we determine the business opportunity of each DR segments by comparing their benefits with the fixed costs of the enabling infrastructure.

Section 6.2 presents the case study inputs, in particular DR capacities and activation costs, as well as consumer-based constraints such as the number of activation and the temporal availability of electric loads. Section 6.3 presents quantitative results about the aggregator benefits, segmented by DR technology. These benefits are then compared with the investment cost of the enabling infrastructure and technologies. Section 6.4 concludes the business case.

6.2 Case study presentation

The model presented here has been calibrated on France with regards to the residual power demand and the current generation mix. The model optimises the economic dispatch of generating units over a complete year in order to satisfy the demand for electricity at the system level. Year is decomposed in periods (or time steps), numbered 52. The 52 time steps represent weeks which are themselves decomposed in 168 sub-periods, accounting for hours. Every time steps last one week, or 168 hours. Time steps are indexed by t, i.e. $t \in \{1,2,\dots,52\}$, and hours by h, thus $h \in \{1,2,\dots,168\}$. In total, we thus have 8736 levels of demand to satisfy, implying a set of 8736 market prices which are the main outputs of interest for this case study. Combined with the dispatch decisions of DR technologies present in the generation mix, the model enables to compute the annual market-based revenues of the DR aggregator, given today system conditions in France. Timeframe of the model begins on January, the 1st and December, the 24th is the last period (see **Figure 6.1** for an illustration).

[31] Such a large scale deployment would probably depreciate wholesale market prices during peak hours, rending necessary to consider the feedback of DR activations on market prices in our analysis. Similarly, DR aggregators would naturally assess their own business opportunity by taking into account this effect.

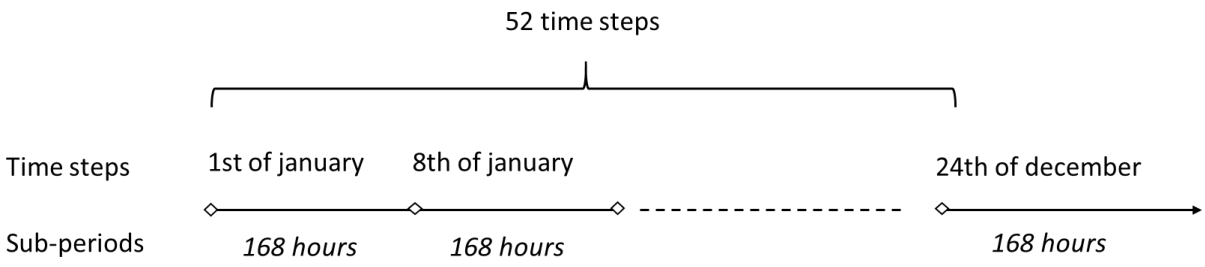

Figure 6.1 – Timeframe of the case study

6.2.1 Residual power demand

In France, hourly power demand is characterised by important seasonal variations. During winter, demand is used to peak around 80 GW between 7 p.m. and 8 p.m. and the minimum is generally around 60 GW. During summer, peak of demand is only of 55 GW while the minimum is of 35 GW (RTE 2016). In parallel, French generation mix has *solar*, *wind* and *run-of-river* renewable energy sources (RES). Usually, the sum of power injection from solar, wind and run-of-river RES amounts between approximately 2 GW and 17 GW each hour. These RES power injections are thus non negligible compared to the power demand. Moreover they are not dispatchable in nature. So we have taken these RES into account by computing the *residual power demand*, which is obtained by subtracting the sum of solar, wind and run-of-river RES power generation from the electricity consumption. We gathered data regarding the power demand in France on a RTE's website[32]. Data used for generation of RES was available on another RTE's website[33]. This data is historical data of realised power demand and RES generation. In the rest of the chapter, we denote the residual power demand by D. It is indexed as follow: $D -> D_{t,h}$ because at each time step t, the model has to satisfy the residual demand for each hour h.

6.2.2 Uncertainty: residual demand scenarios

Principle

Uncertainty stems from the power demand and RES generation. We model uncertainty by twenty scenarios of residual demand based on historical realised data. As in the didactic model, the power system is subject to uncertainty at each time step, but within each period the optimisation is performed under perfect foresight (see section 5.2.2). More precisely, for a given date, let us say January the 1^{st,}, the realisation of a scenario dictates what will be the level of the residual demand at this date, that is to say for the overall 168 hours of the week. On January the 8th, the optimisation process has to deal with another set of 20 possible scenarios, etc., up to the end of the problem horizon, on December, the 24th. Refer to **Figure 5.2** if more clarification is needed.

[32]Data on power demand in France: http://clients.rte-france.com/lang/fr/visiteurs/vie/vie_stats_conso_inst.jsp
[33]Data on renewable electricity production in France: http://www.rte-france.com/fr/eco2mix/eco2mix-telechargement

Construction of the twenty scenarios

At each time step, we consider twenty possible realisations of residual demand. We thus need to put together twenty historical values for the 52 time steps, i.e. we need twenty historical values of power demand and RES generation for the 1st of January, the 8th of January, etc., up to the 24th of December. Data regarding power demand was easily available since RTE provides consumption data dating back from 1996. However, available data for RES generation only dates back from 2012, so we had to construct the twenty RES production scenarios differently. Let us explain this in greater detail. Ideally, in order to get our twenty values of RES infeed for the 1st of January, we would have taken the values of January the 1st of 1996 up to January the 1st of 2015. Since this data does not exist, we took the RES production of the 1st, 2nd, 3rd, up to the 7th of January, that occurred in 2013, 2014 and 2015. This way, we get 21 levels of RES generation from which we randomly remove one value, ending up with twenty values reflecting a probable level of RES production around the 1st of January. We repeat the same methodology for every dates of our optimisation problem.

Scenarios probabilities

Because we use historical data, each residual demand scenario is realisable on equal probability.

Scenarios description

In order to have an overview of the different scenarios, **Table 6.1** displays the minimum, mean, and maximum values of the residual power demand over the year. For each scenario, we add an indicative comment qualifying the level of the residual demand:

- if the maximum value is greater than 90,000 MW, the scenario is qualified as “Extreme”,
- if the maximum value is between 80,000 MW and 90,000 MW, this is a “High” scenario,
- if the maximum value is between 70,000 MW and 80,000 MW, this is a “Medium” scenario,
- if the maximum value is between 60,000 MW and 70,000 MW, this is a “Low” scenario.

Table 6.1 – Description of residual power demand scenarios

Scenario	Residual power demand			Comment
	Min value (MW)	Mean value (MW)	Max value (MW)	
1	23,779	48,437	83,768	High
2	23,725	47,661	77,790	Medium
3	26,366	50,878	84,263	High
4	21,099	47,073	90,927	Extreme
5	22,917	42,778	80,580	High
6	27,283	52,241	93,619	Extreme
7	22,195	50,050	91,115	Extreme
8	25,665	50,698	80,001	High
9	25,968	47,713	87,568	High
10	19,947	39,375	69,200	Low
11	22,813	43,124	73,226	Medium
12	26,829	49,078	80,906	High
13	26,382	47,815	82,854	High
14	23,324	46,564	80,468	High
15	17,902	44,208	75,523	Medium
16	16,732	34,291	59,514	Low
17	22,611	41,699	69,213	Low
18	20,194	41,277	64,549	Low
19	22,747	40,234	66,833	Low
20	21,326	40,087	61,807	Low

6.2.3 Generation mix

6.2.3.1 Capacities and variable costs

Generation mix is made of conventional thermal power plants, the hydroelectric system and DR technologies. Thermal power plants are aggregated by fuel types. For instance, we assume that the bunch of nuclear power plants can be represented by a single nuclear unit operating under the same technical constraints. Installed capacity of this representative nuclear power plant is computed as the sum of capacities of every nuclear power plants existing in France. The hydroelectric system is made of one representative conventional dam and one representative hydro pumped-storage. The conventional dam represents the set of all lake power plants with single reservoirs, and the pumped-storage the set of all hydro pumped-storage facilities existing in France. As described in the previous section, non-dispatchable RES are taken into account in the residual demand. Hydro and thermal

power plants capacities are extracted from (RTE 2016, p.76). They are representative of the French generation mix as of 2016, including the availability of power plants at this date. DR capacities are taken from (Gils 2014, p.3), except for tertiary and residential load-shifting technologies whose capacities are derived from RTE's data accompanying their 2015 annual report about generation adequacy (RTE 2015). Installed capacities of DR technologies should be calculated after the *load profile* of the corresponding process/appliance (see sub-section 4.2.3.1). Further details are provided in the next sub-section. **Table 6.2** gives an overview of the generation mix used for the case study, with installed capacities and variable costs of each technology.

Table 6.2 – Case study generation mix representative of the French power system in 2016

	Generating unit name		Installed capacity (MW)	Variable/Activation cost (€/MWh)
Thermal power plants		Nuclear	63,100	23
		Coal	2,400	35
		Gas CCGT	5,200	75
		Decentralised peaking units	4,700	100
		Gas turbine	5,100	150
		Fuel oil	2,000	250
Hydro power plants		Conventional dam	9,600	7.53
		Pumped-storage	4,200	9.54
Demand Response	Industrial load-shedding	Steel	409	411
		Aluminium	135	164
		Chemicals	198	96
	Industrial load-shifting	Industrial cooling	336	16
		Cement	342	10
		Paper and pulp	1,257	10
		Cross-tech ventilation[34]	104	16
	Tertiary load-shifting	Air conditioning	1,950	11
		Tertiary heating	4,260	11
	Residential load-shifting	Residential heating	5,840	11
Mandatory curtailment		Slack[35]	∞	Price cap: 3,000

Thermal and hydro power plants variable costs are mostly taken from the International Energy Agency report "Projected costs of Generating Electricity – 2015 Edition" (IEA and NEA 2015). Price cap is set at 3,000 €/MWh, in accordance with the current price cap of EPEX Spot.

[34] Cross-tech ventilation refers to cross-sectional technologies which are not part of an industrial process per se but are present on industrial sites, like for example, the ventilation system.

[35] Slack variable is introduced to make sure the optimisation always be feasible. It represents a mandatory curtailment handled by the TSO at a very high variable cost which corresponds in a market context to the price cap.

DR activation costs comes from:

- (Gruber, Biedermann, and von Roon 2014) for the industrial sector,
- our own assumption for load-shifting on the tertiary and residential sectors.

Activation costs for load-shifting are low in the industry because the change of the electricity consumption does not modify the overall quantity of the output. Load-shedding however implies a net loss of the industrial output, thus a high activation cost. On the tertiary and residential sectors, we justify the low activation costs by the underlying non-disruptiveness hypothesis we have made throughout this thesis (see conclusions of chapter 1- section 1.6 and of chapter 2 - section 2.5).

6.2.3.2 Power plants time availability and DR load profiles

Power plants time availability

A time varying availability constraint is imposed on the nuclear power plant in order to account for seasonal maintenance operations and campaigns management, while we assume that other power plants can be operated at full installed capacity at any moment. Availability constraints for nuclear is presented in the Appendix A – Nuclear power availability over time.

DR load profiles

As explained in chapter 4, section 4.2.3.1, DR installed capacities are determined by the load profile of the corresponding appliance/industrial process. Following Gils (2014), we assume that:

- all industrial load-shedding technologies have flat load profiles,
- paper and pulp have flat load profiles as well.
- However, cement, cross-tech ventilation, industrial cooling, tertiary heating, tertiary air conditioning and residential heating have time-varying load profiles.

Load profiles are available in the Appendix B – Demand Response load profiles.

6.2.3.3 Reservoir sizes

Conventional dams and hydro pumped-storage facilities

Reservoir sizes of hydro power plants are shown in **Table 6.3**. We assume that efficiency factors of hydro power plant Eff^{hp} (MWh/Mm^3) are equal to 1 for all hydro power plants hp. We can thus directly express reservoir size in MWh, since one volume unit of turbined water through the plant produces one equivalent unit of electrical energy. The 16,800,000 MWh available in conventional dams correspond to the yearly electricity generated on average by lake power plants over the last ten years in France. Lake power plants have storage capacities of more than 400 hours, ensuring that the reservoir is never short of water and that the generating capacity of the plant is available, barring unforeseen circumstances, all year long independently of hydrological conditions (RTE 2016). This is

of course an approximation of how hydro power plants work in practice. In real life, water stored in dams is managed by taking into account random hydrological conditions, such that dry years result in less energy produced than during rainy ones. A more accurate way to represent the management of hydro reservoirs would have been to model water inflows. The issue which arose by including this additional source of uncertainty concerns the tractability of our model. Besides, doing it properly would have required to distinguish lakes geographically in order to represent at least differences in meteorological regimes between the Alps and the Pyrenees. This implies two hydrogeological zones to be modelled, thus two stochastic dimensions instead of one, increasing calculation time even more. With already twenty-four hours needed to solve the optimisation problem, we decided to overlook the modelling of stochastic water inflows for lake power plants, and to calibrate the size of conventional dam reservoirs by their average annual generated electricity. French power system has six main hydro pumped-storage facilities with different storage capacities, see (RTE 2016, p.58). The 80,160 MWh corresponds to the sum of reservoir sizes over all units.

Table 6.3 – Hydro system features

Hydro system	Reservoir name	Reservoir size (MWh)
Conventional dam	Conventional dam	16,800,000
Hydro pumped-storage	PS_upstream PS_downstream	80,160 80,160

Demand Response

As explained in chapters 4 and 5, size of DR reservoirs is determined by:

- $Duration$ multiplied by the $Installed\ capacity$, for physical reservoirs,
- $Number\ of\ activations$ multiplied by physical reservoir size, for contractual reservoirs.

Except for tertiary and residential sectors, DR reservoir sizes are calibrated according to Gils' paper (Gils 2014) which provides values for number of activations and duration parameters. For tertiary air conditioning, tertiary heating, and residential heating, number of activations is our own assumptions, based upon empirical evidences highlighted in chapter 2. **Table 6.4** presents the values used with the corresponding reservoir size for each DR technologies.

Table 6.4 – Demand Response features

Demand Response	DR technology	Duration (h)	Number of DR activations	Reservoir size (MWh)
Industrial load-shifting	Steel	4	/	1,636
	Steel_contract	/	40	65,440
	Aluminium	4	/	540
	Aluminium_contract	/	40	21,600
	Chemicals	4	/	792
	Chemicals_contract	/	40	3,168
Industrial load-shifting	Cooling_upstream	2	/	672
	Cooling_downstream	2	/	672
	Cooling_contract	/	1,095	735,840
	Cement_upstream	3	/	1,026
	Cement_downstream	3	/	1,026
	Cement_contract	/	365	374,490
	Paper and pulp_upstream	3	/	3,843
	Paper and pulp _downstream	3	/	3,843
	Paper and pulp _contract	/	365	1,402,695
	Cross tech ventilation_upstream	1	/	104
	Cross tech ventilation_downstream	1	/	104
	Cross tech ventilation_contract	/	1,095	113,880
Tertiary load-shifting	Air conditioning_upstream	1	/	1,950
	Air conditioning_downstream	1	/	1,950
	Air conditioning_contract	/	100	195,000
	Tertiary heating_upstream	1	/	4,260
	Tertiary heating_downstream	1	/	4,260
	Tertiary heating_contract	/	100	426,000
Residential load-shifting	Residential heating_upstream	0.5	/	2,920
	Residential heating_downstream	0.5	/	2,920
	Residential heating_contract	/	50	146,000

6.3 Results

6.3.1 Distribution of the aggregator's benefits

In this section, we first show the scenario distribution of the aggregator's annual benefits for each DR category. On the following charts, the x-axis represents the twenty scenarios and the y-axis the value of benefits expressed in €/MW/year. Then we analyse distributions by explaining the differences between sectors.

6.3.1.1 Industrial load-shedding

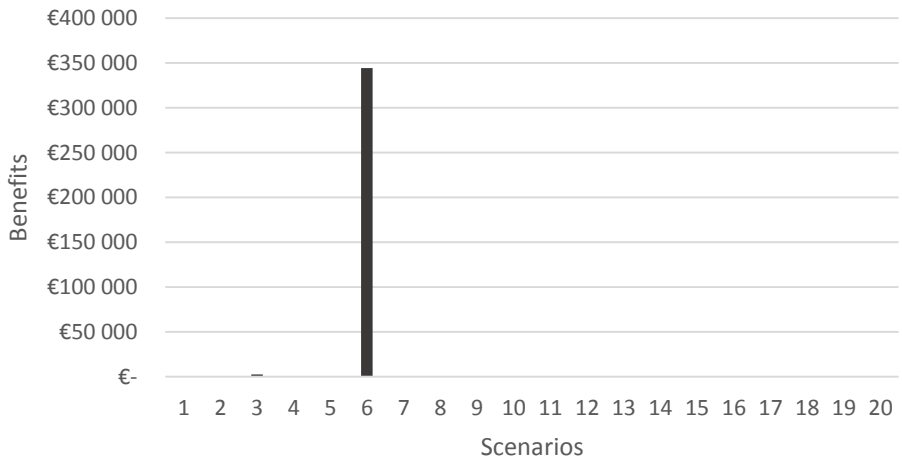

Figure 6.2 – Steel scenario-based benefits distribution (€/MW/year)

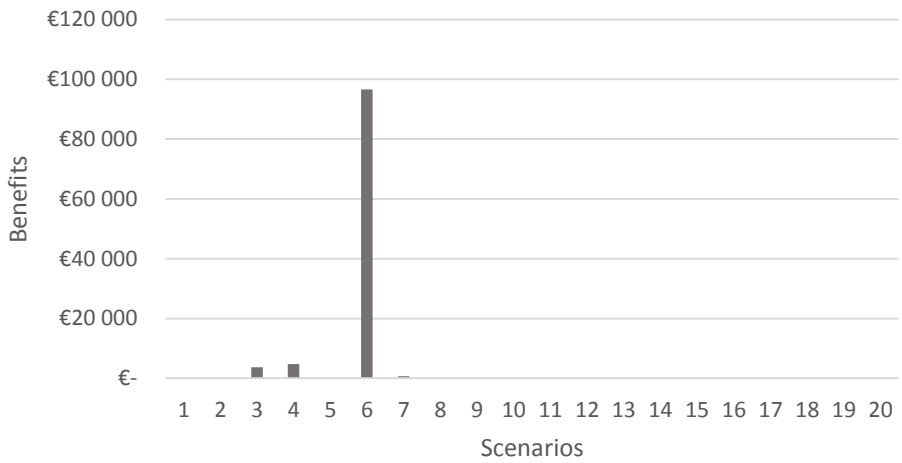

Figure 6.3 – Aluminium scenario-based benefits distribution (€/MW/year)

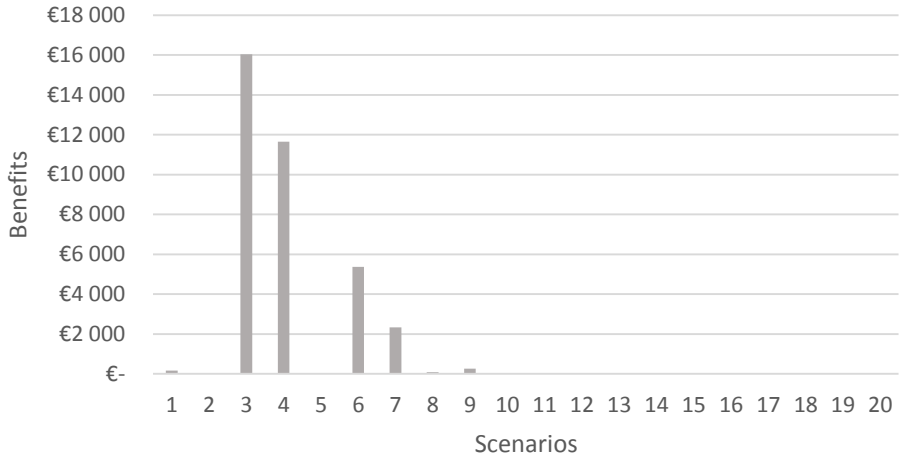

Figure 6.4 – Chemicals scenario-based benefits distribution (€/MW/year)

6.3.1.2 Industrial load-shifting

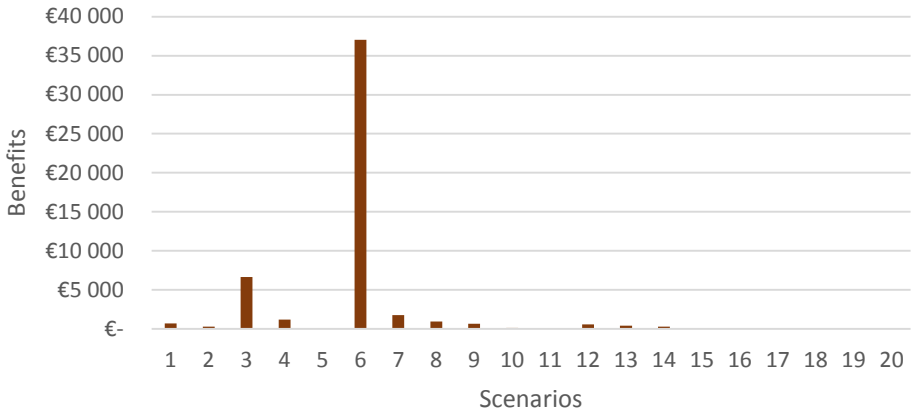

Figure 6.5 – Industrial cooling scenario-based benefits distribution (€/MW/year)

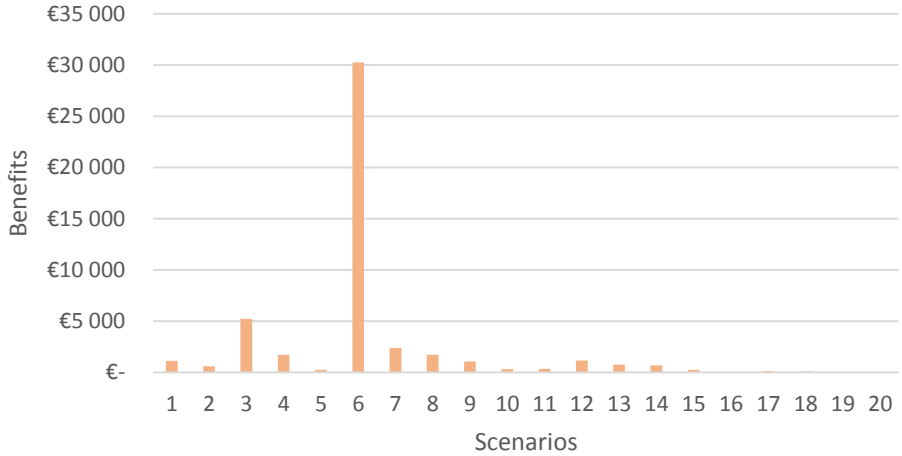

Figure 6.6 – Cement scenario-based benefits distribution (€/MW/year)

