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EFFICIENT IMPLEMENTATION AND POTENTIAL BENEFITS OF DEMAND RESPONSE IN ELECTRICITY DISTRIBUTION NETWORKS

Tesis para la obtención del grado de Doctor

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1. Introduction

This first chapter introduces the motivation that led to the development of this thesis and presents its main objectives and a general overview of the structure of the document.

1.1. Motivation

One of the major challenges being faced nowadays by electric power systems worldwide is the requirement to sustainably satisfy an increasing load with high peaks that occur during a few hours per year while coping with growing penetration levels of intermittent renewable energy sources (RES)[1] (Siano, 2014). Ensuring a reliable electricity supply under these circumstances can be extremely costly. On the one hand, large investments may be needed to dimension electric power generation resources and transmission and distribution infrastructure. On the other hand, fast ramp and back-up generation is necessary to guarantee the security of supply. In this context, enhancing flexibility is vital to ensure a reliable and safe operation of future power systems. In particular, policy makers and regulatory authorities are increasingly valuing load flexibility, also known as demand response, as a key and cost-effective solution to this challenge (CEER, 2014a; Eid et al., 2016; FERC, 2009).

Interest in demand response in electricity systems already arose back in the early days of the electric power industry in the U.S. around the possibility of applying time-of-day differentiated rates, as described in (Cappers et al., 2010). At the beginning of the 1970s, the interest became more tangible in the United States, as load management programmes started to be implemented by utilities and a variety of pricing experiments were being carried out (Faruqui and Malko, 1983). However, it was probably the California energy crisis in 2000-01 that draw the greatest attention to demand response utility in electricity markets not only in the U.S. but also worldwide (Faruqui and Sergici, 2010). Nowadays the value and necessity of demand response as a flexibility means is widely recognized by stakeholders and also at high policy level, especially in the U.S. (DOE, 2006; FERC, 2012), Europe (EC, 2012a, 2013b, 2013c), and elsewhere[2].

[1] In fact, both factors are likely to rise over coming decades due to the expected increased electrification of energy consumption for heating (through electric heat pumps) and transport (electric cars) (EC, 2013a; Siano, 2014), and as long as energy policy objectives continue to pursue the decarbonization of the electricity sector.

[2] For instance, in the U.S., the Energy Policy Act of 2005 (EPACT) established the elimination of barriers to demand response participation in wholesale and retail markets as a key objective of national energy policy and the Energy Independence and Security Act of 2007 (EISA) required the Federal Energy Regulatory Commission (FERC), an independent regulatory commission, to conduct a national assessment of demand response potential, develop a national action plan on demand response, and with the Department of Energy

Demand response (DR) refers in general to the ability of the demand side to be flexible, responsive and adaptive to economic signals (Eid et al., 2016). More specifically, a commonly accepted definition of DR in electricity systems is the capacity of end consumers to modify their usage of electricity with respect to their normal habits in response to time-varying prices of electricity or other economic signals, including explicit requests or direct load control in return for incentive payments (Braithwait et al., 2006; CEER, 2011, 2014a; Conchado and Linares, 2010; DOE, 2006; EC, 2013c; SEDC, 2015; Siano, 2014; Strbac, 2008; Wierman et al., 2014). Thus, two complementary (and not necessarily exclusive) approaches can be adopted to activate demand response[3] (FERC, 2012; SEDC, 2015):

- **Implicit**, or **price-based**, schemes incentivize changes in consumption through the dynamism and time differentiation of the different components of the retail price of electricity, intended to reflect the value and cost (real or expected) of electricity in different time periods, so end consumers that respond accordingly can benefit from a lower electricity bill.
- **Explicit**, or **incentive-based**, mechanisms allow consumers to receive a specific reward in return for adjusting consumption (downwards or upwards) upon request, thus providing a reliable and valuable service to the system.

Regarding **implicit** DR, there is a wide variety of retail pricing structures that aim to reflect the real market prices and costs of the system with different degrees of complexity, therefore enabling demand response to price signals by end-consumers. Different components of the final electricity price correspond to the different activities involved in the electricity supply chain (EAHC/FWC, 2010), including generation of electricity, use of the networks (transmission and distribution) and retail[4]. Underneath each of these components, there may be both investment and operational costs. The allocation of these cost items in the final price

(DOE) develop a proposal to implement the national action plan (FERC, 2012). Within the 2030 EU policy framework, demand response is seen as a key tool to achieve the targets of at least 27% for both renewable and energy savings by 2030 (SEDC, 2016). EU stipulations on demand response are included in the Electricity Directive 2009/72/EC, concerning common rules for the internal market in electricity, in the Energy Efficiency Directive (EED) (EC, 2012a), which urges regulatory authorities in Europe to take the responsibility of facilitating DR from both a network and a (wholesale and retail) market perspective, and even references to DR enabling are found in the Electricity Network Codes and Guidelines.

[3] A duality in the classification of demand response options is often present in the literature and among regulatory authorities and institutions, with differences in nomenclature but generally conceptually equivalent. For example, a division of DR mechanisms into Innovative Pricing and Direct load control is proposed in (CEER, 2011). According to (Braithwait et al., 2006), DR mechanisms can be presented in the form of price signals or quantity signals, while market-led DR is distinguished from system-led, or reliability-based, DR in (IEA and OECD, 2003).

[4] Electricity tariffs also include taxes and levies and other regulated costs, such as customer management costs incurred by distributors, functioning of the System Operator, the Regulatory Commission or the Market Operator, stranded costs in systems undergoing substantial regulatory changes and subsidies for renewable generation, energy efficiency or specific industries.

is done separately by each incumbent agent[5], e.g. regulatory authority, or retailers, by means of different structures for each cost component, as illustrated in Figure 1.1. Each of them can be recovered through different cost drivers, or charging concepts, e.g. consumed energy (kWh), installed or contracted capacity (kW) and others, such as connection to the network or number of customers (Reneses et al., 2013). Therefore, different pricing methods can be combined for the different price components, e.g. a fixed flat energy charge for the network tariff with a dynamic retail price for the cost of energy. In addition, pricing schemes differ in the frequency of updating price levels, the length of tariff/price blocks, and in the time of notification in advance (Dupont et al., 2011).

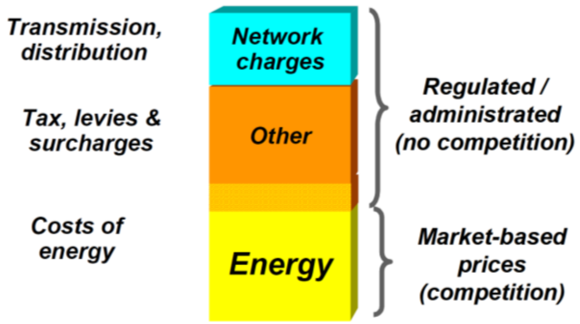

Figure 1.1 Usual breakdown of electricity retail prices in a deregulated environment. Source: (Eurelectric, 2013).

According to this, we may differentiate between static prices that are defined for long periods of time and dynamic prices, which are updated more frequently according to market price and network cost variations. Regarding the length of pricing blocks, prices can be flat or change with time. Most common and well-known time-varying[6] options (see Figure 1.2.) include: real-time pricing (**RTP**), time-of-use (**TOU**) pricing and Critical Peak Pricing (**CPP**) (Albadi and El-Saadany, 2007; Bartusch et al., 2011a; Braithwait et al., 2002; Dupont et al., 2011; IEA and OECD, 2003; Strbac, 2008). Higher complexity could even be incorporated, for instance by increasing price levels progressively along the instantaneous load or the total energy consumption within a period as with Increasing Block Pricing (IBP) (Borenstein, 2009).

Among the common activation options of **explicit** demand response are direct load control and specific payments, such as compensations for interruptibility and peak time rebates (PTR) (Braithwait et al., 2002). Under interruptible capacity programs, certain load volumes can be

[5] Traditionally, electricity systems were operated by large vertically integrated utilities with their own electricity billing structures and tariff levels. This model still reigns in many U.S. states and other countries, where electricity is billed through a central public service utility whose regulated tariffs could reflect combined network and electricity supply costs. Alternatively in a liberalized sector, which is the generalized electricity market model prevailing in Europe, the regulated components of the electricity value chain (transport and distribution) are unbundled from the competitive parts (generation and retail) (Eid et al., 2016).
[6] Time-varying pricing structures commonly apply to the cost driver of consumer energy (kWh) even though capacity charges can also present time differentiation.

interrupted with short notice up to a maximum number of times per year. With PTR, consumers are paid rebates for reducing consumption below a prescribed or ad-hoc estimated baseline (Batlle and Rodilla, 2009; Herter, 2007; Pérez-Arriaga, 2010). Rebates can be given either to increase or decrease consumption. These rebates can also take the form of price/volume signals, to which consumers freely decide to respond and are rewarded as a function of their final consumption (González et al., 2011). Sometimes specific products of committed capacity and activated energy are defined in markets or centralized mechanisms handled by system operators where specialized demand-side resources, i.e. large consumers or load aggregators, can participate directly, and under predefined conditions, just like generation resources do.

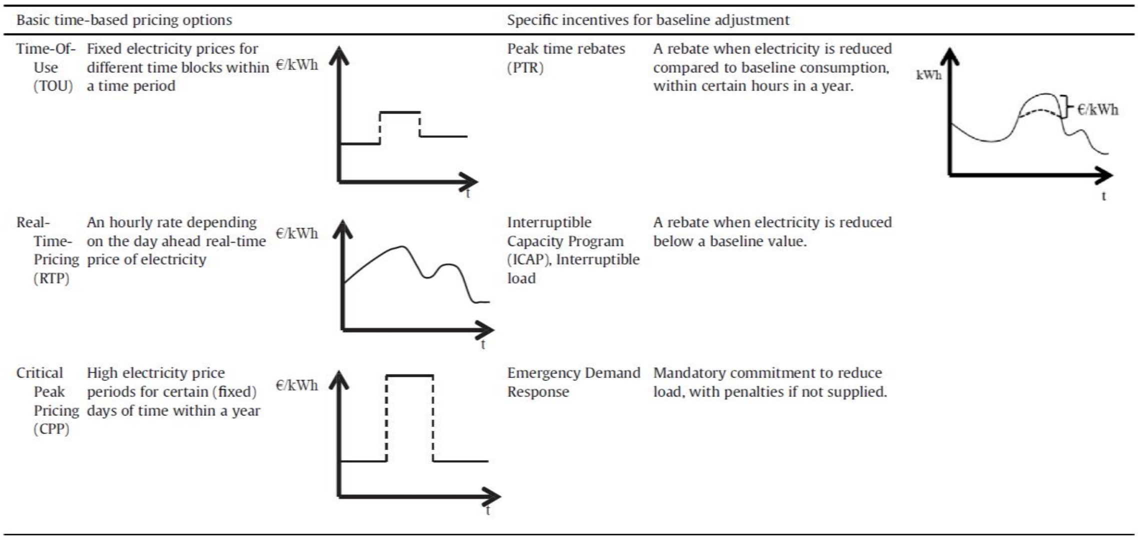

Figure 1.2 Possible time-based pricing options. Source: (Eid et al., 2016).

A variety of examples of basic pricing options and explicit incentives, based on (Eid et al., 2016), are illustrated in Figure 1.2.

To the extent that demand response signals (prices or incentives) accurately reflect the actual costs of the different electricity supply activities, or the market value of the requested flexibility, DR indirectly results in a more cost-effective allocation of resources, improving overall electric power system efficiency (Albadi and El-Saadany, 2007; CEER, 2014a; Siano, 2014). This efficiency improvement can have economically positive short-term impacts on system (generation and/or network) operation and on system expansion in the long term, by reducing the need for additional installed capacity in generation and network assets (Batlle and Rodilla, 2009; Braithwait et al., 2006, 2002; Cronenberg et al., 2012; Juneja, 2010; Linares et al., 2015; Strbac, 2008).

In fact, DR is a natural and essential component of any market of goods or services, where demand responds to prices up to some extent. Notwithstanding, most retail electricity customers are not allowed to provide any kind of flexibility services and are exposed to flat electricity retail prices that are fixed for long periods, so they do not reflect the actual costs of the different electricity supply activities. Under such circumstances, consumers have no incentives to adjust their consumption in time and volume in response to actual market and system conditions (Linares et al., 2015).

Demand response can thus be seen as an implicit or explicit flexibility service coming from electricity consumers that overcomes this deficiency and meets a variety of interests across the value chain of electric power systems, bringing value to different actors. For instance, the flexibility provided by consumers' DR could be used by suppliers and Balance Responsible Parties to optimize their portfolio and adjust their positions in the market. DR could also be a useful tool for Transmission System Operators (TSOs) to balance demand and supply and maintain system security, through the provision of frequency control and balancing services and the participation in mechanisms of capacity remuneration and load interruptibility. At the same time, DR could ideally help Distribution System Operators (DSOs) to manage short-term constraints in their networks and even reduce network losses, possibly allowing them to reduce or postpone network reinforcements (Conchado and Linares, 2010).

Traditionally, the interest on DR has been placed on large industrial customers with direct access to balancing, capacity and wholesale electricity markets and the appropriate technical capabilities to provide system services to TSOs. For instance, in Europe, long-standing agreements that involve energy-intensive industrial consumers through interruptible tariffs are very common and TSOs are increasingly allowing demand side resources to take part in their system balancing markets and mechanisms (SEDC, 2015). Even though active participation of the demand-side in these markets and mechanisms is still limited in most countries, it is mostly due to regulatory and market barriers that are gradually being eliminated (Zancanella et al., 2016).

Meanwhile the contribution of domestic small business consumers to DR, which has usually consisted of TOU tariffs or retail pricing options, and only in some cases in RTP or CPP (Juneja, 2010), remains relatively low but is gradually growing. In fact, until recently, electricity DR has hardly been feasible for small consumers due to technical limitations, but the generalized deployment of smart metering, home automation and advanced control and communication technologies enables the development of different innovative forms of demand response also for these consumers by making economic signal sending, remote control, automation and accurate billing possible (EC, 2012b, 2013b; Eurelectric, 2011; Giordano et al., 2013; Hancher et al., 2013). Thus, interest on dynamic pricing through network tariffs and retail-enabled pricing programs is increasing and experiences are emerging across the U.S., Europe and elsewhere.

For instance, a regulated integral[7] TOU tariff is applied to small residential consumers in Italy since 2010 (Torriti, 2012), demand-based TOU distribution network tariffs are used in Sweden (Bartusch et al., 2011b; Bartusch and Alvehag, 2014) and a dynamic hourly default[8] tariff for the component of the cost of energy based on the day-ahead hourly spot price plus balancing costs exists in Spain.

In contrast with these experiences, a field of application of demand response that could result extremely valuable and interesting but is basically unutilized nowadays is the participation of consumers in the provision of network services for an active management of distribution networks (CEER, 2014b; SEDC, 2016). If allowed to do so, demand response could drastically change the way DSOs operate their networks. Provided DSOs could procure flexibility services from consumers, they could count on an additional tool to operate and plan their networks more actively and efficiently, and so they would possibly be able to reduce network losses, avoid network congestions or better manage network faults and outages. To the extent that outages and grid losses were penalized, DSOs would be incentivized to resort to demand flexibility to reduce them. If grid constraints are visible in the long term, DSOs could partially avoid or defer reinforcement investment costs. Unfortunately, scarcely any experience exists in this sense except for a variety of pilot programs and innovation projects in various countries, e.g. in UK (Cesena and Mancarella, 2014), the Netherlands (Veldman et al., 2013), Sweden (Bartusch and Alvehag, 2014) and France (Levaufre et al., 2014).

Within this local perimeter of DR action, small commercial and residential consumers could play a fundamental role. It is expected that, if the pertinent mechanisms were defined and the regulatory conditions appropriate, these consumers would find it natural to participate in DR arrangements, probably through an intermediary, or DR provider, such as a supplier or a third-party aggregator, delivering the flexibility service on their behalf to DSOs. The economic viability for small commercial and residential end users to provide this type of demand response services is still uncertain given the current limited experience out of trials and pilot programs. Recent studies based on actual DR experiences in distribution grids suggest that consumers would be willing to respond to DR signals reflecting the costs of network capacity to some extent, whether these signals are based on distribution network tariffs, as shown in e.g. (Bartusch and Alvehag, 2014), or specific incentive-based services, as in the ADDRESS[9] project (Linares et al., 2015). However, the potential of DR to help network operators to

[7] Integral refers to a tariff that accounts for the whole final price paid by consumers and is entirely regulated.
[8] The Voluntary Price for Small Consumers (PVPC) is the default tariff for the cost of energy for eligible consumers (contracted power equal to or less than 10 kW) who do not wish to subscribe a different supplier in the competitive retail market.
[9] The ADDRESS project was o-funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 207643 (http://www.addressfp7.org/).

manage grid issues remains to be further explored (CEER, 2014a; Eurelectric, 2016). Policies and programs oriented to improving demand response are commonly believed to enhance the economic efficiency and produce short- and long-term benefits for society as a whole. However, overestimating the benefits of DR can lead to unrealistic expectations and to inefficient and unsustainable market designs and regulations (Ruff, 2002). Therefore, robust methodological approaches are required to estimate the potential benefits of this form of DR. Furthermore, due to the scarce experience in DR to support an active distribution network management, the mechanisms that would allow DSOs to avoid or defer network reinforcements remain to be defined, and the regulatory conditions adapted to this new environment.

Ahead of the challenge of anticipating the feasibility, the economic convenience and the implications of the practical implementation of this type of mechanisms in real networks with real users, a series of questions arise that are common to any other field of application of a novel demand response option.

- To what extent do consumers respond to demand response activation mechanisms (not only prices, but also incentive-based signals)? What type of flexibility characterization is required in by a DR provider that has to guarantee certain level of capacity requirement reduction in the distribution network?
- What is the real economic benefit of counting on demand response as a tool for an active network management in distribution networks? Under what circumstances does it make a difference for DSO operation and planning? How could the task of characterizing consumer responsiveness and that of quantifying the benefits of their flexibility in distribution networks be linked?
- Is the implementation of distribution network-driven DR feasible in current electric power systems? What changes are recommended in the regulatory environment to enable and incentivize this approach efficiently?

The answer to these questions calls for a global approach that entails multiple perspectives of analysis: the technical, the economic, the social and the regulatory. The approach presented in this thesis to study is structured into three points of view. Within each of these areas of study, some gaps have been identified in the literature, which are aimed to be filled in with this thesis:

I. Consumer and DR provider

From the end-consumer perspective, and from the standpoint of the aggregator of flexibility of multiple consumers, an extensive collection of engineering and econometric methods devoted to the quantification of residential demand responsiveness are found in the literature. While the former are best suited for the evaluation of the technical aspects of flexibility, the latter present the advantage capturing the subjectivity and the decisive influence of behavioural factors in demand choices from real data, so they are especially attractive to characterize demand flexibility in situations of real implementation. Among empirical studies it is very rare to find evidence of purely incentive-based demand response programmes addressed to residential consumers, and only mean values of observed flexibility are commonly obtained with the proposed models. However, mere average expected responsiveness levels disregard the risks of consumer behavioural variability and heterogeneity while a probabilistic characterization of flexibility represents a valuable instrument to handle the risk of consumers not always reacting to these DR signals as desired. Empirical methodologies that quantify and provide a probabilistic characterization of residential demand responsiveness to incentive-based DR signals are not found in the literature.

II. Distribution networks

Regarding the system perspective, the quantification of the potential economic benefits of DR as a smart option for distribution networks has not been sufficiently investigated in the literature. Numerous studies explore consumer responsiveness to DR initiatives but do not stress the economic value of that response for the distribution network or its implications in network planning. Only a few studies have been found that explore the potential of DER, in general, as operational resources to support distribution network management. It is generally observed in these studies that either different DR instruments are not distinguished, only simplified network topologies are used or, with a few exceptions, investment decisions and costs are not explicitly addressed.

III. Regulatory environment

The regulatory requirements and the commercial arrangements for the active participation of DR in EU electricity markets are addressed in numerous technical reports of regulatory and scientific institutions and industrial associations. The scope of the studies found is mostly concentrated in reviewing the current regulatory approaches and market models for the participation of demand-side resources in wholesale electricity markets and in the provision of frequency control ancillary services and balancing energy to TSOs. On the other hand, various references in the academic literature address general regulatory features related concerning the adaptation of the distribution activity to a new context of increasing Distributed Energy Resources (DER) and the desired implementation of the Smart Grid concept. Notwithstanding, the regulatory barriers that are specific of the practical implementation of DR to support distribution network operation and planning are not found explicitly in a comprehensive analysis.

This motivation and the identified gaps lead to the definition of the objectives of this thesis.

1.2. Objectives of the thesis

The central objective of this thesis is to analyse the feasibility and the potential economic benefits of the hypothetical implementation of demand response as a flexibility resource for an active distribution network management and its technical, economic and regulatory implications, under a comprehensive approach. For this purpose, several perspectives are adopted and integrated in this thesis: the consumer, the network and the regulatory environment.

The specific objectives of the thesis are defined as follows:

- Propose an empirical methodology to obtain a probabilistic characterization of the responsiveness of a population of residential electricity consumers to explicit incentives. The purpose of this characterization is to serve as a tool that could be used in practice by demand response providers in real scenarios of implementation at distribution network level to forecast in advance the amount of flexibility that could be activated from participating consumers. The modelling approach should depict the full picture of uncertainty and variability of the expected flexibility and allow the definition of specific risk measures about unexpected negative responsiveness levels and their probability of occurrence.
- Present a methodological approach to assess the economic value that DR can bring locally to distribution networks when different options of implementation are considered. The centre of the methodology will be to quantify the potential ability of DR as a resource to defer planned distribution investments by alleviating local peak capacity.
- Test the proposed methodologies in realistic case studies with consumption data from a real demand response experience, realistic exemplary distribution networks based on Spanish locations and assuming an effectiveness of DR programs as observed in different real pilot programs and innovation projects, with the aim of illustrating their applicability and identifying relevant key factors and contexts that hinder or strengthen the ability of network operators to optimize planning strategies counting on DR.
- Analyse the regulatory environment that affects the effective and economically efficient development of DR as a smart resource for the operation and planning of distribution networks in a European context and identify the key regulatory barriers that could slow down its successful development in the near future.

1.3. Structure of the document

The document is structured in three additional chapters, in addition to the conclusions chapter (chapter 5), which correspond to the three perspectives of analysis that have been adopted in this thesis: consumer (and DR provider/aggregator), distribution network (and DSO) and regulatory environment. Chapter 2 presents an empirical methodology to characterize residential demand responsiveness to economic incentives following a probabilistic approach and its illustrative application to a case study based on a real demand response experience carried out in Spain. Chapter 3 addresses the potential economic benefits of incorporating DR into DSO operational strategies through a methodology that lets us quantify the deferral or avoidance of certain grid reinforcement investments in different scenarios of DR implementation and its application to a case study which is built using realistic exemplary distribution networks based on Spanish locations. The market and regulatory conditions that could enable DSOs to put these mechanisms into practice and capture this economic value are dealt with in chapter 4, where the main regulatory barriers that would have to be overcome are analysed.

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2. Quantification of consumer flexibility and responsiveness

Within the framework of research of this thesis, which is the feasibility and the efficient implementation of demand response as a flexibility resource for a more active and efficient operation of distribution networks, the aim of this chapter is to present an empirical methodology to obtain a full characterization of residential consumers' flexibility in response to economic incentives. The aim of the proposed approach is to assist a hypothetical demand response provider in the task of quantifying flexibility of a real population of consumers during a supposed trial that would precede a large-scale implementation of a demand response program. For this purpose, mere average values of predictable responsiveness do not provide meaningful information about the uncertainties associated to human behaviour so a probabilistic characterization of this flexibility based on Quantile Regression (QR) is suggested. The proposed use of QR to model individual observed flexibility, provides a concise parametric representation of consumers that allows a straight application of classification methods to classify the sample of consumers into categories of similar flexibility. The proposed modelling approach also depicts a full picture of uncertainty and variability of the expected flexibility and enables the definition of two specific risk measures for the context of demand response that have been denominated flexibility at risk (FaR) and conditional flexibility at risk (CFaR). The application of the methodology to a case study based on a real demand response experience illustrates the potential of the method to capture the complexity and variability of consumer responsiveness.

2.1. Introduction

End-use electricity consumption has traditionally been characterized at an aggregate level to satisfy the need of TSOs, DSOs and retailers of forecasting a presumably inflexible load profile they would have to supply. The quantification of consumer responsiveness to upcoming or recently introduced mechanisms and technical solutions that enable demand response is essential to explore the business model of demand response (DR) and its economic impact on the energy system at any implementation level. In fact, anticipating the number of consumers willing to participate and their sensitivity to demand response signals is a basic requirement for the feasible implementation of any demand response mechanism. An adequate characterization of available consumers' responsiveness to changing electricity prices or explicit incentive payments is also indispensable to build decision-support systems for retailers and aggregators procuring demand response services in their daily forecasting and decision-making processes. In particular, within the framework of research of this thesis, the implementation of network-oriented demand response in distribution networks, modelling consumer flexibility is a key stepping stone to understand and quantify its efficacy to defer network investments, as will be described in chapter 3.

Network-driven demand response incentivizes more efficient asset utilization by providing additional flexibility in the management of network constraints and stress situations. In this sense, both **incentive-based** and **price-based** (through cost-reflective network tariffs) demand response mechanisms[10] could play an important role. Notwithstanding, the focus of this chapter is placed on mechanisms based on incentives, which could potentially induce more controllable load changes to directly address network local requirements and to which consumers appear to show a clear predisposition with respect to equivalent price signals (Letzler, 2010).

A variety of both engineering and econometric methods devoted to the quantification of residential consumer demand responsiveness can be found in the literature, as described in more detail in Section 2.2. While engineering models are best suited for the analysis of the technical aspects of flexibility at preliminary stages of evaluation, when real data is not always available, an experimental approach with econometric techniques is especially attractive to characterize demand flexibility in situations of real implementation. Given that the technological barrier of smart meter data collection and processing is overcome, empirical research presents the clear advantage of capturing the subjectivity and the decisive influence of behavioural factors of residential demand choices from tangible observations.

Among the empirical studies found in the literature, it is very rare to find evidence of purely incentive-based demand response programmes addressed to residential consumers, as most real experiences for this consumer sector are based on TOU and dynamic prices. Furthermore, it is remarkable that only average values of observed flexibility are commonly obtained with the proposed models, through measures such as relative peak load reductions, or price elasticities of demand, among others. Mere average expected responsiveness levels disregard the risks of consumer behavioural variability and heterogeneity.

Given that responsiveness to temporary and explicit requests may differ significantly from permanent and implicit time-varying prices, as the former do not necessarily interfere with normal consumption patterns during periods of no demand response intervention, a specific methodology for this type of signals is required for an accurate characterization of flexibility. Furthermore, in a realistic scenario of implementation of demand response, such a

[10] Even less intrusive forms of intervention, based on the provision of feedback on electricity consumption, could be taken into consideration as well as they have proved to induce energy conservation attitudes and reduce overall electricity consumption, including during peak hours (Borenstein, 2014).

methodology should be able to provide a quantified picture of the uncertainty of different consumers' responsiveness with information of the entire distribution.

The aim of this chapter is to look into end consumers' flexibility and propose an empirical methodology to obtain a probabilistic characterization of the responsiveness of a population of residential electricity consumers to explicit incentives. The purpose of this characterization is to serve as a tool to forecast in advance the amount of flexibility that could be activated from different sectors of this population in relation to a set of controllable and other surrounding variables. For this purpose, Quantile Regression (QR) models are suggested as a flexible methodology to provide a parametric representation of the full distribution function of flexibility without assuming a specific distribution. A probabilistic characterization of flexibility represents a valuable instrument to handle the risk of consumers not always reacting to these DR signals as desired. The proposed methodology is based on smart meter data collected during a trial period of a demand response program so it could be used in practice by demand response providers in real scenarios of implementation at distribution network level. QR modelling provides a full and at the same time concise characterization of flexibility at individual level that allows an easy classification of consumers into categories of similar flexibility.