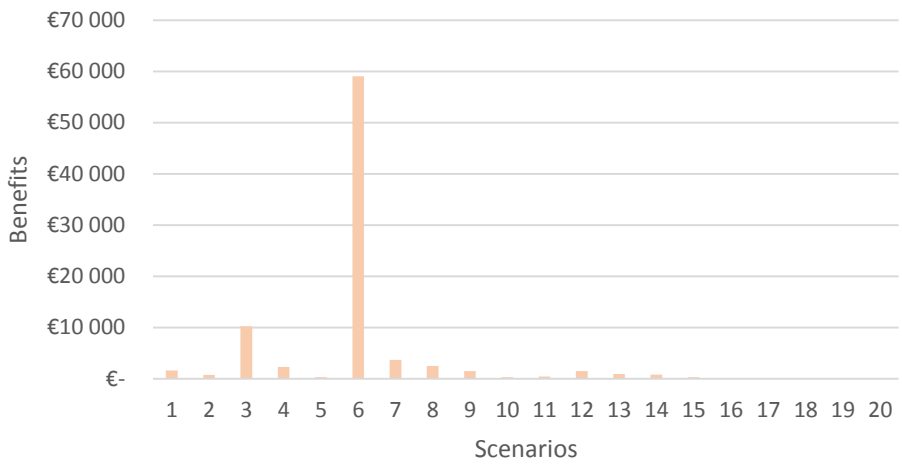

Figure 6.7 – Paper and pulp scenario-based benefits distribution (€/MW/year)

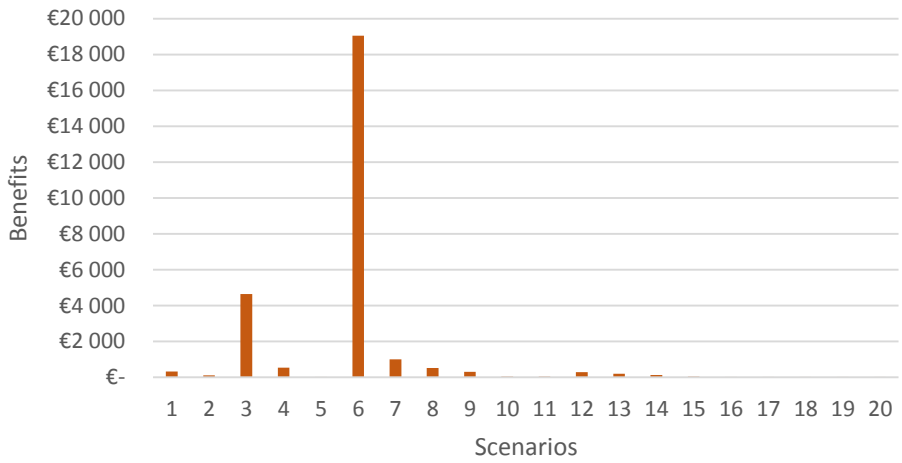

Figure 6.8 – Industrial ventilation scenario-based benefits distribution (€/MW/year)

6.3.1.3 Residential and tertiary load-shifting

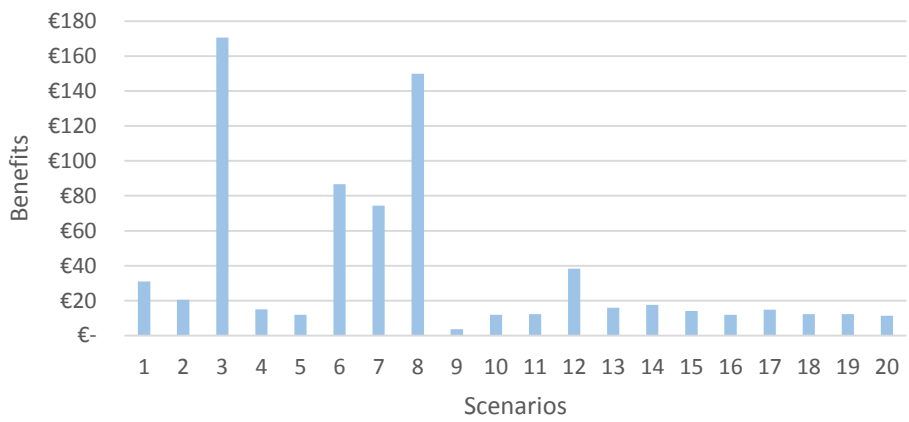

Figure 6.9 – Tertiary air conditioning scenario-based benefits distribution (€/MW/year)

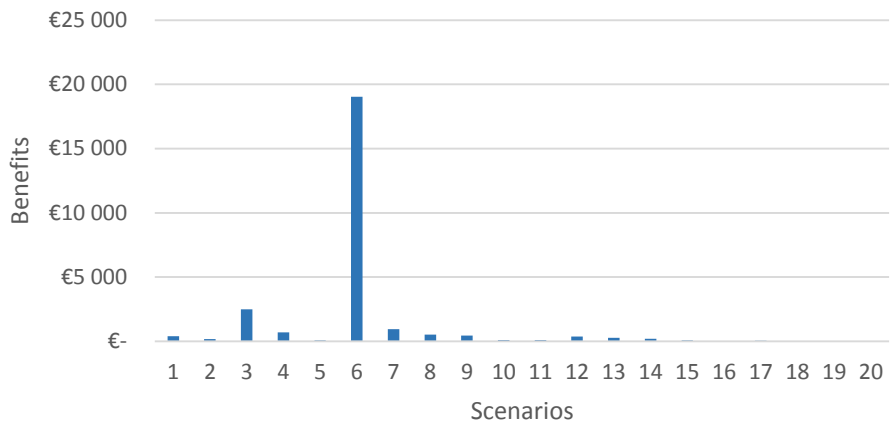

Figure 6.10 – Tertiary heating scenario-based benefits distribution (€/MW/year)

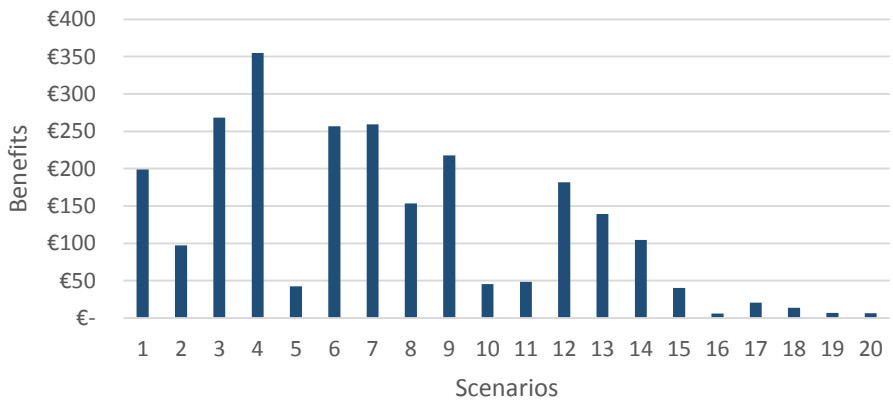

Figure 6.11 - Residential heating scenario-based benefits distribution (€/MW/year)

6.3.1.4 Analysis

Distributions highlight the fact that the aggregator's benefits can rise significantly in one particular scenario, namely scenario 6. Besides, although lower than in scenario 6, benefits in *scenario 3* are also quite substantial. This trend is observable for all DR technologies within the industrial sector. On the tertiary sector, high benefits of tertiary heating also arise on scenario 6. However, for air conditioning on the tertiary sector, benefits in scenario 6 are not dominating. The same observation can be made for heating on the residential sector.

What are the particularities of scenarios 6 and 3? If we look back on **Table 6.1**, we observe that scenario 3 is labelled as "high" and 6 as "extreme". In fact, other scenarios like scenarios 4 and 7 are labelled as "extreme" as well, but what differentiate scenarios 3 and 6 from the others is that during a few hours of the year, power demand cannot be satisfied. At these moments, market prices go up to the price cap, that is to say 3,000 €/MWh, as shown on **Figure 6.12**. Scenarios 3 and 6 thus exhibit a situation of *scarcity* for the system whereby the power demand cannot be satisfied by the available capacity of generating units. In our case, this long-term *capacity value of the system* is manifesting

whenever the market price reaches 3,000 €/MWh. This is especially the case in scenario 6, for which the number of hours at 3,000 €/MWh is significant. In scenario 3, there is only one hour at 3,000 €/MWh, but we see that the overall level of prices remain higher than in other scenarios, which means that the system is more under stress than in other scenarios. Nevertheless, at the exception of one hour, there is still enough capacity to cover power demand.

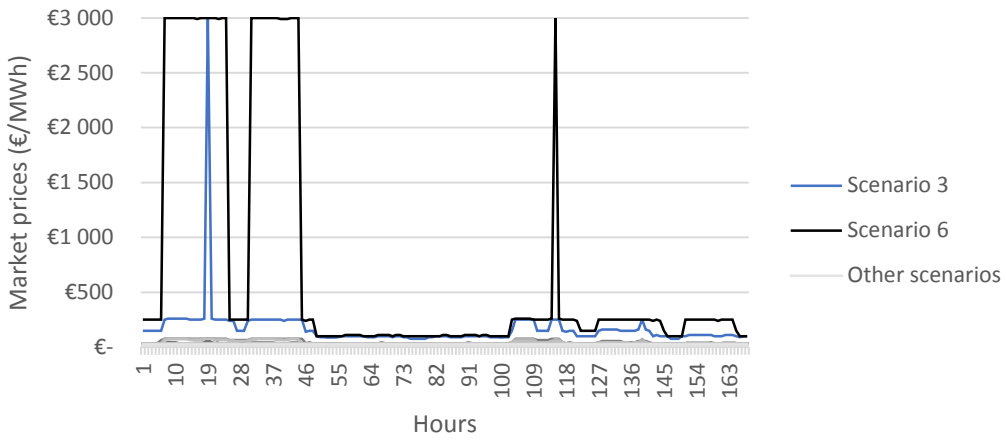

Figure 6.12 – Evolution of market prices during a winter week for the twenty scenarios

If we compare the evolution of market prices during the same week in other scenarios, we note that they are not higher than 75 €/MWh (on **Figure 6.13**, scenarios 3 and 6 have been removed in order to re-scale the chart and to provide a zoom on market prices in other scenarios).

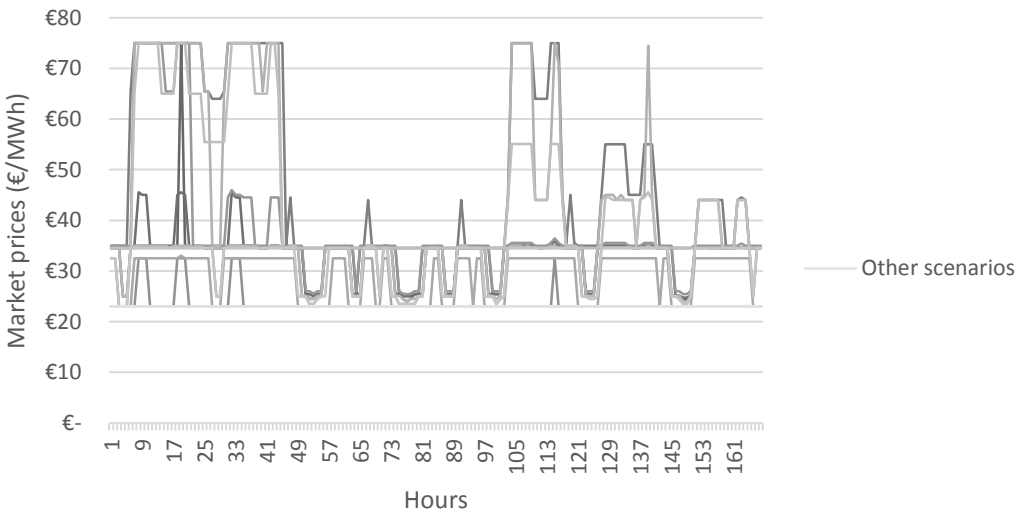

Figure 6.13 – Market prices during the same winter week without scenarios 3 and 6

In these other scenarios, unlike the previous situation, there is no scarcity in the system: power demand is satisfied at all time and all generating units producing at these moments provide *energy value* to the power system. By comparing the gap between benefits realised in scenario 3 and 6 and other scenarios, we understand that the distinction between the capacity value and the energy value is key in order to account for the distribution of the aggregator's benefits. For any given DR technology, we then define its capacity and energy value as follow:

- Capacity value of DR is defined as *market revenues earned by the DR technology during periods of scarcity*.
- Energy value of DR is defined as *market revenues earned by the DR technology whenever the power demand is satisfied.*

Our results show that the capacity value of DR, mostly captured in scenario 6, is much higher than its energy value. DR technologies activated by the aggregator during periods of scarcity take advantage of high prices and generate substantial benefits. The second key question to address pertains to the ability of DR technologies to be activated during these periods of scarcity. Why are some DR technologies activated in scenario 6 while others are not?[36] First and foremost, les us precise what DR technologies earn very high benefits in scenario 6:

- Steel (industrial load-shedding)
- Aluminium (industrial load-shedding)
- Industrial cooling (industrial load-shifting)
- Cement (industrial load-shifting)
- Paper and pulp (industrial load-shifting)
- Cross-technology ventilation (industrial load-shifting)
- Tertiary heating (tertiary load-shifting)

These DR technologies derive their benefits from their capacity value, while the following mostly gain from their energy value:

- Chemicals (industrial load-shedding)
- Tertiary air conditionning (tertiary load-shifting)
- Residential heating (residential load-shifting)

We can identify three effects explaining why chemicals, tertiary air conditioning, and residential heating are not activated during scarcity periods of scenario 6. For chemicals, the reason is economic. Activation cost of chemicals is of 96 €/MWh, which is below the variable cost of power plants like decentralised peaking units (100 €/MWh), gas turbines (150 €/MWh) and fuel oil units

[36] In the rest of the analysis, we abstract from scenario 3 because it has only one hour of scarcity, which is negligible compared to the 91 hours of scarcity in scenario 6.

(250 €/MWh). If these power plants are marginal in the merit-order, market price would be set at the level of their variable costs, providing a positive infra-marginal rent for chemicals. Moreover, the presence of DR technologies like steel and aluminium, whose activation costs are respectively of 411 €/MWh and 164 €/MWh extends the range of possible infra-marginal rents for chemicals. Therefore, chemicals does not need scarcity rents of scenario 6 to be activated with profits. We must however remember that chemicals could have waited for better infra-marginal rents opportunities, when the market price reaches 3,000 €/MWh. Indeed, decision to activate a DR technology depends on its marginal cost, not on its activation cost. The analysis conducted in chapter 5 with the help of the didactic model underlined that DR marginal cost could be significantly increased by the opportunity cost, which depends itself on (i) the price cap, and (ii) the annual number of activations. In this case study, it seems that given the structure of the generation mix, the level of the price cap, and the number of activations, the marginal cost function of chemicals remains lower than 411 €/MWh (the activation cost of the most expensive generating unit in the system) for a large range of values of its contractual reservoir level[37].

For tertiary air conditioning, reason lies in the temporal availability of this particular end-use. **Figure 6.14** shows the consumption of air conditioning in the tertiary sector over a year. This load profile means that this DR technology is only available around and during summer. Besides, peaks of demand usually occur during winter in France. Total capacity of the system has been calibrated accordingly, implying a situation of over capacity during summer days, thus low market prices. Our model simulations are consistent with this reality. Scarcity situations in scenario 6 occurs during weeks of the 10th and 17th of December, a period when the capacity of tertiary air conditioning is not available.

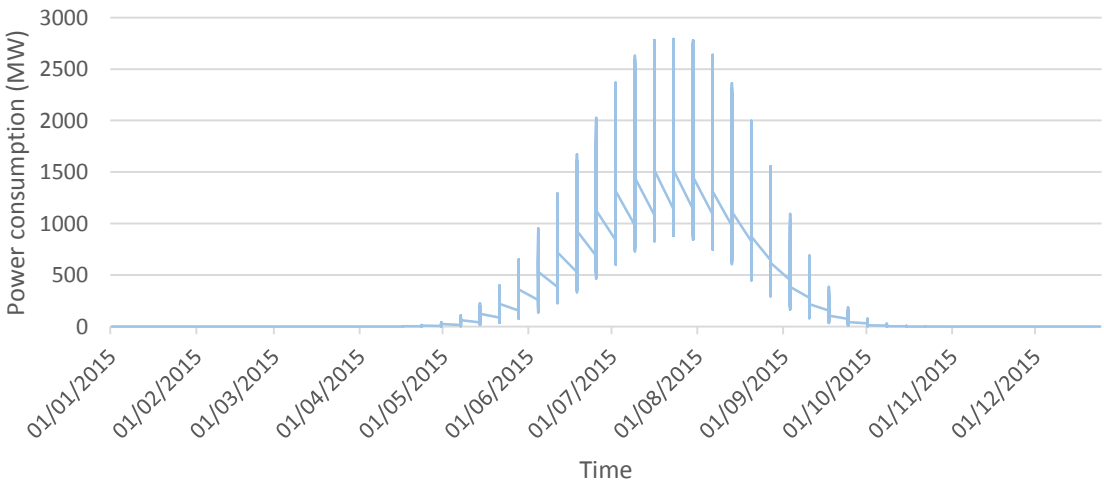

Figure 6.14 – Load profile of tertiary air conditioning over the year

[37] We recall here that the marginal cost of DR is a decreasing function of the "contractual reservoir" energy level. For low values of reservoir level, the marginal cost could be higher than 411 €/MWh.

On the residential sector, our results suggest that load-shifting of electric heaters is not activated during periods of scarcity. This outcome might be surprising if we confront it with reality. In France, electric heaters are widely use. They introduce a strong seasonal variability in the global consumption in the country; this is why the power demand reaches its highest level during winter evenings, when all households simultaneously turn their appliances on, in particular electric heaters. Therefore, power demand in winter is extremely sensitive to the outside temperature, and when it gets very cold, electric heating can represent up to 40% of the total power demand. One would then expect that in our simulation, residential heating provides some DR capacities during scarcity periods. If we look at the load profiles of residential and of tertiary heating, we see that they have similar time-related constraints and that both are available in December. Furthermore, unlike residential heating, tertiary heating is activated during periods of scarcity (refer to the benefits distribution of tertiary heating on **Figure 6.10**).

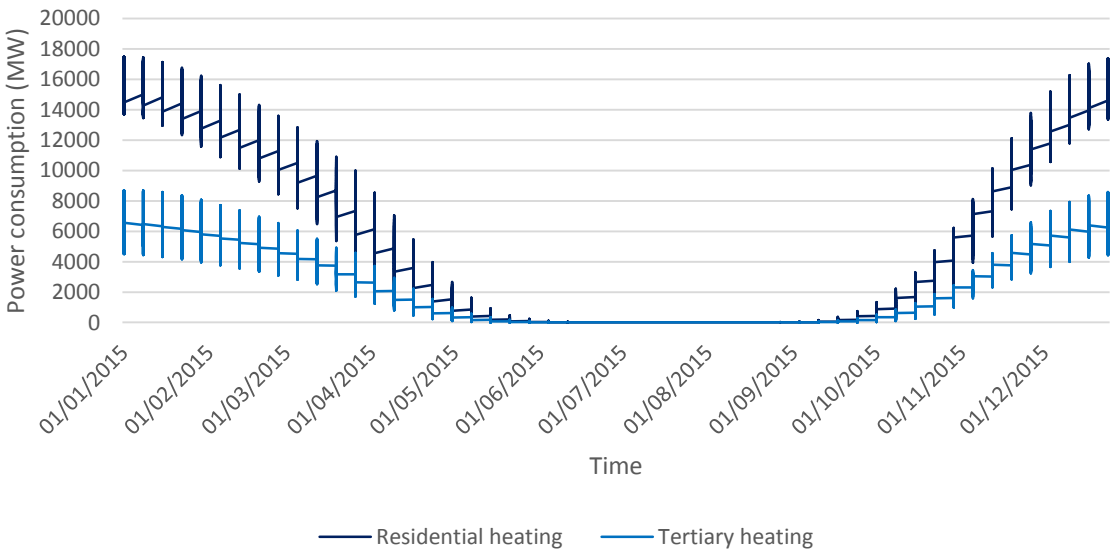

Figure 6.15 – Load profile of residential and tertiary heating over the year

Activation of residential heating in scarcity periods is thus impeded by other factors. An explanation can be found by looking at the level of energy into the contractual reservoir. Looking back on **Table 6.4**, we note that the annual number of activations allowed for residential heating is of 50 per year. Same figure for tertiary heating is 100 per year. Furthermore DR events can last thirty minutes on the residential sector while the duration is of one hour on the tertiary sector. This entails that the contractual reservoir of residential heating is almost four times as smaller as the one of tertiary heating. If we look at the evolution of the energy level in those contractual reservoir over the year, we note that at the end of the timeframe, residential heating has been entirely emptied, implying that the aggregator can no longer activate DR events from this DR category. On the contrary, tertiary

heating still has energy in the contract, allowing the aggregator to use it in December, when market prices rise up to 3,000 €/MWh.