In particular, the contributions of this chapter can be summarized below:

- An original empirical probabilistic approach is proposed to characterize residential electricity consumer responsiveness to economic incentives, which has scalable[11] properties and could be applied in real pre-implementation situations.
- Original and informative specific risk measures for the uncertainty of consumer flexibility to economic incentives that are directly originated with the proposed approach are defined.
- The methodology is applied to a case study based on a real demand response experience. In particular, a pilot field test based on incentives carried out among residential consumers in a Spanish location within the context of the European research project ADDRESS[12] is analysed.

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[11] The methodology is said to be scalable in the sense that from the characterization of a representative sample of consumers, the flexibility of each member of the whole population from which the sample has been extracted can be classified and characterized.

[12] ADDRESS (Active Distribution network with full integration of Demand and Distributed Energy REsourceS) is a research project co-funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 207643, which aimed to enable Active Demand through the active participation of small and commercial consumers in power system markets and in the provision of system services (http://www.addressfp7.org/).

The chapter is structured as follows. Section 2.2 presents an overview of the characteristics of residential demand responsiveness and the approaches found in the literature to characterize it. In Section 2.3, the proposed empirical methodology for the quantification of flexibility is described. Its application to a case study based on a real demand response experience is presented for illustrative purposes in 2.4. Finally, the conclusions of the research presented in this chapter are drawn in Section 2.5.

2.2. Residential demand responsiveness

Characterizing the responsiveness of loads to demand response signals requires a detailed understanding of how electricity is used at individual consumer level. This is particularly difficult for electricity as a product because of its "invisible" nature. The fact that its perceived value is determined by its ability to provide some set of desired services, either in the industry or in the household, so its consumption is the result of a set of simultaneous decisions complicated by many factors (Hunt and Evans, 2011). This is particularly relevant among residential consumers, for whom behavioural aspects play a significant role and whose decisions sometimes present gaps between knowledge, value, attitude or intention and final actions (Frederiks et al., 2015). It is not surprising that, in general, households present highly volatile and heterogeneous load patterns mostly conditioned by their daily activities and strongly influenced by personal preferences and behavioural factors.

In the context of demand response, both price-based and incentive-based signals can incentivize changes in electric usage with respect to normal consumption patterns (Eurelectric, 2013). In this framework, electricity consumers that become aware of their actual consumption and the signals received may be willing to optimize their loads in response to these signals to reduce their energy bills (Hancher et al., 2013). For instance, appliances that can be operated on a flexible schedule could be shifted in time (e.g. "wet appliances", such as washing machine, tumble dryer and dishwasher). On the other hand, the load of certain appliances that let regulation or have energy storage capacity could be reduced or interrupted, such as electric vehicles or thermal loads (e.g. refrigerators, electric boilers, air conditioning and heat pumps) (Sajn, 2016). In extreme and occasional situations, it is even feasible to interrupt total consumption for very short periods of time.

With this aim, loads can be manually controlled by customers with the guidance of an in-home display with information regarding consumption and external signals. Alternatively, they can be automatically controlled by an Energy Management System (EMS), acting as a gateway that receives information of the external signals, communicates with the smart meter and the smart appliances and coordinates their functioning (Albadi and El-Saadany, 2007; EC, 2013;

Eurelectric, 2011; Juneja, 2010). Home appliances can be operated at various levels of automation, from the delayed start, a rather common functionality in normal appliances, to functions that allow consumers to manually set the time when the task has to be finished, leaving it to the EMS to decide the optimal schedule. Alternatively, a "set-and-forget" operation mode is also possible in which the consumer sets his preferences once at the beginning and the controllable loads are automatically activated unless the user decides to override them. Finally, some appliances, e.g. fridges and freezers, in principle allow a fully automated operation that would barely be noticed by users (Albadi and El-Saadany, 2007). There is empirical evidence that smart appliances and enabling technologies significantly improve the responsive ability of consumers (Faruqui and Palmer, 2012), as they considerably reduce the burden of manually adjusting consumption schedules to external signals.

It becomes clear that the first limiting factor of the potential load flexibility of a consumer is technical, as it depends on the amount and characteristics of the flexible appliances that compose the load mix and the technical assistance to schedule loads efficiently. We refer to this as the **technically available flexibility**, or technical potential, indistinctly. It is determined exclusively by aspects such as the nature of the electrical equipment, its controllability, its capacity of energy storage or self-generation and its level of automation.

On the other hand, even with a high technical potential, only those consumers for whom the incentive that is provided through the DR signal is worth at least as much as the utility of consuming at certain point in time will be willing to suffer the burden of altering consumption with respect to normal habits. The utility of electricity consumption is subjective so the price sensitivity or value perceived is a personal characteristic of the consumer that is intrinsically conditioned by personal preferences and economic, cultural and social circumstances (Hunt and Evans, 2011). Preferences among consumers with similar technical possibilities vary widely in relation to the acceptance of price risk, the complexity of tariffs or contract terms and the loss of control over own appliances (Hancher et al., 2013). **Behavioural price sensitivity** thus constitutes the second limiting factor of a consumer's potential flexibility and it certainly has a considerable relative weight for residential consumers.

As a final remark, the nature of the response is also deeply conditioned by **the characteristics of the signal** (price or request) and **the time in advance of its notification**. If the signal is permanent, the response is expected to be stable, while if the signal is transient and sporadic, so will be the reaction of the consumer. In this sense, consumers can react to sporadic and transient, signals, such as critical peak pricing (CPP) or explicit requests, by postponing immediate actions for short period of time or occasionally re-planning the daily activities on the day ahead. Alternatively, in response to more stable signals, such as TOU prices, consumers can systematically modify their consumption habits so that part of their activities is shifted from high-price periods to low-price periods on a more permanent basis. In addition to the timing aspects, it seems that consumers are strongly influenced by the aspect of the signal received and show a clear predisposition to prefer incentive-based mechanisms to dynamic and CPP prices, even when final economic savings are equivalent (Letzler, 2010).

Understanding the influences of all these factors is vital to get the picture of demand responsiveness and estimate the potential effect of time-varying prices or explicit demand response requests on consumption. There is a wide interest in the literature on the measurement of demand flexibility to demand response signals, with a special focus on residential electricity consumers. Overall, methods found in the literature that provide tools to estimate consumer responsiveness can be divided into two major groups: technological engineering models and econometric empirical studies.

Engineering demand models characterize the fundamental components of electricity consumption and model their technical characteristics to build up realistic load profiles with different aggregation levels. This is often done following a bottom-up approach, i.e. each consumer, or consumer archetype, is modelled individually so that afterwards the results can be scaled to regional levels, as done in (Capasso et al., 1994), (Paatero and Lund, 2006), (Conchado and Linares, 2009) or (Koliou, 2016). Nevertheless, sometimes loads of different appliances are modelled from a top-down perspective as well (Conchado et al., 2016). Engineering models sometimes consist of statistical predictions of appliance use relying on measured data to simulate stochasticity, see (Torriti, 2014) for examples of time use models. In the absence of any load data, a variety of models proposed build up synthetic load curves that could be used in a preliminary step, e.g. (Armstrong et al., 2009; Capasso et al., 1994; Dickert and Schegner, 2011; Gottwalt et al., 2011; Paatero and Lund, 2006; Walker and Pokoski, 1985; Yao and Steemers, 2005). Other approaches suggest a disaggregation of real load curves into feasible and realistic combinations of individual usages, like (Conchado and Linares, 2009) and (McLoughlin et al., 2013).

The applications of these models are manifold but the main interest is usually placed in the evaluation of the impact of demand response programs on final consumers. In fact, a large tradition of technically explicit load curve models for the residential sector for general purposes exists, of which a complete review is found in (Grandjean et al., 2012). Engineering models present the advantage of not depending on the availability of real data of consumers' reactions so they can be used to evaluate the potential effects of pricing options and other strategies preceding any demand response implementation. They are valuable to understand the implications of individual uses and let us assess the impact of technological choices, such as renewed equipment or appliances that will not be available until the near future. However, they present clear limitations to incorporate the influence of human behaviour, not so much in normal consumption patterns but especially on estimated reactions to prices and incentives. Only a few proposals incorporate price elasticities, such as (Linares and Lago, 2012) or (Althaher and Mutale, 2012), or inconvenience cost parameters (Bapat et al., 2011) for this purpose. Thus, engineering models are best suited for the evaluation of the technical potential of flexibility rather than for the quantification of expected responsiveness in real situations. They are also a good basis for the construction of algorithms for households' EMS to optimally control smart appliances[13], e.g. (Alvarez et al., 2004; Chen et al., 2012; Conejo et al., 2010; Dupont et al., 2012; Roe et al., 2011; Zehir and Bagriyanik, 2012).

On the other hand, **econometric models for load responsiveness** do not require information regarding the actual consumption processes but rather rely on statistical analysis and economic theory to regress functional forms of power demand in relation to a set of variables (e.g., seasonal indicators, prices, income, weather conditions, household size, type of dwelling, social aspects, and even available equipment). The most interesting feature of empirical approach is that observations of real behaviour are considered, which already incorporate the behavioural component of responsiveness that would be impossible to know otherwise. Then again, empirically tuned models present a series of drawbacks, the most significant being that they fail to quantify the impact of technologies or mechanisms that have not been experienced when the data was collected and that their estimations are difficult to extrapolate to other contexts. Therefore, these models can produce convenient results for a specific population of consumers from which an amply representative sample is available.

Data availability has traditionally been the main barrier to adopt empirical approaches. However, with the recent and ongoing deployment of smart meters for all electricity customers throughout many countries worldwide (EC, 2014) and the fast advances that are taking place in information and communication technologies, storage devices and more powerful processors, it is becoming much easier for suppliers to collect and process huge volumes of energy consumption data with high granularity. In this context, the focus of ongoing research in relation to demand response is likely to focus more intensely on empirical approaches.

The literature on econometric estimations of load responsiveness based on empirical research in the residential sector is abundant, essentially concerning experiences from the United States, e.g. see (Cappers et al., 2010; Faruqui and George, 2005; FERC, 2012; Herter, 2007; Herter and Wayland, 2010; King and Chaterjee, 2003; Peters, 2010; Summit Blue, 2007) but also more recently from other countries as well, e.g. a TOU/CPP pilot study in British Columbia, Canada is presented in (Woo et al., 2013b, 2013a). Numerous empirical studies of pilot or real demand

[13] A practical application of these models outside the scientific context is the development of feedback tools for customers by retail companies to help consumers to manage their loads and choose the pricing products that best suit their preferences to improve consumer engagement.

response experiences taking place across Europe can be found as well, e.g. the application of TOU tariffs to residential electricity users in Italy since 2010 is studied by (Torriti, 2012), a TOU trial carried out in Ireland is analysed in (Di Cosmo et al., 2012), a dynamic pricing pilot with automated smart appliances in Belgium (*Linear* pilot) is examined in (Vanthournout et al., 2015), the results of a large-scale TOU tariff trial for households in the London area (*Low Carbon London*) are investigated in (Schofield et al., 2014) and the effectiveness of implemented demand-based TOU distribution tariffs in Sweden is evaluated in (Bartusch et al., 2011; Bartusch and Alvehag, 2014). In addition to the well-known 2010 survey of 15 pricing experiments carried out by Faruqui (Faruqui and Sergici, 2010), two additional examples of up to date reviews of demand response experience results, most of them carried out over the past decade are (DECC, 2012) and (Faruqui and Palmer, 2012). Furthermore, an interesting compendium of bibliographical references is given in (Enright and Faruqui, 2015).

In general, it can be observed that experiences in the residential sector predominantly concentrate on dynamic pricing, either with respect to the retail price, the network tariff or an integral regulated tariff, and some of them on feedback programs. In contrast, it is not common to find real experiences of incentive-based demand response mechanisms with residential consumers, so empirical studies in this sense are difficult to come across. Given that the nature of the reactions to infrequent explicit requests may differ considerably from habitual patterns of responsiveness to time-varying prices that are present on a more permanent basis, specific methodologies are required to quantify and characterize real consumers' flexibility to incentive-based signals.

In addition, the attention of these studies is naturally set on the potential of price signals to achieve peak load reductions and energy shifting from peak to off-peak periods, measures of which are frequently provided through relative performance indicators (% load changes) or price elasticities[14], or equivalent dimensionless parameters, such as the "arc of responsiveness" presented in (Faruqui and Palmer, 2012). Overall, even if these are robust measures of flexibility suitable for cross-case comparison, only average values of observed flexibility are obtained. However, the variability and uncertainty of consumer responsiveness calls for the application a probabilistic modelling approach to fully characterize probability distribution of flexibility. Probabilistic modelling is commonly applied to other fields, such as electric load

[14] Two types of price elasticity of electricity demand are commonly used in the evaluation of time-varying pricing options: own price elasticity and elasticity of substitution. Own price elasticity measures the behaviour of the consumer under price changes within a particular period. It is the relative change in consumer demand that results from a unit change in the price. Elasticity of substitution measures a customer's shift in consumption across periods. It is calculated as the percentage change in the ratio of consumption of electricity in two different periods as a consequence of a percentage change in the ratio of prices of electricity in these periods.

(Hong and Fan, 2016) and price (Bello et al., 2017) forecasting, and a few examples of individual electricity load probabilistic modelling are found, e.g. (Arora and Taylor, 2016) and (Taieb et al., 2016). However, no references have been found that model electricity demand responsiveness in a probabilistic way.

In conclusion, given the difficulty of engineering models to capture the complexity and subjectivity of residential demand choices, it is desirable to include an experimental approach in the evaluation of the potential of demand response whenever possible, especially in relation to the residential sector. This is particularly important at a stage in which a demand response mechanism is likely to be implemented in practice, especially if the mechanism is based on incentives, as there is little knowledge of consumer flexibility to this type of signals. The research presented in this chapter is aimed to fill this gap by proposing a specific methodology to measure and characterize in a probabilistic way the flexibility of a population of residential consumers in response to incentive-based signals from real observations (e.g. during a trial period or pilot program), which could be the basis of a decision support system. The methodology is described in the following section.

2.3. Empirical methodology for the quantification of flexibility

This section is the core of this chapter as it presents the proposed methodology to characterize the inherent flexibility of a population of residential consumers that could be applied in real situations during a trial period of an incentive-based demand response program. The purpose of this characterization is not only to better understand the nature and the drivers of consumer responsiveness to non-permanent punctual DR signals, but also provide a tool to forecast in advance the amount of flexibility that could be activated from different sectors of this population in real time operation, in relation to a set of controllable variables, such as the timing of the DR signal, the value of the incentive, the type of consumer and other surrounding variables. The proposed methodology is aimed at estimating the full conditional distribution function of this flexibility in relation to a set of covariates, thus giving the DR provider a valuable instrument to handle the risk of unpredictable variability in consumer responsiveness to DR signals.

The remainder of the section goes through the different stages of the methodology. First, the most relevant boundary conditions for the application of the methodology are discussed in 2.3.1. Afterwards, an overview of the methodology is presented in 2.3.2 and each step is further developed in subsequent sections 2.3.3 - 2.3.5.

2.3.1. Boundary conditions

This methodology stems from a series of assumptions that make up its boundary conditions of application, the first of which is the nature of the DR signals used. The concept of flexibility that is of interest in the context of this chapter is the response of a consumer to an explicit request to lower or increase demand during a short period and on an occasional basis, unlike the traditional dynamic pricing or feedback programs to which customers are exposed on a permanent basis. An example of these is the so-called price & volume (P&V) signals, which are analysed in the case study that is presented in Section 2.4 of this chapter. In accordance with their definition (Eyrolles et al., 2011), the requests received by consumers are to increase or lower demand at least to a pre-determined consumption level (i.e. firm service level) in return for an absolute incentive-payment. An example of a P&V signal is shown in Figure 2.1, where the load profile of an exemplary consumer changes in the event of a P&V signal that is requesting a drop of consumption during one hour and has two levels of remuneration depending on the power band where the final electric usage lies. P&V signals are supposed to be notified in advance, e.g. in the day ahead, giving the consumer sufficient time to anticipate the scheduling of electrical shiftable appliances, either manually or with the assistance of automation technologies.

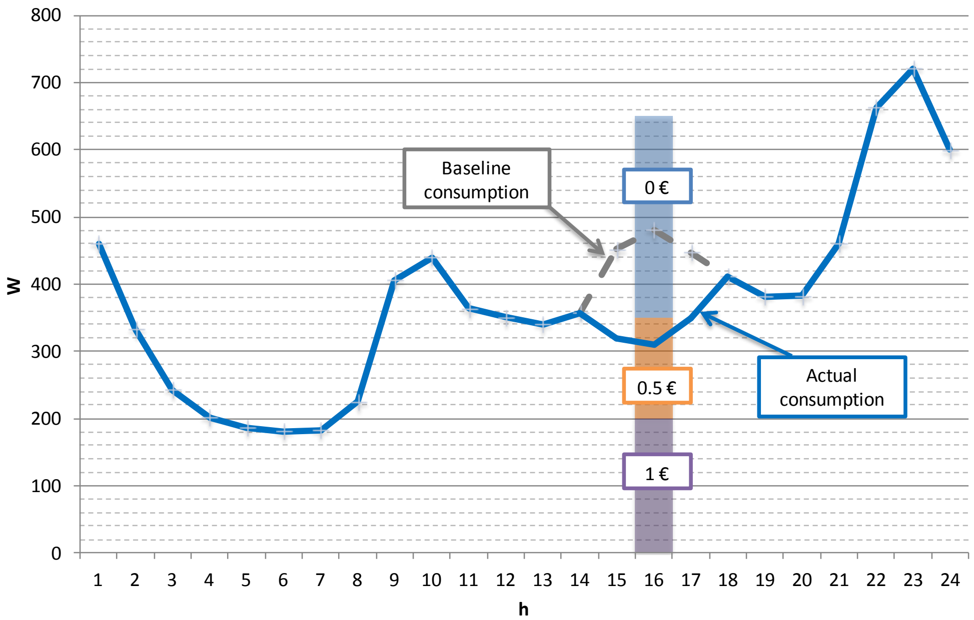

Figure 2.1 Example of a daily load profile of a single consumer during a DR event day in response to a price & volume signal requesting to lower consumption from 15:00 to 16:00 hours, with two compliance bands and the corresponding incentive payments (0.5 € and 1 € per hour).

Like Critical Peak Prices (CPP), P&V signals are supposed to be sent randomly and during critical events and local network stress situations that are not necessarily aligned with periods of system peaks and high electricity prices. These signals are equivalent to an inverse capacity charge, as they reward customers for keeping consumption within some limits instead of penalizing them if consumption surpasses these limits, with the particularity that they are occasional and have a limited duration. In this sense, they are similar to Peak Time Rebates (PTR), except that the economic compensation provided is not determined by an endogenous reference based on the customer's consumption in the recent past, but on objective and neutrally predefined thresholds. This relevant aspect rules out any chance of manipulation by the consumer by artificially changing consumption during non-DR event days (Borenstein, 2014).

These P&V signals are sent to customers regardless of the pricing structure they are exposed to, hence they represent an extra revenue stream for those who accept to participate in the demand response program and do not have an impact on load behaviour during non-event days. Note that, in principle, this revenue stream is a compensation to the customer for their readiness and willingness to provide flexibility and should come from the savings that could be achieved through the activation of this flexibility; for instance, as will be studied in chapter 3, from the avoided or deferred investments in distribution network assets. The valorisation of this flexibility as a network resource is upon the DSO to estimate based on the quantification of flexibility that should be carried out by the DR provider following the methodology presented in this section.

Furthermore, in the context of this methodology, we can imagine that throughout a sufficiently long trial period (from several months to one year), the DR provider has been able to send a series of test signals to a wide sample of the participant network users of certain distribution area and is aware of a series of basic environmental and personal characteristics of these consumers.

2.3.2. Overview of the methodology

This section presents an overview of the suggested methodology for the characterization of flexibility in a population of residential consumers, summarized in Figure 2.2. The methodology stems from the collection of interval consumption data of a sample of consumers that is representative of a larger population that we aim to characterize and that has been participating in a trial period of the DR program of several months during which a variety of signals (of different volume, in kW, and intensity, in €) have been sent to them. The granularity of the data must be sufficiently high (at least hourly but preferably in shorter time slots).

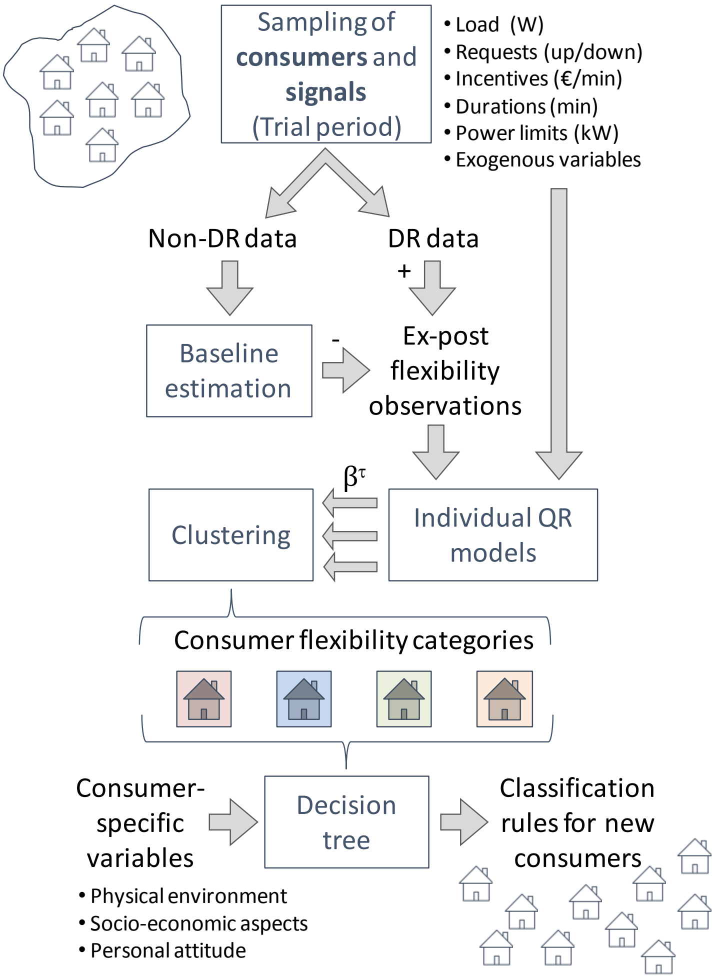

Figure 2.2 Overview of the proposed methodology to characterize residential consumers' flexibility.

The first step consists of carrying out an ex-post quantification of the magnitude of the observed individual responses of consumers to the DR signals. The quantified variable will be referred to as flexibility. As will be described in more detail in Section 2.3.3, an estimated reference or baseline will be required to measure the contribution of each consumer in terms of flexibility, both in ex-post quantification and in ex-ante estimation during real-time operation of the DR program.

Once flexibility is computed, a characterization procedure based on Quantile Regression (QR) will be applied to estimate the full probability distribution function of this flexibility in relation to a set of controllable and non-controllable (surrounding) variables, such as the type of signal, the value of the economic incentive and the outside temperature, as explained in Section 2.3.4. By modelling separately each of the percentiles of the distribution function of the variable flexibility, a full picture of the uncertainty of each consumer's flexibility can be concisely parameterized (through the β^{τ} that appear in the diagram of Figure 2.2).

The following stage of the process is to find representative groups of consumers within the sample with similar expected responsiveness according to the previously modelled individual flexibility representations. With the aim of later allocating consumers of the population that are out of the sample to one of these categories, a set of personal characteristics of the analysed consumers will be used to build a decision tree that will assign a flexibility category to each new participant[15]. This decision-making tool is not only a key element in the procedural guideline for implementation of a DR program but also a very informative instrument to better understand the drivers of consumers' flexibility and responsiveness. The details of this step are given in Section 2.3.5.

With a full characterization of flexibility allocated to each participant in the DR program, during real time operation of the DR program, the expected behaviour of each consumer, or group of consumers in an area, could be estimated by combining an ex-ante forecast of electricity consumption in normal circumstances, as proposed in Section 2.3.3, and the consumer's flexibility model.

2.3.3. Quantification of flexibility: the baseline

The first concern is to find an unambiguous definition of flexibility, which is the variable that we aim to characterize. Load flexibility, or responsiveness, can be defined as the ability of the customer to adjust consumption with respect to normal consumption habits in response to an external signal with an economic incentive to do so. Thus, we need to identify a reference load level with respect to which actual consumption must be compared to measure the contribution of a consumer in terms of flexibility. This benchmark consumption is generally referred to as customer baseline (CBL) in the literature (Coughlin et al., 2008; Crowe et al., 2015; Heshmati, 2014; Park et al., 2015) and represents an estimate of the electricity that would have been consumed in the absence of any demand response request or signal. The concept of baseline is illustrated in Figure 2.3.

[15] The methodology is scalable in this sense.

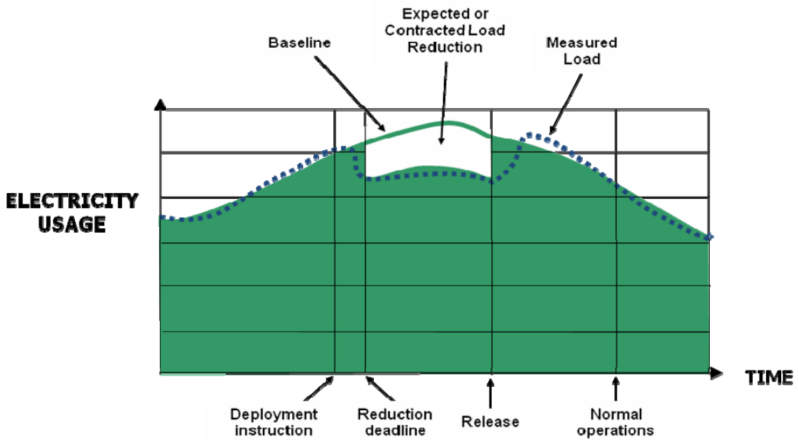

Figure 2.3 Illustration of the baseline concept. Source: North American Energy Standards Board (NAESB)[16]

The notion of baseline comes in very useful to quantify consumer responsiveness in the context of event-based demand response, i.e. when the demand response event, being it a request with an incentive payment or a critical peak price, is clearly defined in the time horizon, has a limited duration and takes place only on certain occasions. As stated earlier, it is presumable that the irregular and occasional occurrence of demand response events does not necessarily disturb normal consumption patterns the rest of the time. As a result, each consumer's behaviour during non-DR event time intervals works as the control group that allows us to establish a reliable baseline to compare the behaviour when a DR signal is sent. This means that the time series of consumption data during the demand response trial period is a valid basis to construct the baseline consumption as long as those values that take place during DR events are taken out of the sample.

It should be noted that the need for a reference baseline is not related to the settlement of the economic compensation for DR, as it is assumed here that this could depend on predefined thresholds instead. Figure 2.4 illustrates the difference between the estimated load adjustment with respect to the expected consumption in the absence of DR (on the left) and the compliance level with respect to the signal threshold (on the right).

[16] http://www.nyiso.com/public/webdocs/markets_operations/committees/bic_prlwg/meeting_materials/2008-10-06/Draft_Wholesale_DR_MV_Standards_Recommendation.pdf

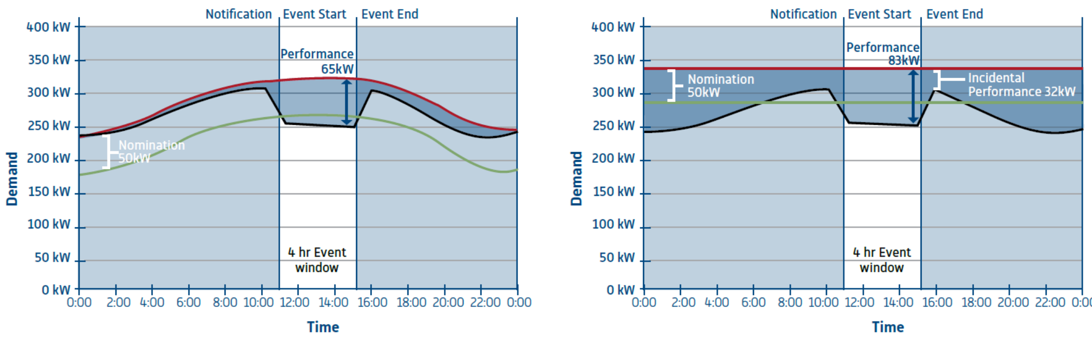

Figure 2.4 Illustrative example of the difference between the compliance level and the performance, or activated flexibility, in the response to a DR signal. Source: (EnerNOC, 2011)

Baseline estimation is a basic step within this methodology in two different situations:

- In the **ex-post quantification of flexibility** observed in the historical record of DR events for every consumer within the selected sample. Flexibility observations in this case are measured as the difference between real consumption and the estimated baseline profile during each DR event.
- In the **ex-ante estimation of the expected normal load** from each individual consumer, or group of consumers, i.e. what they would consume in the absence of a DR signal, during real-time operation of the DR mechanism.

It is assumed that a large history of consumption data from the DR trial period with a high time granularity is available for each individual consumer. The consumers of the sample have been exposed to DR signals of different types and varied intensity and duration. With this in mind, initially the electricity consumption data set is split into two subsets: **DR data** and **non-DR data**. For the reasons stated earlier, the non-DR consumption dataset is the basis for the estimation of the baseline in both situations.

As will be shown in the case study, individual characterization of each consumer is required because of the great variability of flexibility that can be observed from one customer to another. Individual models are much more informative but at the same time they entail greater complexity in the estimation process because individual residential demand patterns present high variability and volatility. As the subsequent treatment of individual information in a large population would be unmanageable, it is proposed that consumers are subsequently classified into typical behavioural categories in a final stage (section 2.3.5).

Another relevant aspect is the time resolution of the consumption data, especially in a potential context of application of the proposed methodology. For peak load or local stress conditions that may occasionally lead to emergency situations in the distribution network, the contribution of DR is more accurately measured in very short (from 5-minute to hourly) intervals, as measured by smart meters, especially if the duration of the signals can be short as well (e.g. shorter than one hour). Aggregation in larger time intervals may hide the real flexibility and the real contribution in terms of load adjustments, as can be appreciated in Figure 2.5.

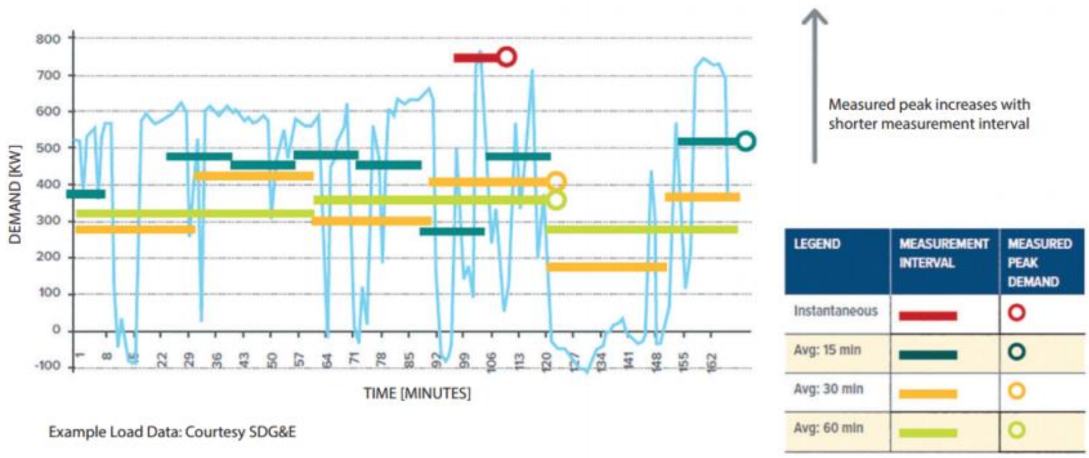

Figure 2.5 Illustrative effect of different measurement intervals on customer peak load of a group of customers. Source: (NARUC, 2016).

An adequate baseline methodology should present a balance between accuracy and simplicity and would always be conditioned by the characteristics of the consumption data, the signal and the consumer (EnerNOC, 2011). A variety of short term load forecasting (STLF) techniques can be chosen to predict a customer baseline. Load forecasting techniques are commonly classified into two major groups: statistical techniques and artificial intelligence (AI) techniques, although the boundary between them is not always clear[17] (Hong and Fan, 2016; Weron, 2006). Statistical methods in general forecast loads through a mathematical combination of previous values of the load and previous or current values of exogenous variables, mostly calendar effects and weather conditions, among others (Hong et al., 2011). In contrast to AI methods, these techniques fail to capture non-linear behaviours, but they commonly perform well in practical applications and present the clear advantage that some physical interpretation may be associated to its components. In addition to a higher transparency, statistical techniques generally present better generalization capabilities than AI methodologies. Statistical techniques cover a broad range of approaches, such as similar-day (or naïve), exponential smoothing, regression and time series methods. Similar-day methods are the simplest approach, as they calculate the baseline as the average demand observed across a number of similar time intervals, given the seasonal nature of electricity consumption, usually applying some exclusion and adjustment rules. Quite the opposite are time series models, which are more versatile as they can capture various aspects of the internal structure

[17] In the literature of current practices in the industry we can find two major trends in electricity baseline consumption modeling: averaging methods, which are analogous to the similar-day approach, and statistical models, which in practice involve some type of regression model (Crowe et al., 2015; EnerNOC, 2011).

of the data, such as autocorrelation, trend and seasonal variation. At the same time, they are more complex to estimate and require a larger history of data (Weron, 2006). Half way in between are regression methods, which estimate load as a (usually linear) function of one or more exogenous explanatory factors, such as weather and calendar variables, and whose area of application extends far beyond load forecasting (Berk, 2015).

Individual smart meter data typically exhibits serial dependence within the demand time series (McLoughlin et al., 2013; Taieb et al., 2016). For this reason, time series models, such as autoregressive moving average (ARMA) models, have been extensively applied to STLF. In the ARMA model the current value of the time series is expressed linearly in terms of its past values (AR(p)) and in terms of previous values of the noise (MA(q)).

ARMA models describe a stationary stochastic process. As electricity load data is widely known to be non-stationary, a generalization that explicitly includes differencing in the formulation is commonly applied, the autoregressive integrated moving average (ARIMA) or Box-Jenkins model. In addition, the electricity consumption time series presents different seasonal blocks (hours of a day, days of a week, months of a year, and so forth). Seasonal ARIMA models (SARIMA) are able to capture these seasonal and other periodic patterns by including additional seasonal terms in the ARIMA models (Weron, 2006). It is also well known that load time series can be influenced by present and past values of exogenous factors, especially ambient weather conditions. The problem is that these time series models allow for the inclusion of information from the past observations of a series, but not for the inclusion of other information that may be relevant. Thus, a generalization of the previous models, denoted as a **transfer function model with a white noise SARIMA component**, which also includes exogenous variables, is finally chosen as the best alternative for individual baseline estimation. Sometimes this model is also called **dynamic regression model**, although there is no consensus among the practitioners in this sense[18].

The first step of the empirical model building procedure is the identification of the model structure (for instance, the degrees of the respective autoregressive and moving-average polynomials or the order of differentiation of the series to turn them into stationary) (Berk, 2015). There are different procedures for this, such as the ones described in (Box and Jenkins, 1976) and (Pankratz, 1991). In the process of identifying the model specification, the fitting should be guided by the principle of parsimony, by which the best model is the simplest possible, this is, the model with the fewest parameters that better describes the data. Following (Weron, 2006), the identification can be performed by looking at the autocorrelation and partial

[18] In this thesis, both terms are used indistinctly.

autocorrelation functions (ACF and PACF, respectively)[19]. To avoid dependence on visual inspection, an alternative automated iterative procedure consisting of fitting different possible model structures and using a goodness of fit statistic or information criterion can be used to select the best model. In general, by increasing the complexity of the model structure (that is, the number of parameters) we get an artificial improvement in the fit. The Information criteria compensates for this by penalizing the size of the model. Some possible goodness-of-fit statistics are the Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC).

The exogenous variable that is included in the models is the hourly ambient temperature, as usual in STLF. Other factors could be added in, such as electricity prices; however, it is assumed in the context of the application of this methodology that electricity rates to which the consumers are exposed are either invariant in very long periods or even if they have block or hourly modulation, they present similar patterns from day to day so that they have a stable and almost permanent influence on normal daily habits, already inherent in the structure of the demand series. It is the effect of occasional explicit DR incentives over these normal consumption habits that constitute the baseline that is of interest here.

It is suggested that the transfer function model is used both for ex-post and ex-ante baseline estimation, although simpler methodologies could be applied to the ex-post analysis without a significant loss of accuracy in certain circumstances. This is because the ex-post estimation relies not only on historical consumption data before the DR event but also on load values following the DR event. The implications of applying one or another in the ex-post quantification of flexibility were explored in the data of the case study of this chapter; in particular, some interpolation techniques were tested.

2.3.4. Probabilistic characterization of flexibility

Once the baseline profiles are estimated for each consumer *i* and each interval, or time slot, *t* of each DR event, a set of flexibility observations can be computed along the DR data set for each consumer as:

$$Flex_{it} = L_{it} - L'_{it} \tag{1}$$

[19] Autocorrelation measures the direction (positive or negative) and strength of the relationship among observations within a time series at different points of time. The partial autocorrelation of the time series y_t at lag n is the amount of correlation between y_t and y_{t-n} that is not already explained by the fact that y_t is correlated with other lags and these lags are correlated with y_{t-n}.

Where L_{it} is the observed load and L'_{it} is the predicted baseline consumption, for all t belonging to the DR data set of consumer i.

Note that instead of individual consumers, groups of consumers or representative typical consumers can also be modelled equivalently although this approach is preferred because representative consumers can be identified in a subsequent stage. A high amount of observations of different characteristics allows us to characterize the flexibility of each consumer, or consumer type, in relation to a set of controllable and non-controllable factors, such as type of request (downward or upward), volume of the signal, intensity of the economic incentive, outside ambient temperature and time factors, among others. For this reason, as will be explained in 2.4.3, it is very important that the signal testing procedures carried out in the trial period are designed to capture a wide variety of combinations of these characteristics avoiding any bias.

Regression methods are able to capture that dependence relationship. Notwithstanding, classical linear regression models (LRM) exclusively focus on the conditional mean of the dependent variable and do not consider its full conditional distributional properties (Davino et al., 2014a). This is a drawback of LRM in this context because it is never fully certain that consumers will respond as desired to DR incentive signals and the nature of their response is not necessarily intuitive as it is conditioned by many implicit behavioural factors. As mentioned, the aim or the suggested approach is to depict the full picture of uncertainty and variability of each consumer's flexibility profile by modelling the impact of the explanatory variables on the full conditional distribution function of flexibility based on observed responses. This is particularly relevant since the final step of the methodology aims at classifying consumers according to their response to the incentives.

A common approach to do this is to assume a form of the conditional distribution (e.g. a normal distribution), and estimate its corresponding parameters form data (Taieb et al., 2016). However, it may not be realistic in the framework of demand responsiveness to assume normality in the distribution of flexibility. In a risk management context, two common deviations from normality that generate special concerns in expected returns or, in this case, expected responsiveness for a given incentive, are fat tails[20] and skewness[21]. For example, a DR provider could find it preferable to count on demand responsiveness from a group of consumers with lower conditional mean of expected flexibility[22] for a given incentive with

[20] Fat-tailed refers to a distribution with a higher probability of observations occurring in the tails, or extreme events (such as would be a very low or very high response in this case), relative to a normal distribution.
[21] Skewness is a measure of the lack of symmetry in the shape of the probability density function. A risk manager is more concerned when there is a higher probability of a large negative return than a large positive return.
[22] The conditional mean would be estimated with the traditional linear regression model.

respect to another group of consumers if the distribution of that flexibility presents a lower risk of poor responsiveness, e.g. if it presents a lower probability of occurrence of extremely low response values (thinner tails).

Quantile Regression (QR) is chosen for characterizing the full conditional distribution function of flexibility because it represents a very general approach as it does not make any assumption on the type of distribution. More specifically, QR models separately any conditional τ-quantile of the distribution of the dependent variable for a set of Q probabilities τ_j for $j = 1, \dots, Q$ in relation to the covariates. Thus, by modelling a set of equally spaced conditional τ-quantiles (e.g. every 1% or 5%), the shape and scale of the conditional distribution as well as its central location can be characterized (Hao and Naiman, 2007).

The classical linear functional form for the conditional quantile function (Koenker, 2005) is used, as shown in Eq. 2, where the regressors are the observed or expected values of the of the P exogenous variables X_k, $Q_\tau(Flex_i)$ is the τ-quantile of the flexibility of consumer i, and $\beta_{i,0}^{\tau}$ and $\beta_{i,k}^{\tau}$ are the quantile coefficients that characterize each consumer's flexibility quantile function:

$$Q_\tau(Flex_i) = \beta_{i,0}^{\tau} + \sum_{k=1}^{P} \beta_{i,k}^{\tau} X_k \qquad (2)$$

The estimation of the coefficients of the quantile functions is carried out following the standard minimization of the asymmetric least absolute deviation loss function. The most common approach to estimate quantile regression curves is to fit a function for each target percentile individually. In the end, this approach could lead to a loss of monotonicity (i.e. the quantile curve should be increasing as a function of the probability index τ), or quantile crossing (Davino et al., 2014b). Thus, a non-crossing restriction is added to the estimation of the target percentiles, following (Bello et al., 2017). If a sufficiently large set of quantiles were modelled with QR, and quantile crossings were avoided, the predictive distribution could be recovered completely from the regressed quantiles at any time using interpolation.

Following the principle of parsimony, the final selection of variables has been based on the minimization of **Schwarz Information Criterion (SIC)** (Koenker, 2005). The set of explanatory variables X_k of the QR could include the properties of the DR signal and other surrounding factors, such as:

- The direction of the request (upwards or downwards)
- The incentive provided (per time unit or as an equivalent price per consumption unit)
- The duration of the signal
- Exogenous factors that affect the demand, e.g. the ambient temperature.
- Type of day or time of the day

Instead of including these relevant factors as explanatory variables, given a sufficient amount of data are available, separate specifications of the QR models could be used for different categories of these variables. For instance, separate models could be defined for upward and downward signals or for different types of days (week days and holidays) or hours of the day, or combinations of both.

Each individual consumer, or consumer group, and percentile would present different explanatory variables if the choice is optimized independently. The alternative of simultaneously select the explanatory variables for all consumers and percentiles can also be convenient if consumers are expected to be classified afterwards in relation to the coefficients of the QR functions, as proposed in the next level of the methodology.

The individually estimated conditional distribution of flexibility as a function of a set of controllable and non-controllable variables by means of QR constitutes a flexible and informative tool to characterize the flexible behavior of a group of consumers. On the one hand, QR formulation is particularly flexible because it allows to model single (or aggregated) consumers at a convenient computational cost while it provides a concise parametric representation of consumers (through the estimated coefficients $\beta_{i,0}^{\tau}$ and $\beta_{i,k}^{\tau}$) that allows a straight application of classification methods on the modelled individuals, as suggested in the following stage of the methodology. On the other hand, QR depicts a full picture of uncertainty and variability of the expected flexibility of a consumer without assuming a specific parametric distribution and from which valuable risk measures can be directly evaluated.

More precisely, a common probabilistic measure of risk exposure, which is the Value at Risk (VaR), could be directly translated into **Flexibility at Risk (FaR)** function. In parallel with the concept of VaR, the FaR function could be defined, for a given probability p, as the lower threshold of flexibility such that the probability that the flexibility provided by the customer for a given incentive (and a set of other surrounding factors) were below that value is p. In other words, the FaR function would provide the lowest flexibility value that could be expected (1-p) % of the time, conditional to the explanatory variables, where the FaR would simply be the QR model equation for percentile p. It would be upon DR provider to choose the risk exposure level p of interest, usually 1% or 5%, to specify the worst-case quantile. Similarly, an extension of FaR, the **Conditional Flexibility at Risk (CFaR)**, would be the average of the flexibility values that already fall behind the flexibility at risk (below percentiles P1 or P5), this is the expected value of flexibility in unfavorable circumstances. CFaR could be estimated as the probability-weighted average of the values of flexibility that could be observed below the FaR. Both measures, which have not been found in the context of demand response and under these denominations anywhere else, could be powerful indicators of the risk exposure of the

DR provider in relation to each consumer, or consumer group, participating in the demand response scheme.

2.3.5. Classification of consumers based on their flexibility

Flexibility is more complex to predict than normal consumption behaviour. While usual electricity consumption is conditioned mostly by daily activities and weather conditions, many economic and behavioural factors affect the ability and the willingness of consumers to be responsive. It is assumed that in the context of application of this methodology a set of customer-specific personal characteristics and environmental factors associated to the participants in the DR program or trial are known. In this step, we focus on understanding which of these characteristics would have an influence on their flexibility through unsupervised learning algorithms.

As these customer-specific properties are in principle constant throughout the development of the test, they are ignored in the construction of the individual QR models proposed at the previous stage. Instead, these factors play a significant role in the categorization of consumers according to the characteristics of their flexible load behaviour contained in the QR models.

The first step is to partition the sample into a **reduced number of clusters** through the application of a simple clustering algorithm such as K-means on the coefficients of the individual QR models, which contain a rich parameterized description of the flexible behaviour of each consumer. The number of clusters cannot be know a priori and would be case-specific, so certain evaluation criteria should be used to decide on the optimal number of flexibility categories that each population may present. As a result, by assigning each consumer to one of a limited set of flexibility categories, the complexity of the characterization of the sample is significantly reduced making it more suitable for a realistic implementation of a DR programme without renouncing the probabilistic representation.

With the aim of allocating consumers that are out of the sample to these new categories or consumer types, for instance to scale the characterization of flexibility to the whole population from which the sample has been extracted, a **decision tree** can be built. A decision tree classifies observations based on a set of decision rules that are applied in a sequential manner, where the ramifications in this case would represent the personal characteristics of consumers. For this purpose, an automatic procedure, such as the ID3 algorithm (Quinlan, 1986), splits the data into successively smaller groups of a single category and iterates to identify the attributes and values of the variables that better explain the division. In order to avoid over fitting the data, stopping rules control the growing process so not all variables are always finally included in the decision tree. As a result, a symbolic representation of the classification rules of consumers into the different categories is obtained which can be easily applied to new consumers as long as we have information regarding the personal characteristics that appear in the tree.

2.4. Case study based on a real experience

The present section describes a case study based on a real demand response pilot experience that has been used to illustrate the presented methodology. The practical application of the methods previously exposed on real data has shed light on two relevant subjects:

- The nature of residential electricity consumer responsiveness to economic incentives.
- The key aspects that have to be considered in the design of a DR trial program that would precede a real implementation at a larger scale.

2.4.1. The data set and pilot program description

The basis of the case study is a demand response field test that was carried out in the Spanish city of Castellón de la Plana[23], in the context of the European research project ADDRESS[12]. The aim of the field test was to empirically validate the downstream segment of the active demand (or demand response) chain for consumers connected to the distribution network, i.e. the interaction between the aggregator and the consumers, regardless of the usage of aggregated flexibility in the electricity system. More precisely, among the objectives of the pilot program were: the technical testing of a series of proposed solutions for home system infrastructure, the corroboration that the aggregator functionality could work effectively and the validation of consumers' social acceptance and commitment with active demand. More details regarding the description of the pilot site, the objectives of the research project and the results obtained can be found in (Barbato and Carpentieri, 2012; Bouffard et al., 2011; Caujolle et al., 2011; EU, 2008; Eyrolles et al., 2011).

Thanks to the demand response experiments carried out with real electricity consumers in the context of the ADDRESS project in the Spanish field test, it is now possible to look further into the collected data to understand responsiveness to economic incentives and illustrate the proposed methodology to characterize and study consumer flexibility with real data.

[23] This Spanish pilot test was developed by the DSO *Iberdrola Distribución Eléctrica, S.A.*, within the framework of the ADDRESS Project, co-funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 207643 (http://www.addressfp7.org/).

2.4.1.1 *The pilot program*

The Spanish field test of the ADDRESS[12] project was especially dedicated to the technical validation of the interaction between the aggregator and consumers under a proposed technical and commercial framework. The aggregator or DR provider, indistinctly, is assumed to be the key intermediary in charge of gathering the responses of individual consumers to build aggregate flexibility services for other agents of the electricity system. The aggregator is therefore expected to be connected to all involved customers with whom they exchange information, signals, requests, etc.

In the field test of this case study, the gateway through which a simulated aggregator communicated with each of the participant residential consumers was the Energy box (Ebox). This device coordinated the load of a set of controllable appliances at the consumers' facilities and optimized the aggregate load profile in response to the signals received from the aggregator, considering a set of personal customer preferences and objectives.

The conceptual architecture of the pilot is presented in Figure 2.6 (blue lines represent the information exchanged within the pilot while red lines represent information that would be handled by the DSO).

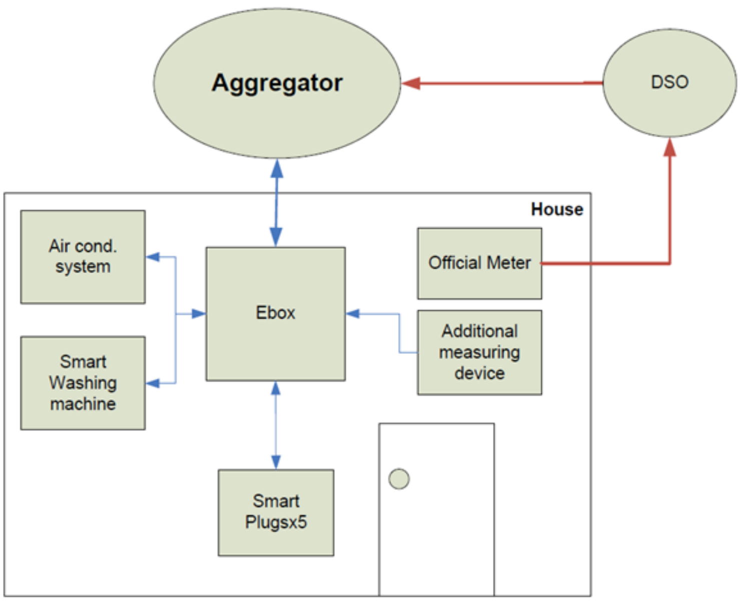

Figure 2.6. Overview of the technical architecture of the Spanish field test of the ADDRESS project. Source: (Eyrolles et al., 2011).

The program was designed for the management of around 260 consumers, most of which had only the basic set of instrumentation: the Ebox, an additional metering device, other than the official smart meter, and several smart plugs for controllable appliances, such as the dryer, the water heating, the refrigerator, the air conditioning, and other customer-specific additional ones. Only a few of them also had more sophisticate smart appliances (e.g. an air conditioning system or a smart washing machine) and separate metering systems (clamps) for individual devices (see a fully equipped home in Figure 2.7). Previously to the start of the field test, Advanced Metering Infrastructure (AMI) had been fully deployed in the area, including smart metering and data management systems for all participants. Collected information regarding electricity usage throughout the development of the field test was collected in the aggregator's server. During the project, a series of technical incidences occurred with the metering and communication infrastructure, that led to difficulties in the reception and recording of part of the information, as could have naturally been expected in a test program. As a result, relevant data from only 122 consumers participating in the experiment could effectively be gathered.

Figure 2.7. Schematic representation of a fully equipped home in the pilot program. Source: (Caujolle et al., 2011).

During the trial program, consumers received a series of price & volume (P&V) signals requesting explicit load changes (both downwards and upwards) in return for economic incentives subject to strict compliance with the request, as described in section 2.3.1 of the methodology. The DR request had clear power limits over which the incentive would be provided, start time and duration. Consumers were rewarded based on their actual consumption during the DR event, not in relation to the load adjustment made with respect to their baseline consumption.

The parameters considered in the PV signals include:

- Direction of the request: increase / reduce consumption.
- Number of power bands of compliance the price & volume signal (either 2 or 3), and values of the thresholds (1 or 2) that delimit those bands [kW].
- Time of the day when the action is requested (or start time).
- Value of the economic incentives for each band of consumption [€/time slot].

- Duration of the signal:
    - Two-band signals could last for: 30 min / 1 h /1 h 30 min.
    - Three-band signals: 45 min

For instance, Figure 2.1 represented an example of the load profile of a consumer responding to a two-band downward P&V signal that starts at 16:00 and lasts for one hour. In this example, if the consumer had disregarded the signal and had kept consuming as usual, he/she would not have obtained any incentive but by lowering demand below the threshold, he/she can get 0.5 €.

At the consumers' premises, the Ebox carries out an optimization and schedules the functioning order of certain appliances communicating these orders directly to the devices through the smart plugs. The consumer may make corrections before the definitive schedule or even decide to deactivate the Ebox from making any arrangements that day (override mode option). The internal algorithm of the Ebox carried out a multi-objective algorithm (González et al., 2011), which included overall cost minimization and personal satisfaction maximization, in relation to comfort and certain scheduling preferences. Thus, even though consumers had technical assistance to manage consumption, both technical limitations (amount and characteristics of the electrical equipment and planned usage in normal conditions) and behavioural factors (personal preferences set in the Ebox, corrections and possibility to ignore the signals received) constrained the final response of consumers to the DR signals.

Assuming there is a sufficient variability of signals with different characteristics, the activated flexibility with different economic incentives, signal durations and thresholds can be empirically evaluated. It should be noted that even though the occurrence of the DR signals was supposed to happen randomly in time, every time a signal was sent, not all customers would receive it. Besides, the characteristics of some signals were not decided randomly (in size, duration, and incentive) but were the result of the aggregator algorithm in response to an overall reduction objective (González et al., 2011). The targeted consumers for these signals were chosen through the same algorithm based on a segmentation[24] of consumers that had been carried out before the start of the pilot based on their average hourly load profiles, from December 2011 to December 2012, for different types of days and seasons (Caujolle et al., 2011). The reason for this is that the functionality of the aggregator was also being tested. Therefore, the sample of signal types appointed customers is not strictly random. Nonetheless, the data variability is sufficiently complete to illustrate the application of the methods previously

[24] Note that this clustering was done before any DR intervention had ever occurred, so it does not interfere with the classification that is proposed in the presented methodology to categorize consumers based on their flexibility, not in relation to normal consumption habits.

described, even if the conclusions that could be drawn from the quantified flexibility are very specific of this case study.

2.4.1.2 *The data set*

The data set is composed of interval load data (every 5 minutes) collected through the additional measuring device, which can be observed in Figure 2.7, from 122 individual consumers who participated in the demand response field test from 1st December 2011 to 31st July 2013, with different starting dates.

No. consumers	No. signals	Start of data record	Start of pilot (signals)	End of pilot and of data record
122	129	01/12/2011	01/06/2012 (8784 pre-pilot hours)	31/07/2013 (5856 pilot hours)

The data record starts on the 1st of December 2011, but it is not until the 1st of June 2012 that the signals start being sent to customers. The pilot ends on the 31st of July of 2013, lasting for 13 months in total. In total, 129 signals of different characteristics were sent to different groups of consumers (55 were downward and 73 were upward). Note that baseline and flexibility are computed separately for each time interval, or slot, determined by the granularity of the data series (from 5 min to 1 h) and per consumer. Therefore, the sample of responses grows considerably with 5-minute interval data, as each signal of one hour would be composed of 12 observations per consumer. The timing of the signals concentrates mostly between 13:00 and 21:00, the period of higher consumption among residential consumers in this region.