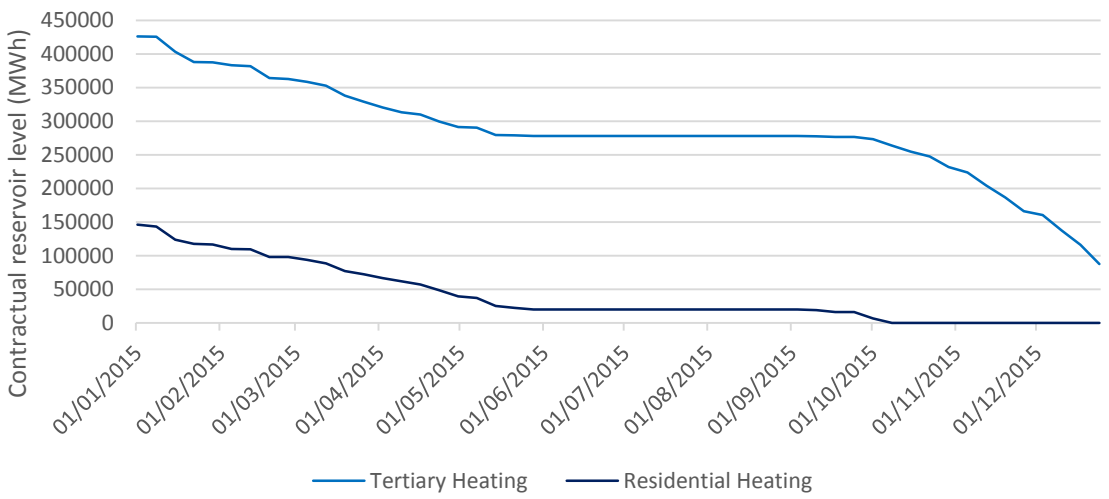

Figure 6.16 – Tertiary and residential contractual reservoir levels in scenario 6

We then may ask ourselves why the contract of residential heating has been managed this way by the model. Perhaps it would have been more appropriate to wait until December to use the contract, in order to seek for higher market prices. In fact, it seems that among the set of DR facilities, residential heating is at a critical point in the sense that using it enables the model to satisfy the demand, and not using it creates scarcity periods. Indeed, since the model handles dispatch decisions by taking future costs into account, it is optimal to use the residential heating contract at the beginning of the timeframe. To not have used it during months of January and February would have probably resulted in scarcity periods at these periods. This makes sense if we think about how the penetration of DR based on electric heaters would impact the power system reliability in France. Given the power consumed by these appliances during winter (up to almost 30,000 MW on weekly average in the residential sector (RTE 2016, p. 43)), shifting their consumption from peak hours to off-peak hours would keep the system in balance, i.e. scarcity situations would be alleviated.

6.3.2 The aggregator business case

The previous section highlighted that DR technologies derive most of their benefits from their capacity value. In this section, we analyse the economic viability of the DR aggregator by questioning the role of capacity and energy revenues in remunerating the investment in the fixed costs of the enabling technologies. We tackle this issue by comparing the annual fixed costs with the

annual benefits averaged over all scenarios. First and foremost, let us compute average benefits for each DR technology and split them up between capacity and energy revenues[38] (**Table 6.5**).

Table 6.5 – Demand Response benefits segmented by capacity and energy value

		Average benefits (€/MW/year)		
		Total value	Capacity value	Energy value
Industrial load-shedding	Steel	17,337	17,337	0
	Aluminium	5,290	4,805	485
	Chemicals	1,797	189	1,608
Industrial load-shifting	Industrial cooling	2,549	1,814	735
	Cement	2,419	1,464	955
	Paper and pulp	4,347	2,878	1,469
	Cross-tech ventilation	1,369	930	439
Tertiary load-shifting	Air conditioning	37	3	34
	Tertiary heating	1,302	934	368
Residential load-shifting	Residential heating	123	7	116

Unsurprisingly, the averaged capacity value is much higher than the energy value. However we must not forget that capacity revenues are only generating in one scenario characterised by scarcity periods, over a total of twenty scenarios. The occurrence of such a scenario is thus essential, otherwise average benefits may drastically tumble. With that regard, examples of steel and aluminium are striking. Without any scarcity situations in the system, steel would actually generate no profits, and aluminium only 485 €/MW/year. Therefore, although dominating in the total economic value of DR, the capacity value comes with a low probability of occurrence, since the existence of scarcity conditions in the system determines it. In our case study, the probability of the occurrence of such a scenario is of 0.05, more exactly once in twenty years. With that regard, investment in sectors whose benefits rely on the capacity value are risky for the aggregator. On the contrary, the energy value of DR constitutes of steadier stream of revenues. With that regard, sectors like chemicals, paper, pulp, cement, industrial cooling, and cross-technology ventilation might be an interesting opportunity, provided that fixed costs of enabling infrastructure and technologies can be covered.

Fixed costs of enabling infrastructure and technologies

To carry out the aggregator business case, we should now compare annual average benefits with annual fixed costs of the enabling infrastructure/technology that the aggregator needs to invest in. Fixed costs considered here are investment costs plus eventual fixed costs associated to the operation

[38] Here, the capacity revenues are computed as the benefits made in scenario 6. This is an approximation, because the exact value of capacity revenues should be calculated as the benefits generating only during hours of scarcity in scenario 6. However, in scenario 6, energy revenues are negligible compared to capacity revenues, justifying this approximation.

of the process/appliances. First, we have gathered figures for fixed costs within different sources displayed in **Table 6.6**. Range of values displayed by Stede (2016) and Zerrahn and Schill (2015) are actually data compiled from different studies while Léautier (2014), Prüggler (2013) and Steurer et al. (2015) propose their own assumption and calculation.

Table 6.6 – Fixed costs of Demand Response enabling infrastructure

		Fixed costs	Source
Industrial load-shedding		[200 ; 8,000] €/MW	(Stede 2016)
Industrial load-shifting	Industrial cooling Cement Paper and pulp Cross-tech ventilation	745 €/kW 10 €/kW 10 €/kW 1,517 €/kW	(Zerrahn and Schill 2015)
Tertiary load-shifting		[200,000; 900,000] €/MW	(Stede 2016)
Residential load-shifting		500 € / smart meter 25 € / smart meter / year [5.84; 7.7] € / kW / year	(Prüggler 2013) (Léautier 2014) (Steurer et al. 2015)

Second, we have harmonised the units in order to express these numbers in €/MW/year (**Table 6.7**). To do so we computed the net present value, assuming:

- an interest rate of 7%[39],
- an equipment lifetime of 10 years[40],
- and that a smart meter can control 4 kW in the residential sector.

Table 6.7 – Annualised fixed costs of Demand Response enabling infrastructure

		Fixed costs (€/MW/year)	Source
Industrial load-shedding		[25; 997]	(Stede 2016)
Industrial load-shifting	Industrial cooling Cement Pulp paper Cross-tech ventilation	92,851 1,246 1,246 189,068	(Zerrahn and Schill 2015)
Tertiary load-shifting		[24,927; 112,169]	(Stede 2016)
Residential load-shifting		15,579 6,250 [5,840; 7,700]	(Prüggler 2013) (Léautier 2014) (Steurer et al. 2015)

[39] In (Steurer et al. 2015) the annuity of the investment is calculated with a 7% discount rate.
[40] (Zerrahn and Schill 2015) assume a 10 years technical lifetime of the equipment.

Results about the aggregator business case are presented in **Table 6.8**. Our findings suggest that industrial load-shedding is an economically viable business for the three sectors in consideration. Capacity value provided by steel and aluminium, associated with low fixed costs, make load-shedding profitable within these industries. Although chemicals average benefits are lower (because chemicals only provides energy value to the system), load-shedding remains profitable on this sector.

Among industrial load-shifting, cement, paper, and pulp sectors are profitable whereas industrial cooling and cross-technology ventilation are not, due to much higher fixed costs. Cement and paper fixed costs are lower because the storage lying behind load-shifting is a physical storage of industrial products. Thus, on the contrary of ventilation and industrial cooling, they do not necessitate a control technology to remotely stop the process. Finally there is no business opportunity for load-shifting on tertiary and residential sectors.

Table 6.8 – Business case of the Demand Response aggregator

	Energy value	Capacity value	Economic value	Annual fixed costs (€/MW/year)	Business opportunity
Steel	0	17,337	17,337		Yes
Aluminium	485	4,805	5,290	[25 ; 997]	Yes
Chemicals	1,608	189	1,797		Yes
Industrial cooling	735	1,814	2,549	92 851	No
Cement	955	1,464	2,419	1 246	Yes
Paper and pulp	1,469	2,878	4,347	1 246	Yes
Ventilation	439	930	1,369	189 068	No
Air conditioning	34	3	37	[24 927 ; 112 169]	No
Tertiary heating	368	934	1,302		No
Residential heating	116	7	123	15,579[41] 6,250[42] [5,840 ; 7,700] [43]	No No No

6.4 Conclusion

In this chapter, we carried out the business case of a DR aggregator assuming large scale deployment of DR capacities in France. We performed this case study with a model calibration on the French power system as of 2016. Model simulations provide us with numerical outcomes regarding the DR aggregator's annual energy-only market benefits, split up by DR categories, which are then compared with annualised fixed costs of DR enabling infrastructure/technologies.

Key insights are that industrial load-shedding is profitable as well as industrial load-shifting on cement, paper, and pulp sectors. On the contrary, load-shifting in industrial cooling and from

[41] (Stede 2016)
[42] (Léautier 2014)
[43] (Steurer et al. 2015)

industrial cross-technology like ventilation are not economically viable, due to much higher fixed costs. Regarding load-shifting on tertiary and residential sectors, the business opportunity seems poor as well.

Nevertheless these findings can be nuanced with regards to several aspects. Firstly, although our simulations show a significant gap between fixed costs and market benefits for non-profitable DR applications, one should not forget that the investment cost in the enabling infrastructure will not necessarily be taken on by the aggregator. For instance, French Distribution System Operator Enedis is currently rolling-out nationwide its smart meter “Linky”. In the coming years, households will thus be equipped with the DR enabling infrastructure, meaning that DR aggregators do not have to handle this investment by their own. In this context the business case on the residential sector should be assessed by only considering the cost of enabling technology, such as control technologies.

Secondly, our findings highlight the high share of capacity value in total benefits made by some DR applications, raising questions about the influence on DR valuation by the capacity market being currently launched in France. On the one hand, our energy-only market framework does not enable to exactly replicate the remuneration scheme offered by a capacity market. In particular, the stream of revenues from a capacity market is steadier than from an energy-only market, as shown by the simulated benefits distributions. On the other hand, the price cap level set at 3,000 €/MWh in the present case study is an underestimation of the system capacity value. Since the French capacity market recognises DR capacities as contributors of the power system generation adequacy, the aggregator business case should be pushed further by analysing the impact of increasing the market price cap on DR valuation.

Thirdly, we should remember that DR activations rely on consumers’ empowerment that we assume to be ensured by the contract proposed by the aggregator. It is then of high interest to wonder what contract terms would affect consumers’ acceptance and to consequently challenge assumptions made about them. Among contract terms presented in chapter 1 section 1.5, annual number of activations represents a promising avenue to explore because it both reflects degree of intrusion on customers’ consumption and defines the global volume of DR energy present in the system.

In the next and last chapter of this thesis, we carry out sensitivity analysis on the price cap level and number of activations to see how the aggregator business case might evolve.

CHAPTER 7 THE SCARCITY RENT AT THE SOURCE OF THE CAPACITY REMUNERATION OF THE AGGREGATOR

7.1 Introduction

This chapter aims to challenge some assumptions made in chapter 6 which might have an influence on the aggregator business case. In previous chapter, we highlighted that aggregator's benefits were split up between a capacity value and an energy value and we showed that the capacity value was much more significant than the energy value. At the origin of this capacity value is the existence of scarcity rents whose amplitude depends on the price cap and occurrence on the mismatch between demand and supply (when demand exceeds supply).

A first interesting test to perform is thus to increase the price cap of the market: this is a straightforward way to extend the amplitude of the aggregator's scarcity rents. The resulting additional capacity remuneration offered to the aggregator can be viewed as the remuneration that he would obtain from the capacity market launched in 2017 in France. The impact of this capacity remuneration on the aggregator's benefits is quantified by increasing the price cap from its initial value 3,000 €/MWh (the price cap currently set on EPEX Spot) to 10,000 €/MWh (representing an intermediate level of capacity valuation) and to 20,000 €/MWh (an estimation of the VoLL).

In a second sensitivity analysis we test a diminution of the contract size proposed by the aggregator to electricity consumers. Here, size of the contract refers to the maximum annual number of DR activations the aggregator is allowed to trigger. The test is motivated by the fact that consumers might be reluctant to contract with the aggregator. In the chapter 6, we assumed a high degree of acceptability of consumers. Indeed, data used for the annual number of activations were derived from Gils' paper which does not deal with acceptability issues (see **Table 6.4**). While the test on the price cap aims to modify the amplitude of scarcity rents, this one changes their occurrences. Indeed, reducing the size of DR contracts has two consequences. First, the smaller the contract the lower the energy volume of DR available in the system, thus possibly more periods of scarcity. Second, the smaller the contract the lower the possibilities for the aggregator to trigger DR events. The core question here is what effect will outweigh the other: as periods of scarcity in the system get more frequent, will the aggregator be able to benefit from more scarcity rents, or will his dispatch possibilities be impeded by the reduction of the contract size?

The rest of the chapter is organised as follow. Section 7.2 presents the price cap impact, section 7.3 the contract size impact, and section 7.4 concludes.

7.2 Price cap impact on the aggregator's benefits

7.2.1 Motivation

Currently, the French power system is experiencing a significant change with the launch of its capacity market initiated by the NOME law of December 7, 2010, completed subsequently by a series of legislative texts defining the organisation rules of the mechanism. The idea of the mechanism is to compel electricity suppliers to have capacity guarantees ensuring they would be able to meet their portfolio of customers' demand, in particular when the national power demand peaks at winter. These capacity guarantees can be traded on the capacity market in the form of certificates delivered by the TSO to both electricity producers and DR providers, remunerating them for the provision of capacity during periods of peak demand. The actual delivery of these certificates started on January 1, 2017. For a DR aggregator, they would provide additional streams of revenues that should be assessed in a business case.

How to simulate capacity market-based revenue within our framework? Given the economic dispatch under uncertainty optimisation model used in this thesis, an easy way to represent this additional capacity valuation is to relieve the energy-only market from the price cap which was set at 3,000 €/MWh in the case study of chapter 6. By increasing the price cap level, the missing capacity is valued over a wider range of scarcity rent: from 3,000 €/MWh (as in the real world; ie as currently set by EPEX Spot) up to 20,000 €/MWh (usually an upper bound of the VoLL). The latter market design can be referred to as an *energy-only market with scarcity pricing*.

Questions are then whether an energy-only market with scarcity pricing can replicate the outcome of a *price-capped energy-only market supplemented by a capacity remuneration mechanism* (CRM); under what assumptions this approach remains valid; and what precaution should be taken when comparing those two models?

Academic literature addressing the effectiveness of capacity mechanisms versus energy-only markets under scarcity pricing to trigger optimal level of generation adequacy is vast. Theoretically, energy-only markets with scarcity pricing are an efficient institutional frame for coordinating optimal consumption, dispatch and investment decisions. In that regard, they can be viewed as a benchmark for the design of power markets. In practice though, scarcity pricing has not been widely set up due to various market failures. As an example, inelasticity of demand during scarcity periods creates favourable conditions for the marginal technology to exercise market power. Rather than reflecting scarcity rents, sudden price spikes are then suspected to arise from strategic bidding-decisions and prices manipulation. In this context price caps have been common practice in numerous wholesale energy-only markets, aiming at mitigating market power (Zöttl 2011).

The missing money problem, due to market imperfections, refer to a lack of market revenues preventing private investors to trigger a socially desired level of generation adequacy. It has been addressed by CRM schemes both practically and theoretically. Practically, various forms of CRM

have been implemented in American and European power markets as a remedy to the missing money issue. Theoretically, they are presented by several authors as an efficient market design to reach optimal levels of capacity, unlike real-world imperfect energy-only markets (Joskow 2008; Cramton and Stoft 2008; Vries and Heijnen 2008; Keppler, Finon, and Geoffron 2013; Keppler 2014).

As a theoretical benchmark model, energy-only market with scarcity pricing tested in this sensitivity analysis is a superior approach than a capacity market. In terms of capacity valuation, our numerical results should thus be seen as an upper bound of CRM-based revenues. However this statement holds under the assumption of risk-neutrality: if agents are risk-averse, energy-only market exacerbates underinvestment compared to a capacity market (Keppler 2014). Moreover (Petitet, Finon, and Janssen 2017) show that risk aversion make the case for capacity mechanisms, while under the assumption of risk-neutrality, they prove that a capacity market leads to comparable outcomes than an energy-only market with scarcity pricing, in terms of loss of load, production costs and social cost of loss of load[44].

Since our framework overlooks agents' risk aversion, we can assume that an energy-only market under scarcity pricing will correctly replicate capacity-based revenues that would be earned by the DR aggregator under a CRM regime.

7.2.2 Results

In **Table 7.1** we see that increasing the price cap (abbreviated PC) leads to higher benefits for all DR technologies. Observing the ratio column helps to see to what extent benefits are increased. Ratio "10/3" (resp. "20/3") is the ratio between benefits made with a price cap of 10,000 €/MWh (resp. 20,000 €/MWh) and with a price cap of 3,000 €/MWh. In particular, we note that some categories of DR are more sensitive. Unsurprisingly, these technologies are those which derive their value from the capacity value. Remuneration of capacity offered by a higher price cap is significant for technologies such as steel, aluminium, chemicals, among others. However technologies getting their revenue on the energy value only benefit to a small extent. This is the case for residential heating and tertiary air conditioning.

The price cap increase has mechanically created higher scarcity rents that the aggregator takes advantage of. Nevertheless, if we look back on the fixed costs of the enabling infrastructure and technology (**Table 6.6**), we see that this additional capacity remuneration is still not enough to cover these costs. Furthermore, technologies benefiting the most are those which were already profitable, i.e. steel, aluminium, chemicals, cement, paper, and pulp. The exception being cross-technology ventilation and industrial cooling. However, the very high fixed costs prevent those to be economically viable.

[44] The loss of load is defined as the number of hours per year where the power demand cannot be satisfied.

Table 7.1 – Price cap impact on the aggregator benefits

	Average annual benefits (€/MW/year)			Ratio	
	PC=3,000	PC=10,000	PC=20,000	"10/3"	"20/3"
Steel	17,337	60,332	123,456	3.5	7.1
Aluminium	5,290	16,976	32,219	3.2	6.1
Chemicals	1,797	4,975	8,909	2.8	5.0
Industrial cooling	2,549	8,071	15,495	3.2	6.1
Cement	2,419	6,136	11,216	2.5	4.6
Paper and pulp	4,347	12,299	24,434	3.0	5.6
Industrial ventilation	1,369	4,407	8,511	3.2	6.2
Tertiary air conditioning	37	50	63	1.4	1.7
Tertiary heating	1,302	3,438	6,202	2.6	4.8
Residential heating	123	143	161	1.2	1.3

7.3 Contract size impact

7.3.1 Motivation

For a given DR technology, we define the contract size as the size of the contractual reservoir of the corresponding technology, determining the maximum volume of energy it can contain. Since neither installed capacities nor events duration parameters can be modified (because installed capacities and duration are technical parameters characterising the physical DR reservoir), the parameter at stake in order to change the contractual reservoir size is the number of activations[45].

Questioning the optimal contract size is especially interesting from the aggregator viewpoint because, unlike price cap which comes under a regulator's decision, the choice of its value is a private agreement between himself and consumers. If the contract size is reduced (resp. increased), does it necessarily come with smaller (resp. bigger) benefits? Not necessarily since reducing or increasing the energy volume of DR in the power system will modify market prices. For instance, if we reduce the contract size, market prices might go up, due to less energy in reservoirs present in the system. In the case study of chapter 6, we calibrated contractual reservoir sizes based on a non-restrictive number of activations. Therefore, the sensitivity analysis presented throughout this section aims at testing the impact of reducing contract sizes. From a long-term perspective (several consecutive years), reducing the contract size creates customer portfolio dynamics linked to the recruitment process and to the

[45] Contractual reservoir size is calculated as: Installed Capacity * Duration * Number of activations

durability of participation. By proposing big contracts, end-users might be more reluctant to sign in ex-ante and tempted to either definitively drop out the contract or to frequently override the aggregator's event trigger ex-post. This portfolio effect would thus result in a loss of DR capacity, entailing a diminution of contractual reservoir sizes that the aggregator precisely intended to make as big as possible. Assessing variations of market revenues after a diminution of the contracts size would then be a useful insight to get.

7.3.2 Results

First of all, **Table 7.2** presents the range of variations for the two parameters in consideration within the sensitivity analysis. We progressively reduce the contract size by multiplying each contractual reservoir by a *contract factor* (shorten as CF) ranging from 1 to 0.5. At the maximum, the total amount of DR available in the system is thus scaled down by half its initial amount. Results should be read as follow: for instance (CF=1; PC=3,000) refers to a model run with the contract factor set at 1 and the price cap at 3,000 €/MWh (PC standing for price cap). Results are provided for every combined levels of price cap and contract factor. The sensitivity analysis thus led to 15 additional runs of our model.

Table 7.2 – Contract factor range of variations combined with price cap levels

CF / PC	*3,000*	*10,000*	*20,000*
1			
0.9			
0.8			
0.7			
0.6			
0.5			

Before going to the aggregator's benefits which are our main outcomes of interest, we must have a look at how the system generation adequacy is impacted by variations of the two parameters. Here, we define *generation adequacy as the quantity of energy demand that cannot be satisfied during the year, summed over all scenarios*. Adequacy level determines the amount of scarcity rents in the system. This intermediate step is thus key in order to understand the sensitivity analysis results. Let us look at **Table 7.3** where the effects of the contract size diminution is shown, for three levels of price cap. First of all, looking at the table column-wise, we observe that the amount of non-served demand increases as the contract factor decreases. This is not astonishing, since decreasing the number of DR activations entails a smaller amount of energy available in the system. However, surprising is the leap when the contract factor goes from 0.9 to 0.8 (when the price cap equals 3,000 €/MWh) and from 0.8

to 0.7 (when the price cap equals 10,000 €/MWh and 20,000 €/MWh): the amount of non-served demand is almost doubled although the quantity of energy in DR contractual reservoirs has only been slightly diminished. What is the reason of this threshold effect?

Table 7.3 – Total non-served energy demand (MWh) summed over all scenarios

CF / PC	*3,000*	*10,000*	*20,000*
1	497,636 MWh	497,636 MWh	497,636 MWh
0.9	497,636 MWh	497,636 MWh	497,636 MWh
0.8	915,250 MWh	499,801 MWh	499,801 MWh
0.7	944,011 MWh	944,011 MWh	944,011 MWh
0.6	973,545 MWh	973,545 MWh	973,545 MWh
0.5	980,089 MWh	980,089 MWh	980,089 MWh

To explain such a significant gap in the amount of non-served demand, we should have a look at the use of hydro conventional dam. Let us then compare the reservoir level of conventional dam in three key runs for which the overall non-served demand amounts respectively:

- 497,636 MWh -> run (CF=0.9; PC=3,000)
- 915,250 MWh -> run (CF=0.8; PC=3,000)
- 499,801 MWh -> run (CF=0.8; PC=10,000)

Figure 7.1 displays reservoir levels of hydro conventional dam for these three runs. In run (CF=0.8; PC=3,000), we observe that the reservoir level decreases more steeply at the beginning of the year compared with the two other run outputs, which in turn causes a lack of energy in the system at the end of the year. In this scenario, this missing energy creates scarcity conditions in December, the capacity of conventional dam being unavailable at this date due to the absence of water in the reservoir.