In addition to key indicators describing each consumer's normal consumption characteristics, e.g. average yearly consumption (MWh) or contracted power (kW), and the hourly measurement of the outside ambient temperature (ºC), the following personal information was gathered from each of the pilot participants through personal interviews:

- Physical and technical variables:
    - Type of dwelling (flat, cottage, detached, semi-detached or duplex flat)
    - House size (number of rooms in the house)
    - Number and list of appliances divided into different types of loads (interruptible, shiftable and not controllable)
    - Level of thermal insulation (very well, sufficiently or poorly insulated)
    - Presence of electric water heating with / without thermostat
    - Presence of electric heating with /without thermostat
- Socio-economic aspects:

    - Occupancy in the morning during weekdays (occupied, unoccupied except lunchtime or irregular)
    - Number of people living in the house and ages (in ranges)
    - Share of income spent on electricity (slight, moderate, significant or no noticeable hardship)
    - Educational qualification of most members of the family (high school or equivalent and higher education – degree/diploma)
- Personal attitude variables:
    - Settings preferences in the Ebox (relative importance of: comfort, savings and availability).
    - Frequency of air conditioning usage (almost every day, only when needed, n.a.)
    - Level of air conditioning usage (in all the rooms, only in some rooms, n.a.)

2.4.2. Findings: Results and discussion

Due to its high granularity, the consumption data of this case study naturally presents irregular patterns and has a considerable amount of missing values. Therefore, an extensive work of pre-processing and cleaning has been required to reject anomalous data and produce quality observations that can serve as input to the methods proposed to provide coherent results.

The daily and weekly periodicity of the non-DR data, i.e. the normal electricity consumption data series, can be observed in the autocorrelation (ACF) and partial autocorrelation (PACF) functions of a single consumer in Figure 2.8 and Figure 2.9, respectively. The ACF and PACF have been computed on the hourly data for greater clarity although 5-minute data has been used in the model estimations. The raw data is clearly non-stationary and presents seasonality at multiple scales (intra-day, weekly, at least).

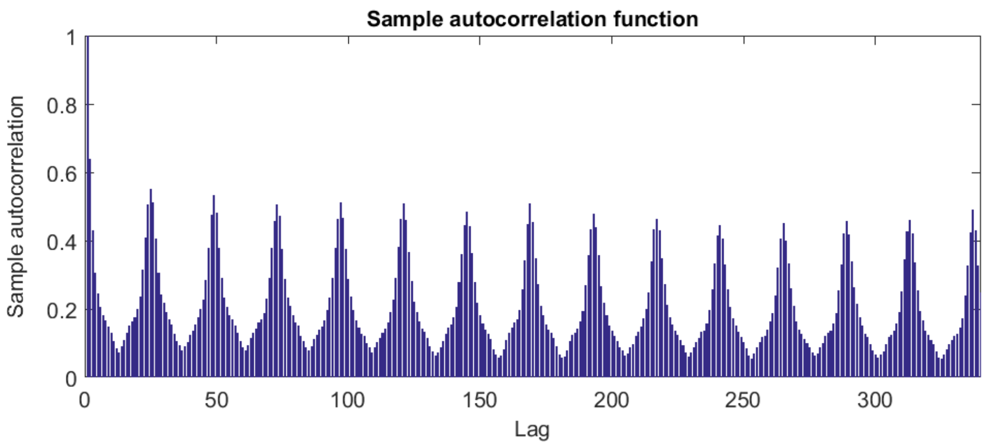

Figure 2.8. Example of the ACF of the hourly electricity consumption of an individual consumer of the sample.

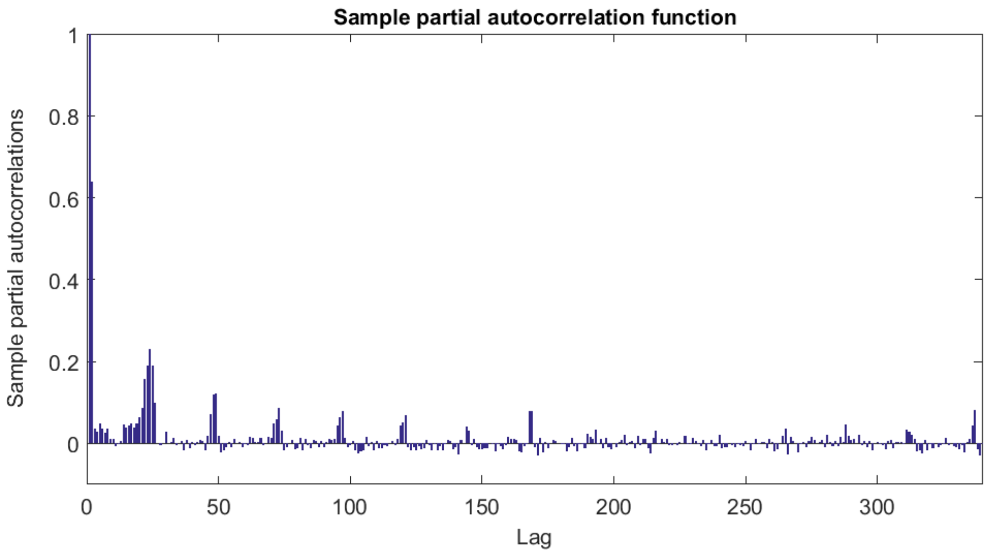

Figure 2.9. Example of the PACF of the hourly electricity consumption of an individual consumer of the sample.

For ex-post baseline computation, specific transfer function models with white noise ARIMA component have been fitted for each consumer and DR signal, with seasonal components that capture the daily and weekly periodicity observed in the ACF and PACF figures. Thus, seasonal orders of 288 and 2 016 have been used in the 5-minute interval data, which correspond to 24 and 168 hours, respectively. In an initial step, a logarithmic transformation, as a particular case of Box-Cox transformation, has been applied to stabilize the variance (Weron, 2006). Due to the large number of baseline estimations required, automatic selection procedures based on the Schwarz Information Criterion (SIC) criteria on have been applied to select the best final structure of each model.

Afterwards, flexibility has been calculated for each consumer and time slot under each DR event by subtracting the estimated baseline from real consumption. Flexibility calculations with the proposed model were compared to the use of simpler interpolation techniques. No significant differences were found between methods for short durations of the DR signals but these differences increased for longer DR events, evidencing the need for the more sophisticate predictive model and its ability to capture the load pattern trend with respect to the naïve interpolation techniques.

Overall, given the preliminary character of the pilot experience under study, an acceptable level of responsiveness could be observed from this ex-post quantification. Figure 2.10 presents the percentage of observations from the whole sample that complied with the DR signals at different hours of the day, i.e. consumed below or above the estimated baseline in the direction of the request, distinguishing between upward (“Up”) and downward (“Down”) requests. As can be noticed, households of the pilot programme were slightly more likely to respond positively by reducing consumption when asked to do so than to increase it. The absolute quantities of observed flexibility present a high variability between consumers and observations, which is finally captured through the quantile regression models.

Quantile regression (QR) models have been fitted in this case study for each consumer's flexibility as observed throughout the pilot period in relation to a set of explanatory variables, which have been chosen using backward elimination methods, following (Bello et al., 2017). Among the variety of explanatory factors under consideration (see 2.3.4), the incentive provided and the temperature were found to be statistically significant for the sample under study. Separate models have been inferred for upward and downward signals but it was not possible to define separate models for different periods of response, e.g. one model per type of day or per hour of the day, due to the relative scarcity of signals in the sample.

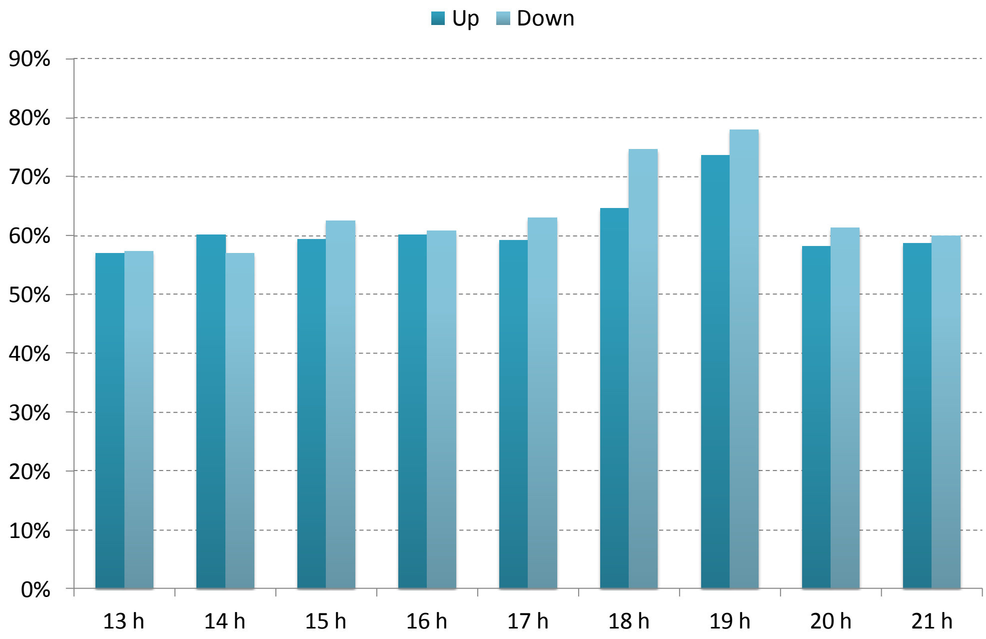

Figure 2.10. Percentage of compliance with upward and downward signals at different hours of the day on the pilot data

QR modelling provides useful information regarding the effect of the predictors on the shape of the distribution function of flexibility. For illustrative purposes, Figure 2.11 and Figure 2.12 examine how the coefficients associated to the incentive as explanatory variable estimated for the QR specification of a single consumer vary along the range of percentiles for "Up" and "Down" signals, respectively. The coefficient associated to each percentile τ can be interpreted as the rate of change of the τ-quantile of the distribution of expected flexibility per unit change in the value of the regressor in question, which in this case is the incentive value. It should be noted that all variables are normalized to per unit (p.u.) values (from 0 to 1) so the coefficient units are p.u. (load flexibility)/ p.u. (economic incentive). As can be seen in both figures, the effect of the economic incentive is significantly positive on flexibility for all values of the τ-

percentile but it is by no means symmetrical between "Up" and "Down" requests. The shape of the upward-sloping curves indicates that this positive effect increases with the percentile, being this relationship especially steep for high percentiles for the "Up" signal in this example[25]. QR demonstrates its potential to capture the complex and not always intuitive relationship between responsiveness and economic signals or any other influencing factors.

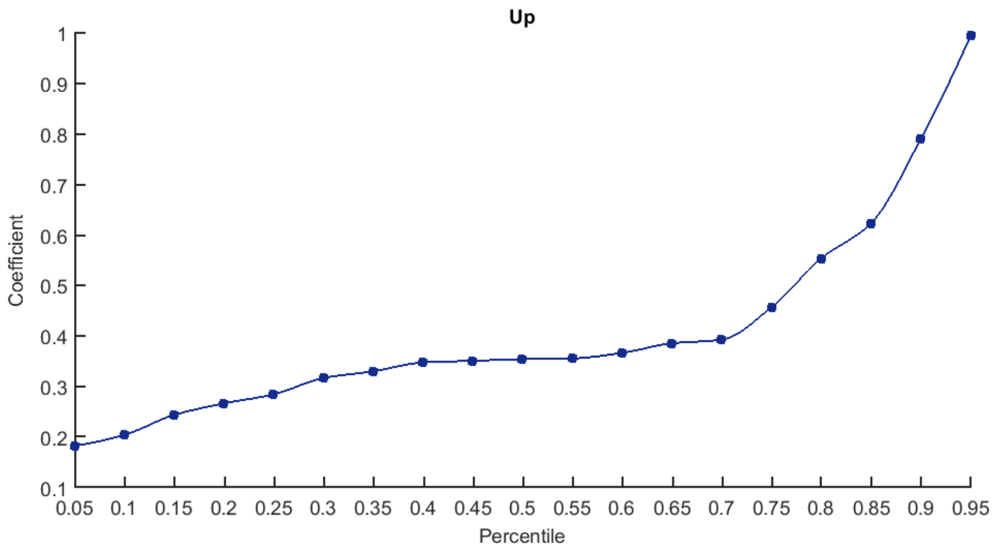

Figure 2.11. Variation of the coefficient β associated to the value of the incentive along the percentiles in the QR model of flexibility of a single consumer in response to upward signals.

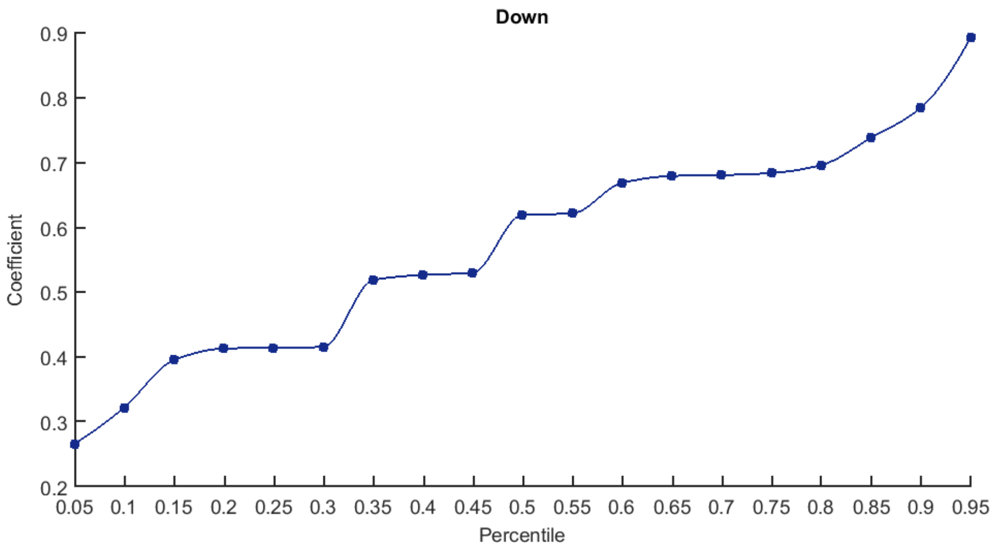

Figure 2.12. Variation of the coefficient β associated to the value of the incentive along the percentiles in the QR model of flexibility of a single consumer in response to downward signals.

[25] The presented examples are only illustrative and are not aimed at drawing general conclusions for all consumers.

As explained in 2.3.5, the coefficients of the individual QR models provide a descriptive and concise characterization of each consumer's responsiveness and allow for a straightforward categorization of consumers in relation to their flexibility. The application of a clustering algorithm on the parametric representation of each consumer is flexible to any final specification of the models, as long as there is coherence between consumers. For instance, it could be directly applied to the whole set of coefficients of their individual QR models that define each consumer. Alternatively, only a subset of these coefficients that is deemed more representative or relevant could be used, e.g. the ones that belong to the equation of the conditional percentile 50 (P50), or median, of flexibility.

As an illustrative example of the applicability of the proposed approach, consumers of the sample have been partitioned into a limited set of consumer classes through a basic K-means clustering algorithm applied on the QR coefficient β associated to the incentive value for the median, or P50, of the variable flexibility to downward signals. This coefficient alone is a good measure of consumers' sensitivity to the economic incentive associated to the request to reduce consumption.

The quantization error[26] (QE) allows us to find the optimal number of clusters. As can be seen in the elbow of the Pareto type Figure 2.13, a trade-off between minimal QE and minimal complexity (reduced number of clusters), is found in K = 3. The three categories of consumers identified in the sample have been labelled for greater clarity and simplicity as "High", "Moderate" and "Low", in reference to their responsiveness to the incentives.

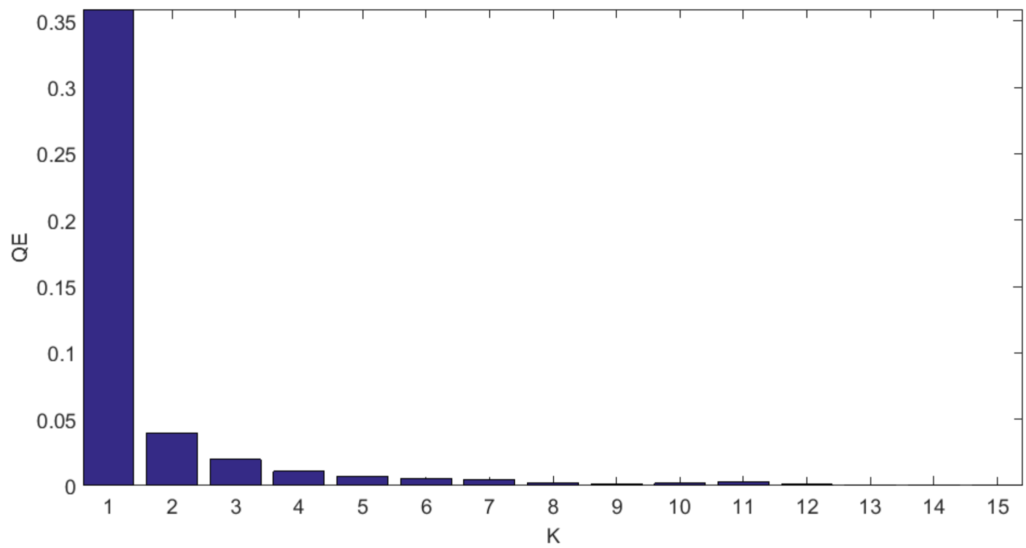

Figure 2.13. Quantization error (QE) for different numbers of clusters (K)

[26] The quantization error (QE) measures the sum of squared distances of the observations to their respective cluster centroids.

Finally, a decision tree has been built for the three flexibility categories of responsive consumers with information of their personal characteristics. The variables that turned out to better explain the division of consumers from this sample into the defined flexibility categories are:

- Electricity consumption, as a measure of the energy intensity of the household (expressed in MWh/year).
- The number of occupants in the house.
- The number of rooms, which is indicative of the size of the house.
- The level of education of the house dwellers (coded as 0 if the dwellers had a qualified education and 1 otherwise).

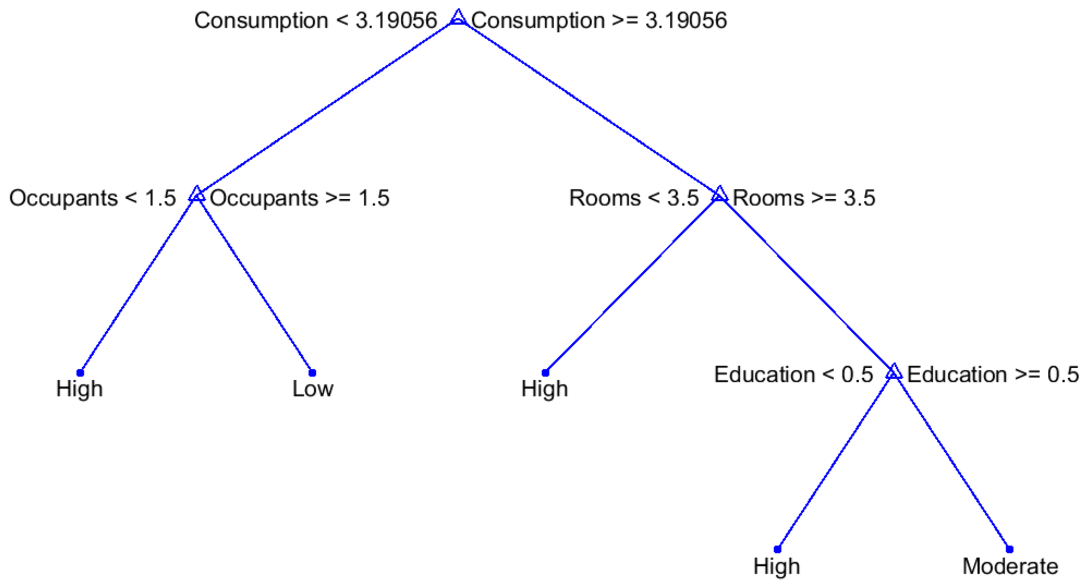

Figure 2.14. Decision tree that classifies the sample of consumers into "High", "Moderate" or "Low" flexibility groups

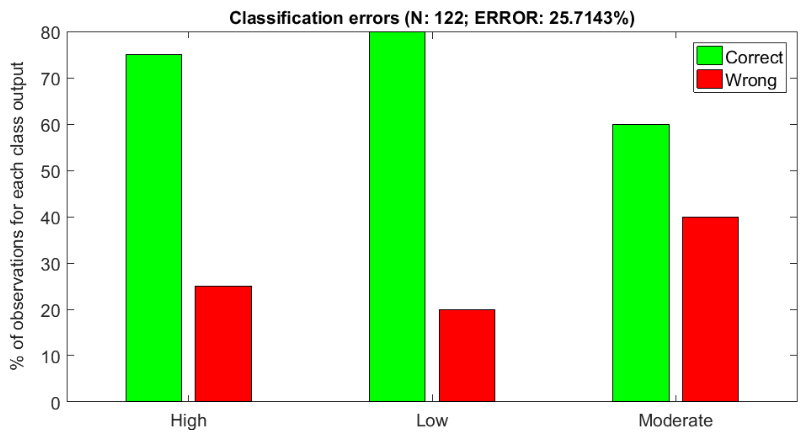

Figure 2.15. Percentage of observations in the training set correctly classified with the resulting decision tree

The resulting decision tree is presented in Figure 2.14, for which the classification errors made on the training data set are depicted in Figure 2.15. In this particular example it is interesting to observe that the physical variables that give an idea of the size of the consumer (yearly electricity consumption and number of occupants and rooms in the house) are key determinants in the distinction of consumers regarding their flexibility. The education level also appears to have a great relevance to boost the potential flexibility in this particular example. A relevant feature of the decision tree is that it allows us to differentiate subclasses of consumers within each division made through an explanatory variable. For instance, apparently, energy saving consumers (low electricity consumption with a high number of occupants) could have limited possibilities to provide additional flexibility while single occupants could be especially flexible even if their consumption is already low in a regular basis.

2.4.3. Practical implications in the implementation of a DR program

The application of the proposed methodology to a small-scale case study has illustrated the potential of QR to characterize the variability and complexity of consumer responsiveness and its flexibility to be the basis of the categorization of a wider population into flexibility groups. Therefore, it has the potential of becoming a decision-making support tool for a DR provider contracting and managing the flexibility resource of a large population of consumers. In this section, several practical implications of its potential application to the implementation of a real DR program are briefly discussed.

In a scenario of real application of the proposed approach, special attention should be paid to the design of the trial tests during which sufficiently representative data should be collected to obtain statistically significant results. This representative sample of consumers should be randomly selected from the population that is aimed to be characterized. The size will be conditioned as well by the technical capabilities of the DR provider to collect and process the required amount of data. Assuming there are no major difficulties with the installation of advanced metering and communications infrastructure, the next step would be the realization of the trial program. With the aim of covering a full spectrum of signal possibilities, a wide variety of features should be tested among all consumers: duration, direction of the request, time of the day, type of day, intensity, incentive, etc. Due to relative data scarcity of the case study it was not possible to measure the effects of some of these variables, some of which could have a significant impact on the observed flexibility. Simplicity in the testing could be gained for example through the limitation of the signals tested to a reduced set of configurations that would be afterwards implemented in practice.

Once the sampling process is completed and the trial period has taken place, the characterization of the flexibility of the consumers in the sample can be completed through the application of the methodology proposed in this chapter. With the decision rules drawn from the definition of the decision tree, not only the sample but also a bigger population can be segmented into as many flexibility categories as considered, according to the complexity of the final QR specifications and the available information regarding consumers' personal characteristics. As a result, each consumer with a contract with the DR provider would be concisely represented through the conditional distribution function of flexibility in relation to a set of controllable and non-controllable variables.

From this detailed picture of the flexibility of multiple consumers, any configuration of these groups of consumers in different areas of the network could be characterized from the aggregation of the individual or representative distributions, considering possible correlation effects observed between consumers, or groups of consumers. This aggregation entails certain complexity that should be addressed in detail and is out of the scope of the work developed in this thesis. In this sense, it should be remarked that the aggregation effect of many consumers and a low correlation between them contributes to achieve a lower portfolio risk than the sum of the individuals. With this information, the DR provider could potentially sell aggregated demand response services to a third party, e.g. the DSO, knowing in advance the expected responsiveness of each group of consumers in different locations of the network, and the associated measures of risk obtained, for instance, through the QR aggregate function.

2.5. Conclusions

This chapter has presented an original empirical methodology to obtain a full characterization of a population of electricity residential consumers participating in a demand response scheme regarding their flexibility to economic incentives. The suggested methodology counts on smart meter data collected during a trial period of a hypothetical demand response program. Relying on Quantile Regression modelling of individual observed flexibility, the proposed approach can account not only for expected average values of responsiveness but also for the whole conditional distribution function of flexibility in relation to a variety of controllable and non-controllable variables.

It has been discussed how the proposed use of Quantile Regression constitutes a flexible and informative tool to characterize the flexible behavior of a group of consumers. On the one hand, it provides a concise parametric representation of consumers that allows a straight application of classification methods to categorize a sample of consumers into categories of similar flexibility. On the other hand, it depicts a full picture of uncertainty and variability of the expected flexibility of a consumer from which valuable risk measures can be directly evaluated More concisely, two specific risk measures for the context of demand responsiveness that are directly obtained from the QR models have been proposed and denoted as flexibility at risk (FaR) and conditional flexibility at risk (CFaR).

The proposed methodology has been tested for illustrative purposes in a small-scale case study based on a real experience. This application has illustrated the potential of QR to characterize the variability and complexity of consumer responsiveness to incentives with respect to a set of controllable and non-controllable variables. Furthermore, several practical implications of its potential application to the implementation of a real DR program have been discussed.

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3. Potential benefits of integrating demand response in distribution network operation and planning

In a context of growing need for flexibility and increasing presence of smart technologies in distribution networks, the role of DSOs and the usual practices for grid operation and planning could evolve in future years to integrate Demand Response (DR) to alleviate network congestions and decrease peak capacity requirements, which could in turn reduce or postpone the need for network reinforcements. This chapter explores the mechanisms that would allow DSOs to incorporate DR procedures into their network operation and planning strategies. A methodological approach based on the use of a Reference Network Model (RNM) is presented and used to quantify the potential economic benefits that DR could bring to distribution grids. The analysis is supported by a case study of two rural and urban areas of Spain, based on realistic large-scale exemplary networks and real consumption.

3.1. Introduction

Distribution System Operators (DSOs) are responsible for the secure operation and management of the electricity distribution system and for ensuring network access to new users. They are also required to plan and develop their networks so as to accommodate a potential peak demand increase and the future connection of new loads and Distributed Generation (DG) units (Eurelectric, 2014; Gómez, 2013; Pudjianto et al., 2013), always seeking the maximization of overall economic efficiency. Following the traditional approach for planning and design of distribution networks, under the paradigm of passive behaviour of loads and DG, large investments may be required in future years to reinforce the network capacity in order to ensure a reliable supply of electricity even during periods of critical loading and congestion, which generally occur only a few hours a year (Batlle and Rodilla, 2009). This challenge is particularly relevant in a foreseeable imminent environment of higher volumes of DG and new intensive loads, such as electric vehicles (EV) and public charging stations, connected to low voltage levels (Siano, 2014).

In this challenging context, the recently rising deployment of advanced metering infrastructure (AMI) and information and communication technologies (ICT) could modify this paradigm. More specifically, by allowing network users to interact with the market and the network operator, traditionally passive consumers could become active players. Thus, innovative forms of Demand Response (DR), in the form of time-varying price, requests of load changes or feedback about individual consumption, could be developed at local level for a more active and smart distribution network management (CEER, 2014b; Eurelectric, 2010; SEDC, 2016). As discussed in chapter 1, DR is believed to offer a broad range of potential benefits across the different stages of the value chain of electricity supply, through a more efficient allocation of resources on system operation, system expansion and market efficiency of electric power systems (Braithwait et al., 2006; CEER, 2014a; Conchado and Linares, 2010; DOE, 2006; Siano, 2014; Strbac, 2008). Particularly, at distribution network level, DR could become a new valuable resource for network operators to face the mentioned challenges. Following the characterization of demand-side flexibility of residential customers that has been proposed in chapter 2, it is interesting to focus now on the value this flexibility can bring locally to distribution networks. As will be further discussed in this chapter, if DSOs were allowed to use flexibility services from the demand-side provided through DR or other local flexibility sources[27] to solve capacity constraints on the network, grid reinforcements could possibly be partially avoided or deferred, if that were the most efficient option (Andreas Schröder, 2011; CEER, 2014b; Poudineh and Jamasb, 2014; Pudjianto et al., 2013; Sheikhi Fini et al., 2013; Veldman et al., 2013). It is therefore becoming increasingly necessary that DR mechanisms can be integrated as a resource for distribution network optimization already in the planning stage in order to make the most efficient use of the grid capacity (CEER, 2014b).

One of the key challenges of this likely future scenario is to understand how demand-side flexibility could be effectively incorporated into DSO operational strategies and the implications it would have in network planning. A proper definition of the procedures to incorporate DR and the ex-ante estimation of the potential economic benefits would facilitate the evaluation of the cost-effectiveness for DSOs of investing on DR and the suitable design of such mechanisms in the future. Due to the relatively scarce experience on DR to support distribution network management, these issues largely remain to be solved. In fact, the ability of DSOs to resort to DR to support the operation and planning of their grids has been negligible up to now, except for a variety of pilot programs and innovation projects in various countries, e.g. in UK (Cesena and Mancarella, 2014), the Netherlands (Veldman et al., 2013), Sweden (Bartusch and Alvehag, 2014) and France (Levaufre et al., 2014).

Several studies have recently been conducted to investigate the regulatory conditions and the technical aspects required for the practical implementation of DR to support distribution network operation and planning. For instance, the authors of (Pilo et al., 2014) review current practices in distribution network planning and looks into the adaptation of traditionally passive methodologies to incorporate an active management of local resources, in (CEER,

[27] Including energy storage and the dispatch of DG.

2014a) the regulatory aspects of the potentially active role of DSOs are explored and in (Poudineh and Jamasb, 2014) a market-oriented approach to defer network investments with the aid of Distributed Energy Resources (DER), including DR[28], is proposed. Even so, the quantification of the potential economic benefits for distribution networks has not been sufficiently investigated in the literature. Numerous studies explore consumer responsiveness to DR initiatives but do not stress the economic value of that response for the distribution network or its implications in network planning. Only a few studies have been found that explore the potential of DER, in general, as operational resources to support distribution network management, being it e.g. responsive demand to locational price signals, as in (Liu et al., 2014) and (Morais et al., 2014), demand response and energy storage, as in (Andreas Schröder, 2011) and (Pudjianto et al., 2013), peak load control, as in (Veldman et al., 2013), or centralized management of electric vehicles, as in (López et al., 2015). It is generally observed in these studies that either different instruments to implement DR are not distinguished, only simplified network topologies are used or, with the exception of (Pudjianto et al., 2013) and (Andreas Schröder, 2011), investment decisions and costs are not explicitly addressed.

The main objective of this chapter is to explore the potential applicability and economic benefits of DR as a tool for a more efficient distribution network operation and planning. For this purpose, a methodological approach to evaluate the economic impact of DR use by DSOs, when different options of implementation are considered, is presented. This methodology relies on the evaluation of the potential ability of DR to defer planned distribution investments by alleviating local peak capacity. The market and regulatory conditions that could enable DSOs to put these mechanisms into practice and capture this economic value are dealt with in chapter 4. The proposed approach would require the utilization of the methodology suggested in chapter 2 for the characterization of consumer responsiveness to economic incentives to quantify the costs of activating DR for different scenarios of DR participation and efficacy. It should be noted that this dependency is only theoretical, as will be explained in section 3.3.3, because the scarcity and poor representativeness of the estimations obtained in the previous chapter made them unsuitable for scalability and application in the quantitative analyses of this chapter.

The methodology presented here is supported by a case study which is built using realistic exemplary distribution networks based on Spanish locations, with real consumption data and assuming an effectiveness of DR programs as observed in different pilot programs and innovation projects worldwide.

[28] Distributed Energy Resources (DER) include distributed generation, energy storage facilities and Demand Response in the context of distribution networks.

Among the relevant contributions of this chapter with respect to the literature are the proposal and application of a realistic methodological approach that could be used to estimate in advance the potential benefits of using DR as a resource in distribution network planning. The suggested approach relies on the use of a complex network planning tool that allows us to simulate network investment scenarios in very detailed. The proposed case study counts on load profiles that are based on real consumption data, effectiveness levels observed in real DR experiences and realistic MV and LV networks for different capacity requirements. From this quantification of the potential benefits of DR for distribution networks, relevant key factors and contexts that hinder or strengthen the ability of network operators to optimize planning strategies counting on DR can be identified. It should be highlighted that the contents of this chapter are based on the journal paper (Vallés et al., 2016) written during the development of this thesis.

The remainder of the chapter is structured as follows. In Section 3.2, the value and implications of incorporating DR into network planning and the mechanisms by which this could be done in practice are analysed. Section 3.3 presents the methodology proposed for the quantification of the economic impact of DR on network planning. In Section 3.4 the case study based on Spanish networks is described. The results and discussion are shown in Section 3.5. Finally, the conclusions of this work are drawn in Section 3.6.

3.2. The value of DR and its realization in distribution networks

In this context of growing need for flexibility and increasing presence of smart technologies in distribution networks, the role of DSOs and the usual practices for grid operation and planning could evolve in future years to integrate DR into the network operation and planning strategies. If DSOs could procure flexibility services from consumers, they would have a valuable tool to operate and plan their networks more actively and efficiently. With the aim of better understanding where the real value of DR for distribution networks lies, this section explores the circumstances in which DSOs could be willing to resort to demand-side flexibility, the procedures by which they could procure this flexibility and the economic implications of this utilization.

There is a variety of situations where a DSO could potentially be willing to make use of the flexibility coming from DR in their network[29] to reduce costs. For instance, in the unexpected

[29] It should be noted that DR could bring opportunities as well as challenges (Pérez-Arriaga, 2013). Critical states in the network could also arise due to certain DR actions that are not driven by network needs or that result in a higher simultaneity of loads or a new local peak, straining network conditions (Gwisdorf et al.,

event of a network element failure, a very fast demand response might be used to assist the restoration of customer supply minimizing the negative impact on customers, e.g. b reducing the duration and costs of involuntary interruptions and the use of stand-alone diesel generators. In more realistic time horizons, such as with a few hours of anticipation or one day ahead, DR could help DSOs to deal with undesired planned or foreseeable situations. For example, in case of planned outages for network maintenance works, DR could possibly let DSOs ease restrictions in the timing and duration of these maintenance works (they would not have to be necessarily carried out at night or during the weekend) and better optimize the availability of human and technical resources for that purpose. In addition, under special circumstances, depending on the characteristics of the power flow patterns in the network and the monitoring abilities at different voltage levels, DSOs could be inclined to have some influence in load behaviour to reduce network losses. Finally, in the event of temporary overloads and congestions, maybe due to the simultaneous occurrence of peak loads or DG injections, DSO might prefer to resort to DR to alleviate those stress network conditions, reducing the need to enhance network capacity with additional reinforcements and possibly avoid or defer planned distribution investments.

Given that the typical cost structure of a DSO is usually dominated by capital costs (investment and financing), it seems clear that the local value of DR in distribution networks is fundamentally driven by the ability of postponing or avoiding planned distribution investments by reducing local peak capacity needs. Ideally, by integrating DR into distribution network planning and operations, it would be possible to manage foreseeable local congestions caused by sporadically coincident peak loads, so that the unused capacity could host another customer's load growth. This way, by alleviating capacity requirements while still satisfying operational constraints and without endangering reliability of supply, DR could result in lower reinforcement needs. In such a scenario, the DSO would need to look at the business case for both the investment solution and the service-based solution and decide on the most cost-efficient combination. Therefore, DR considerations should, if possible, be effectively incorporated in the decision-making process of network planning, which is a rather unusual practice in the long-established planning schemes.

Traditionally, distribution network investments are costly and made for long time horizons (e.g. ten years[30], as in the case study described in Section 3.4). For this reason, the commitment of DR participation to provide distribution relief should be guaranteed to some extent with

2010). Once DSOs could resort to DR as a practical tool for network operation, these problematic situations could be controlled by the DSO or the DR provider in charge of handling the demand-side flexibility.

[30] Ten years is the time horizon used in the case study of this chapter but in theory thirty or forty years is the usual investment horizon and lifetime of network assets.

enough lead time to incorporate it into the network planning process and defer an investment that would have been necessary otherwise. For instance, if grid constraints became visible in the long-term planning process, the DSO could be interested in contracting in advance different forms of DR from the providers of DR that act on behalf of network users. At this stage is where an adequate characterization of demand flexibility of different consumer segments that provides some information regarding the uncertainty consumer responsiveness is extremely valuable.

Regardless of the contractual arrangements in place, DR could be implemented in the DSO perimeter through price signals or other types of interaction with consumers. For instance, cost-reflective network tariff structures could be designed, either centrally or by each DSO, so that a more efficient consumption pattern is incentivized in relation to network conditions, e.g. the form of an explicit charge for installed capacity, Time-of-Use (TOU) volumetric tariffs (Braithwait et al., 2006; Eurelectric, 2013; Picciariello et al., 2015; Procter, 2013) or Critical Peak Pricing (CPP) (Batlle and Rodilla, 2009; Braithwait et al., 2007; Wang and Li, 2011). Instead, network operators could be allowed to procure flexibility services from consumers (via retailers/aggregators) for temporary congestion management of distribution networks by means of direct and specific requests to raise or lower demand (CEER, 2014a), for instance through the procedures described in chapter 2 of this thesis. Alternatively, other forms of interacting with customers would result in promoting a more efficient consumption in the long term, either by offering subsidies for equipment renewal or by raising awareness among consumers through the provision of some feedback about their own consumption. These Energy Efficiency (EE) measures do not strictly fall under the umbrella of DR programmes, but in the context of this chapter they are analysed on an equal footing with DR as a possible mechanism by which peak load requirements could be relieved in distribution networks in an amount that could be easily envisaged long in advance.

As will be apparent in the analysis that follows, the economic value of DR activated for network purposes is case specific and very dependent on the local characteristics of the network and its users. Thus, the methodological approach preferred to adequately assess the potential distribution investment deferral value of DR should be sufficiently general as to allow the consideration of local specifities. From the network topology to the initial level of congestion, including the projected scenarios of load growth, DG penetration, the applicable DR tools and the specific consumption and generation patterns of network users, all these are relevant factors that should be internalized in the economic assessment. Thus, such a methodology would require treating different distribution areas independently and should consider all possible boundary conditions in a strategic definition of investment and DR scenarios. As can be seen in the following section, the presented methodology fulfils these requirements and allows us to observe the relevance of these boundary conditions in a case study presented in Section 3.4.

3.3. Methodology for the economic assessment

This section presents the suggested methodology for the analysis of the potential economic benefits of different models for the promotion of DR in electricity distribution networks. The economic impact of DR is quantified in terms of potentially avoidable or deferrable investments in network reinforcements within a specified long-term planning horizon and with respect to a Business as Usual (BaU) scenario without any option to use DR. In addition to this, the estimated changes in the resulting energy losses are computed. As previously described, the investment deferral is the main source of value of DR for distribution networks, but the energy losses are evaluated too because they are directly related to the electricity demand and could affect the regulated remuneration of the distribution activity. This quantification can be done in specific distribution areas for a variety of scenarios of: type of DR mechanism, consumer participation rate and geographical location of participative consumers. Thus, the methodology serves as a tool to evaluate the convenience of employing DR as resource for distribution network optimization already in the planning stage. With its application to real situations it helps us to better understand the factors that determine the local economic value of DR.

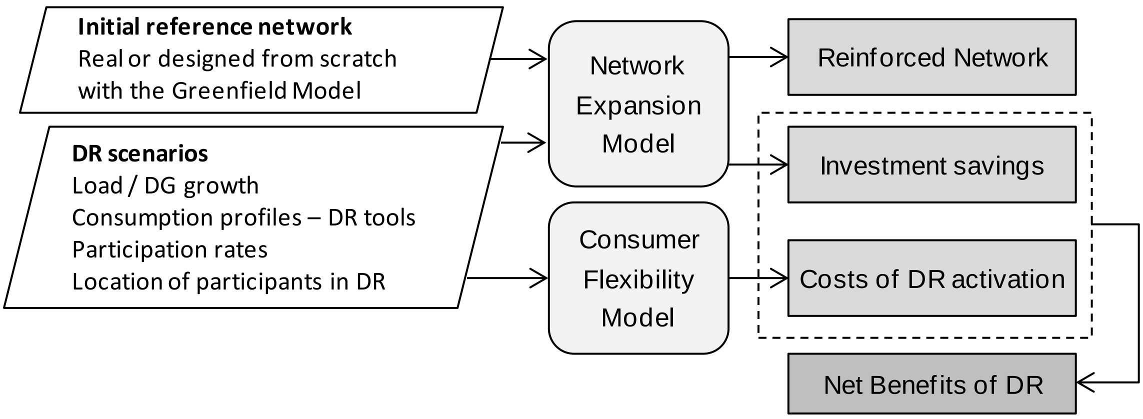

Figure 3.1 Overview of the methodology

An overview of the methodology is presented in Figure 3.1. Initially, a realistic distribution network is designed from scratch using a network planning tool called Reference Network Model (RNM), in its so-called "greenfield" modality, as will be explained in 3.3.1. The expansion version of the same optimization tool allows us to simulate optimal network planning scenarios for different capacity requirements driven by new connected loads and DG and projected load growth, by means of a detailed geographical and technical modelling. These planning scenarios are designed in accordance with network users' load and generation patterns and their assumed commitment to provide DR in future years, as explained in 3.3.2. The net economic benefit of DR implementation would be finally estimated as the difference between the investment savings achieved with respect to the benchmark scenario and the net present value of the estimated cost of activating the necessary DR in each scenario in the years ahead. The so-called "consumer flexibility model" in Figure 3.1 for this purpose would ideally be based on the characterization of consumer responsiveness of the participant consumers following the methodology presented in chapter 2, as described in section 3.3.3. As will be explained, due to insufficient consumption and responsiveness data, the quantification of DR costs for different scenarios is only addressed theoretically and has not been included in the case study presented in this chapter.

3.3.1. Quantifying the investment deferral value of DR

In the context of this methodology, a large-scale distribution planning tool, named Reference Network Model (RNM), is used to build exemplary realistic networks and estimate the efficient reinforcements that would be necessary (and the resulting energy losses) to meet the local demand growth in a specific planning horizon and with different load assumptions for different DR scenarios.

The RNM, presented in (Gómez et al., 2013; Gonzalez-Sotres et al., 2013; Mateo et al., 2011), is a software tool made up of optimization models that are able to design an electrical reference network for a very large distribution area. A reference network is a theoretical but realistic quasi-optimal grid that is subject to the same geographical, technical and quality of supply constraints than the actual network. The RNM has two modalities: the "greenfield" model and the expansion model. The former designs an optimal network from scratch while the latter builds the necessary reinforcements on an existing network (or on a reference network built with the "greenfield" model) to cope with the expected load growth and new connections.

Figure 3.2 illustrates the functional architecture and the main required inputs at each stage of the RNM, both for the "greenfield" and the expansion modes. In a first stage, the geographical location, voltage level and load/generation characteristics of all network users are required at the "Load/DG modelling" stage. Secondly, the optimal layout of the grid is designed, considering geographical constraints such as orography, street maps and, in the case of the expansion planning modality, the topology of the initial network. The third step consists of optimally assigning the electrical equipment to each element of the topological grid, carefully considering technical constraints such as voltage and capacity limits. Finally, additional reinforcements are incorporated to meet all continuity of supply constraints.

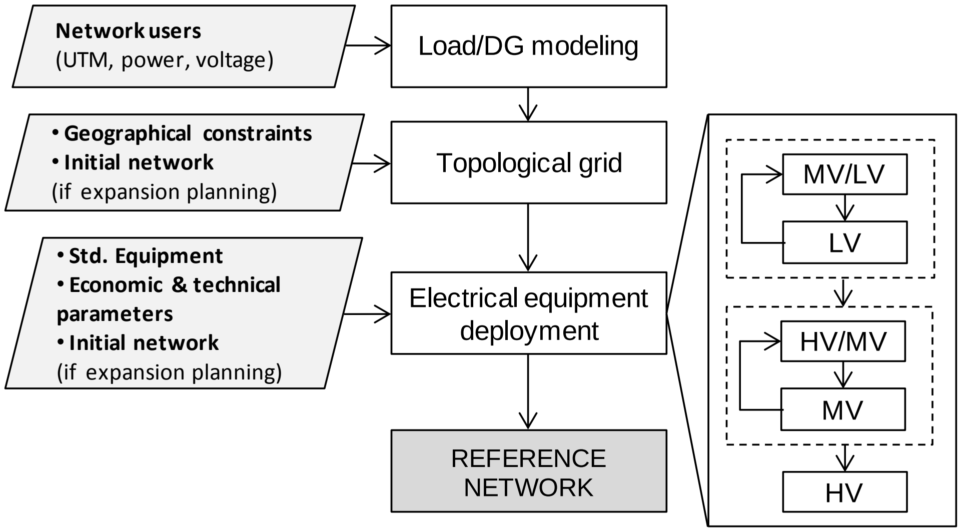

Figure 3.2 Logical architecture of the RNM

The methodology for the electrical design of the network follows a bottom-up approach sequence, as represented on the right side of Figure 3.2. First, the number, size and location of MV/LV transformers are optimized based on the power density of network users and a K-means algorithm. Then, the LV network is planned to connect the network users to the MV/LV transformers. For this purpose, consumers are clustered and allocated to MV/LV transformers applying an electric momentum criterion. Then, a quasi-optimum LV network is obtained by means of a minimum spanning tree and a branch-exchange optimization algorithm, subject to technical constraints. This optimization may require going back to the first step to relocate MV/LV transformers. In the third and fourth stage, the number, size and location of HV/MV substations and the map of the MV network are designed, following a similar approach as for the MV-LV grid and including new elements that allow taking quality of service targets into account. The final step involves the HV network planning, which incorporates an N-1 reliability criterion, i.e. every node must be supplied through at least two paths. Overall, the algorithms for the deployment of network assets seek to minimize the present value of investments and operation and maintenance costs, as well as the cost of losses, both for the "greenfield" and the expansion versions of the model.

By comparing the outcomes of the expansion model of the different DR scenarios with respect to a benchmark scenario without any DR, the potential of these energy efficiency and demand response alternatives to avoid network investments and the impact on energy losses in distribution networks can be evaluated.

3.3.2. Integration of DR in distribution planning scenarios

Network reinforcements and expansions are generally carried out to comply with reliability and security constraints for a few worst-case scenarios of expected future needs. For instance, these states may result from a combination of a simultaneous maximum (peak) demand in the absence of any generation and the minimum demand with the maximum of DG. DR could help to ease both planning scenarios, reducing the local peak load or shifting part of the demand from periods of higher saturation and bottlenecks to the hours of maximum DG production.

In this thesis, DR is integrated into the different planning scenarios by modifying the assumed load behaviour of consumers during the planning horizon. A Benchmark scenario ("No DR") is considered in which it is assumed that no DR measures are implemented, so the electric load is assumed to continue to grow normally and not to change its pattern. This base case is compared to different scenarios of demand alterations due to different options of DR programs, several degrees of implementation (economic and regulatory boundary conditions that affect the consumer participation rate) for different distribution network configurations, e.g. rural and urban. The investment needs for each scenario are estimated with the RNM, described in 3.3.1, for similar requirements of load growth and reliability constraints but with different expected consumption patterns from those consumers participating in DR.

For the purpose of better evaluating the chronological sequence of the time-dependent effects of DR on consumption, the authors of (Pilo et al., 2014) suggest applying characteristic daily load profiles to model the forecasted demand instead of single values that represent particular extreme conditions for the network. The use of representative load profiles is also very convenient to evaluate the foreseeable network energy losses, which may affect the DSO operating costs depending on the regulatory incentives or penalties in place.

Two basic approaches can be used to estimate the support of each scenario of DR to adjust forecasted load patterns for network planning:

a) On the one hand, **permanent changes**, because of DR, could be anticipated in the normal **consumption patterns** that are used to determine the network expansion requirements. In this case, the DSO, or the DR intermediary, should estimate beforehand how different DR scenarios would affect the expected future load profiles. For instance, a 5% of expected participants' peak load reduction during certain hours of the year could be assumed according to the expected effectiveness of the demand response mechanism that is planned to be implemented.
b) On the other hand, an **acceptable probability of overload** occurrence could be tolerated, assuming certain degree of assistance of flexibility services from the demand-side to neutralize it, which would be needed only occasionally. In this case, load

patterns should be designed with certain confidence interval, leaving aside those extreme load conditions that have a very low probability of occurrence. For instance, 5% of the time when demand reaches its highest levels could be ignored in the planning process, so the percentile P95 of the expected load throughout the year would be used instead of the maximum, assuming that at least during 5% of the time, the network operator (or DR provider) would have to resort to demand response to reduce demand to the corresponding required level.

It can be observed that certain degree of expected effectiveness of the DR action must always be exogenously defined to adjust the future expectations of daily load profiles resulting from each type of DR application because the network capacity requirements are anticipated beforehand in the decision-making process of network expansion planning. In a) it takes the form of an assumed level of peak load reduction while in b) takes the form of an assumed number of hours in the year of required intervention to restrict the load of active consumers.

3.3.3. Estimating the costs of DR activation in theory

Regarding the estimation of the costs of activating the required load flexibility through the planned demand response mechanism, different assumptions and calculation methods can be opted. This section describes the suggested application of the methodology proposed in chapter 2 to carry out this task[31] whenever responsiveness data is available for a sample that is representative of the population of consumers connected to the network under study. As this is not the case, any approximation based on the results of chapter 2 would be very difficult so the assessment of DR costs has been left out of the scope of the case study. Instead, only investment savings are analysed and scenarios and the impact of DR on the load profiles used to build network planning scenarios is based on the estimated technically available flexibility and the observation of real experiences.

The methods used in chapter 2, which will be referred to as consumer model, let us estimate a distribution function of demand flexibility for individual typical consumers or groups of consumers as a function of the value of the economic incentive and possibly a set of other controllable factors (e.g. duration of the signal and intensity of a request) and surrounding variables (e.g. temperature, day of the week, hour of the day, etc.). Thus, as explained in chapter 2, these functions contain information not only regarding the expected level of responsiveness for a given incentive (and a given set of circumstances), but also determine the amount of

[31] It should be noted that this approach is directly applicable if the assumed DR mechanism is an explicit flexibility service through explicit incentives and requests. In the case of other mechanisms, such as feedback and TOU tariffs, an approximation or an alternative method should be used.

responsiveness for any given probability level[32]. Therefore, we could directly evaluate from these functions the costs that would have to be incurred to guarantee certain level of response with a defined confidence level. For instance, the expected cost of activating a desired amount of responsiveness with a confidence of 95% can be estimated through the incentive required so that the percentile P5 of the flexibility function coincides with the target level of response.

During the expected number of hours per year in which the consumer would normally consume beyond the new capacity level that is used to dimension the network expansion requirements[33], we assume that a DR intervention would be required to reduce the demand in the amount of the surpass. Thus, the total yearly cost of DR would be equal to the sum of these individual costs evaluated for all consumers, or consumer groups, and for as many hours throughout a year in which their flexibility activation will probably be required.

This approach is highly recommended from a risk-management perspective, from which the possibility of occurrence of extremely low values of responsiveness cannot be ignored. Estimations based on expected values, unlike probabilistic estimations, even when they are very accurate, provide no information on risk exposure.

3.4. Case study

The case study is based on two large and realistic distribution networks that have been built with the RNM based on the geographical location and consumption characteristics of network users of two areas of Spain, one urban and one rural. These networks connect the transmission network to the final users, comprising both medium (MV) and low voltage (LV) levels. It should be noted that such networks are not representative of all real urban and rural networks in the country but are realistic examples that allow us to quantify the potential of DR to defer investments in real distribution grids for different options and scenarios of DR implementation in Spain. These networks have been designed to sufficiently accommodate the peak consumption capacity needs and meet the minimum reliability requirements for urban and rural areas as indicated by the Spanish regulation definitions. Current and foreseeable distributed generation capacity at LV and MV has been neglected in these networks for the sake of simplicity. The equipment used to model the networks, both initially and in the expansion scenarios, has the standard sizes, power rates and average costs.

[32] It is reminded that as a result of the Quantile Regression proposed in chapter 2, different functions are obtained that relate each percentile of the conditional flexibility with a set of covariates.

[33] For instance, through the load duration curve that is expected locally in different areas of the network could be the basis of this estimation.

3.4.1. Incorporating demand response assumptions in the characterization of network users

Network users are characterized by means of a series of distinctive load and generation daily profiles that are sufficiently representative of the conditions of the network. As load patterns can vary extensively across different distribution areas, the idea of this methodology is to derive these representative load profiles from real local consumption data from a recent past, not only to design the network expansion requirements but also to determine the required level of DR needed for a determined capacity requirement. Likewise, historical data could let us estimate the costs of activating it as well, as previously described, even though this calculation is not made in the case study presented. Following this approach, not only can the chronological sequence of the effects of DR actions be captured, but also the risk of simultaneity of peak loads can be implicitly considered.

Historic real demand data is collected per customer and in discrete short time intervals (15 minutes or one hour) to build the benchmark representative load profiles per season and type of day. Furthermore, consumers are categorized into several clusters of similar behaviour. These distinctive profiles are escalated so that the peak load coincides with the contracted power of each consumer or in such a way that the resulting yearly consumption matches the actual average demand, depending on the available data.

These normal load profiles are adjusted for each of the network planning scenarios that incorporate DR strategies, only among the proportion of consumers that are assumed to participate. This is done per each associated mechanism for DR, as follows:

- **Feedback on consumption**, e.g. through an in-home display, informative bills, or a website, or other type of incentives for energy efficiency improvement, are assumed to encourage an overall reduction in energy consumption that is reflected uniformly in the load profile, i.e. by applying the same energy reduction in every hour of the profile.
- **Cost-reflective network tariff structures**, e.g. dynamic or **TOU**, in line with the usual local peaks and per type of area and voltage level, are expected to induce changes in normal consumption patterns reducing the load in the peak hours, to an extent given by the effectiveness of the price signal and the consumer responsiveness.
- The procurement of **flexibility services**, managed through an aggregator or a retailer, provided by the demand-side to solve constraints on the network that occur sporadically could avoid a percentage of the most extreme conditions to which the network can be exposed. A similar effect would be expected if the DSO had the possibility to activate **CPP** signals through the supplier or aggregator during some critical days for the local network conditions, e.g. at substation level. By statistically

analysing the consumption data used to build the load profiles for network design, a percentage of those critical situations can be left aside. An example of this new load profile is one that is built with the percentile 99 of demand at each hour, i.e. the load profile below which the consumption at each hour of the day lies during 99% of the days of similar type and season.

The assumed effectiveness used for a) and b) is an average realistic value per type of DR program that has been estimated from the experience observed in real life EE and dynamic pricing (DP) pilot programs (Vallés et al., 2015). This effectiveness is measured as an average potential to reduce total energy consumption (in EE) or peak load (in DP).

Figure 3.3 reveals how an exemplary typical load profile ("No AD") is adjusted[34] to several AD scenarios for network planning purposes: "TOU (5%)", which refers to the use of Time of Use tariffs with an effectiveness of 5%, "EE (5%)", which refers to Energy Efficiency with an effectiveness of 5%, and "P99" which refers to the percentile 99 of the load at each hour of the day.