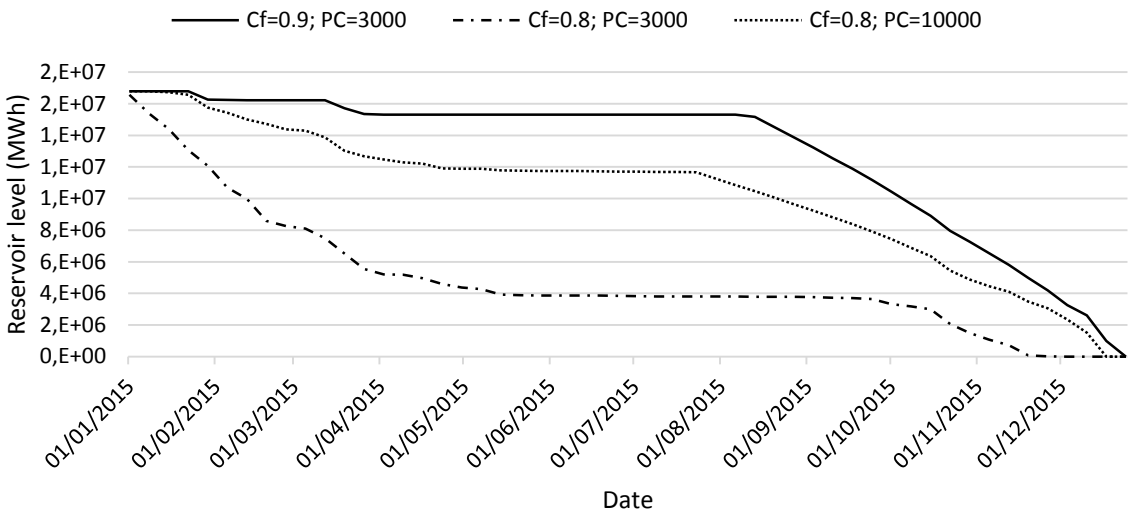

Figure 7.1 – Hydro conventional dam reservoir level in scenario 9

In the two other runs (CF=0.9; PC=3,000) and (CF=0.8; PC=10,000), the water is kept in the reservoir in case of probable later periods of high demand. This is because opportunity (or future) costs associated to the use of the conventional dam reservoir are higher than current operating costs. Similarly, regarding run (CF=0.8; PC=3,000), if the energy contained in conventional dam reservoir is mostly used early in the year, it means that future costs at these dates are lower than operating costs. This comparison between future and current operational costs explains that even a slight change in the initial quantity of energy available in DR contractual reservoirs can lead to significantly different release strategies from other types of reservoirs (here this is primarily illustrated throughout the conventional dam, but a similar effect is likely observable on other reservoirs). The same reasoning can be applied with a change in the price cap level. Indeed, in chapter 5, we showed that a greater price cap and a smaller contractual reservoir entailed higher opportunity costs. Therefore, when we increase the price cap from 3,000 €/MWh to 10,000 €/MWh and when the contract factor goes from 0.9 to 0.8, opportunity costs increase. The threshold effect occurs because the comparison between opportunity and current operating costs is based on a strict mathematical inequality.

7.3.2.1 Average annual benefits

Average annual benefits are presented for every DR categories on **Figure 7.2**, **Figure 7.3**, etc., **Figure 7.11**. On these graphs, for each price cap levels, benefits are displayed in function of the contract factor. Three general trends, common to all DR technologies, can be drawn from the sensitivity analysis. When the price cap steps up, benefits increase. Benefits diminish with lower contract factor values at the exception of when the threshold is reached. Having in mind the generation adequacy threshold effect described in previous section, we understand this third trend more easily: when the non-served energy demand shoots up at the threshold, benefits increase accordingly due to

more episodes of scarcity. Surprisingly, depending on the DR application, this increase of benefits due to the threshold effect even compensates the second trend mentioned above: average benefits can be higher even when the contract size is reduced by half its initial size. This impact is observable on graphs of next sub-sections as well as on **Table 7.4** which shows the ratio between benefits generated when the contract factor is equal to 1 and when it is equal to 0.5. For example, we note that for aluminium, industrial cooling, cement, paper, pulp, and ventilation, the ratio is lower than 1, which means that benefits are higher, although contracts have been reduced by half their size. This is not astonishing given the more numerous hours of scarcity in the system. This effect is outlined by the graphs on next sub-sections.

Table 7.4 – Ratio between benefits with a contract factor of 1 and of 0.5

	PC=3,000	PC=10,000	PC=20,000
Steel	1.7	1.6	1.6
Aluminium	0.8	0.8	0.8
Chemicals	1.3	1.3	1.3
Industrial cooling	0.6	0.6	0.6
Cement	0.6	0.6	0.5
Paper and pulp	0.6	0.7	0.7
Industrial ventilation	0.7	0.7	0.8
Tertiary air conditioning	1.3	1.3	1.3
Tertiary heating	1.4	1.5	1.4
Residential heating	1.3	1.3	1.2

Industrial Load-shedding

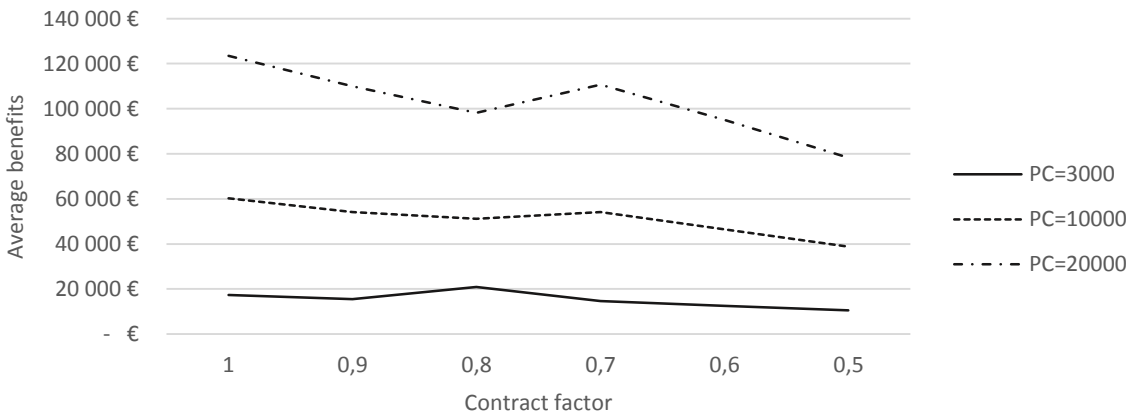

Figure 7.2 – Steel average annual benefits: price cap and contract size impact (€/MW/year)

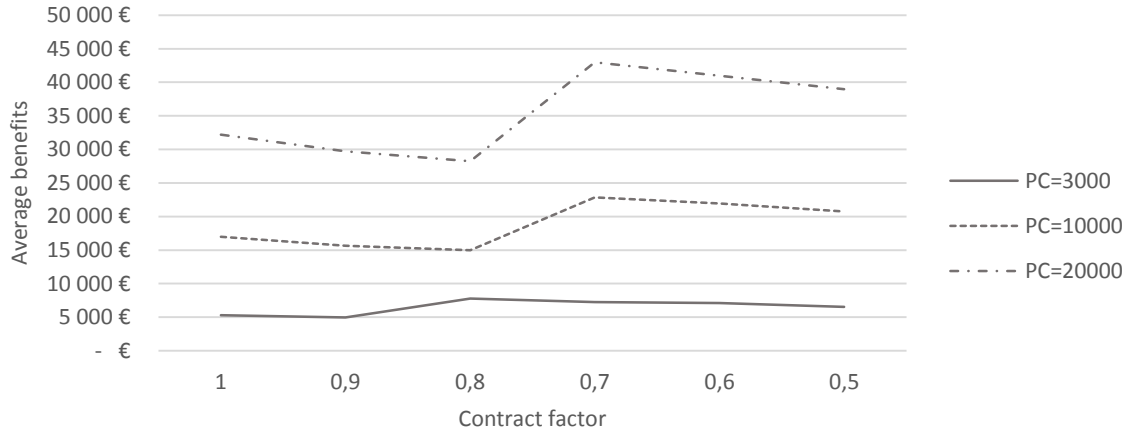

Figure 7.3 – Aluminium average annual benefits: price cap and contract size impact (€/MW/year)

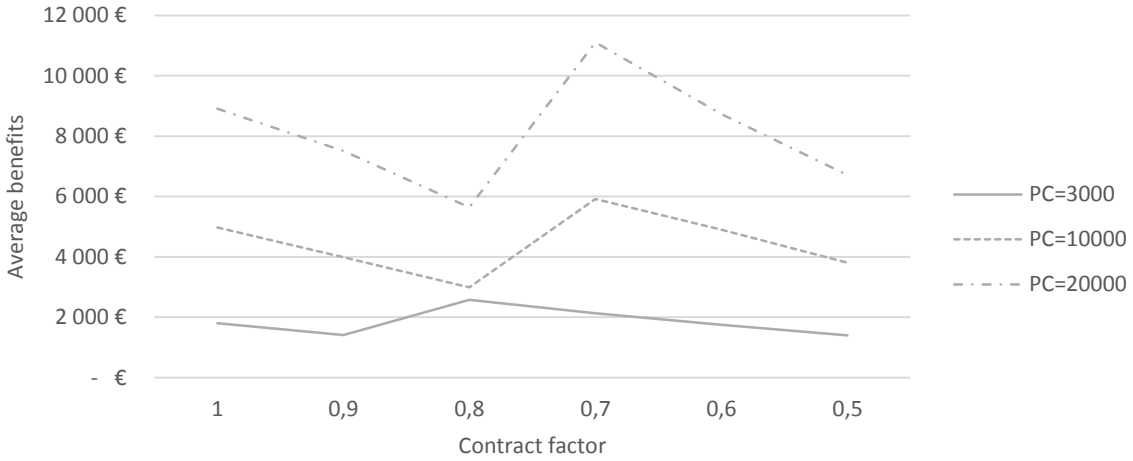

Figure 7.4 – Chemicals average annual benefits: price cap and contract size impact (€/MW/year)

Industrial Load-shifting

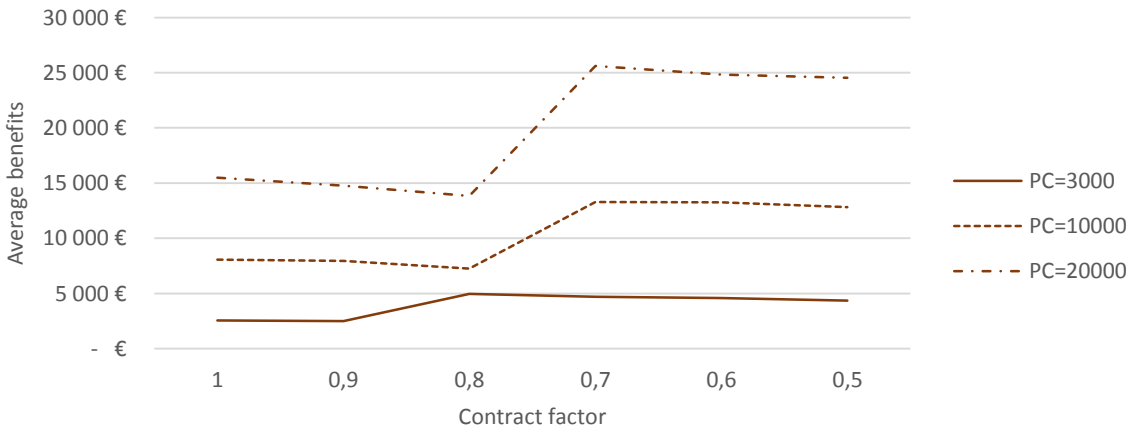

Figure 7.5 – Industrial cooling average annual benefits: price cap and contract size impact (€/MW/year)

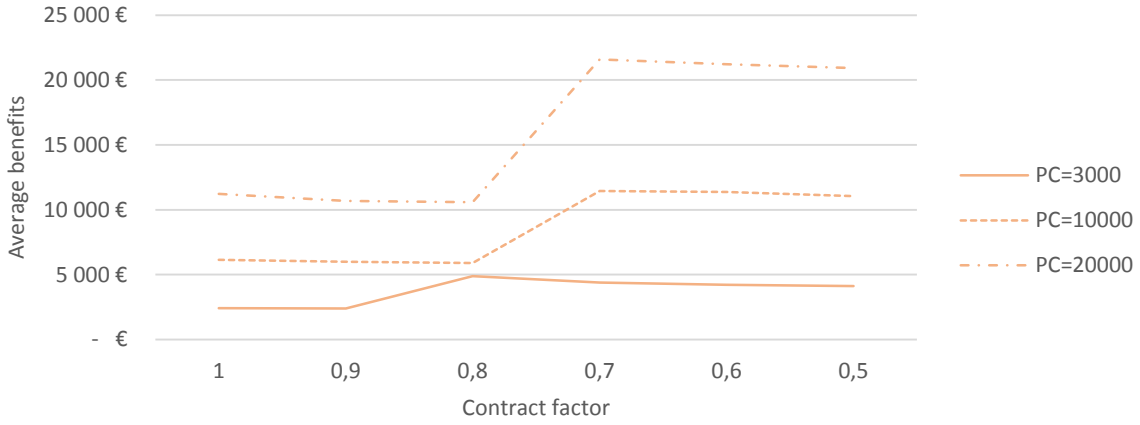

Figure 7.6 – Cement average annual benefits: price cap and contract size impact (€/MW/year)

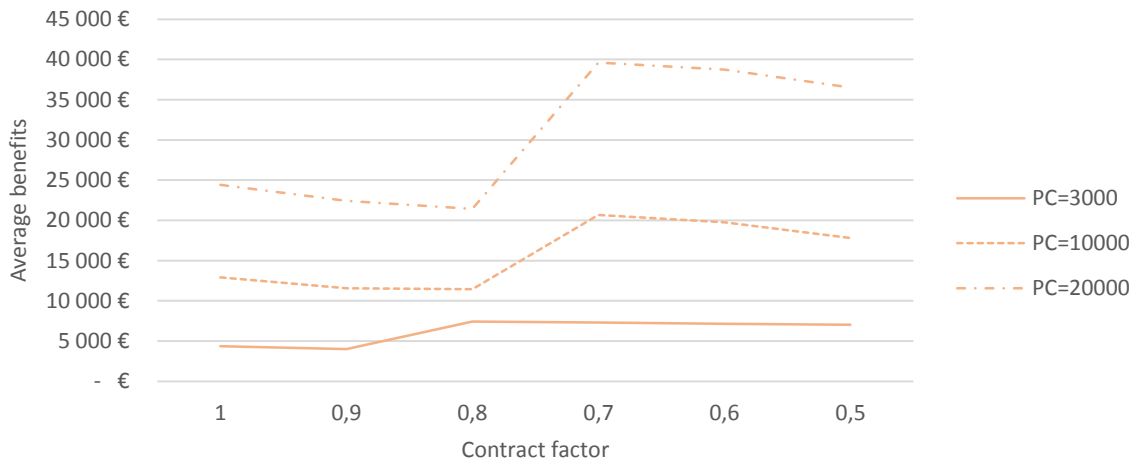

Figure 7.7 – Paper and pulp average annual benefits: price cap and contract size impact (€/MW/year)

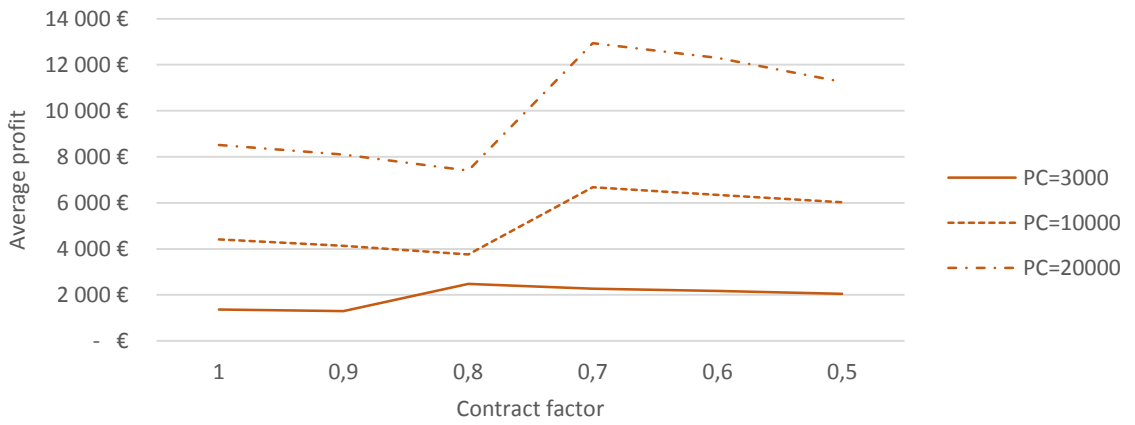

Figure 7.8 – Indus. ventilation average annual benefits: price cap and contract size impact (€/MW/year)

Residential and tertiary load-shifting

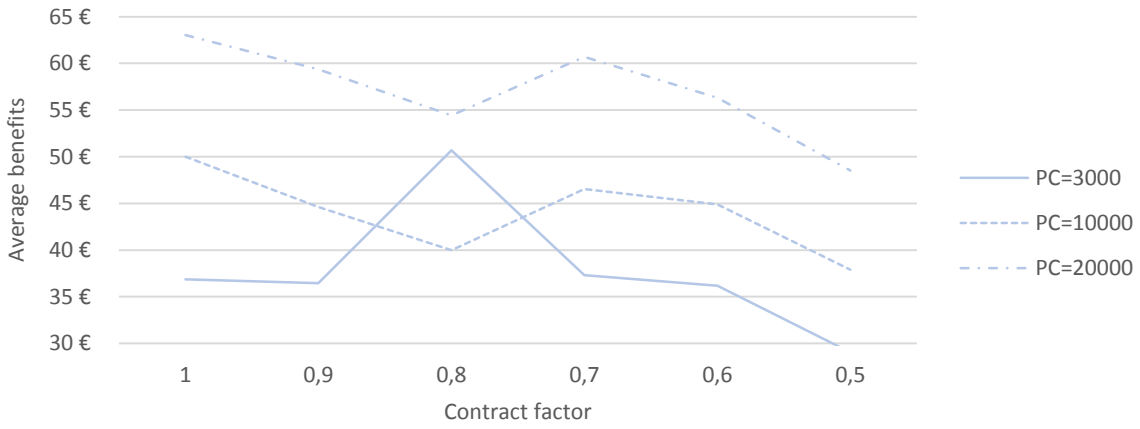

Figure 7.9 – Tertiary air cond. average annual benefits: price cap and contract size impact (€/MW/year)

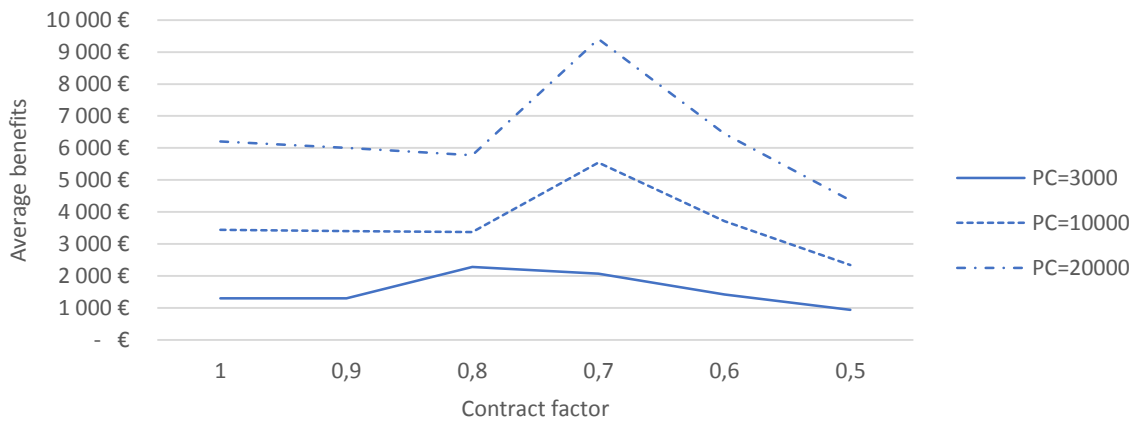

Figure 7.10 – Tertiary heating average annual benefits: price cap and contract size impact (€/MW/year)

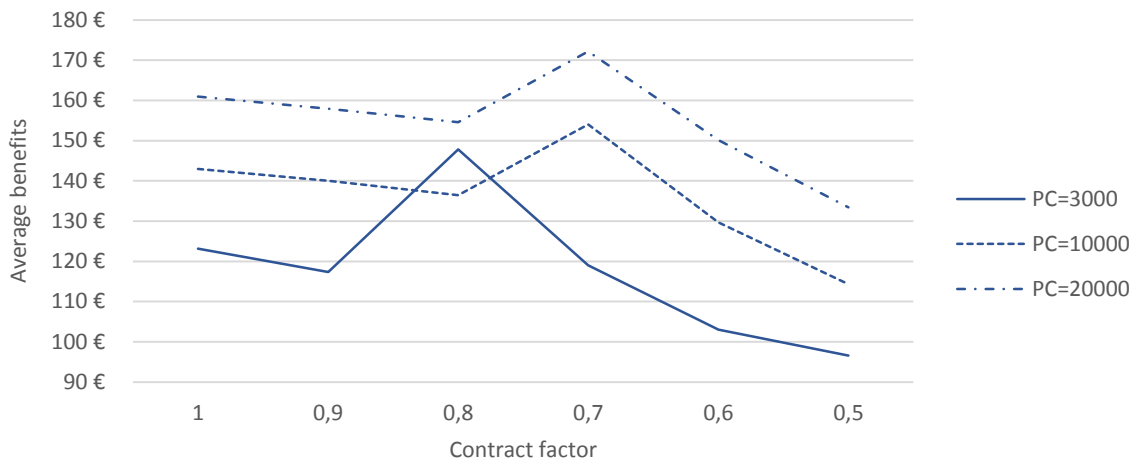

Figure 7.11 – Residential heating average annual benefits: price cap and contract size impact (€/MW/year)

7.3.2.2 Impact on the business case

If we look at conclusions drawn in chapter 6 (refer to **Table 6.8**), our sensitivity analysis suggests that neither the price cap nor the contract size impacts are sufficient in order to make residential heating a profitable DR activity. Same conclusions apply to tertiary eating, tertiary air conditioning, industrial cooling and industrial cross-technology ventilation. Indeed, for these sectors that were not originally viable, if we compare the annual fixed costs with benefits made in the best possible outcomes of the sensitivity, we see that conclusions about the business case still hold (see **Table 7.5**).