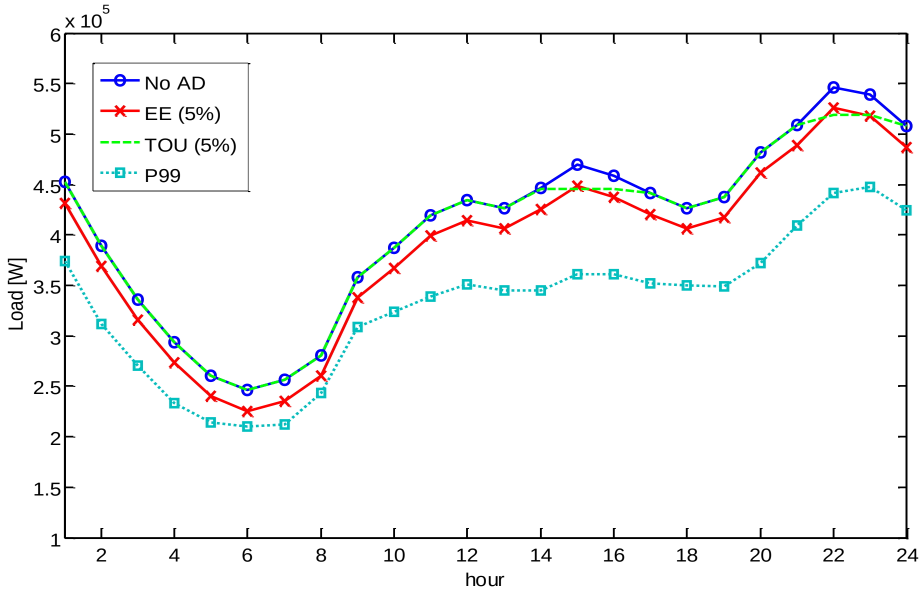

Figure 3.3 Adjustments of a standard load profile to network planning scenarios incorporating DR

[34] It should be noted that the realistic effect of time-varying prices on final consumption would involve not only a peak-load reduction during periods of high prices but generally an increase of consumption during periods of lower prices as well, a fact that is not reflected in the figure. The reason for this is that these load increases during off-peak periods do not affect load requirements for network dimensioning as they do not create greater stress conditions in the grid, so they are not taken into consideration in the design of network expansion scenarios.

3.4.2. Characteristics of the reference networks

The configuration of the exemplary reference networks built with the "greenfield" model is presented in Figure 3.4, for the rural reference network, and in Figure 3.5, for the urban reference network. The rural network is made up of dispersed small locations that are radially connected to the substation and to each other through MV bare overhead conductors. The blue squares indicate the location of the distribution HV/MV (132 /20 kV) substations, the thick green lines represent the MV (20 kV) network feeders, the green dots represent the location of MV/LV (20 kV/ 380 V) transformers and the thinner brown lines represent the LV (380 V) network.

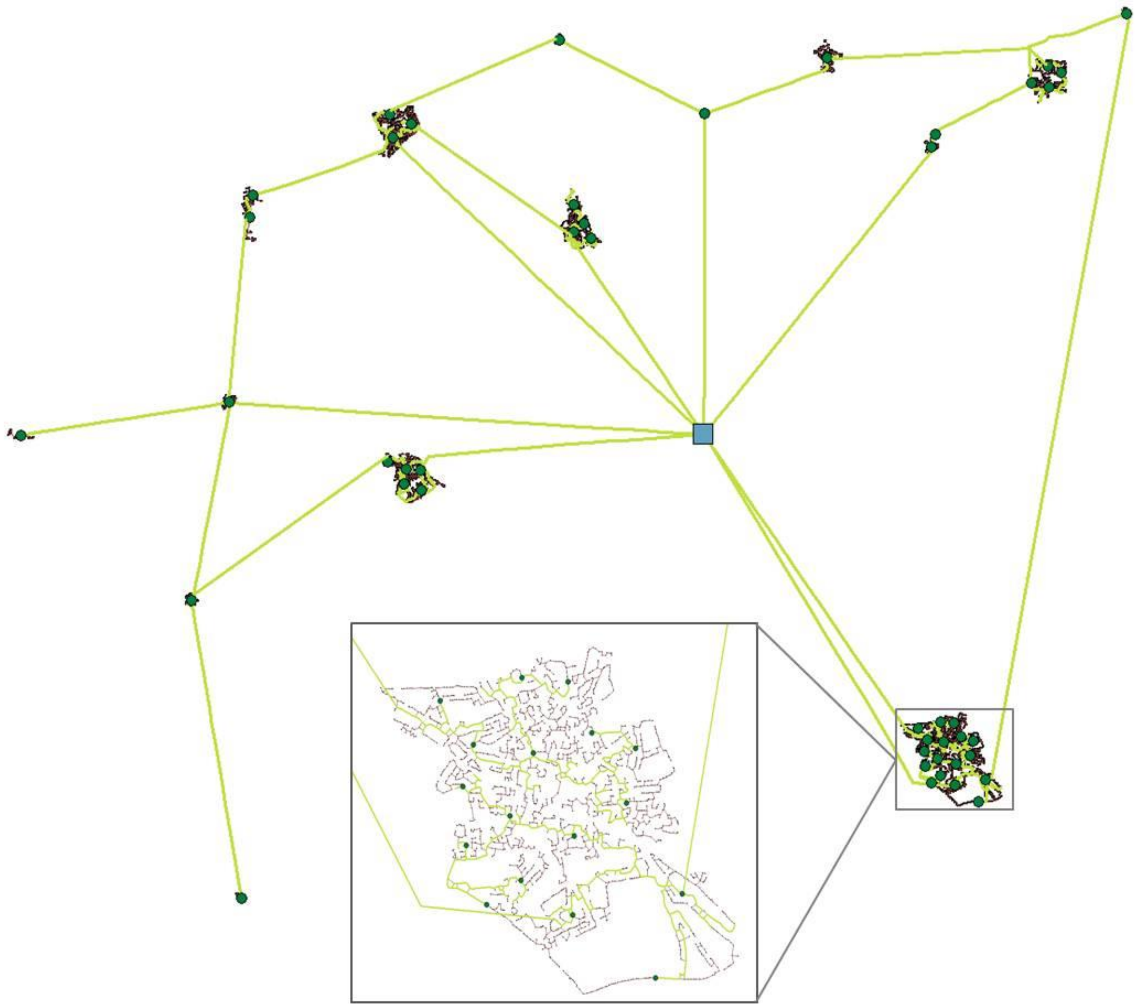

Figure 3.4 Exemplary reference network for a rural area in Spain

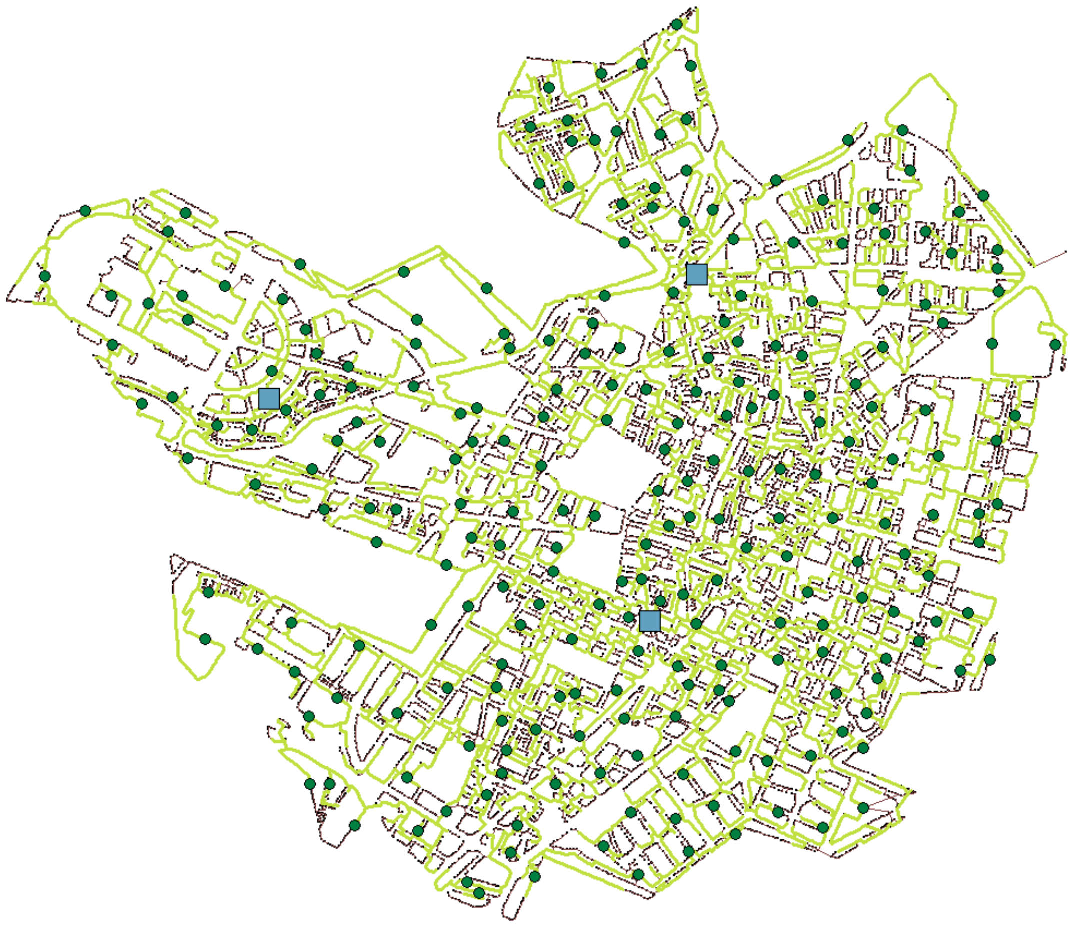

Figure 3.5 Exemplary reference network for an urban area in Spain

The urban and the rural networks differ mainly in structure, population density, reliability requirements, the proportion of aerial lines and the number and size of transformers, which are generally lower in size in the rural network Table 3.1 and Table 3.2 summarize the main characteristics of the reference networks, including facilities and network users.

Table 3.1 Summary of network characteristics and users in the reference networks

		Consumers		Peak power		Network length	
						Aerial	Underground
		No.	%	MW	kW/cons.	km	km
Urban area network	**LV**	65 848	97%	424.2	6.4	20	266
	MV	2 276	3%	186.7	82	39	258
Rural area network	**LV**	11 218	99%	60.8	5.4	140	18
	MV	156	1%	12.8	82	182	15

Table 3.2 Summary of network facilities in the reference networks

	Sn (kVA)	No.	
		Urban	Rural
HV/MV Substations (132 kV/20 kV)	120 000	1	-
	80 000	1	1
MV/LV Transformers (20 kV/0.4 kV)	1 000	36	3
	630	59	9
	400	44	11
	250	92	15
	100	17	5
	50	-	2

The initial reference networks are designed in line with the traditional criteria of the typical distribution planning process, i.e. to adequate the grid capacity to cope with the worst-case operation conditions, assuming a constant yearly growth rate for a predefined period, coincidence factors considered. The resulting networks comply with all constraints, such as orography, undergrounding requirements, accessibility for maintenance purposes, voltage and capacity limits and quality of service requirements. Worst-case conditions are defined by a single peak load value per consumer.

On the one hand, the contracted power of the non-residential consumers is characterized through the combination of the building census[35] of several Spanish towns and cities and the legal minimum technical requirements established in the low voltage electro-technical regulations[36] for each type and size of buildings. On the other hand, residential consumers are characterized by the distribution of probability of contracted power observed in the sample of

[35] *Censo de Población y Vivienda 2011*, *Instituto Nacional de Estadística* (INE), available at http://www.ine.es/censos2011_datos/cen11_datos_inicio.htm.

[36] *Reglamento Electrotécnico de Baja Tensión* (REBT), available at http://www.boe.es/buscar/doc.php?id=BOE-A-2002-18099.

real consumption data from a demand response pilot program carried out in Spain[37], which is the same on which the case study of chapter 2 was based[38].

3.4.3. Network expansion scenarios with Demand Response

For the network expansion scenarios, consumers are modelled through typical load profiles that are built using real consumption data that has been collected in the same pilot program. Consumers are clustered into 4 different groups of similar consumption pattern for each typical day (working and non-working) and season (Winter, Spring, Summer and Autumn), leading to 32 typical representative profiles.

Three types of network-driven AD programs are analysed: feedback on own consumption, TOU network tariffs and flexibility services for local congestion management. A standard effectiveness is associated to feedback programs and TOU tariffs, respectively, according to the average measured flexibility of similar pilot programs, as defined within the European research project ADVANCED[39] (Lombardi et al., 2015; Vallés et al., 2015) (see Table 3.3). The load profiles used in the expansion scenario where flexibility services are deemed available is the percentile 99 of demand at each hour, as defined in Section 3.3.2.

Table 3.3 Effectiveness of feedback and TOU pricing programs in accordance with the experience observed in real pilot programs in the context of the ADVANCED[39] project

	Min - Max	Average
Feedback (FB)	3% - 10%	**5%**
Time of Use (TOU) tariffs[40]	6% - 30%	**10%**

A set of macroeconomic and regulatory boundary conditions determine the participation rates for three different scenarios as defined in the context of the ADVANCED project[39] (Lombardi et al., 2015; Vallés et al., 2015), which can be seen in Table 3.4. The **Baseline scenario** projects

[37] The data comes from a Spanish pilot test developed by the DSO *Iberdrola Distribución Eléctrica, S.A.*, within the framework of the ADDRESS Project, co-funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 207643 (http://www.addressfp7.org/).

[38] It is reminded that the characterization of flexibility of these consumers could not be used in the estimation of the costs of activating DR in the case study presented in this chapter.

[39] ADVANCED (Active Demand Value ANd Consumers Experiences Discovery) is a research project co-funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 308923, that aimed to shed light on ways to overcome the barriers hindering the mass deployment of Active Demand (AD) in Europe (http://www.advancedfp7.eu/).

[40] The observed effectiveness of Time of Use tariffs in terms of percentage peak load reduction was calculated in the context of the ADVANCED project from different time varying pricing pilots, including dynamic pricing, as an approximation of Time of Use. This simplification is justified on the basis that finally an average effectiveness level is used to define load requirements in the network planning scenarios, which resembled that of many TOU pricing experiments.

the business as usual trends of the current economic and regulatory progress and could resemble the expected participation rate in an early phase of implementation of a demand response program. The **Optimistic scenario** represents a situation in which most of the technical and regulatory barriers are relieved and so a considerable but credible proportion of network users is providing flexibility to the network through DR. In contrast, the **Technical Potential** is defined as a hypothetical scenario where the full potential of DR that is physically and technologically feasible is exploited, i.e. all consumers connected to the network are actively participating. The effectiveness of DR for each program type in the Baseline and Optimistic scenarios is the average value while the maximum is applied in the Technical Potential scenario.

Table 3.4 Assumed consumer participation rates for each DR program and scenario

DR Program/Scenario	**Baseline**	**Optimistic**	**Technical Potential**
Feedback (Energy Efficiency)	20%	40%	100%
TOU distribution network tariff	12%	40%	100%
Flexibility services for local congestions	12%	40%	100%

Consumers assumed to be participating in DR can be randomly dispersed throughout the network, or rather concentrated in specific locations. The reason for this sensitivity is to test whether, for instance, a high concentration of participative consumers in certain zones could possibly avoid the reinforcement of power intensive assets that affect a large group of consumers, or rather not be sufficient to avoid reinforcements if these are widely scattered geographically.

Separate expansion scenarios in a ten-year horizon per DR program type, participation rate, location of responsive consumers are simulated for each one of the network configurations, for an annual 3% load growth.

3.5. Results and discussion

The investment costs required in the scenario without any AD for the rural and urban networks are expressed in Table 3.5 as a percentage of the initial cost of the corresponding voltage level or type of network component. The total reinforcement cost is expressed with respect to the total initial cost of each network. This base case scenario for network planning is taken as a benchmark to compare with the total reinforcement needs for a similar time horizon and annual demand growth rate under the described AD scenarios, which are compared in Figure 3.6 and Figure 3.7, for the rural and the urban area network, respectively.

Table 3.5 Costs of the required reinforcements in the benchmark scenario of no DR in the reference networks, as a percentage of the total costs of the initial network per component or voltage level (LV, MV/LV, MV, HV/MV)

Reinforcement costs (%)	**LV network**	**MV/LV subs.**	**MV network**	**Total**
Rural area network	14.7%	31.2%	0.0%	**5.3%**
Urban area network	16.2%	28.1%	3.4%	**6.6%**

The technical potential scenario is a theoretical upper limit that cannot be achieved in practice because it would imply that all consumers are responding to the DR mechanisms with the highest level of effectiveness. This scenario allows us to draw up the technical boundaries of demand-side actions to potentially become a substitute of distribution network assets given the actual demand flexibility observed in real DR experiences. As can be observed in Figure 3.6 and Figure 3.7, for most combinations of other boundary conditions, the Technical potential scenario proves to be insufficient to avoid all necessary investments in the analysed time frame. The more realistic scenarios Baseline and Optimistic, which impose technical, economic and regulatory barriers to this technical potential, indicate that the highest savings vary greatly, from 20% to 60%, most of which would be concentrated in the LV network and the MV/LV transformers.

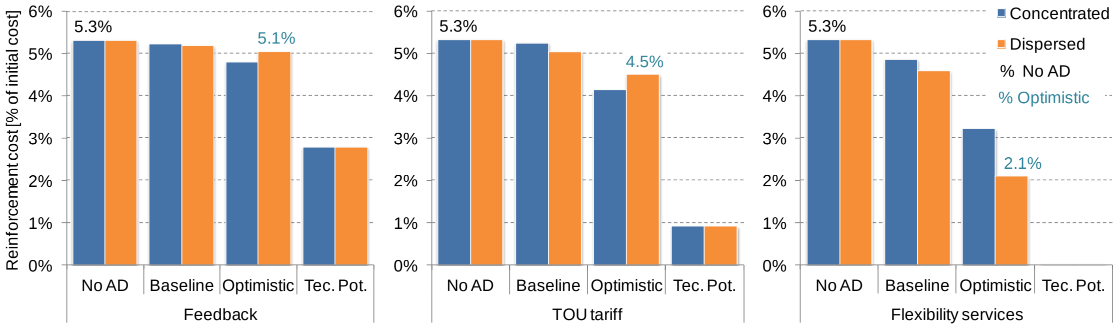

Figure 3.6 Reinforcement investments needed in the rural area network for each scenario

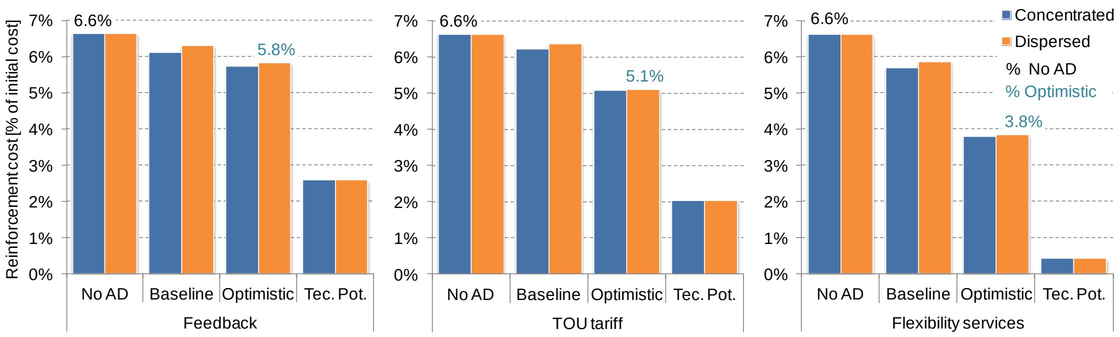

Figure 3.7 Reinforcement investments needed in the urban area network for each scenario

The obtained results suggest that the highest investment reduction is expected in the scenario where explicit flexibility services can be provided by consumers to network operators, even for similar or lower participation rates. By comparing the performance of feedback and TOU tariffs, dynamic tariffs appear to be more successful, as would have been expected because the assumed average effectiveness of dynamic pricing is higher than that of feedback programs. This assumption reveals that shifting energy consumption from some periods to others is generally easier for normal consumers than reducing overall consumption permanently.

The results show that the effect of having a concentrated or dispersed DR participation may have opposite consequences in the different distribution areas. A dispersed participation appears to bring more benefits in the rural area while the concentrated is more beneficial to the urban area. This is one of the key aspects that better indicate that impact of DR is very dependent on local characteristics of the networks and therefore can be significantly different from one distribution area to another.

In relation to the type of network configuration, it seems that for very low participation rates, DR has a greater potential to bring benefits in urban area than in the rural, but this potential changes as the participation rate increases. The reason for this is that when networks are constrained close to capacity limits, at LV or MV, a small increase in demand or new connections would necessarily require a huge amount of reinforcements that could be easily avoided by slight DR interventions. This can occur more easily in urban networks with a high density of population. On the contrary, fewer investments are expected and so, the potential to reduce investment costs is lower for networks designed with ample capacity to absorb new connections and load increases, which occurs mainly in rural networks that supply scattered and relatively low loads.

Overall, it seems that DR could have a great potential to defer network investments whenever these are driven by large load increases and small or hardly any new DG penetration, as is the case of these networks. Notwithstanding, such a positive performance would only be possible with a very high level of consumer involvement. As can be observed in Figure 3.6 and Figure 3.7, avoidable or deferrable investments are very slight in the Baseline scenario and only a bit better for the Optimistic scenario, while a sound economic impact could only occur in the Technical Potential scenario, which can only be taken as a theoretical scenario where the full potential of AD with the highest effectiveness is exploited.

The incidence of the consumer participation rate in the effectively achievable savings can be appreciated more accurately and for each network component (LV network, MV/LV transformers, MV network) in Figure 3.8. It presents the scenario of consumers geographically dispersed being exposed to a TOU tariff scheme in the urban reference network. A sensitivity analysis has been carried out with respect to the percentage of participative consumers in the DR program to appreciate the transition between regulatory scenarios (Baseline, Optimistic and Technical Potential), as can be seen in the figure. It is remarkable that in relative terms, the highest economic impact of DR corresponds to MV/LV transformers, and that the incidence of participating consumers is especially significant for this type of component, in contrast to the LV and MV networks. The shape of the curves suggests that the larger the number of responsive consumers, the higher the marginal benefit of DR for the network, especially for the investments required in MV/LV transformers.

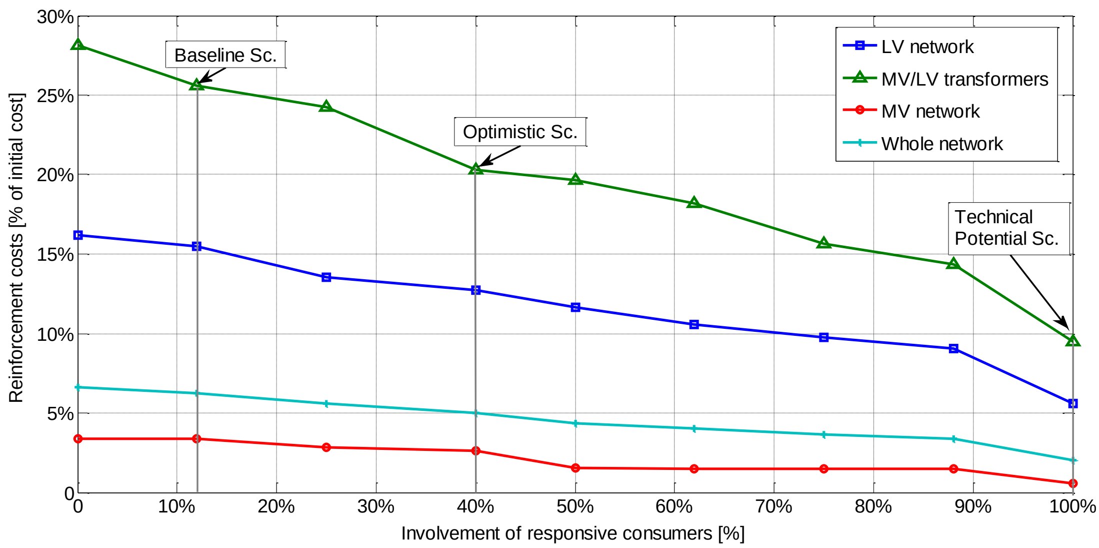

Figure 3.8 Sensitivity of the reinforcement costs to the number of responsive consumers under a TOU tariff in the urban network, expressed as a percentage of the costs of the initial network per component (LV, LV/MV, MV, whole network)

It should be noted that the technically available potential benefits of DR in distribution networks could be diminished by the so-called payback effect, which would lead to an increase in the load because of a previous reduction caused by a request from the DR operator. In the event of simultaneous payback effect on many consumers, a new local peak may occur, which could compensate the positive effect of the previous DR action. In theory, this effect could be neutralized by an adequately designed flexibility service mechanism.

Figure 3.9 and Figure 3.10 depict the estimated reduction in energy losses observed in each AD scenario with respect to the scenario of no AD, for the rural and the urban networks, respectively. In general, it appears that a decrease of energy losses can be expected when some form of DR is implemented because overall consumption decreases. Surprisingly, losses are generally reduced to a greater extent in the MV network except for the case of the flexibility services, which has a deeper impact at LV level.

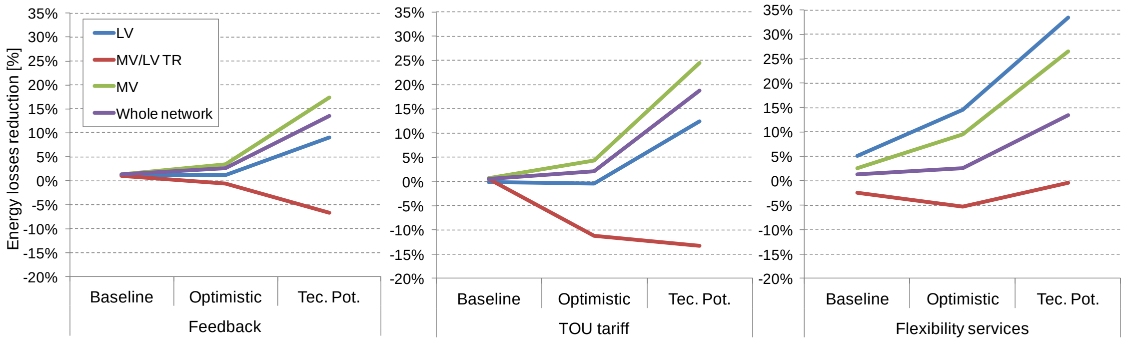

Figure 3.9 energy losses reduction in relation to the scenario of no AD, in the rural area network

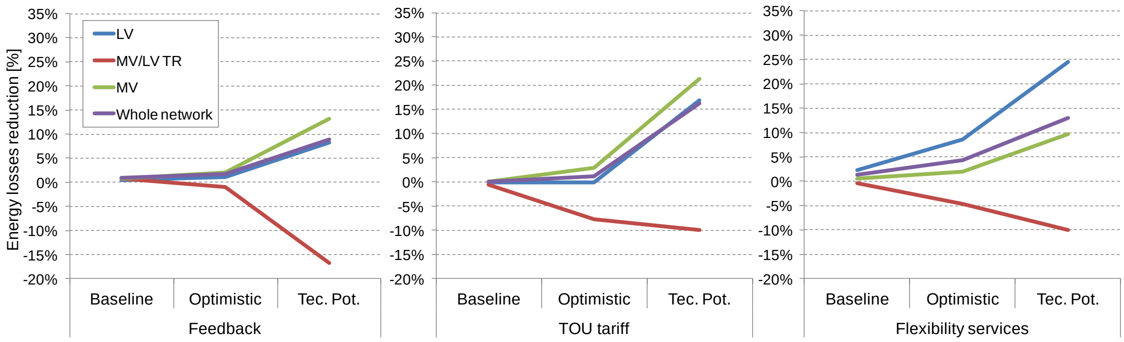

Figure 3.10 energy losses reduction in relation to the scenario of no AD, in the urban area network

Notwithstanding, losses do not always seem to follow a clear reduction trend with increasing penetration rates of DR in every voltage level, e.g. losses seem to intensify in MV/LV transformers. Thus, DR would not be justified as a regulatory instrument to contribute to reduce energy losses but only to optimize overall economic performance of network operators. To better understand this, it must be considered that two different factors may affect energy loses, having opposite implications. It is true that the load reduction effect of DR could always lead to a reduction of the power loses with respect to a similar expansion scenario. However, insofar as DR allows the network operator to avoid certain reinforcements, some assets could be increasingly overloaded, which could in turn lead to higher energy losses. Therefore, it can be seen that the costs of energy losses is an extremely relevant factor to be internalized in the overall cost function in order to adequately dimension grid components, especially in a context where DR becomes an available tool to optimize network operation and planning.