Table 7.5 – Business case of the Demand Response aggregator in the best case

	Maximum average benefits (€/MW/year)		**Annual fixed costs (€/MW/year)**	**Business opportunity**
Industrial load-shifting	Industrial cooling	25,624	92,851	No
	Cross-tech ventilation	12,936	189,068	No
Tertiary load-shifting	Air conditioning	63	[24,927; 112,169]	No
	Tertiary heating	9,402		No
Residential load-shifting	Residential heating	172	15,579	No
			6,250	No
			[5,840; 7,700]	No

Similarly, let us take sectors that were already profitable in the business case of chapter 6 and compare their annual fixed costs with benefits in the worst possible case of the sensitivity. **Table 7.6** shows that conclusions remain the same as in chapter 6. These DR technologies remain profitable.

Table 7.6 – Business case of the Demand Response aggregator in the worst case

	Minimum average benefits (€/MW/year)		**Annual fixed costs (€/MW/year)**	**Business opportunity**
Industrial load-shedding	Steel	10,485	[25; 997]	Yes
	Aluminium	4,952		Yes
	Chemicals	1,395		Yes
Industrial load-shifting	Cement	2,401	1,246	Yes
	Paper pulp	4,002	1,246	Yes

7.4 Conclusion

The sensitivity analysis performed in this chapter aimed at assessing whether capacity market-based revenues and consumers' reluctance to contract with the aggregator might change the business case of DR in France. We modelled the additional capacity market valuation by an energy-only market under scarcity pricing, and we assumed that the reduction of the contract size, throughout the annual number of activations, could represent customers' willingness to engage in DR actions. Different levels of price caps as well as different contract sizes were tested.

Our results highlight that higher price caps lead to dramatically higher average benefits for every DR category, but gainers are industries with capacity value rather than the sectors capturing only energy value. Furthermore, although the contract size can restrain benefits, system-wise effects characterised by more hours with scarcity rents can increase those, meaning that reducing the contract size can be beneficial for the aggregator.

CONCLUSION

The work achieved throughout this doctoral thesis consisted in assessing the economic potential of Demand Response in liberalised electricity markets, in particular for the French power system which has engaged in a transition towards more renewable energies. This ongoing change may strengthen in the near future in order for France to comply with the 20-20-20 objectives, raising even more the need for flexibility of the power system. Among flexibility technologies such as gas power plants, electricity storages, and the interconnected power networks, DR constitutes an appealing option because it consists in exploiting the deferrable nature of certain end-uses of electricity which are, by essence, already present in the power system. In France, the potential of flexible end-uses is significant but remains largely unexploited, especially for small and medium consumers. Consequently, the deployment of DR would be associated with a deeper involvement of electricity consumers in the management of their demand, paving the way towards more competitive electricity markets. In this regard, the emergence of DR aggregators can be seen as a first step toward an improved efficiency of European electricity markets.

The existing academic literature never performed such a quantitative assessment for France. In this regard, the work achieved in this thesis contributes to improve the current state of the art. Another contribution lies in the methodology we used to model DR.

In order to estimate the economic potential of DR in France, we have developed an electricity market model which enabled us to calculate the economic value of DR if it was integrated in the French power system on a large scale. The methodology relies on mathematical optimisation tools enabling to deal with power demand uncertainty, an extensive representation of DR technologies, and endogenous market prices. Furthermore, the model formulation ensures that the outcomes are equivalent to those of an electricity market under pure and perfect competition. Therefore, the dispatch of DR technologies handled by the model can be seen as the bidding decisions of a DR aggregator seeking to maximise his profits. One essential constraint impacting the aggregator bidding decisions is the number of DR events that consumers allow the aggregator to trigger over the course of a year. This constraint represents the propensity of consumers to participate in DR programmes.

As far as we know, our electricity market model is the first including at the same time this type of stock constraint, featuring an extensive representation of DR, uncertainty, and endogenous market prices. In addition to bringing a more accurate description of actual interactions between DR and power systems, our modelling approach is especially relevant to tackle our research question.

The answers to the research question addressed in this thesis are the following. Generally, the economic value of DR is characterised by large variations across categories of consumers. This result holds in the case of France, where the activation of DR involving small and medium consumers in residential and tertiary sectors generates lower benefits than in the industry.

This discrepancy is explained by the important weight of the capacity value in the total economic value of DR. Compared with the revenues based on the energy value, capacity revenues of DR are much more significant. However, according to our model simulations, they depend on the realisation of episodes of scarcity which do not occur more than once every twenty years in France. On the contrary, the flow of energy revenues is steady over time.

Given current conditions of electricity markets in France, business opportunities for DR aggregators are to be found in the load-shedding of several industrial consumers: steel, aluminium, and chemicals. The market revenues generated by DR in the steel and aluminium industries are quite significant, because they are mostly derived from the capacity value. Benefits of chemicals are lower because they are to found in the energy value, due to lower activation costs. Nevertheless, these three categories of DR constitute an economically viable business for aggregators because they are characterised by low fixed costs of the enabling infrastructure.

Load-shifting of industrial consumers (industrial cooling, cement, paper, pulp, and ventilation) also comes with benefits based on the capacity value. However among this category, only cement, paper, and pulp are profitable. Due to higher fixed costs, load-shifting of industrial cooling and ventilation are not profitable. Load-shifting of electric heating in the tertiary sector is not profitable as well, despite revenues based on the capacity value. As for industrial cooling and ventilation, fixed costs in the enabling infrastructure are too high.

Load-shifting of air conditioning in the tertiary sector, and of electric heating in the residential sector is characterised by a small share of the capacity value in the total economic value, thus low benefits. Unlike other DR technologies, it seems that these two segments of DR cannot benefit from scarcity situations that might occur in the power system. For air conditioning, this is explained by the temporal availability which is not concomitant to the peaks of demand (load-shifting of air conditioning can be activated during summer while peaks of demand happen during winter). In France, because of the high penetration of electric heaters in the households' electricity consumption, activation of DR in the residential sector results in a power demand reduction which relieves the power system from scarcity situations. However, our results also suggest that this category of DR could be activated during scarcity events if residential consumers accept more activations per year.

These results obviously depend on assumptions we made. We challenged some of them below to see whether the conclusions drawn in the aggregator business case would change. The first test we did concerns the capacity remuneration of the aggregator. In the economics of electricity markets,

capacity remuneration mechanisms have become an increasingly debated topic. In many European countries, they have also arisen in the agenda of policy makers who supported their integration in the market design. In France, a capacity market is now operational, allowing aggregators to finance the investment in new DR capacities. We simulated the additional revenues that the capacity market would provide to the DR aggregator by letting our energy-only market work under scarcity pricing. To do so, we increased the price cap from 3,000 €/MWh to 20,000 €/MWh. Our results show that the capacity value of DR is substantially higher under scarcity pricing, but that the impact on the energy value is negligible. Thus, with a price cap of 20,000 €/MWh, the aggregator benefits are drastically increased for DR technologies like industrial load-shedding, industrial load-shifting, and tertiary heating, whereas they remain almost unchanged for residential heating and tertiary air conditioning. Nevertheless, this increase of profits is not enough to cover fixed costs of the enabling infrastructure in industrial cooling, ventilation, and tertiary heating. Fixed costs still need to come down further in order to fully exploit the potential of this type of DR. Our second test concerns the reluctance of consumers to enter into contract with the aggregator. To analyse this effect we progressively decreased the annual number of activations up to half their initial level. The first result of this test is the following: the lower the number of activations the lower the aggregator benefits. This is not surprising since reducing the number of activations means less possibilities for the aggregator to bid DR on the market. We also observed a second result which is more counterintuitive. If the reluctance of consumers reaches a certain threshold, the aggregator can be better off in terms of benefits. This is explained by more scarcity periods in the power system. Indeed, the more reluctant the consumers, the lower the volume of DR available in the system, the higher the number of scarcity periods. For the aggregator, the consequence of this result is twofold: (i) the reluctance of consumers should not be considered as an issue of prime importance, and (ii) there might be an optimal amount of consumers to contract with.

To sum up, this thesis feeds the academic and political debate about the value of DR with the following elements: in France, DR economic value is mainly to be found in capacity value, but only certain industrial consumers would be able to benefit from it. Although key to foster investment in the enabling technology, either capacity value of DR is still too small for private investors, or some segment of consumers like households cannot properly capture it. The latter conclusion holds because the analysis is based on the results from an energy-only market. It would be different with an additional remuneration from an actual capacity market, such as the one launched in France in 2017. Therefore, our analysis claims that the capacity market is necessary to support the deployment of DR from residential consumers.

Obviously, the model used to derive these results has some limits that we should be aware of. First and foremost, we must recall that the model developed in this thesis is an energy-only market model which thus does not assess the value of DR related to the short-term balancing of power networks. The capability of DR to provide ancillary services and to participate in balancing mechanisms refers to the short-term flexibility value of DR which is yet essential in actual power systems. Most power systems have indeed developed programmes designed to remunerate DR if they provide capacity and energy in case of contingencies. For instance, balancing mechanism is currently the main source of revenues for DR providers in France. We think that overlooking the reliability-based value of DR is the most important limit of our model. To not have dealt with it stands for a simple reason: models needed to capture the reliability value of DR involve a different class of optimisation problems than our SDDP-based model. Indeed, in order to capture the reliability value of DR, one needs to resort to unit commitment models in order to represent start-up decisions which come with non-convex set of constraints. Non-convexity implies that the dual variables of the demand satisfaction constraint can no longer be interpreted as the market prices. Moreover, the inclusion of randomness in unit commitment models is possible but the resulting stochastic unit commitment model cannot be handled by SDDP (because SDDP only works with convex sets). Stochastic unit commitment models are costly to solve if there are a lot of state variables, i.e. several DR technologies, whereas our SDDP-based model remains tractable even with a detailed and exhaustive representation of DR. Put differently, it is extremely difficult, if impossible, to assess the reliability value of DR in a framework such as the one use in this thesis. Nevertheless, the literature is rich in studies addressing this issue and we think that they should be seen as complementary to the insights brought by this thesis, given the difficulty to combine both approaches into a single model.

Our model can however be extended on many points. Potential improvements could be: a network representation, randomness on water inflows for a more accurate representation of hydro reservoir management, and risk aversion.

In 2012, a cold wave stroke Europe for several days in a row and French power system recorded its highest peak of power consumption. It was kept in balance with the help of exchanges with interconnected countries, in particular Germany which fortunately had its installed wind turbines producing at full capacity. A representation of the power network, in particular the interconnection with neighbouring countries, could answer interesting questions such as: how DR would compete with interconnections in case of extreme demand peaks? Would the capacity value of DR be affected by importations from neighbouring countries?

Hydropower from conventional dams and pumped-storage facilities provides almost 15 GW of capacity to the French power system. These flexible facilities are generally used as reserves in order to respond to peaks of demand. They are thus natural competitors of DR. Therefore, a valuable extension

to the model would be to better account for water release decisions. This would add a stochastic dimension to the model stemming from water inflows into reservoirs that SDDP can however manage.

Integration of risk aversion would modify the management of storages present in the system. Compared with the risk neutral case, the model with risk aversion would be more careful in terms of water release and DR activations, preferring to satisfy the demand with more expensive thermal power plants during low and medium demand scenarios. Indeed, the risk aversion model would try to avoid system outages as much as possible, by keeping the energy available in hydro reservoirs and DR contracts in case of very high demand scenario. Our intuition is that the risk averse case would outweigh even more the capacity value of DR. Given the importance of capacity revenues for the economic viability of DR aggregators, we think that it would be valuable to confirm this intuition, and to assess to what extent risk aversion may increase the capacity value of DR.

Overall, the work achieved during this thesis is an economic analysis of the integration of consumers in the electricity markets tackled from the angle of DR. We intended to assess whether the emerging business of DR providers such as aggregators constitutes today a promising answer to fully exploit the potential of load management brought by smart gird technologies. We proved that in France, DR is economically viable on certain industries, but that for small and medium consumers, the fixed costs of smart grid technologies, more than a widespread adhesion of consumers, remain an important barrier. The capacity market implemented in France, as well as the financing of the investment in the enabling infrastructure by the distribution system operator, constitute therefore appropriate supports for the further development of Demand Response in this country.

APPENDICES

Appendix A – Nuclear power availability over time

In the case study of Part III, the time power availability of nuclear power plants is define for each week, i.e. for each period of the model. Data was gathered on RTE website. In the model, the available capacity for each time step is defined by the installed capacity multiplied by the scalar factor shown on the figure below.

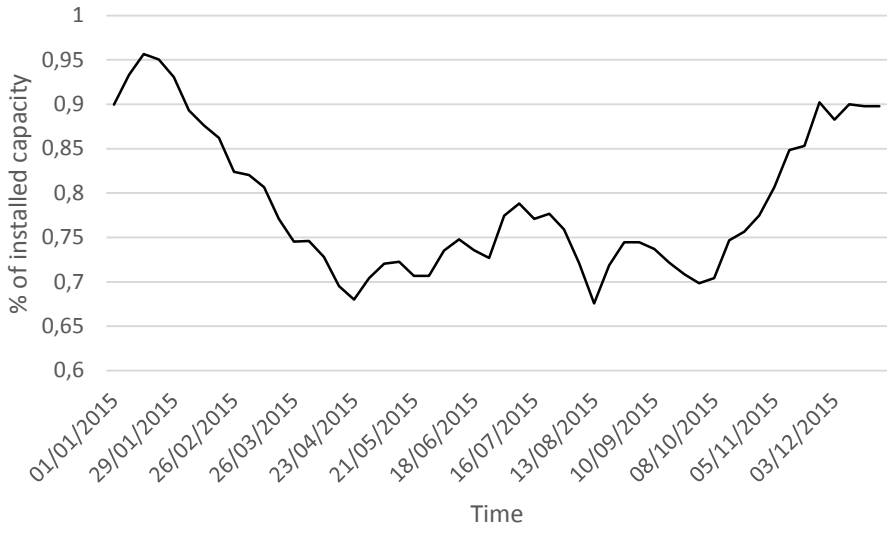

Figure A. 1 – Nuclear power availability over time

Appendix B – Demand Response load profiles

For sake of readability, load profiles are given only for the first week of January. For cement, they have been built internally by team members of the CEEME in Engie. For industrial cooling and ventilation, we have built those relying on indication and methodology given by Gils (2014, p. 4), and for tertiary and residential sectors, we used data provided by RTE.

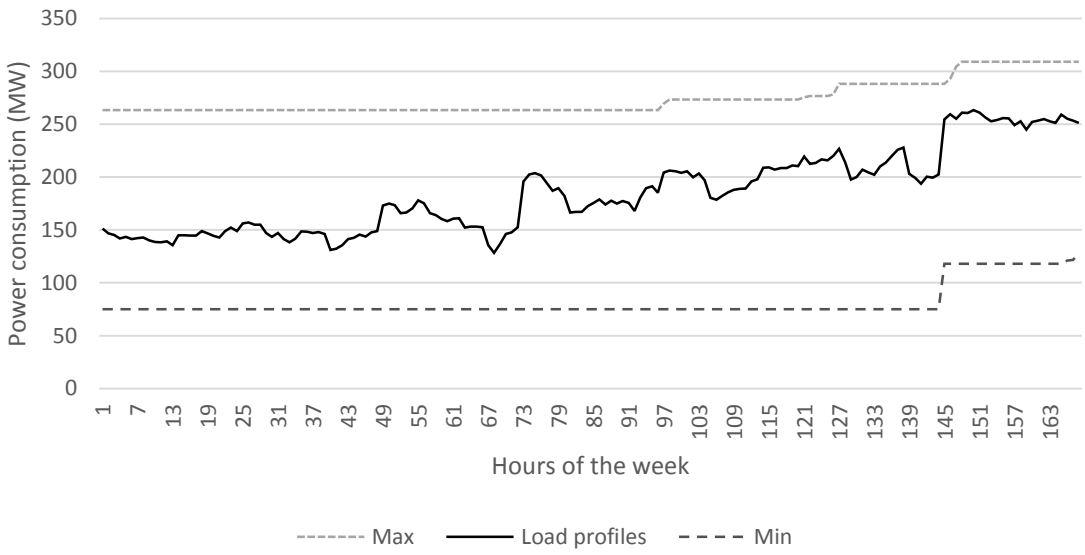

Figure A. 2 – Load profile of cement

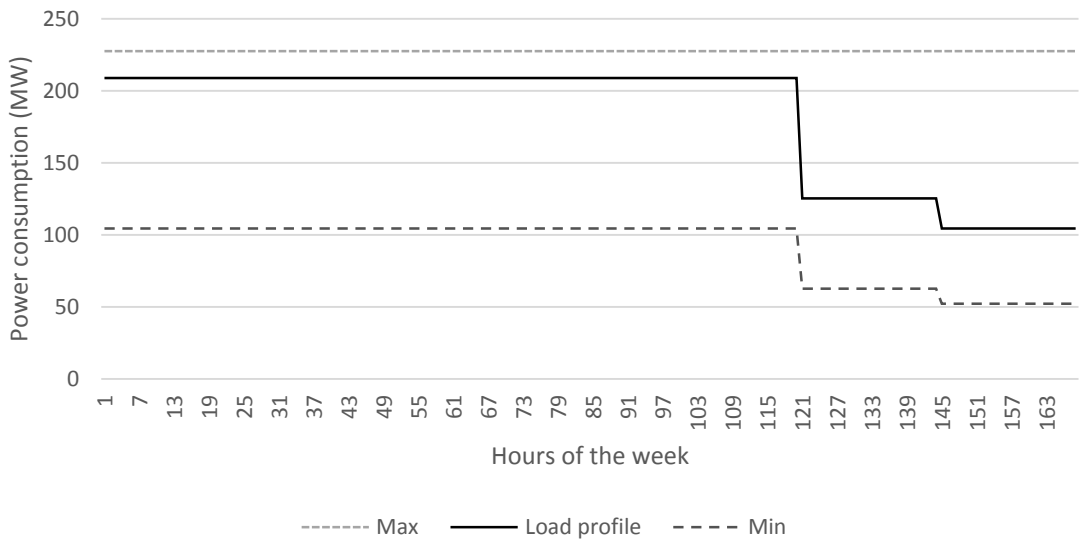

Figure A. 3 – Load profile of industrial ventilation

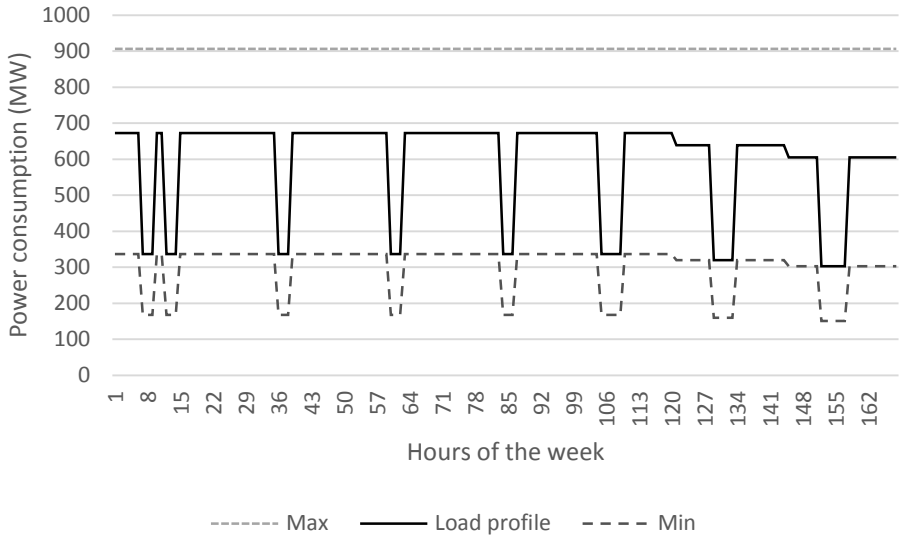

Figure A. 4 – Load profile of industrial cooling

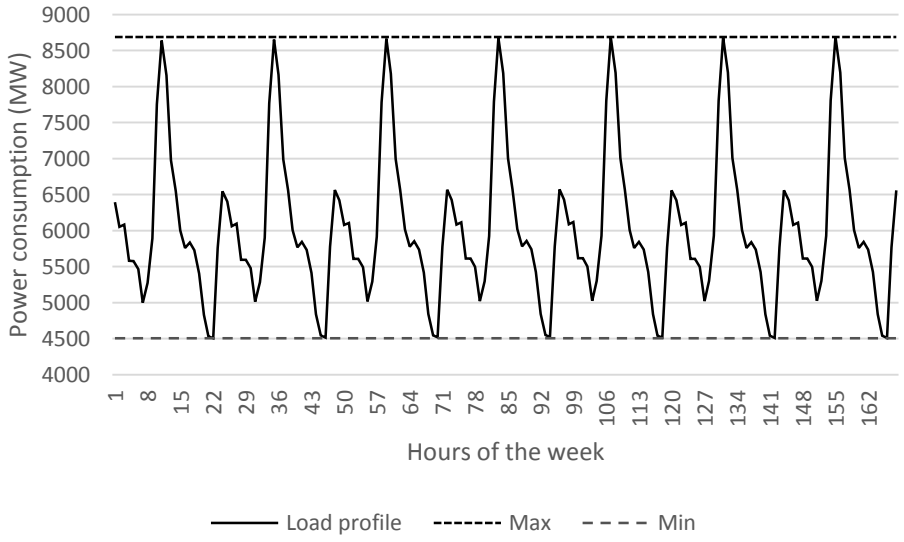

Figure A. 5 – Load profile of tertiary heating

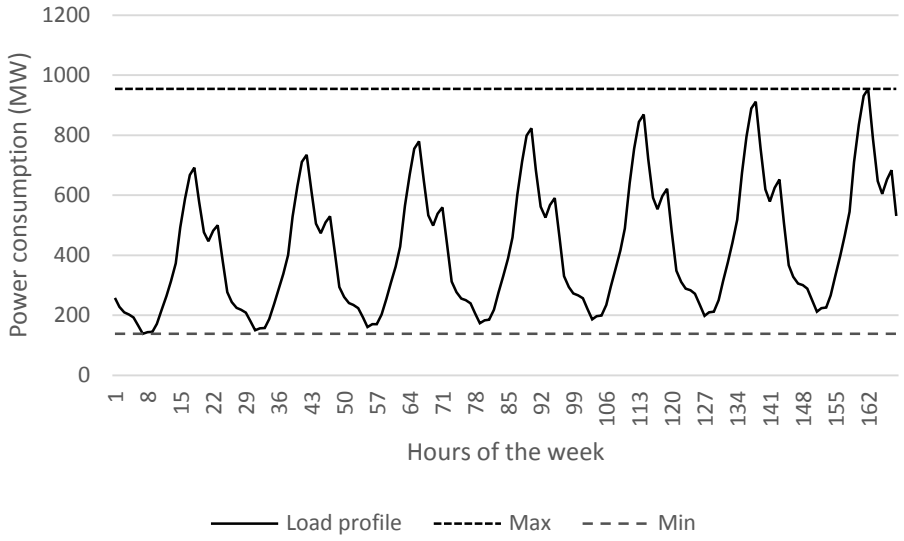

Figure A. 6 – Load profile of tertiary cooling

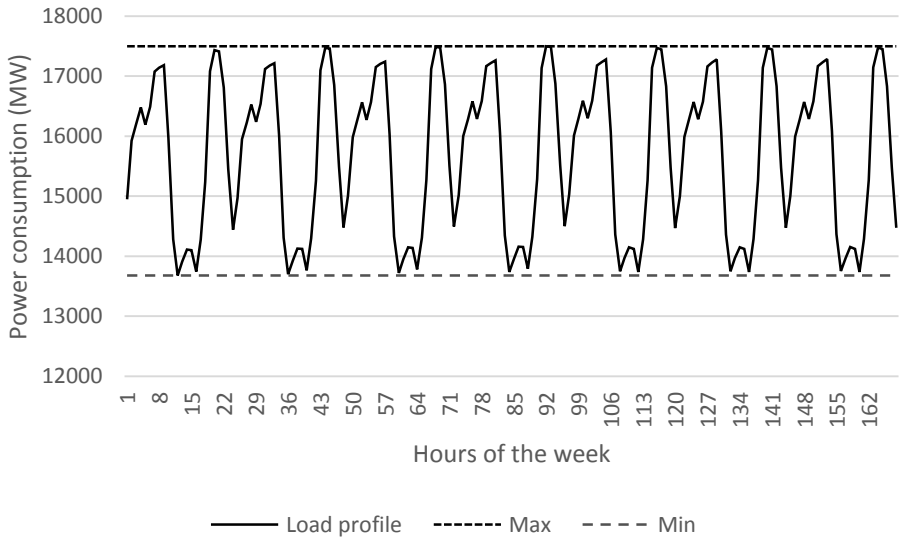

Figure A. 7 – Load profile of residential heating

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SYNTHÈSE EN FRANÇAIS

INTRODUCTION

Les réformes de libéralisation de l'industrie électrique initiées dans les années 1990 furent d'abord guidées par l'idée que la concurrence entre producteurs aboutirait à une réduction des coûts de fourniture de l'électricité (Kirschen 2003). En se concentrant essentiellement sur l'amont de la chaîne de valeur, ces réformes introduisirent effectivement des marchés de gros concurrentiels au niveau de l'offre, mais le côté de la demande resta fidèle à ses caractéristiques d'avant réformes, c'est-à-dire peu, voire pas réactive à l'évolution des prix. Pour les économistes, cette caractéristique est source d'inefficacité pour le fonctionnement d'un marché. Mais cette inélasticité de la demande d'électricité aux prix ne pose pas que des problèmes en termes d'efficacité des marchés. En ce qui concerne la gestion du réseau électrique par exemple, celle-ci pose des problèmes d'équilibrage en temps réel qui sont exacerbés par le fait qu'à l'heure actuelle l'électricité ne se stocke pas à coût raisonnable. Ainsi, les décideurs publics s'attachent depuis quelques années à développer de nouveaux outils de gestion de la demande, communément appelés *effacements de la demande* (ED).

Les ED sont aujourd'hui considérés comme un outil largement inexploité qui pourrait cependant accompagner la transition des systèmes électriques vers plus d'énergies renouvelables. Avec l'appui de l'industrie des réseaux intelligents (smart grids) et des nouvelles technologies de l'information et de communication (NTIC), les consommateurs d'électricité, notamment les plus petits comme les ménages ou les bâtiments du tertiaire, seraient incités à modifier leurs modes de consommation sur le court-terme. Cette modification occasionnelle et de court-terme des usages permettrait en outre une réduction de la facture d'électricité pour les consommateurs et une gestion plus économe du système électrique pour l'ensemble des partie prenantes (producteurs, opérateurs de réseaux, et fournisseurs) (IEA 2003; Faruqui and George 2005; Spees and Lave 2007; Albadi and El-Saadany 2008; EPRI 2012).

Dans le champ de la recherche académique, la valeur d'une intégration à grande échelle des ED dans les systèmes électriques fait néanmoins débat. Malgré un potentiel théorique évident et une faisabilité technique démontrée, les ED se heurtent à la problématique du coût de leur développement. Ce constat est bien reflété par la réalité : aujourd'hui l'activité des ED reste embryonnaire comparée à son potentiel. Pour pallier à cette situation, les pouvoirs publics pourraient éventuellement subventionner l'investissement dans les smart grids, à condition que la valeur générée ensuite par les ED soit suffisante. Il semblerait que les études dont le but est d'évaluer la valeur économique des ED ne proposent pas assez de garanties pour obtenir la confiance des pouvoirs publics. Ceci provient du fait qu'évaluer l'impact d'une intégration à grande échelle est relativement compliqué d'un point de

vue méthodologique. D'un côté, il faudrait pouvoir rendre compte des comportements précis des consommateurs, et de l'autre évaluer leur impact à l'échelle du système électrique dans son ensemble. Ceci nécessite deux types d'approches. L'étude des comportements des consommateurs d'électricité est aujourd'hui l'objet des pilotes démonstrateurs de smart grids. Ces études empiriques se basent sur l'analyse statistique d'échantillons de consommateurs. En revanche, l'évaluation de la valeur des ED à l'échelle du système électrique demande une approche plus fondamentale basée sur la modélisation mathématique des marchés électriques. La divergence entre ces deux approches explique qu'il soit difficile de rendre compte à la fois du comportement précis des usagers et de leur impact en termes de valeur économique à l'échelle de l'ensemble du système.

Cette thèse vise justement à rapprocher ces approches divergentes. Notre approche sera d'évaluer la valeur économique des ED en intégrant, au sein d'un modèle d'optimisation mathématique de marché électrique, des caractéristiques comportementales des consommateurs d'électricité.

Cette approche nous permettra de simuler une intégration à grande échelle des ED sur le système électrique français. Nous répondrons à la question de leur valeur économique en quantifiant les profits générés sur le marché de l'énergie par des agrégateurs d'effacements. Aujourd'hui, les agrégateurs sont à l'origine de la plupart des activations d'effacements en France et en Europe. Aussi, nous entreprendrons une analyse de rentabilité de cette activité commerciale pour le cas de la France. Cette thèse cherchera donc à répondre aux questions suivantes :

Quelle est la valeur économique des effacements de la demande ?
Quelles sont les opportunités commerciales des agrégateurs en France ?

Nous développerons notre analyse en sept chapitres répartis dans trois parties:

- La première partie rappelle les notions théoriques d'ordre général (chapitre 1) et précise comment les consommateurs réagissent dans la pratique lorsqu'ils sont incités à participer à des programmes d'ED (chapitre 2).

- La deuxième partie dresse le cadre de modélisation développé dans cette thèse. Tout d'abord, une revue de la littérature sur les modèles d'ED est proposée dans le chapitre 3. Le chapitre 4 décrit en détail notre propre modèle de marché de gros de l'énergie sous incertitude, et le chapitre 5 en fait un usage à teneur didactique afin d'expliquer la formation des coûts marginaux des ED dans un cadre stochastique, c'est-à-dire lorsque le modèle prend en compte l'incertitude sur le niveau de la demande et de la production des énergies renouvelables intermittentes.

- La troisième et dernière partie s'intéresse à la valeur économique des ED sur le système électrique français. Nous y présentons, au travers du chapitre 6, des résultats quantitatifs obtenus par des simulations de notre modèle que nous avons calibrés sur le mix électrique de la France en 2016. Ces résultats correspondent aux profits générés par un agrégateur d'effacements sur le marché de gros de l'énergie. Dans un premier temps, le chapitre 7 étudie l'impact d'une rémunération de la capacité des ED par le marché de capacité actuellement en vigueur en France. Dans un second temps, il analyse l'impact sur la valeur des ED de la propension des consommateurs à s'engager dans un contrat avec l'agrégateur.

PREMIERE PARTIE – Effacements de la demande : notions théoriques et implémentations pratiques

Dans cette première partie, nous cherchons à justifier l'idée que les différentes définitions données à la notion d'effacement de demande peuvent se comprendre dans une conception harmonisée grâce à l'agrégateur d'effacements, dont le rôle doit néanmoins être confirmé par les études empiriques.

Chapitre 1 – Effacements de la demande : théorie et pratiques

Les définitions données aux ED sont assez nombreuses du fait des divergences de point de vue entre économistes et ingénieurs du système électrique. Les anglo-saxons distinguent par exemple, la demande réactive aux prix (*price-responsive demand*), pour les économistes, de la réponse de la demande (*demand response*), plutôt pour les ingénieurs. Cette distinction a souvent conduit à séparer les ED en deux approches : ils sont vus soit comme une demande élastique aux prix (Figure 1), soit comme une ressource pour le système électrique (Figure 2).

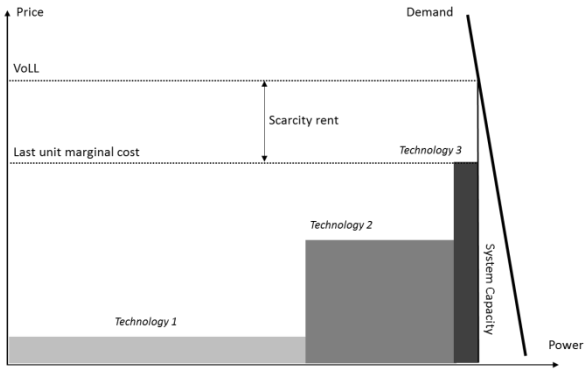

Figure 1. ED vue en demande élastique

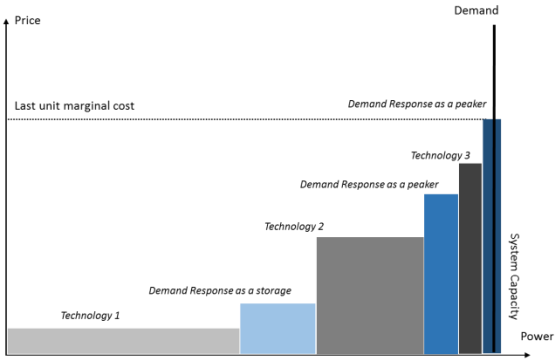

Figure 2. ED vue en resource du sytème

Cependant, la notion d'ED renvoie toujours à la participation des consommateurs dans l'élaboration du prix sur les marchés de l'électricité. Aussi, l'activation des effacements a toujours la même origine physique, à savoir une modification de la part des usagers de la consommation de certains de leurs équipements. Par exemple, les sites industriels peuvent décider de stopper leur chaîne de production si des incitations leurs sont proposées pour le faire. Il en va de même pour les clients résidentiels et tertiaires, qui peuvent par exemple couper momentanément leur chauffage, leur climatiseur, ou d'autres usages. D'ordinaire, les ED sont classifiés selon deux grands schémas en lien avec la nature de l'interruption des usages :

- L'effacement pur *(load-shedding)*, mode selon lequel les usages sont interrompus sans être retrouvés, impliquant une perte nette de la consommation d'énergie.

- Le déplacement *(load-shifting)*, mode selon lequel les usages sont lissés dans le temps, c'est-à-dire que la quantité d'énergie consommée reste la même.

Si la consommation de ces usages est modifiée, il en résulte soit une demande élastique aux prix, soit une ressource pour le système électrique. Cependant, si la modification des usages est entièrement laissée à la discrétion des consommateurs, il est vrai que l'opérateur de réseau ne pourra ni l'anticiper, ni considérer l'effacement comme une ressource, puisque ce dernier a besoin d'un engagement vis-à-vis de la disponibilité de la capacité des ressources. Aussi, dans la mesure où les consommateurs acceptent de déléguer la gestion de la demande de certains de leurs usages à un intermédiaire de type agrégateur, les ED peuvent être considérés de manière équivalente comme une demande élastique et une ressource pour le système. La demande est en effet réactive aux prix, puisque modulée par l'agrégateur selon le niveau des prix sur le marché. Elle est aussi *dispatchable* dans le système (c'est-à-dire que la quantité d'énergie à retirer du réseau est notifiée à l'opérateur, et engageante pour l'agrégateur), puisque fiabilisée par l'agrégateur. Ce mode de fonctionnement reste valable à la condition que les consommateurs soient durablement engagés avec l'agrégateur. Dans le cas contraire, ils pourraient décider de reprendre le contrôle de leurs usages, rendant l'ED indisponible. L'acceptation des consommateurs peut être renforcée si elle est formalisée via un contrat entre le consommateur et l'agrégateur (Figure 3).

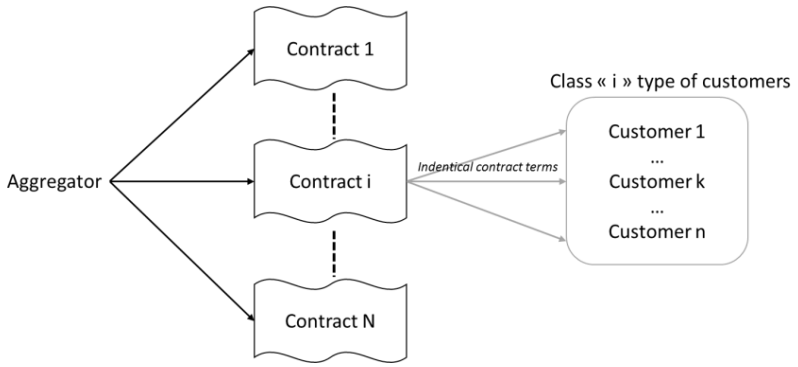

Figure 3. Contrat entre agrégateur et consommateurs

A priori, si les termes du contrat sont négociés par les deux parties, il n'y a pas de raison que les consommateurs décident de contrecarrer la décision de l'agrégateur d'activer un ED sur les marchés. Une compensation financière différenciée par usage doit être proposée, en accord avec la valeur que les consommateurs affectent à chaque usage. De plus, un nombre maximum de déclenchements d'ED par l'agrégateur permet de s'assurer que le consommateur reste globalement au contrôle de sa demande (par exemple, on peut imaginer que l'agrégateur ne puisse pas déclencher plus de 40 coupures par an). Enfin, ce cadre nécessite qu'un compteur puisse enregistrer correctement les flux de consommation et que l'agrégateur puisse contrôler à distance les équipements électriques, de sorte que l'activation de l'ED soit mesurable, fiable pour le marché, et non-intrusive pour le consommateur. L'agrégateur ou le consommateur doit se munir de cette infrastructure, et dans cette thèse, nous ferons l'hypothèse que l'investissement dans ce type de technologie est entrepris par l'agrégateur.

Chapitre 2 – Effacements de la demande : évidences empiriques

Pour comprendre comment les consommateurs d'électricité vont s'accommoder aux nouvelles technologies de smart grid et quel sera l'impact sur les modes de consommation, des démonstrateurs de terrain sont mis en place dans plusieurs régions du monde, à partir desquels des *études sur les comportements des consommateurs* (ECC) sont menées. Ce chapitre vise à dresser les principales conclusions de ces études empiriques, notamment pour comprendre comment les termes du contrat peuvent être définis par l'agrégateur.

Le principal problème des ECC est le manque de coordination parmi les différents projets pilotes qui conduit à des conclusions peu harmonisées, et parfois même assez divergentes, notamment sur les valeurs de l'élasticité de le demande. Comment alors comparer les résultats entre projets ? Auxquels peut-on le plus se fier ? Est-il possible d'étendre les conclusions d'un projet mené dans une région particulière à une population plus vaste ?

Depuis quelques années, le Department of Energy (DOE) pilote la coordination de projets de smart grids aux États-Unis et s'attache à ce que les ECC menées dans ce cadre se fassent selon une

méthodologie robuste et harmonisée. Nous avons donc récupéré les principaux résultats empiriques de ces projets en ce qui concerne les ED. Par ailleurs, nous nous sommes aussi intéressés à certains projets menés en Europe et en France. En voici les principales conclusions :

- Les consommateurs répondent positivement aux incitations financières de type tarification dynamique (une tarification évolutive dans le temps et qui reflète les prix de l'électricité sur les marchés de gros).

- L'installation de technologie de contrôle à distance renforce la réponse des consommateurs. De plus, une fois installée, l'acceptation et l'utilisation de ces technologies par les usagers est bonne. Cependant, la volonté d'installer ces technologies est encore peu comprise : il semblerait que les consommateurs y soient réticent de prime abord, ce qui laisse suggérer qu'une installation doive être imposée par l'agrégateur.

Enfin, bien que les EDD ne puissent pas assurer la robustesse des résultats concernant la préférence des consommateurs sur la durée des effacements et le nombre d'activations autorisées par an, nous avons récupéré ces données pour nous en servir dans le modèle développé dans cette thèse. Au global, les ECC montrent qu'aujourd'hui, les consommateurs semblent prêts à s'engager dans des actions d'effacements grâce au rôle d'intermédiaire joué par l'agrégateur.

DEUXIEME PARTIE – Cadre de modélisation

Dans cette deuxième partie, nous développons la description du modèle utilisé dans cette thèse. Il s'agit d'un modèle de marché de gros de l'énergie. Les technologies de production sont dispatchées pour répondre à la demande d'électricité. Parmi celles-ci, les effacements de la demande sont modélisés comme un stockage hydroélectrique. Mathématiquement, le modèle appartient à classe des problèmes d'optimisation linéaire stochastique à plusieurs périodes. La résolution du modèle est géré par l'algorithme *Stochastic Dual Dynamic Programming* (SDDP) introduit par Pereira et Pinto (1991).

Chapitre 3 – Revue de littérature des approches pour la modélisation des effacements de la demande

Tout d'abord, nous proposons une revue de la littérature sur les approches usuelles de modélisation des ED. Comme nous le verrons par la suite, notre modèle est un problème d'optimisation linéaire stochastique à plusieurs périodes dont l'apport est qu'il intègre un pas de temps horaire sur une période d'un an, ainsi qu'une limite annuelle sur le stock d'énergie des ED.

Les modèles d'ED peuvent être divisés selon trois catégories. Les *modèles physiques* rendent compte très précisément de l'évolution physique des charges électriques. Par exemple, pour une maison résidentiel, ces modèles intègrent l'influence du comportement des différentes personnes vivant en son sein, ou encore l'apport de l'ensoleillement sur la consommation d'électricité. L'avantage de ces modèles repose sur leur précision par rapport à la réalité, mais ils sont difficilement intégrables à un modèle de marché électrique. En d'autres termes, ces modèles font abstraction des interactions entre la demande et l'offre d'électricité. Parmi ces modèles nous pouvons citer Stadler (2008), Chassin and Fuller (2011), Ali et al. (2014), Mathieu et al. (2013), Everett and Philpott (2004), Materassi et al. (2014). A l'inverse, l'approche consistant à modéliser les ED par une *fonction de demande* rend compte des effets mutuels entre offre et demande. Mais ces modèle ne permettent pas de modéliser les contraintes techniques des ED, ni de segmenter les consommateurs par catégorie. Borenstein et Holland (2003), (P. Joskow and Tirole 2006), (P. Joskow and Tirole 2007), (Léautier 2014), Madaeni et Sioshansi (2011), et De Jonghe, Hobbs, et Belmans (2011) sont des exemples de papiers utilisant cette approche. Enfin, les modèles représentant les ED comme des *unités de production négatives* exploitent la similarité entre l'activation des ED et le comportement des stockages d'électricité. Nous avons optés pour cette approche car elle permet une représentation détaillée des contraintes des ED ainsi qu'une segmentation par type de consommateur. La validité de cette approche tient au fait que du point de vue du système, il est équivalent de réduire la demande ou d'augmenter l'offre de production. En outre, certains usages électriques possèdent des propriétés similaires au stockage : reporter sa demande de chauffage en la réduisant temporairement pour la récupérer plus tard reproduit le comportement d'un stockage. Nous pouvons trouver ce type d'approche parmi Papavasiliou et Oren (2014), Papavasiliou, Cambier, and Scieur (2015), Steurer et al. (2015), et Zerrahn et Schill (2015). Etant donné que les ED sont modélisés comme des stockages, il est intéressant d'intégrer une dimension stochastique dans le modèle. En effet, lorsque des stockages sont gérés dans un cadre déterministe, leur valeur est surestimée par le modèle. Puisque le but de notre modèle est de fournir un cadre de modélisation qui permette d'estimer la valeur économique des ED, nous avons choisi de développer un modèle de marché de l'électricité sous incertitude.

Chapitre 4 – Le modèle : marché de gros de l'énergie sous incertitude

Le modèle développé pour cette thèse est un modèle de dispatch économique, selon lequel il faut répondre à la demande d'électricité au cours d'une période déterminée à l'aide des technologies de production. Economiquement le modèle de dispatch peut être interprété comme un marché *energy-only*, tel que le marché *day-ahead* d'EPEX Spot en France.

Au sein de ce modèle de marché, les ED sont intégrés comme une technologie de production similaire à un stockage d'hydroélectricité. Les ED sont distingués selon les deux schémas décrits dans

le chapitre 1. Pour les ED type load-shifting, nous utilisons une représentation de stockage hydroélectrique comme une station de pompage (car la consommation ne peut être récupérée). Quant aux ED type load-shedding il convient de les modéliser comme un stockage hydroélectrique avec un seul réservoir (car la consommation ne peut être récupérée).