3.6. Conclusions

This chapter has explored the methodological and economic implications that demand response mechanisms could have in distribution network planning in a hypothetical future scenario where the tools to implement them could be available to DSOs. It has been discussed that existing planning tools and methodologies could be used and adapted to identify the best technical and economic balance between traditional network reinforcement and demand-side actions.

A methodology to determine the economic benefits of DR in terms of avoided investments in grid reinforcements using a Reference Network Model and historical consumption data within a distribution area has been proposed and applied to a case study for Spanish distribution networks. The results indicate that only a very high level of consumer involvement in DR could bring significant savings in deferred or avoided network reinforcements

From this quantification, which is strongly based on actual data from real experiences and real size networks, some relevant key boundary conditions that would hinder or strengthen the ability of network operators to optimize planning strategies counting on DR have been identified. For instance, it has been shown that the economic value of DR would be very dependent on local network characteristics, such as the network configuration and the congestion level, the expected load growth, location of consumers providing flexibility, etc. In principle, the higher cost of the required investments in the absence of any DR, the higher the local value of DR would be, especially if the reinforcement needs were driven by a lack of excess capacity and by a sharp projected load growth. On the other hand, the cost of activating the demand response services would be lower if consumption patterns observed among network users showed great concentration of peak loads in a few hours of the year because that way DR would not have to be available and activated so frequently and for so long periods of time. This aspect conditions extensively the nature of the intervention required in terms of magnitude, duration and frequency. In addition, the resulting energy losses have been estimated concluding that they are generally reduced in the presence of DR, but there is not a clear trend that justifies this as an objective of DR implementation, but rather a side effect.

These results offer useful insights into the added value that DR could have for DSOs and the convenience of promoting and investing in certain types of DR services at distribution network level. They also open the discussion about the way DSO remuneration schemes could be adapted to new ways of network operation involving DR in the context of smart grids.

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4. Regulatory conditions, existing barriers and recommendations

Improving electricity Demand Response (DR) to support the operation and planning of distribution networks is an essential component of the European Commission strategy to increase economic efficiency in electric power systems across Europe. Due to the lack of the appropriate infrastructure, end consumers have traditionally been blind to wholesale market conditions as well as from the real costs they cause on the network and the power system operation. With the recent deployment of smart metering and communication technologies, provided an appropriate regulatory environment exists, new forms of local DR involving distribution system operators and small consumers could be developed. In a context where many EU Member States are still in the process of opening their retail sectors up to competition and being any active distribution management procedures still to be defined, DR is materializing at a very slow rate. It is the role of regulators to provide a suitable regulatory framework to allow DR to become effective at distribution level. Having focused on the feasibility and the potential economic benefits of DR as a smart option in the management of distribution networks in previous chapters of the thesis, this chapter examines the most critical regulatory barriers that could slow down its successful development in the near future. In order to illustrate this discussion, an overview of six particular national examples is provided: France, Germany, Italy, Spain, Great Britain and Sweden. Finally, general recommendations for policy makers and regulators are given.

4.1. Introduction

As has been discussed in previous chapters, demand response is widely believed to bring numerous benefits to electric power systems and it is deemed a key resource of flexibility to cope with some of the current and future challenges of power systems, such as the increased electrification of energy consumption and the growing penetration of renewable intermittent energy (Pierluigi Siano, 2014). These issues could become particularly challenging for low and medium voltage distribution grids, which in the future could require substantial investments to cope with extreme operating conditions occurring during just a few hours per year (Ruester et al., 2014). With the recent deployment of smart metering and communication technologies, provided an adequate regulatory environment exists, new forms of local DR involving distribution system operators and small consumers could be developed. It is expected that, if Distribution System Operators (DSOs) could use local flexibility services from DR to solve capacity and voltage constraints on their networks, they could operate and plan their networks more efficiently and investments in grid reinforcements could be partially avoided or deferred.

Making electricity demand response happen is an essential component of the European Union policy strategy to increase not only energy efficiency and sustainability but also consumer empowerment through enhanced choices and opportunities to reduce energy costs. This is reflected in numerous EU initiatives, including the Third Energy Package, with Directive 220/72/EC (EC, 2009), the Network Codes and the Energy Efficiency Directive (EED) 212/27/EU (EC, 2012a). More specifically, the EED establishes the legal basis for further development of DR in Europe and declares DR as an *"important instrument for improving energy efficiency […] through the more optimal use of networks and generation assets, in energy generation, transmission and distribution"* and urges regulatory authorities in Europe to take the responsibility of facilitating DR access, also for small consumers. The EED also makes reference to the need for incentivizing DSOs to improve efficiency in network operation and planning, even relying on DR. In addition to the EU Directive, the inclusion of explicit references to DR in the Network Codes and Guidelines constitutes a positive stepping stone toward a greater participation of consumers in the provision of flexibility services for system operation.

Nevertheless, DR as a whole is far from being fully implemented in Europe (SEDC, 2015), and its realization appears to be happening at a low pace (EC, 2013). This is especially relevant in the case of small consumers connected to distribution networks and its application to innovative forms of active distribution network management solutions (CEER, 2014a; Eurelectric, 2016). While some progress has been made recent years in some European countries regarding the increased participation of the demand-side in the provision of operating reserves and balancing energy to Transmission System Operators (TSOs), the ability of DSOs to resort to DR to support the operation of their grids is negligible up to now (CEER, 2014b; EC, 2015). Due to this scarce, or almost inexistent, experience in DR to support distribution network management and operation, except for a variety of pilot programs in various countries, the required commercial and regulatory arrangements for its successful realization remain unclear. Thus, it is becoming increasingly necessary to provide the appropriate regulatory framework to allow DR to become an effective flexibility resource for the efficient operation of distribution networks.

While the focus of previous chapters has been placed in providing tools to study the feasibility and the potential economic benefits of DR as a smart option in the management of distribution networks, this chapter addresses the changes required in the regulatory environment to efficiently and fairly incorporate it in different national electricity systems. It should be noted that the focus of this work is very specific of the European scene, where the implementation of DR programs is very different with respect to the US, where electric utilities are mostly vertically integrated, at least at distribution and retail levels (Hu et al., 2015; Mathieu, 2012).

The regulatory requirements and the commercial arrangements for the active participation of DR in EU electricity markets are addressed in numerous technical reports of regulatory institutions and industrial associations, e.g. the Council of European Energy Regulators (CEER) (CEER, 2014a), (EG3, 2015), the European commission's Smart Grid Task Force (SGTF) (EG3, 2015) and the Smart Energy Demand Coalitions (SEDC) (SEDC, 2015). The scope of these studies is generally concentrated in reviewing the current regulatory approaches and market models for the participation of demand-side resources in wholesale electricity markets and in the provision of frequency control ancillary services and balancing energy to TSOs. Recently, the discussion has evolved towards the definition of clear and fair rules to coordinate demand response aggregation balancing responsibilities as well (Eurelectric, 2015), due to the conflicts that may arise in relation to balancing responsibilities when actors other than Balance Responsible Parties (BRP)[41] incentivize load changes through DR arrangements. On the other hand, various references in the academic literature address general regulatory features related concerning the adaptation of the distribution activity to a new context of increasing Distributed Energy Resources (DER)[42] (Cossent et al., 2009; Ruester et al., 2014) and the desired implementation of the Smart Grid concept (Crispim et al., 2014). Notwithstanding, to the best of knowledge of the author of this thesis, the particular implications of regulatory conditions for the implementation of DR from small consumers as a tool for active distribution network management are not sufficiently explored in the academic literature.

The objective of this chapter is to revise the main regulatory barriers that may still need to be addressed in order to allow DR to become an effective tool to optimize the utilization and operation of distribution networks in a European context. The analysis is particularized to six focus countries, for which some recommendations are given. These countries are Spain, Italy, Germany, France, Great Britain and Sweden. It should be highlighted that the contents of this chapter are based on the journal paper (Vallés et al., 2016) written during the development of this thesis.

The main contributions of this chapter are summarized below:

- Definition of the procurement of innovative DR network services that would allow a more efficient operation of distribution networks by DSOs, thus facilitating that grid capacity is optimized in the network planning process and so, making it possible to avoid or defer investments in network reinforcements.

[41] A BRP is an entity responsible for the equilibrium between injections and off-takes in a set of points (electrical HV buses) in the network with respect to the program declared at gate closure. Retailers and generators usually take the role of BRP. Sometimes very large consumers assume this role, if they have no retailer. Other times BRPs can be third parties.

[42] Distributed Energy Resources, or DER, generally include Distributed Generation, distributed Energy Storage, enabling technologies for Demand Response and Electric Vehicles.

- Identification of the main regulatory barriers across Europe that obstruct the way for the future development of markets and mechanisms for the provision of flexibility services by small consumers to DSOs, particularizing in a set of representative countries.
- Proposal of a series of EU oriented policy recommendations to facilitate the future implementation of active distribution system management services from DR.

The remainder of this chapter is organized as follows. Section 4.2 provides the conceptual basis for the discussion presented in this chapter by describing the mechanisms that could be expected to allow the implementation of flexibility services provided by DR for capacity support in distribution networks. In Section 4.3 the main regulatory areas affected by the transition towards the possible forms of participation of DR in distribution network operation are analysed. Finally, the main conclusions and general recommendations are provided in Section 4.4.

4.2. DR network services from small consumers for an active distribution network operation and planning

The operational procedures and market mechanisms by which DSOs could resort to innovative forms of active network management solutions involving local DR are not clearly defined by current regulation (Eurelectric, 2013a). This definition is not without difficulties because of the regulated character of the distribution activity and the local scope of DR actions pursued by DSOs. It is not possible to know how these local markets for flexibility services from DR, among other types of DER, could develop, as different mechanisms could be used for their implementation. The most straightforward method of encouraging local DR appears to be the use of cost-reflective network tariffs, which would indirectly incentivize an efficient use of the network capacity (Reneses and Rodríguez Ortega, 2014). Their effectiveness for local purposes could increase if DSOs were allowed to design the end-user tariff structure for their own network provided they stick to a revenue cap set on the average revenue per unit of demand supplied (Gómez, 2013a). However, the efficacy of distribution tariffs has certain limitations as they represent a relatively small share of the overall final retail prices, especially when some regulated costs not directly related to network activities are charged to consumers through tariffs. For instance, as indicated in (ACER/CEER, 2014, p. 33), distribution network costs account for around 20% of the standard retail price break-down in the countries studied in this chapter.

An alternative suggested by some authors, e.g. (Siano and Sarno, 2016), is the use of Locational Marginal Prices at Distribution level (D-LMP) as a price signal for end-user customers to prevent or alleviate distribution network congestions and reduce energy losses. As D-LMP are assumed to accurately represent the locational state of the point of the distribution network where the consumer is connected, in terms of energy cost, congestion, and energy losses, they are expected to incentivize an efficient use of the network capacity[43]. This approach is still far from current practices in Europe, where LMP are not usually applied even at transmission level, but is an interesting tool for distribution network-oriented DR.

Instead, assuming that D-LMP are not present and independently of whichever tariff design is in place, and whether or not the DSO has some control over its structure (Eurelectric, 2013b), DSOs could be allowed to explicitly buy certain ancillary services from DR, among other DER. Due to the peaky and seasonal character of households' electricity load profiles, as observed in chapter 2 of this thesis, these services are expected to require a relatively low call frequency, while potentially providing great economic value in terms of extra network capacity, as observed in chapter 3 and discussed in (Martínez Ceseña et al., 2015). This way, DSOs could actively operate distribution networks as suggested, for instance, in (Poudineh and Jamasb, 2014) and in (Batlle and Rivier, 2012).

Should DSOs be able to develop this kind of ancillary service mechanism for sporadic load adjustments (Batlle and Rivier, 2012; Poudineh and Jamasb, 2014), they could incorporate DR into their expansion planning decisions. In that case, if certain grid constraints become visible in the long-term planning process, the DSO could be interested in buying the capacity to limit demand to some extent in certain distribution area, foreseeing future short-period overloads in that part of the network. DR providers would estimate their own load reduction supply curve, based on the contractual arrangements they have with their respective consumers. Then, given that DSOs should act as neutral market facilitators (CEER, 2015; Eurelectric, 2016), direct contractual arrangements with domestic consumers may not be deemed appropriate because they could be classified as competitive activities. In contrast, through a transparent purchase mechanism under regulatory supervision, the DSO would be able to choose the least cost available long-term DR options or decide to invest in reinforcing that part of the network if the resulting price were too high. An example could be a public auction of standardized products (in size, duration, location, etc.) centralized or supervised by the National Regulatory Agency (NRA).

It is assumed that the DSO would interact with the intermediary DR provider, who, as a commercial agent, would freely arrange a DR contract with the consumers of certain control area, together or independently from a contract for the supply of electricity. In the case of small

[43] Note that D-LMPs indirectly reflect network constraints but are based on energy prices in the market.

consumers, it is foreseeable that the retailers would assume the role of aggregators and that these consumers would not wish to go into the burden of having separate contracts[44].

DR could also become an aggregated source of flexibility for TSOs or in any case have an impact on TSO management of the transmission network. In this case, DR could be channelled through the DSO or coordinated with them, so that it would be DSOs that could provide TSOs with visibility of what is happening at MV and LV. These interactions are illustrated in Figure 4.1. The interaction between DSO and TSO would have to be regulated through clear coordination mechanisms (EG3, 2015) and impartial information exchange systems that reflect network availability (Eurelectric, 2015).

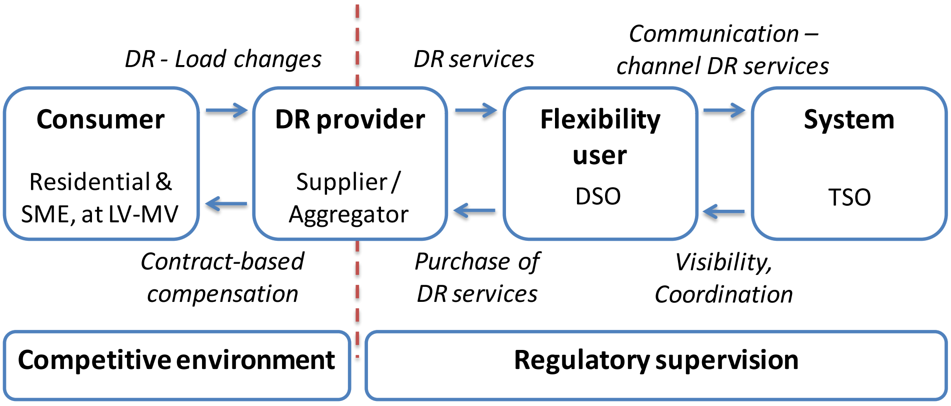

Figure 4.1 Possible forms of interaction of involved stakeholders in the explicit utilization of DR by DSO

It seems clear that the path to facilitate the incorporation of DR flexibility services into distribution network operation and the development of the corresponding procurement mechanisms involves first a transformation of existing regulation concerning the downstream level of electricity systems, i.e. distribution, supply and final consumers. The main regulatory areas that should be addressed in this sense are analysed in Section 4.4.

4.3. Regulation on DR for an active distribution network management

This section is concerned with the main regulatory and market barriers that can be found across Europe for an efficient utilization of local DR mechanisms in distribution grids. Special attention is paid to the following issues: the roles and responsibilities in relation to smart metering and data management (4.3.1), the remuneration of the distribution activity (4.3.2),

[44] And not incurring in balancing responsibility conflicts, as explained in subsequent sections.

the design of network tariffs (4.3.3), the market model for the DR provider (4.3.4) and the indispensable measures for protection and empowerment of consumers (4.3.5).

4.3.1. Smart metering and data management responsibilities

Even if it is true that some simple forms of demand response can be developed by suppliers without complex technologies, it is widely acknowledged that smart metering (SM) and information and communication technologies (ICT) are essential enablers of DR (Shariatzadeh et al., 2015). These technologies are crucial for the accurate measurement of the actual consumption patterns and therefore for an effective billing.

The Electricity Directive (EC, 2009) requires Member States (MS) to ensure that 80% of consumers shall be equipped with a smart meter by 2020 or run a Cost Benefit Analysis (CBA) to decide on their specific roll-out volumes. A good overview of the situation regarding smart metering across EU countries can be found in (EC, 2014) and its accompanying documents. Most countries have decided to accomplish a large-scale roll-out of smart meters by 2020 or earlier, e.g. France, Italy, Spain, Great Britain (GB) and Sweden. However, a relatively large share of countries still has not decided for such deployment due to a negative or inconclusive result of the CBA, e.g. Germany, where only some types of consumers would benefit from smart metering.

In 15 out of 16 MS that have decided to carry out an extensive roll-out of SM (EC, 2014), the DSOs are responsible for implementation and own the meters. Metering activity is usually regulated and handed over to DSOs as well. There are a few exceptions, namely the GB, where suppliers are responsible and Germany, where due to a liberalized metering market consumers may freely choose a metering supplier (DSOs remain as metering suppliers by default), as can be seen in Table 4.1. It should be highlighted that this trend is not usual in the US, especially in those regions with non-restructured markets, where vertically integrated utilities are generally responsible for Smart Meter installation and management. Hence, this discussion around smart metering responsibilities is not such a determinant factor in the development of DR programs in the US.

In relation to metering data collection and management, the alternative where DSOs perform this role seems to be the most common one across EU countries, even in those who have not yet decided to go for a large-scale roll-out. On the other hand, a few countries have opted for the data hub alternative, such as GB; see Table 4.1 (even though the DSO would still be the meter owner in most cases). Fewer countries are still evaluating an alternative model based on a decentralized solution known as data access-point manager, a commercial role that would be assumed by certified companies (EG3, 2013).

Table 4.1. State of the regulation in relation to SM and data management in the European countries under analysis

	Spain	Italy	Germany	France	GB	Sweden
SM CBA	n.a. [a]	+	-	+	+	+
SM roll-out 2020	100%	100% [b]	23%	90% [c]	97%	100% [b]
SM installation & maintenance / ownership	DSO	DSO	Metering point operator (customer's choice)	DSO / local authorities	Supplier	DSO
SM operator [d]	DSO	DSO	Smart Meter Gateway Administrator (SMGA)	DSO - upon customer's agreement	Data Hub [e]	DSO
Metering activity	Regulated	Regulated	Competitive	Regulated	Competitive	Regulated
Financing	Network tariffs & SM rental fees		Not secured – Under study	Network tariff component	By suppliers	DSO resources & network tariffs
SM functionalities – compliance with (EC, 2012b)	All except reading frequency	All but partly with reading frequency	All except remote control	All	All	All but only partly with reading frequency, remote control and privacy

[a] *The Spanish government did not conduct an economic assessment but decided to proceed with the full roll-out.*
[b] *Italy and Sweden have fully completed their SM roll-out by 2013 and 2009, respectively.*
[c] *The French energy regulator, Commission de Régulation de l'Énergie (CRE), downsized the initial national goal of providing smart meters to 95% of power customers to 90%, scheduled by 2020 for the main DSO (ERDF), which operates 95% of continental grids, and by 2024 for the local companies.*
[d] *Responsible for third-party access to metering data.*
[e] *Similarly as in Denmark, Poland and Estonia.*

Smart metering and data management leads to additional costs that comprise both the cost of installing the meters as well as the costs of collecting metering data and settlement. However, the recovery of these expenses is not always clearly guaranteed in the DSO regulation. Thus, regulators should establish a stable framework allowing DSOs to recoup these costs in a way that fits the roll-out schedule and the expected benefits from SM[45]. Most MS secure the recovery of costs through the network tariff or as an additional fee, see Table 4.1.

The standardization of products, operation procedures, and services is also a fundamental requirement for the development of DR in distribution networks. In particular, the lack of homogeneous and complete functionalities related to standardization and interoperability among SM may simply block certain forms of sophisticated DR due to limited capacities. The Commission's Recommendation 2012/148/EU (EC, 2012b) establishes a set of common minimum functional requirements for SM to be rolled-out in Europe in line with standardization and interoperability. Such functionalities are: accurate user-friendly interfaces, 15 min frequency reading, remote reading, two-way communication between the SM and external network, automatic transfer of information to customers (e.g. advanced tariffs), remote on/off control of the supply and/or power limitation, secure data communications, fraud prevention, import/export and reactive power reading. According to (EC, 2014), only half of the countries engaging the SM roll-out comply with all these requirements, being the frequency at which measurements and data can be updated and made available to consumers and third parties the most challenging one, as can be observed in Table 4.1, where the current status and characteristics of the SM roll-out in the analyzed countries is summarized.

4.3.2. Remuneration of electricity distribution

As could be expected, the remuneration of electricity distribution is the key regulatory element that requires a sound revision to enable and incentivize an efficient exploitation of demand response by DSOs. DSOs are responsible for the secure operation and management of the electricity distribution system and for ensuring network access to new and current users by developing and maintaining distribution grids in a reliable manner.

DSOs are regulated entities that have to recover the costs incurred in the development of these tasks through regulated revenues that are collected via network tariffs from network users. The remuneration mechanism for DSOs is thus a key element to provide the right incentives for optimizing network operation and planning decisions in the long run, in general, and for making use of DR in particular. In fact, DR falls within a broader range of recently developed technologies and practices at the distribution level, often referred to as DER. While DER bring new opportunities for a smarter and more active distribution network operation, they challenge the existing regulation of DSOs, calling for a change of paradigm where a more

[45] The responsibility for investment in and owning the non-network DR enabling technologies, in-home displays, smart appliances or load automation are clearly within the scope of liberalized activities and, as such, should not be subject to regulatory intervention (or rather just be regulated on a technical level to ensure compliance with network codes and interoperability).

active role is given to DSOs and innovation is further incentivized (Ruester et al., 2014). In this sense, the regulatory barriers identified in this section bear certain parallelism with those that hamper any investment in innovation in distribution networks, including those that facilitate Renewable Energy Sources (RES) integration (P. Siano, 2014).

It has been discussed that there could be room for greater efficiency in distribution network operation and planning if DSOs were allowed to resort to DR services or directly pay incentives for DR to solve temporary and predictable network constraints, reduce losses and manage faults. Under the assumption that a supervised, efficient and non-discriminatory mechanism is implemented for this purpose, where DSOs would be entitled to purchase DR services, the regulatory scheme that remunerates the electricity distribution activity should also incentivize this participation to the extent that it is the most efficient option. It is generally observed that some aspects of the current economic regulation of DSOs across Europe could be revised in order to better address this objective.

Incentive regulation is a common regulatory scheme across EU member states since the deregulation process started (Eurelectric, 2014). In contrast to the traditional cost-of service regulation (or rate-of-return, RoR, regulation), which in principle allows recovering the total incurred costs, with incentive regulation, the regulatory authority sets a path of allowed yearly revenues or prices to grid operators for a regulatory period of usually three to five years. By decoupling costs from revenues and assuming certain productivity improvement, DSOs gain an extra profit for being more efficient (Gómez, 2013b, 2013a). In principle, incentive regulation should motivate DSOs to procure flexibility from DR to reduce costs, allowing them to capture part of the savings that could be achieved with DR with respect to the ex-ante allowed revenue. These efficiency gains would be partly passed through to all consumers through the network tariff update, while DR participants would be expected to have received an additional explicit reward in compensation for their flexibility.

In practice, due to the difficulty of regulating long technical and economic lifetime of network investments, some regulators opt to exclude capital expenditure (CAPEX) from efficiency requirements (Eurelectric, 2014) so as to prevent insufficient network investments which could cause security of supply problems. This way, by remunerating CAPEX based on actual costs, as in e.g. France, Italy and Sweden, CAPEX-based solutions are being encouraged over those based on operational expenses (OPEX). The problem is that this practice effectively discourages DSOs from deferring or avoiding some investments by exploiting the DR potential.

There are different options to mitigate this effect. A possible way is by equalizing the incentives to reduce OPEX and CAPEX. In order to attain this, a single cost target that applies to total expenditure (TOTEX) has to be established, even if different methods are applied to different cost components. Such an approach is followed in Germany and Great Britain, in this case under the RIIO model. Italy is also planning to move to a TOTEX approach for this reason (AEEG SI, 2015; Lo Schiavo et al., 2013). The convenience of this option is not straightforward since DSOs need to secure a reliable electricity supply. Alternatively, there are several regulatory mechanisms available that could overcome this limitation, such as profit-sharing schemes. Profit-sharing schemes consist of setting an ex-ante revenue path together with an ex-post correction based on pre-defined rules. As discussed in (Cossent and Gómez, 2013), this approach allows mitigating the uncertainties faced by DSOs in a purely ex-ante framework, which can be greater when innovative alternatives to network reinforcements are considered, and at the same encourage cost reductions. Profit-sharing schemes by themselves are more suitable to handle uncertainties rather than equalizing OPEX/CAPEX incentives. In this regard, other measures such as accelerating depreciation could result in investment being remunerated in a shorter period, therefore reducing the riskiness of cash flows and the cost of capital. For instance, a profit/loss sharing scheme for remuneration to new investments, valued on the basis of physical units and standard unit costs, will start to apply in Spain as soon as Royal Decree 1048/2013 enters into force. Based on this scheme, DSOs would be able to keep, or face, 50% of the difference between actual investments and the efficient investment path estimated with a Reference Network Model (RNM).

Another arguable aspect of incentive regulation, as discussed in (Cossent et al., 2009), is whether the length of the regulatory periods incentivizes innovation in general, and investments to enable DR in particular. Regulatory periods, which do not generally exceed 4 or 5 years, with some exceptions such as Great Britain (8 years) and Spain (6 years), could be deemed as short to allow efficiency improvements from DR become effective. At the same time, as suggested in (Gómez, 2013a), it would be advisable that the transition for the allowed revenues between the last year of a regulatory period and the first year of the following period were gradual for it would further incentivize the DSO to lower costs in the long run, as it would be able to retain part of that cost reduction for a longer time.

An explicit mechanism to integrate DR as an operational strategy to improve efficiency in distribution networks is still missing in most countries but the pre-conditions for its implementation are more favourable in some countries than in others. Those that incentivize efficient investments are on the way to enable the implementation of DR for distribution network purposes. Output based regulation of Great Britain seems to be the approach that best fits the incorporation of DR into DSO strategies, with clear incentives for efficiency and innovation in the long term. In addition to this, the Office of Gas and Electricity Markets (OFGEM), Great Britain's National Regulatory Authority (NRA), already developed The Low

Carbon Networks Fund (LCNF) as part of the fifth distribution price control (DPCR5) period that ended in March 2015. It financed DSOs to develop research trials that include the incorporation of DR into active network management programs. This program has been substituted in the RIIO-ED1 price control beginning in April 2015 by a new one called Innovation Stimulus. Also in Italy, for the regulatory period 2012-2015, a 2% extra WACC has been awarded for 12 years to certain innovative investments, which had to be selected ex-ante by the NRA. Such projects did not concern DR explicitly but MV grid automation and installation of batteries.