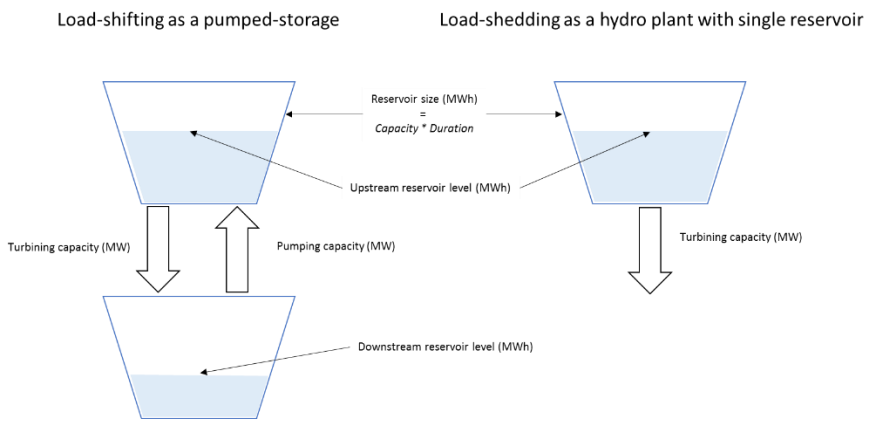

Figure 4. Modélisation des effacements par des stockages hydrauliques

Pour bien comprendre notre approche schématisée sur la Figure 4 ci-dessus, gardons en tête l'équivalence suivante :

Diminuer la demande ⇔ Turbiner l'eau depuis le réservoir supérieur (vers le réservoir inférieur s'il existe)

Récupérer la demande ⇔Pomper l'eau depuis le réservoir inférieur vers le réservoir supérieur

Un certain nombre de contraintes sont ajoutées à cette représentation pour être conforme à la réalité des activations des ED. Par exemple, il est primordial d'intégrer des profils de charge qui vont jouer sur la disponibilité temporelle des capacités d'effacements. Les profils de charge imposent que les ED ne peuvent être activés que si l'usage en question est effectivement en train de consommer de l'électricité. Ainsi, les ED provenant du chauffage électrique ne peuvent être activés durant l'été. Par ailleurs, nous ajoutons une contrainte imposant une limite annuelle sur le volume d'énergie disponible par ED. Cette contrainte provient du nombre d'activations que les consommateurs autorisent l'agrégateur à déclencher chaque année. Elle est essentielle car elle considère une forme de préférence des consommateurs. De plus, comme nous le verrons dans le chapitre 5, elle a une grande importance dans le coût marginal des ED. Cette contrainte est modélisée à l'aide d'un « réservoir contractuel » qui est associé à chaque technologie d'ED, comme le montre la Figure 5 :

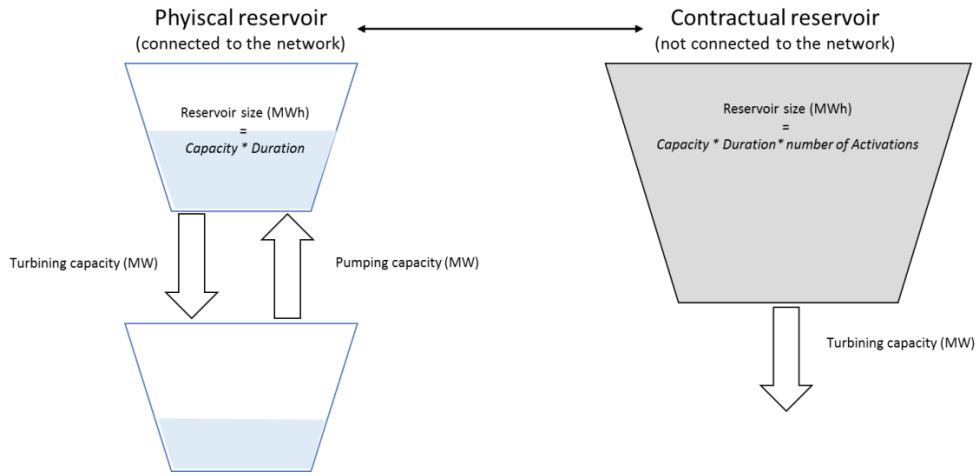

Figure 5. Le réservoir contractuel pour compter le nombre annuel de déclenchements d'effacements

Enfin, avant de passer à la description du modèle de marché dans lequel seront activés les ED, précisons que pour chaque unité d'énergie coupée par l'agrégateur aux consommateurs, celui-ci endure un coût variable que nous nommerons par la suite *coût d'activation*. Le coût d'activation est donc exprimé en €/MWh. Il représente la compensation financière fournie par l'agrégateur aux consommateurs, qui elle-même représente la valeur d'usage de l'électricité.

Le modèle de marché consiste à minimiser le coût opérationnel de production afin de satisfaire la demande en électricité. Le modèle présente plusieurs périodes, dont le nombre est défini selon les besoins de l'utilisateur. Aussi nous ne considérons pas de coûts fixes d'investissement, mais seulement des coûts variables. Economiquement, le modèle peut s'interpréter comme un marché de gros energy-only en concurrence pure et parfaite. Sur ce marché, l'agrégateur décide de dispatcher ses technologies d'effacement selon le prix à chaque période. Etant donnée la parfaite concurrence, il le fera dès lors que le prix dépasse son *coût marginal*. Le coût marginal des ED n'est cependant pas le coût d'activation mentionné plus haut. Comme nous le verrons plus en détail dans le chapitre 5, le coût d'activation n'est qu'une composante du coût marginal. Pour le moment, contentons-nous d'indiquer que l'agrégateur fait face à un coût d'opportunité inter-temporel lorsqu'il doit décider de déclencher un ED. En effet, du fait de la contrainte annuelle d'activations d'ED, l'agrégateur se pose rationnellement la question suivante : si j'active un effacement maintenant, je n'aurais pas l'occasion de le faire par la suite, et donc ne serait-il pas préférable d'attendre des prix de marché plus élevés dans le futur ? On voit bien que la contrainte de stock sur le volume d'effacements activables aura une influence sur le coût marginal de l'agrégateur. Même si le prix de marché est déjà supérieur à son coût d'activation de sorte qu'il puisse engendrer des bénéfices, l'agrégateur s'interroge sur la possibilité d'obtenir des rentes infra-marginal encore plus importantes. En outre, on comprend bien que ce n'est que dans le cadre d'un modèle à plusieurs périodes qu'il est possible de rendre compte de cet effet. Par ailleurs, si l'on imagine la situation dans un cadre déterministe, alors l'agrégateur est en mesure d'anticiper le niveau des prix sur le marché tout au long de l'horizon temporel du modèle. Ainsi, bien

que le coût d'opportunité existe, l'agrégateur saura précisément quand activer ses ED. Par exemple, si son contrat lui autorise 40 activations par an, il sélectionnera les 40 niveaux de prix les plus élevés. En revanche, dans un cadre stochastique, l'agrégateur n'aura pas cette information. Il devra donc arbitrer entre un profit immédiat certain d'un certain montant, et un profit espéré d'un autre montant qu'il évaluera selon la distribution des prix futurs qu'il a à sa disposition. Au mieux, il récupérera la même valeur de profits que dans le cas déterministe, mais c'est peu probable. Cette illustration permet de mieux expliquer pourquoi la valeur des effacements est surestimée en prévision parfaite. Plus généralement, la gestion optimale des stockages nécessite de considérer des *coûts futurs*, c'est-à-dire l'impact d'une décision immédiate sur l'ensemble de nos possibilités de décisions dans le futur. Lorsqu'on applique cette problématique au cas d'un système électrique comportant un grand nombre de stockages à gérer, il en résulte un problème d'optimisation très lourd à résoudre en termes de temps de calcul. L'algorithme Stochastic Dual Dynamic Programming (SDPP) fut développé par des ingénieurs brésiliens, précisément pour répondre au problème du planning optimal des ressources hydroélectriques de leur pays. SDDP est un outil permettant de calculer les coûts futurs pour un grand nombre de stockages ou réservoirs dans des temps de calcul raisonnables. Nous l'avons utilisé pour résoudre notre modèle qui intègre plusieurs technologies d'ED, et donc autant de réservoirs.

Chapitre 5 – La valeur économique et le coût marginal des effacements de la demande dans un cadre stochastique

En se basant sur un jeu de donné simple, ce chapitre décrit la structure du coût marginal des ED et propose une analyse de leur valeur économique en utilisant les résultats du modèle présenté en chapitre 4. Les enseignements tirés dans ce chapitre sont donc basés sur un usage du modèle à vocation didactique. Ces résultats restent néanmoins généralisables tout en permettant de simplifier l'analyse qui aurait été plus difficile à conduire à partir d'un jeu de données conséquent.

Comme indiqué dans le chapitre précédent, nous considérons deux grands types d'ED : le load-shedding, dont le coût d'activation est élevé (200 €/MWh) et load-shifting qui présente un faible coût d'activation (10 €/MWh). A chacune de ces technologies est affecté un réservoir contractuel dont la taille est définit par le nombre contractuel d'activations d'ED. Pour chacun de ces types d'ED, le coût marginal est défini comme suit :

$$Coût\ marginal_t(x_t^{ed}) = Coût\ d'activation + Coût\ d'opportunité_t(x_t^{ed})$$

L'indice t représente les périodes de temps dans le modèle, ed désigne la technologie d'ED, et x_t^{ed} le niveau d'énergie dans le réservoir contractuel. Premièrement, nous constatons que le coût

d'opportunité est une fonction définie sur l'ensemble du niveau du réservoir contractuel x_t^{ed}. En effet, plus le réservoir se videra, moins il restera d'activations possibles d'ED, et donc plus la décision d'activer une ED aura d'impact sur les choix futurs de l'agrégateur. Par ailleurs, s'il reste beaucoup d'énergie dans le réservoir contractuel, l'agrégateur peut faire usage de ses ED à moindre coût, puisqu'il lui restera toujours la possibilité d'en déclencher plus tard. Nous voyons bien que le coût d'opportunité dépend du niveau du réservoir contractuel, mais aussi nous comprenons qu'il est une fonction décroissante de x_t^{ed}. En fait, le coût d'opportunité est défini mathématiquement comme l'opposé de la dérivée partielle de la *fonction de coûts futurs du système*, aussi appelée *fonction valeur*.

$$Coût\ d'opportunité_t(x_t^{ed}) = -\frac{\partial \alpha_t(x_t^{ed}, x_t)}{\partial x_t^{ed}}$$

Ici α_t désigne la fonction valeur définie sur l'ensemble des stockages du système. L'algorithme SDDP construit en réalité une approximation de α_t que nous présentons sur le graphique ci-dessous, avec la fonction de coût marginal, pour la technologie de load-shedding. Nous observons que le coût marginal est une fonction décroissante du niveau du réservoir contractuel, et que pour un niveau suffisamment grand, le coût marginal égalise le coût d'activation fixé à 200 €/MWh. Ce qui signifie que le coût d'opportunité est nul lorsqu'il y a beaucoup d'énergie dans le réservoir contractuel (Figure 6).

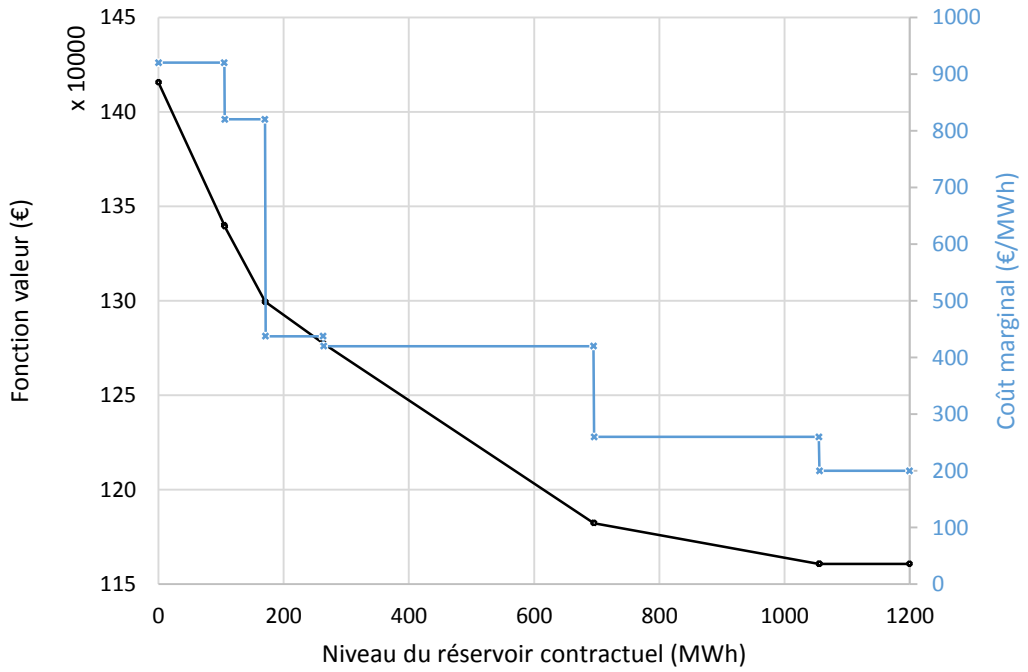

Figure 6. Courbe de coût marginal et fonction valeur des effacements type load-shedding

Analysons maintenant la valeur économique des ED dans cet exemple didactique. Tout d'abord, précisions que nous avons modélisé l'incertitude sur les niveaux de la demande électrique par 5 scénarios. À chaque période du modèle, les décisions à prendre sont soumises à la réalisation possible d'un de ces 5 scénarios dans le futur. Aussi les résultats obtenus sont-ils distribués selon ces 5 scénarios. Pour évaluer la valeur économique des ED, nous calculons le profit réalisé sur le marché par chacune des technologies d'effacement. Ces profits sont montrés sur la Figure 7. Le premier constat est que la valeur économique de load-shedding est bien plus importante que celle du load-shifting. Ceci vient du fait que, contrairement au load-shifting, le load-shedding est en mesure d'être activé lorsque les prix sur le marché sont très élevés. Plus précisément, le load-shedding est activé en période de *rareté de capacité*, qui se manifeste par des prix atteignant une valeur plafond (le *price cap* du marché). Néanmoins, ce résultat reste propre au jeu de données utilisé pour cet exemple didactique. A priori, rien n'empêche que le load-shifting puisse également être activé en période de rareté de capacité. Cependant, de par leurs caractéristiques intrinsèques, le load-shedding est plus à même de capturer cette *valeur capacitaire* du système car le load-shedding engendre une perte nette de la consommation d'énergie et n'est donc activé qu'à un coût variable élevé, c'est-à-dire quand les prix de marché sont élevés. Quant au load-shifting, ses bénéfices se fondent plutôt sur la *valeur énergie* du système, car il se caractérise par un déplacement de la consommation dans le temps, guidé par l'arbitrage des prix d'une période à l'autre. Ainsi, même si les prix sont très hauts, il se pourrait que le load-shifting ne puisse être activé, car seul le différentiel des prix est pour lui significatif.

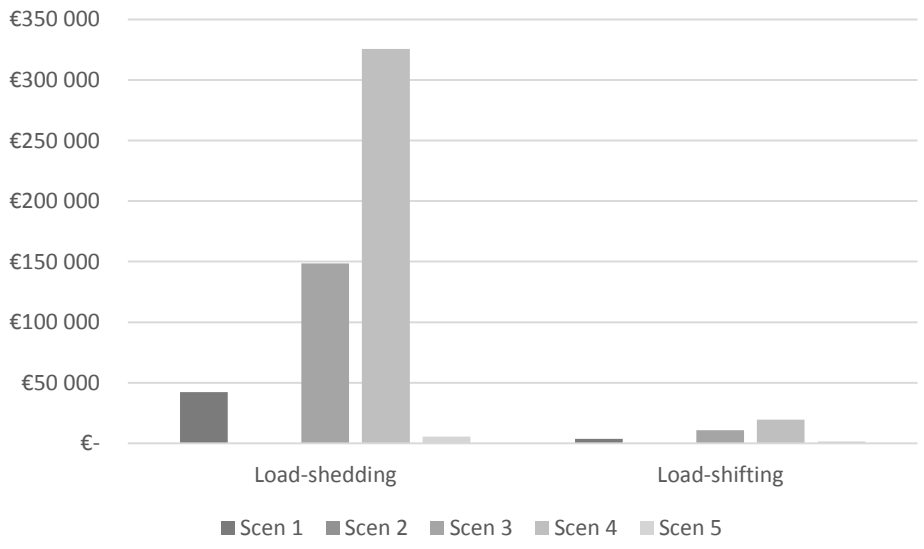

Figure 7. Profits réalisés par type d'effacement

Nous reviendrons plus longuement dans les chapitres de la troisième partie sur cette distinction entre la valeur de capacité et la valeur d'énergie des ED. Gardons à l'esprit qu'au vu des écarts de profits présentés dans ce modèle didactique, elle semble primordiale pour les ED.

TROISIEME PARTIE – La valeur économique des effacements de la demande : une étude de cas sur l'analyse de rentabilité des agrégateurs en France

La dernière partie de cette thèse porte sur l'analyse quantitative de la valeur économique des ED en France. Nous faisons l'hypothèse qu'un agrégateur possède des technologies d'effacements représentatives de la structure de la consommation d'électricité française. Par des simulations du modèle présenté en deuxième partie, nous calculons les profits de l'agrégateur étant donné les conditions actuelles du système électrique français. L'approche est la même que dans le modèle didactique exposé en chapitre 5, sauf qu'ici le modèle est calibré à l'échelle de la France, en particulier dans la représentation du potentiel d'effacement.

L'analyse du chapitre 6 met en avant la prépondérance de la valeur de capacité des ED sur leur valeur énergie. En comparant les profits réalisés par l'agrégateur avec les coûts d'investissement dans l'infrastructure nécessaire, nous montrons que pour nombre de technologies d'ED, la valeur économique est encore insuffisante. Ceci nous invite à étudier dans le chapitre 7 comment cette valeur économique peut évoluer suite à une rémunération complémentaire de la capacité, telle que celle offerte par le mécanisme de capacité français. La rémunération supplémentaire de la capacité est simulée par une augmentation du prix plafond du marché. Par ailleurs nous testons la réticence du consommateur à entrer dans un contrat avec l'agrégateur, en diminuant le nombre d'activations d'ED autorisés dans le contrat. Bien que de nature différente au test sur la rémunération de la capacité, ce test est d'importance pour l'agrégateur, car rien n'indique avec certitude que les valeurs sur le nombre d'activation employés dans le chapitre 6 ne soient conformes à ce que les consommateurs seraient prêts à accepter dans la réalité. Au contraire, dans le chapitre 6, ce paramétrage est basé en partie sur le papier de Gils (2014) qui supposait une acception maximale des ED de la part des consommateurs.

Chapitre 6 – Étude de cas : analyse de rentabilité des agrégateurs d'effacements en France

Pour cette étude de cas, nous considérons les technologies d'effacements suivantes :

Tableau 1. Catégorie d'effacements intégrés à l'étude

	Load-shedding	Load-shifting
Industries	Acier Aluminium Chimie	Froid industriel Ciment Papier Ventilation
Secteur tertiaire		Climatisation Chauffage électrique
Secteur résidentiel		Chauffage électrique

Nos résultats sont présentés selon 20 scénarios de niveaux de la demande résiduelle (l'incertitude prise en compte dans ce chapitre inclut celle sur le niveau de la demande et celle sur la production des énergies renouvelables intermittentes). Observons la distribution des profits annuels de l'agrégateur pour deux technologies d'ED, à savoir le load-shedding sur l'aluminium (Figure 8) et le load-shifting du chauffage électrique des ménages (Figure 9).

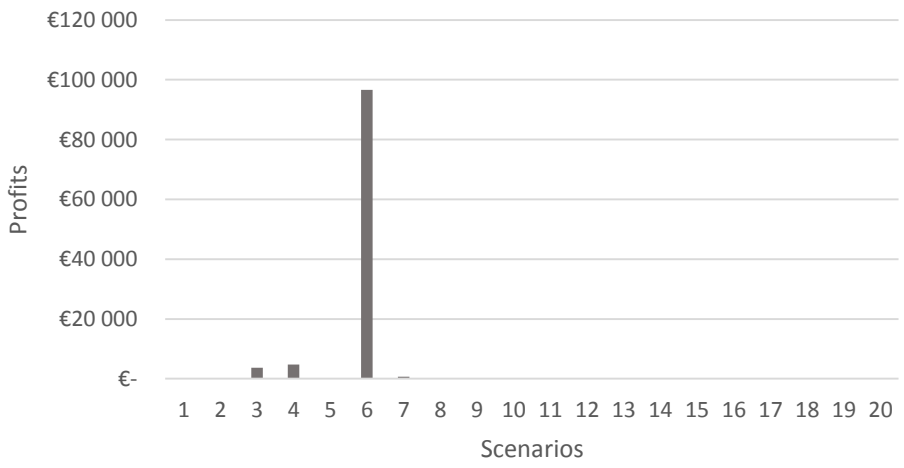

Figure 8. Distribution des profits pour l'aluminium (€/MW/an)

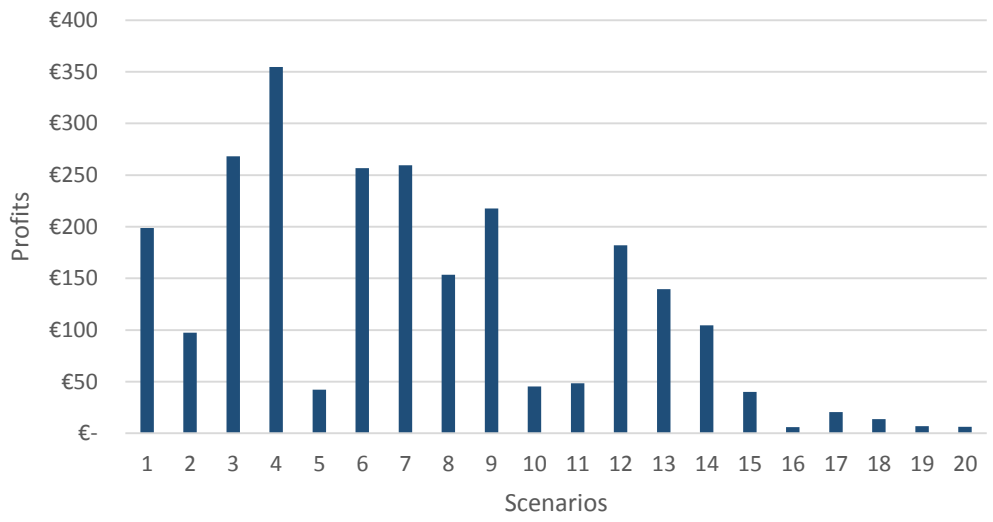

Figure 9. Distribution des profits pour le chauffage électrique résidentiel (€/MW/an)

Deux observations s'imposent. Premièrement, la distribution est bien moins répartie pour l'aluminium que pour le chauffage électrique. Deuxièmement, le niveau des profits est largement supérieur pour l'aluminium dans un scénario très précis, le scénario 6. Pour ce scénario, l'ordre de grandeur multiplicatif entre les revenues de l'aluminium et ceux du chauffage est de 1000. Ce qui signifie qu'une situation particulière caractérise le scénario 6 dont la technologie d'ED du chauffage électrique ne tire pas profit. Cette situation particulière est une situation de rareté de la capacité de production qui n'est pas suffisante pour répondre à des pics extrêmes de la demande. Durant ces périodes de rareté, les prix sur le marché atteignent le prix plancher, c'est-à-dire dans le présent cas 3 000 €/MWh. Cette hauteur de prix explique pourquoi l'aluminium génère autant de profits dans le scénario 6. En revanche, si le chauffage ne génère pas de tels profits, cela signifie que cette technologie n'est pas activée durant ces périodes de rareté. A ce stade, il devient utile de préciser les définitions suivantes :

- La valeur de capacité des ED est définie par les revenus générés durant les périodes de rareté.
- La valeur de l'énergie des ED est définie par les revenus générés durant les périodes où la demande est satisfaite.
- La valeur économique des ED est constituée de la somme de la valeur de capacité et de la valeur énergie.

Précisons que dans notre simulation, cette situation de rareté ne se produit qu'en très large partie dans le scénario 6. Nous pouvons ainsi isoler la valeur de capacité de la valeur énergie en ne prenant que les profits générés dans ce scénario. Dans le Tableau 2, nous exposons les profits moyennés sur l'ensemble des scénarios. Nous pouvons voir à quel point la valeur de capacité est bien plus importante que de la valeur énergie pour les consommateurs industriels, mais également pour le chauffage électrique tertiaire.

Tableau 2. Analyse de rentabilité de l'agrégateur avec différenciation des valeurs de l'énergie et de capacité

	Valeur de l'énergie (€/MW/an)	Valeur de capacité (€/MW/an)	Valeur économique (€/MW/an)	Coûts fixes annualisés (€/MW/an)	Rentable
Acier	0	17 337	17 337		Oui
Aluminium	485	4 805	5 290	[25 ; 997][1]	Oui
Chimie	1 608	189	1 797		Oui
Froid industriel	735	1 814	2 549	92 851[2]	Non
Ciment	955	1 464	2 419	1 246[3]	Oui
Papier	1 469	2 878	4 347	1 246[4]	Oui
Ventilation	439	930	1 369	189 068[5]	Non
Climatisation tertiaire	34	3	37	[24 927 ;	Non
Chauffage tertiaire	368	934	1 302	112 169][6]	Non
				15 579[7]	Non
Chauffage résidentiel	116	7	123	6 250[8]	Non
				[5 840 ; 7 700][9]	Non

Les valeurs présentées pour les coûts fixes sont issues des études suivantes. Certaines études présentent des plages de valeurs plutôt que des valeurs uniques. Voici les références pour chaque secteur : [1,6] Stede (2016) [2,3,4,5] Zerrahn and Schill (2015) [7] Prüggler (2013) [8] Léautier (2014) [9] Steurer et al. (2015).

De plus, si l'on met en regard la valeur économique totale avec les coûts fixes de l'infrastructure nécessaire, nous observons qu'en France, seuls les effacements des consommateurs industriels est aujourd'hui rentable. Cette conclusion tient autant aux écarts entre secteurs sur le niveau des coûts que sur le niveau des revenus de marché. Si l'on s'en tient aux valeurs issues de notre modèle, force est de constater que même dans une optique de moyen-terme, la commercialisation d'offre viable d'ED sur les secteurs résidentiel, tertiaire et sur le froid et la ventilation industriel semble peu probable. L'écart entre les coûts fixes et les revenus est trop important, même si l'on peut s'attendre à une baisse des coûts dans les années à venir. Cependant, il faut rappeler que dans la pratique, l'investissement dans les technologies de smart grid n'est pas nécessairement pris en charge par l'agrégateur. D'autres agents peuvent y avoir un intérêt, en particulier l'opérateur du réseau de distribution. En France, le compteur intelligent Linky est d'ailleurs déployé par Enedis. D'ici quelques années les consommateurs résidentiels et tertiaires seront donc équipés de compteur intelligent, qui est donc un outil que l'agrégateur aura à sa disposition sans avoir eu à le financer lui-même. L'analyse de rentabilité devrait donc uniquement prendre en compte les technologies de contrôle à distance. Par ailleurs, avec un prix plancher établi à 3 000 €/MWh, le marché de l'énergie utilisé dans ce chapitre pour valoriser les ED sous-estime la valeur réelle de la capacité. Le marché de capacité lancé en France en début d'année 2017 sert à remédier aux possibles revenus manquant pour financer l'investissement dans de nouvelles capacités de production. En outre, il prévoit de certifier des fournisseurs sur les capacités d'effacements, ce qui porte légitimement à vouloir étudier l'impact de ce

revenu complémentaire sur notre analyse de rentabilité. Ce test est l'objet de la première section du chapitre 7. Dans une seconde section, nous testerons l'impact de la réticence des consommateurs à s'engager dans un contrat avec l'agrégateur, afin d'étudier si un volume moindre d'ED dans le système ne créerait pas d'avantage de rareté, dont l'agrégateur pourrait bénéficier in fine.

Chapitre 7 – La rente de rareté à l'origine de la rémunération de capacité de l'agrégateur

Dans ce dernier chapitre, nous analysons l'impact de deux paramètres sur les profits de l'agrégateur d'effacements. Le premier implique le prix plancher, fixé dans l'exercice du chapitre 6 à 3 000 €/MWh. Dans ce chapitre, nous testons deux autres niveaux de prix plancher, à savoir 10 000 €/MWh et 20 000 €/MWh. Comme nous l'avons déjà mentionné, cette analyse de sensibilité permet de quantifier la rémunération de capacité de l'agrégateur proposée par le marché de capacité français. Précisons d'emblée que l'équivalence entre (i) un modèle de marché energy-only avec un prix plafond à 20 000 €/MWh et (ii) un modèle de marché energy-only plafonné à 3 000 €/MWh mais complémenté par un mécanisme de rémunération de la capacité n'est pas triviale. Cependant, sous l'hypothèse de neutralité face au risque, les revenus de marchés générés par l'un ou l'autre des modèles sont équivalents d'après Petitet, Finon, and Janssen (2017). Le second test concerne le nombre annuel d'activations autorisé par les consommateurs. Autrement dit, il évalue la diminution de la taille du contrat d'ED de l'agrégateur (rappelons que c'est le nombre annuel d'activations qui définit la taille du réservoir contractuel). Cette analyse de sensibilité se justifie en outre par le fait que l'on ne connaît pas la propension des consommateurs à participer à des actions d'effacements. Elle permet également de déterminer si l'agrégateur a réellement intérêt à augmenter son portefeuille de clients ou s'il existe une sorte de taille optimale de contrat. Bien que notre but ne soit pas de déterminer cette taille optimale, nous pouvons néanmoins évaluer s'il est utile à l'agrégateur de proposer des contrats plus importants/conséquents.

Les résultats de l'impact sur les profits annuels moyens de l'agrégateur de l'augmentation du prix plafond sont présentés dans le Tableau 3. Nous constatons que tous les secteurs bénéficient de ce changement, bien que dans des proportions différentes. Les colonnes de ratio indiquent le facteur multiplicatif des profits quand on passe le prix plafond de 3 000 €/MWh à 10 000 €/MWh, et de 3 000 €/MWh à 20 000 €/MWh respectivement. A l'exception du chauffage résidentiel et la climatisation tertiaire, cette rémunération de capacité est importante pour tous les secteurs. Cependant, si l'on regarde à nouveau les coûts d'investissement dans les technologies de smart grid, on peut voir que cette rémunération supplémentaire n'est toujours pas suffisante pour faire des secteurs comme le froid, la ventilation industrielle, et le chauffage tertiaire des options économiquement viables pour les

ED. Augmenter le niveau des rentes de rareté en augmentant le prix plafond n'est donc pas suffisant pour que ce type d'ED devienne rentable.

Tableau 3. Impact d'une rémunération de capacité sur les profits de l'agrégateur

	Profits annuels moyen (€/MW/an)			**Ratio**	
	PC=3 000	PC=10 000	PC=20 000	"10/3"	"20/3"
Acier	17 337	60 332	123 456	3,5	7,1
Aluminium	5 290	16 976	32 219	3,2	6,1
Chimie	1 797	4 975	8 909	2,8	5,0
Froid industriel	2 549	8 071	15 495	3,2	6,1
Ciment	2 419	6 136	11 216	2,5	4,6
Papier	4 347	12299	24 434	3,0	5,6
Ventilation industrielle	1 369	4 407	8 511	3,2	6,2
Climatisation tertiaire	37	50	63	1,4	1,7
Chauffage tertiaire	1 302	3 438	6 202	2,6	4,8
Chauffage résidentiel	123	143	161	1,2	1,3

Regardons maintenant l'effet de la diminution de la taille des contrats d'effacement sur les profits de l'agrégateur : créera-t-elle plus de rentes de rareté, de sorte que la valeur des ED augmente ? Tout d'abord, précisons la manière dont nous faisons varier la taille des contrats. Nous multiplions tous les contrats par une série de facteurs, que l'on nommera le *facteur de contrat* (FC). La plage de variation sur le facteur de contrat est la suivante 1 ; 0,9 ; 0,8 ; 0,7 ; 0,6 ; 0,5. Ainsi lorsque nous fixons le FC à 0,5, nous avons diminué de moitié la taille des contrats. Nous avons mené ce test pour les trois niveaux de prix plafonds définis précédemment. Voyons comment évolue les profits en fonction de FC pour l'aluminium, le froid industriel et la climatisation (sur les graphiques suivants, PC est une abréviation pour les prix plafonds).

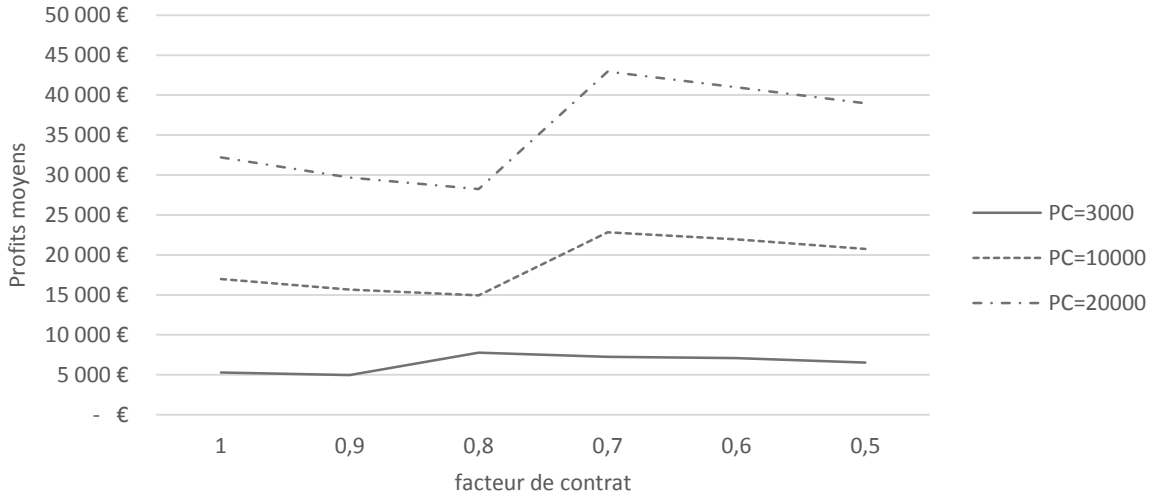

Figure 10. Impact de la taille du contrat sur les profits moyens de l'aluminium (€/MW/an)

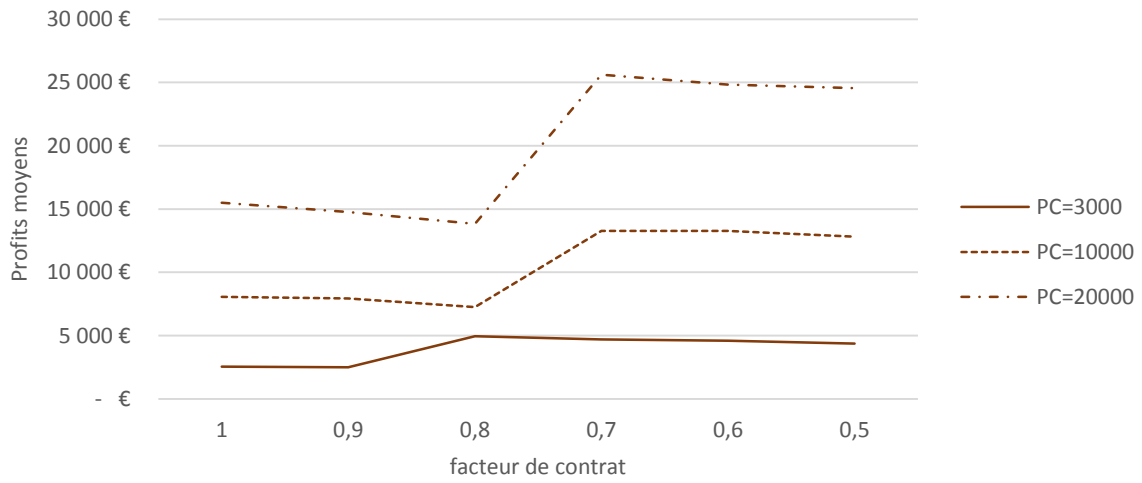

Figure 11. Impact de la taille du contrat sur les profits moyens du froid industriel (€/MW/an)

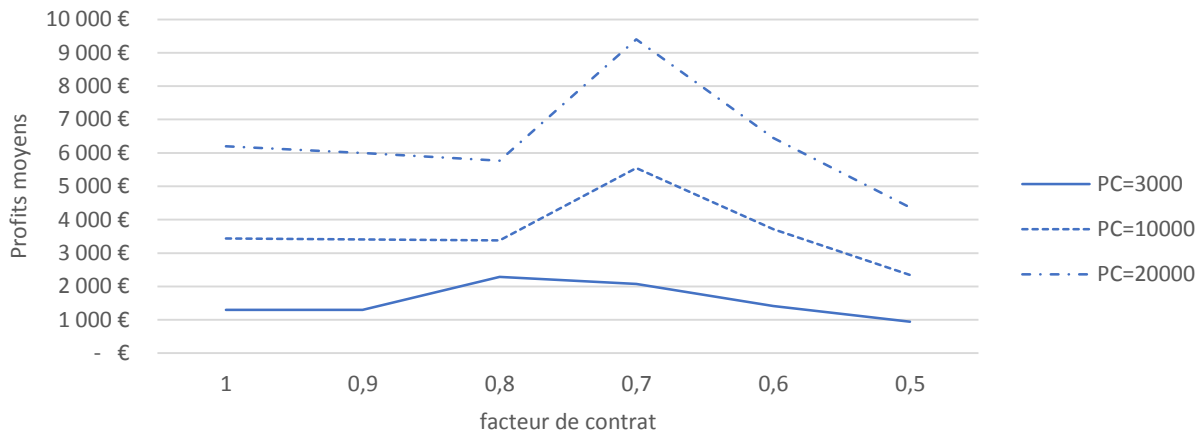

Figure 12. Impact de la taille du contrat sur les profits moyens du chauffage tertiaire (€/MW/an)

Pour tous ces secteurs, deux effets sont à noter. Le premier effet consiste en une diminution du profit à mesure que la taille du contrat diminue. L'ampleur de cette diminution est variable. Par exemple pour le chauffage tertiaire elle est assez légère quand le FC est réduit de 1 jusqu'à 0,8 mais devient plus marqué quand il diminue de 0,7 à 0,6 puis 0,5. Le second effet, peut-être plus intéressant pour notre analyse de rentabilité, est que la réduction de la taille du contrat génère à un moment une augmentation des profits pour toutes les technologies d'ED. Les profits atteignent un maximum si le FC vaut 0,7 pour un prix plafond de 10 000 et 20 000 €/MWh. Quand le prix plafond est à 3 000 €/MWh, ce maximum se situe à 0,8. Comme nous l'envisagions, cette augmentation de la valeur des ED provient de l'existence de délestage dans le système, et donc plus de rentes de rareté pour l'agrégateur. Ainsi, il n'est pas indispensable pour les agrégateurs d'effacements de proposer des contrats de grande taille, c'est-à-dire autorisant un grande nombre d'activations. Les courbes de profits ci-dessus indiquent même qu'il peut être préférable de proposer des plus petits contrats, mais ce résultat dépend de l'évolution que cela engendrerait sur l'état du système, ce qui est en soit un effet compliqué à prévoir.

Pour clore ce chapitre, rappelons qu'aucun des deux effets testés ne permet de changer les résultats de l'analyse de rentabilité du chapitre 6. Bien qu'en termes de nouveaux profits générés par l'augmentation du prix plafond ou par la réduction de la taille des contrats, toutes les technologies d'ED soient gagnantes, les secteurs qui n'étaient pas économiquement viables auparavant ne le deviennent pas. En somme, notre analyse suggère que les coûts fixes demeurent une barrière importante à l'activation des ED sur ces secteurs (froid industriel, ventilation industriel, chauffage tertiaire et résidentiel).

CONCLUSION

Le travail réalisé dans cette thèse a consisté en une évaluation du potentiel économique des effacements de la demande sur les marchés de l'électricité, en particulier pour le système électrique français. Nous avons développé une modélisation du marché de gros de l'électricité dans lequel les ED sont intégrés et valorisés. L'apport de ce modèle est de considérer à la fois l'impact des ED sur les prix du marché, l'incertitude du système électrique, la limite du nombre d'effacements autorisés par les consommateurs, et une représentation détaillé par secteur et par usages des technologies d'effacements.

Les réponses aux questions de recherche posées en introduction sont les suivantes. En général, la valeur économique des ED est assez variée d'un secteur à l'autre. C'est également le cas pour la France, où les effacements industriels sont par exemple viables économiquement, contrairement à ceux des secteurs résidentiel et tertiaire. Ces écarts s'expliquent par la distinction entre valeur de

capacité et valeur de l'énergie des ED. Nos résultats indiquent que la valeur de capacité est bien supérieure à celle de l'énergie. Ainsi les secteurs pouvant bénéficier de rentes de rareté sont plus à même d'être rentables.

Bien entendu, ces résultats sont contestables dans la mesure où un modèle ne peut jamais rendre compte parfaitement de la réalité. Aussi pensons-nous que la principale limite de notre modèle est de ne pas prendre en compte la valeur d'équilibrage du réseau de court-terme. En France, le mécanisme d'ajustement est pourtant une source essentielle de revenues pour les agrégateurs d'ED commercialement actifs. La prise en compte de cette valeur serait néanmoins délicate, si ce n'est impossible à intégrer dans un modèle tel que celui utilisé dans cette thèse, car cela nécessiterait de recourir à des problèmes d'optimisation qui n'appartiennent pas à la même classe. Notre travail peut cependant être vu comme complémentaire aux études sur la valorisation des ED fournissant de la réserve pour l'équilibrage ou des services systèmes.

Les extensions possibles de notre modèle sont les suivantes : la modélisation du réseau électrique, la prise en compte de l'incertitude sur le système hydroélectrique, la modélisation de l'aversion au risque. La modélisation du réseau permettrait par exemple d'analyser la concurrence entre les ED et les interconnexions avec les pays frontaliers, qui durant la vague de froid de 2012, furent capitales dans le maintien de l'équilibre du système. L'incertitude sur le système hydroélectrique rendrait plus réaliste la gestion des stocks d'eau dans les réservoirs. Quant à l'aversion au risque, elle pourrait également simuler des comportements plus proches de la réalité, expliquant peut-être mieux comment les agrégateurs décident d'enclencher des effacements.

En somme, cette thèse est une analyse de l'intégration des consommateurs dans les marchés de l'électricité abordée sous l'angle des effacements de la demande. Nous avons montré qu'en France, le développement de l'activité commerciale des agrégateurs était pour le moment restreint au secteur industriel. Pour les secteurs tertiaire et résidentiel, le coût d'investissement dans les capacités d'ED reste une barrière importante. En ce sens, le marché de capacité ainsi que le déploiement des compteurs Linky peuvent être perçus comme des éléments essentiels au développement des effacements à plus large échelle.

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Résumé

Dans l'industrie électrique, le progrès technologique apporté par les réseaux intelligents vient défier l'idée selon laquelle les consommateurs ne pourraient pas réagir aux prix des marchés de gros. L'intégration des Effacements de Demande (ED) dans le système électrique se heurte néanmoins à la question de leur efficacité économique.

Cette thèse évalue la valeur économique des ED en s'appuyant sur un modèle de marché de l'énergie sous incertitude permettant de calculer les profits d'un agrégateur, par classe de consommateur et d'usage final. Le modèle appartient à la classe des problèmes linéaires stochastiques à plusieurs périodes. Sa résolution s'appuie sur Stochastic Dual Dynamic Programming.

Il apparaît qu'en France, les secteurs rentables sont le load-shedding industriel et le load-shifting du ciment et du papier. Le load-shifting du chauffage électrique n'est pas profitable pour le tertiaire et le résidentiel. De plus, la valeur capacitaire des ED est déterminante. Dans l'ensemble, les ED deviennent viables mais le développement de leur potentiel semble conditionné à une baisse des coûts fixes dans les technologies de réseau intelligent.

Abstract

In liberalised power markets the inability of consumers to adapt their demand in accordance to wholesale prices is increasingly challenged. Nowadays technical progress within the smart grid industry constitutes promising changes for the integration of end-users into the power system, but the deployment of Demand Response (DR) still faces the challenge of its economic viability.

This thesis aims to assess the economic value of DR. We rely on an energy-only market model under uncertainty in order to quantify the revenues of DR aggregators, classified by category of consumers and end-uses of electricity. The model is formulated as a multi-stage stochastic linear problem and solved by Stochastic Dual Dynamic Programming.

It appears that in France, industrial load-shedding and load-shifting of cement, paper, and pulp are profitable. For residential and tertiary consumers, load-shifting of electric heating is not profitable. We also show that the capacity value of DR is crucial. Overall, results show that DR is beginning to become economically attractive, but that fixed costs of smart grid technologies still need to come down further to fully develop its potential.

Mots Clés

Effacements de Demande ; Agrégateur ; Marchés de l'électricité ; Incertitude ; Stochastic Dual Dynamic Programming.

Keywords

Demand Response; Aggregator; Electricity markets; Uncertainty; Stochastic Dual Dynamic Programming.