Table 4.2. Main aspects of distribution remuneration in relation to DR in the European countries under analysis [a]

	Spain	Italy	Germany	France	GB	Sweden
Remuneration system	Revenue cap on OPEX with X efficiency. Profit/loss sharing scheme for new investments valued on the basis of standard unit costs. Allowed new investments and network-related Operation and Maintenance costs evaluated annually with Reference Network Model.	Price cap on OPEX with X efficiency. RoR on CAPEX – Regulatory Asset Base (RAB) based on 'historical revaluated costs'.	Revenue cap on TOTEX with X efficiency. Benchmarking over TOTEX using book values.	Revenue cap on controllable OPEX with X efficiency. RoR for CAPEX and non-controllable OPEX, based on real accounting value.	Output based regulation (RIIO –ED1 formula). TOTEX incentive mechanism based on the performance in relation to a set of output categories [b]	Price cap on controllable OPEX with X efficiency. RoR on CAPEX and non-controllable OPEX, planned investments in the regulatory period are included in the RAB based on standard costs.
Regulatory period	6 years	4 years	5 years	4 years	8 years	4 years
Financial incentives for quality of service and losses performance	Targets with premiums and penalties	Targets with premiums and penalties	Targets with premiums and penalties	Targets with premiums and penalties	Incentive adjustments within the allowed revenue formula	Revenue cap adjusted annually based on actual costs vs. a reference level
Active network management by DSOs allowed	Not explicitly	Not explicitly	Tariff incentive/ interruptible loads.	Not explicitly. Only CPP regulated tariffs	Innovation trials with LCNF and Innovation Stimulus funding.	Not explicitly

[a] *Based on information from* (Eurelectric, 2014), (Eurelectric, 2013b) *and* (EC, 2015).
[b] *RIIO: Revenues = Incentives + Innovation + Outputs. Output categories: reliability and availability, safety, customer satisfaction, timely connections, environment impact and social.*

Finally, distribution remuneration formulas that incentivize efficiency usually include a system of economic incentives to lower energy losses and improve quality of supply with bonuses and penalties that are charged according to the performance in relation to established target values (Gómez, 2013b). Their presence in the analysed countries, as can be seen in Table 4.2, is a favourable factor for the development of DR in distribution networks inasmuch as it contributes to stabilize and flatten demand profiles.

4.3.3. Distribution network tariffs

Among the costs incurred in electricity supply, the remuneration of those that correspond to regulated activities (mostly networks, plus other regulated charges) is generally determined by the corresponding regulatory authority. Both under traditional and competitive regulation of generation and retail, this regulatory authority determines how these costs will be allocated and charged through regulated tariffs. Under a competitive regulatory framework, end consumers pay an agreed market price to the chosen supplier plus this regulated Use of System Charge. In turn, under traditional regulation, also the costs of electricity production and commercialization are regulated and included in a final integral tariff (Reneses et al., 2013). It should be noted that this situation is very similar to what occurs in many states of the US where electric utilities are vertically integrated and electricity rates, in which all incurred costs (purchase of electricity, transmission costs, etc.) are included, are finally decided by the corresponding state-level public utility commission based on the utilities' service costs. In contrast, across Europe, many countries are fully open to retail competition while others are still in the process, as will be discussed in Section 4.3.5, so network tariffs are clearly defined and separable component of the final retail price.

Regulated tariffs aimed at recovering network costs, i.e. distribution network tariffs, could be an effective tool for DR with a network perspective, alone or in combination with additional mechanisms for the explicit provision of DR services to DSOs. In principle, the latter option is preferable because network tariffs, on their own, present two basic limitations. On the one hand, as tariffs are updated rather infrequently, they may not be flexible enough to account for non-systematic and unpredictable network conditions. In this sense, greater flexibility can be achieved if tariffs can be set differently per distribution areas or companies, as happens in Germany, Sweden and Great Britain (see Table 4.3). On the other hand, other components of the final electricity rate paid by end customers, such as the price of energy charged by suppliers and other regulated costs, may dilute the strength of the economic signal provided by network tariffs.

Table 4.3. State of the regulation in relation to the design of distribution network tariffs for households in the European countries under analysis [a]

	Spain	Italy	Germany	France	GB	Sweden
Network tariff charges (and breakdown for typical consumer)	Capacity (84%) + Energy (16%)	Fixed (4%) + Capacity (12%) + Energy (84%)	Fixed (20%) + Energy (80%)	Fixed (6%) + Capacity (14%) + Energy (80%)	Daily fixed (14%) + Energy (86%)	Fixed (80%) + Energy (20%)
Tariff structure, i.e. Time-of-Use (TOU) or space-differentiation, tariff groups, etc.)	Nationwide uniform, set by the government [b] Voltage and optional TOU, from 1 to 3 energy time periods (small consumers usually no TOU).	Nationwide uniform; Voltage; no TOU for network charges although mandatory integral tariffs for small consumers are TOU [d].	Each DSO sets own tariffs; under NRA approval. Voltage, no TOU but for certain installations of atypical consumers (heating systems, heat pumps etc.).	Nation-wide uniform, set by NRA; Voltage and optional TOU.	Each DSO sets own tariffs based on a Common Distribution Charging Methodology (CDCM) [d], under NRA approval. Typically one or two time periods (day-night).	Each DSO sets own tariffs (NRA sets the allowed revenue); DSO can use any structure that is non-discriminatory and objective – Some DSOs are using TOU.

[a] *Based on information from* (Eurelectric, 2013b) *and* (EC, 2015).
[b] *According to Law 24/2013 of the Electric Power Sector, it is the role of the Ministry of Industry, energy and Tourism to define the final tariff structure based on the methodology designed by the National Regulatory Authority, "Comisión Nacional de los Mercados y la Competencia" (CNMC). The distribution tariff is bundled to an integrated tariff (Access tariff).*
[c] *See* https://www.ofgem.gov.uk/electricity/distribution-networks/charging-arrangements
[d] *Specific values for each tariff group and charge can be found in* http://www.autorita.energia.it/it/elettricita/auc.htm. *Note that tariffs recovering network and regulated costs do not have TOU differentiation, but mandatory integral tariffs for small consumers do since 2010, as described in section* 4.3.5.

In order to serve this purpose, tariffs must be designed so as to ensure full cost-recovery for DSOs allowed expenses while encouraging a more efficient use of the grid capacity to network users (EC, 2015; Eurelectric, 2013b). If adequately designed, distribution tariffs following the cost-causality principle, as described in (Reneses and Rodríguez Ortega, 2014), have the ability of sending efficient economic signals to network users while ensuring full cost recovery. All MS appear to allocate costs to consumers based on some cost-reflectivity criterion, e.g. consumers are usually not allocated costs of network levels downstream of their connection level (EC, 2015). Notwithstanding, many of them fail to send the expected long-term signal of truly cost-reflective tariffs (Eurelectric, 2013b).

Special attention has to be paid both to the tariff structure, built according to cost drivers, i.e. the fundamental variables that are directly related to the origin of the costs, tariff categories (size, voltage levels, etc.) and space and time-differentiation. Given that the largest component of the network costs are related to the contribution of network users to the peak power flows, which is determined by the peak demand (and peak generation in the case of DG), that could be reflected in the tariff in two ways:

i. By charging the tariff through at least two **components**: a **capacity** or demand component (€/kW) and an **energy** or **volumetric** component (€/kWh), and finding the right balance between them. The aforementioned capacity charge can be based on an ex-ante contracted capacity defined at the moment of connection to the grid or on the maximum instantaneous consumption[46] observed ex-post through the meter. Capacity charges on contracted capacity are sometimes believed to be only partly cost-reflective in contrast to charges on highest used capacity in a year or shorter periods of time, for instance, during pre-specified peak periods of several hours in certain days. In any case, this tariff structure would discourage high instantaneous power consumptions, thus allowing DSOs to defer or avoid grid reinforcements. However, network tariffs for households and small businesses in Europe are frequently almost entirely based on energy volume (kWh) through the volumetric component (CEER, 2015; Eurelectric, 2013b), as in Germany. Moreover, even when there is a capacity component, which is the case of the other countries, as can be seen in Table 4.3, it often represents a low share of the revenue recovery with the exception of Spain. In Europe as a whole is on average around 20-30% (EC, 2015).
ii. By providing a smart **structure** to the **volumetric component** of the tariff (€/kWh), allowing it to vary according to the Time of Use (TOU) or even according to other forms of dynamic pricing, such as sporadic Critical Peak Pricing (CPP), or even interruptible tariffs, driven by local network conditions. This way, the use of the network during hours of high probability of congestion would be discouraged, shifting consumption of hours of lower network saturation (assuming the other components of the final price do not go in the opposite direction). Network tariffs for small consumers are still flat in many countries, impeding this form of DR. In particular, as seen in Table 4.3, there is Time of Use differentiation in network tariffs for Spain, Italy and France, but regulated CPP are only used in France.

[46] A clear and standardized definition of how peak demand is measured is needed, especially in relation to its time granularity. In the absence of clear guidelines in this sense, it is very difficult that SM allow to update measures frequently enough to accurately capture maximum consumption, as referred to in the Commission Recommendation (EC, 2012b), according to which there is a general consensus that 15 minutes is the minimum update rate needed to support advanced tariff systems.

The first recommendation turns increasingly important when residential consumers that have small generation units installed for self-consumption, or self-generation as preferred by the Council of European Energy Regulators (CEER, 2016), i.e. prosumers, become widespread in the network. In spite of their potential impact on network costs (connection, operation and reinforcement), prosumers are frequently incentivized to install on-site generation by being charged less for network and other regulated charges through a combination of volumetric tariffs and/or net metering (Picciariello et al., 2015). Insofar as consumers are charged for network and other regulated costs through a volumetric rate (€/kWh) on their net demand (i.e. consumption not satisfied with self-generation), prosumers can avoid part of those payments by instantaneously compensating consumption with generation[47]. The incentive is even higher when a net metering policy is in place, by which the consumer may offset consumption with self-generation, not instantly, but within a whole billing period. The income reduction due to these prosumers' savings could lead to a problem of cost recovery for DSOs. Alternatively, if the value of volumetric rates is increased to compensate this effect, cross subsidies will occur (Eid et al., 2014), as the same costs would have to be paid by fewer kWh of net consumption, and by fewer consumers, to the detriment of consumers without self-generation, who would be charged excessively. In turn, this rate increase would enhance the incentives for self-consumption, worsening the problem.

Hence, it is highly recommended that network tariffs consist of a fixed component related to the grid connection and a TOU dependent capacity component (€/kW), or even a volumetric component (€/kWh) also with TOU differentiation, or in the form of CPP, always reflecting the contribution to local network peak utilization. In contrast, flat and purely volumetric tariffs should be avoided, especially if applied on net measurements. In this sense, network tariffs should provide end users with efficient economic signals that reflect the value of the network, regardless of what is behind the meter, and on their contribution to the actual utilization of the grid.

4.3.4. Regulation of DR provision: suppliers and aggregators

A clear definition of the roles and responsibilities of DR providers towards consumers and other market parties is an essential requirement for a fair and efficient development of DR in distribution networks. This is of particular relevance when the role of supply and DR services provision are separated into different agents. In such a case any load adjustment resulting from

[47] In contrast, the contracted capacity can hardly be reduced as consumers would still need a similar amount of power in those months with low generation (e.g. winter months in case of solar PV). Similarly, the observed maximum instantaneous consumption may only be reduced in times of generation availability. Therefore, prosumers would not avoid network payments if network tariffs have a capacity based component.

a DR action by the DR provider, or aggregator, will result in an imbalance in the retailer, or Balance Responsible Party (BRP) position (Eurelectric, 2015).

The easiest and most straightforward market model that solves this problem is that in which suppliers assume the role of DR provider and simultaneously optimize their portfolio of energy and flexibility services to their customers, taking the responsibility for their net imbalances. In those countries where third party DR aggregation is allowed by existing regulation, it is necessary that DR contracts with aggregators involve an agreement with the supplier or the BRP (SEDC, 2015). Under these circumstances, it is assumed that the imbalances resulting from the DR actions are neutralized by the TSO and that the BRP/supplier is financially compensated. Financial adjustment mechanisms that neutralize the impact of DR actions on BRP and suppliers are being suggested across Europe (EG3, 2015; Eurelectric, 2015). Basically, as described in (Eurelectric, 2015) there are two main market design options for this adjustment: (i) a bilateral contractual model, by which the BRP and the aggregator agree on the compensation, (ii) a centralized regulated model, by which the BRP is directly compensated by the third party aggregator at a regulated price. Standardized correction mechanisms centralized by the TSO, e.g. the one being proposed in France (SEDC, 2015), are generally preferred to bilateral arrangements between the aggregators and other actors, not only suppliers but also DSO, TSO, etc. It is also suggested that a standardized methodology to measure flexibility should be defined in each MS (EG3, 2015), a challenge on which there is no clear consensus.

Such a framework is missing in most European countries. Independent DR aggregators are arising in some European markets but not all, e.g. they are not allowed by regulation in Spain or Italy, while their activity is enabled in Germany, France Great Britain and Sweden, even though difficulties to coordinate different roles and players remain. In other countries the regulator is working to develop mechanisms to facilitate it (SEDC, 2015).

The root of this problem lies in the nature of incentive-based DR. While it is straightforward to measure electricity consumption in relation to price variations, measuring load reductions with respect to a baseline consumption profile and pricing those reductions entails great difficulties and potential inaccuracies. It is therefore highly recommended that while DR providers may be allowed to freely arrange any type of DR contract with final consumers, included volume-signalling and load control; DR services from the standpoint of a network or system operator, including DSOs, are linked to total consumption and the incentives provided based as much as possible on transparent market and remuneration mechanisms.

For the development of DR involving small consumers in distribution network, load aggregation is a relevant tool that allows individual flexibility to become valuable for the network, but third-party aggregation is not always a necessary prerequisite. It may even bring additional difficulties if the implications of DR actions on BRP and suppliers are not adequately regulated. Suppliers are widely believed to be the most suitable actors to play the role of DR provider (Batlle and Rivier, 2012; Eurelectric, 2015; Hancher et al., 2013). It is advisable that retailers are encouraged to assume the role of DR aggregation so that they are enabled to provide DR services to DSOs through clear and transparent market mechanisms.

4.3.5. Consumer choice and protection

Empowering consumers and making them aware of the implications of their own consumption decisions is a basic key element to guarantee the success of any DR mechanism. For this purpose, it is crucial that consumers are provided with the tools to comprehend the implications of their engagement in DR, e.g. expected benefits, obligations, data access and privacy, etc. Furthermore, the promotion of a competitive retail market is the most straightforward way of encouraging the emergence of the efficient amount of DR by market instruments. In a European context, it is the responsibility of market actors to transform the complexity of the system into simple and attractive products that consumers can understand. However, the reality is that residential consumers are not fully participating actively in the market by exercising choice among available suppliers and product offers, and many times find it difficult to understand complex tariffs or mechanisms for DR (ACER/CEER, 2014). This is in direct contrast with electric power systems with vertical integration of distribution and retail activities, as happens in many states of the US. Note that DR can be developed where regulated prices are still in place. In this situation, DR would be fostered directly by the regulator or the utility. Notwithstanding, in electricity systems moving towards a full competitive regulation, as happens in Europe, advanced products and demand response aggregation addressed to end-consumers are more likely to take off when regulated retail prices are completely phased out.

In this sense, simplicity is best guaranteed if the retailer remains the main point of contact for customers, assuming the role of DR provider, as previously suggested. For this reason, a really competitive retail market is the first step to let DR arise naturally in the form of a greater choice of products and contractual arrangements for flexibility being offered to final consumers.

Many European countries are still opening up to retail competition (ACER/CEER, 2014). Regulated prices, or at least standard offer prices determined by the public authorities, usually the NRA, even now coexist with competitive retail prices in several MS for small consumers, e.g. Italy, France and Spain. Regulated retail prices should be progressively phased out, as suggested by the European Commission's recommendation COM(2012) 663 (EC, 2012c), as their continuation is unlikely to encourage the development of any form of DR. As part of the progressive trend towards retail price deregulation in Europe, Italy and Spain have modified the calculation methodology for standard offer prices in 2010[48] and 2013[49], respectively, and linked them to the wholesale market prices. Still, even if competition is not distorted with these standard offers, because regulated prices are not being set below underlying supply cost levels, they represent a reference value that may discourage competition and prevent consumers from making their own decisions. In contrast, in a minority of MS, including Great Britain, Sweden and Germany, retail prices are fully liberalized, favouring the development of DR products and initiatives.

It would be in the best interest of DR providers, above all stakeholders, to engage consumers to have a wider range of options to choose the most convenient for them. Thus, it is expected that not only under regulatory pressure but also by stimulating competitiveness in the retail and local flexibility markets will the market agents be encouraged to engage consumers, providing them with the tools to manage their own consumption and to understand the benefits of getting involved. In this sense, Germany, Great Britain and Sweden, where liberalization is more mature and which present higher levels of switching activity and a wider diversification of available products for consumers (ACER/CEER, 2014), appear to be best positioned to incorporate DR commercial arrangements at retail level in the near future.

In addition to transparency and simplicity in the retail products, data security and privacy is also required for a well-functioning retail market. Regulation has traditionally contemplated the need for data processing for billing on cumulative consumption only a few times a year. Now the task becomes a more complicate issue given that under a DR approach, consumers could have to be billed on actual near real-time consumption, as indicated in the EED (EC, 2012a). In addition, the possibility of gathering high-resolution consumption data raises privacy concerns because it contains detailed information of individual energy behaviour (Pallas, 2012).

The European Commission recommends various provisions regarding data privacy protection, such as the Directives 95/46/EC and 2002/58/EC, which are fully applicable with regard to personal data collected by smart metering systems. Another example is the Commission Recommendation 2012/148/EU (EC, 2012b), which establishes specific data

[48] The Italian regulatory authority (AEEG) approved in July 2010 the entry into force of a mandatory Time-of-Use tariff among residential consumers subject to the standard supply regime, with two time slots: one for peak hours (from 8 am to 7 pm of weekdays) and the other for off-peak hours (nights and weekends). The single buyer ("*Acquirente Unico*") is in charge of procuring electricity on the wholesale market and to resell it to standard offer retailers at a price reflecting the actual costs incurred in this purchase.

[49] In Spain, the Voluntary Price for Small consumers ("*Precio voluntario del Pequeño consumidor"*, PVPC) is calculated on the basis of the hourly day ahead wholesale electricity prices. Note that even though this standard offer has been in place ever since 2013, it has not been until October 2015 that incumbent suppliers have been required to bill consumers according to their actual hourly consumption.

protection measures in relation to SM. In the process of deciding on future legal obligations in this sense, the Commission has proposed a Data Protection Impact Assessment (DPIA) Template (SGTF, 2014). This is a harmonized decision-making tool to evaluate smart grid investments in the early stage of deployment. It allows risks to data protection, privacy and security to be identified and anticipated. The use of this template by data controllers is not compulsory but highly recommended in a two-year test phase and it is unclear whether it will become mandatory or not. Therefore, it is advisable that at MS level, governments and NRA get ready for this new scenario and develop national procedures to regulate the application of the DPIA; otherwise the development of DR arrangements could be further slowed down.

4.4. Conclusions and policy recommendations

This chapter reviews the main regulatory barriers that could slow down the successful development of demand response mechanisms oriented to small consumers and to an active distribution network management across Europe. Overall, a series of general regulatory recommendations can be provided to help in the transition to their possible future implementation, as presented in Table 4.4.

One of the main conclusions that can be drawn is that DSO regulation should be revised to allow and incentivize network operators to count on DR as a valid flexibility resource to operate and plan their networks efficiently. For this purpose, clear incentives for efficiency and innovation in the long term must be provided without endangering regulatory stability. It is important to bear in mind that there is not a single perfect solution that fits all national realities in this sense, especially given the many differences among EU countries about the technical characteristics of distribution networks, the amount and type of DSOs present in each and the different challenges that each of them might be facing.

When DSOs are responsible for the design of the tariff structure in their network area, CPP and interruptible tariffs could become a clear and sound DR tool to manage occasional congestions in the grid. However, network tariffs usually have a limited significance in the final electricity price and are rather inflexible to allow an active management of networks. Furthermore, sometimes network tariffs cannot be separated from other components of the regulated tariff, reducing their ability to reflect network-related costs. Thus, specific DR mechanisms with the potential participation of other types of DER as well would be more suitable for this purpose. The responsibilities of DR providers towards other market parties still must be defined more clearly in most European countries. In the case of small consumers providing flexibility to the DSO, third-party aggregation does not seem to be a necessary requirement. Instead, ensuring a truly competitive retail market in all countries and encouraging suppliers to create DR products for consumers would be a more straightforward and simple approach.

Table 4.4. Main regulatory recommendations to support an active involvement of DR in distribution networks

Smart Metering	• Adequate availability of advanced metering infrastructure • Interoperability and standard functionalities to enable DR • Stable framework for cost recovery
DSO remuneration	• Definition of an explicit DR mechanism • Incentives for long-term innovation avoiding regulatory uncertainty (output based regulation, profit sharing schemes, incentivized efficient OPEX and CAPEX, accelerated depreciation, longer regulatory periods) • Smooth transition between regulatory periods
Network tariffs	• Cost-reflective tariff structure: capacity charge and dynamic tariffs • Flexibility to adapt tariffs to local conditions • Separation of the non-network related component of the tariff
DR Provider	• Allowing aggregation and define clear responsibilities • Encouraging retailers to assume the role of DR provider for small consumers
Consumer protection	• Enhancement of retail competitiveness • Improvement of transparency to increase consumer understanding and awareness • Development of national procedures to regulate the application of DPIA to safeguard privacy

Finally, special care should be taken with data privacy legislation and the rights of consumers to be informed and be provided the tools to understand the new smart tariffs and complex contracts to which they can be exposed. This key challenge must be dealt almost in all countries with if consumers are expected to be engaged in DR.

4.5. References

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5. Conclusions, contributions and future research

This last chapter summarizes the developments of this thesis. The main conclusions drawn are presented and the original contributions highlighted. Finally, suggestions for future research are discussed.

5.1. Summary and conclusions

Demand response could drastically change the way DSOs operate their networks. Provided DSOs could procure flexibility services from consumers, they could count on an additional tool to operate and plan their networks more actively and efficiently, and so they would possibly be able to reduce network losses, avoid network congestions or better manage network faults and outages. If grid constraints are visible in the long term, DSOs could partially avoid or defer reinforcement investment costs. Within this local perimeter of DR action, small commercial and residential consumers could play a fundamental role. It is expected that, if the pertinent mechanisms were defined and the regulatory conditions appropriate, these consumers would find it natural to participate in DR arrangements, probably through an intermediary, or DR provider, such as a supplier or a third-party aggregator, delivering the flexibility service on their behalf to DSOs.

This thesis has studied the feasibility and the potential economic benefits of demand response as a flexibility resource for an active management of distribution networks and analyzed its economic and regulatory implications from a threefold perspective: the consumer, the network and the regulatory environment.

From the perspective of the consumer and DR providers, en empirical methodology has been proposed to obtain full characterization of residential consumers' flexibility in response to economic incentives. The methodology, which is intended to assist DR providers in real implementation cases, enables the estimation of distribution function of flexibility in relation to a set of controllable and non-controllable variables. In this sense, it has been discussed how the proposed utilization of Quantile Regression (QR) for this purpose constitutes a flexible and informative tool. On the one hand, it provides a concise and parametric representation of flexibility allowing for an easy categorization of consumers. On the other hand, it depicts a full picture of uncertainty and variability of the expected flexibility of a consumer, from which valuable risk measures can be directly evaluated.

From the perspective of the distribution network, the mechanisms that would allow DSOs to incorporate DR procedures into their network operation and planning strategies have been explored. Furthermore, a methodological approach based on the use of a Reference Network Model (RNM) has been presented and used to quantify the potential economic benefits that DR could bring to distribution grids and applied to a case study for Spanish distribution networks. It has been discussed that existing planning tools and methodologies could be used and adapted to identify the best technical and economic balance between traditional network reinforcement and demand-side actions. From this quantification, which is strongly dependent on the availability of actual data from real experiences and network characteristics, it has been concluded that the economic value of DR would be very dependent on local network characteristics, such as the network configuration and the congestion level, the expected load growth, location of consumers providing flexibility, among others.

Finally, the regulatory environment that could affect the potential development of DR as a smart resource for the operation and planning of distribution networks has been analyzed, from a European perspective, and the key regulatory barriers that could slow down its successful development in the near future have been identified. A series of general regulatory recommendations in specific areas (smart metering, DSO remuneration, network tariff design, DR provider regulation and consumer protection) have been provided to help in the transition to their possible future implementation. One of the main conclusions that can be drawn is that DSO regulation should be revised to allow and incentivize network operators to count on DR as a valid flexibility resource to operate and plan their networks efficiently. For this purpose, clear incentives for efficiency and innovation in the long term must be provided without endangering regulatory stability.

5.2. Original contributions

The main contributions of this thesis have been the following:

- Proposition of an original empirical probabilistic approach based on Quantile Regression techniques to characterize residential electricity consumer responsiveness to economic incentives, which is flexible and informative, has scalable properties and could be applied in real pre-implementation situations.
- Definition of original and informative specific risk measures for the uncertainty of consumer flexibility to economic incentives that are directly originated with the proposed approach. These measures are directly applicable to a robust estimation of the cost of activating certain target levels of demand response from a consumer or group of consumers.

- This empirical methodology has been applied to a case study based on a real demand response experience. In particular, a pilot field test based on incentives carried out among residential consumers in a Spanish location within the context of the European research project ADDRESS[50] has been analysed.
- Proposal of a methodological approach to assess the economic value that DR could bring locally to distribution networks when different options of implementation are considered. The centre of the methodology is the quantification the potential ability of DR as a resource to defer planned distribution investments by alleviating local peak capacity. The approach is illustrated by a case study of two rural and urban areas of Spain, based on realistic large-scale exemplary networks and real consumption.
- Definition of the alternatives for the procurement of innovative DR network services that would allow a more efficient operation of distribution networks by DSOs, thus facilitating that grid capacity is optimized in the network planning process and so, making it possible to avoid or defer investments in network reinforcements.
- Identification of the main regulatory barriers across Europe that obstruct the way for the future development of markets and mechanisms for the provision of flexibility services by small consumers to DSOs, particularizing in a set of representative countries, and proposal of a series of EU oriented policy recommendations to facilitate the future implementation of active distribution system management services from DR.

Part of the research work carried out during the development of this thesis has been materialized the following journal publications, conference papers and book chapter.

Journal publications

- Vallés, M., Reneses, J., Cossent, R. and Frías, P. (2016) 'Regulatory and market barriers to the realization of demand response in electricity distribution networks: A European perspective', Electric Power Systems Research, 140, pp. 689–698. doi: 10.1016/j.epsr.2016.04.026.
- Vallés, M., Reneses, J., Frías, P. and Mateo, C. (2016) 'Economic benefits of integrating Active Demand in distribution network planning: A Spanish case study', Electric Power Systems Research, 136, pp. 331–340. doi: 10.1016/j.epsr.2016.03.017.

[50] ADDRESS (Active Distribution network with full integration of Demand and Distributed Energy REsourceS) is a research project co-funded by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 207643, which aimed to enable Active Demand through the active participation of small and commercial consumers in power system markets and in the provision of system services (http://www.addressfp7.org/).

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Conference papers

- Vallés, M., Reneses, J., Frías, P. and Linares, P. (2013) 'A residential load behavior model to analyze DR and end-use tariffs', in. 36th Annual IAEE International Conference, Daegu, Korea: IIT.
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Book chapters

- Linares, P., Vallés, M., Frías, P., Conchado, A. and Lago, Ó. (2015) 'System-Level Benefits of Demand Response', in Vicino, A., Losi, A., and Mancarella, P. (eds) Integration of Demand Response Into the Electricity Chain. John Wiley & Sons, Inc., pp. 143–172.

Working papers (to be sent to a scientific journal with impact factor)

- Vallés, M., Bello, A., Reneses, J., Frías, P.. (2017) 'Probabilistic characterization of electricity consumer responsiveness to economic incentives', Working Paper.

5.3. Future research

Fields of future research stemming from the work developed in this thesis could be:

- Study of the implications of different levels of aggregation in the estimation of the conditional quantile functions of load flexibility and the effects of correlation between individuals when grouping different categories of consumers in relation to their flexibility.
- Incorporation of the estimation of the costs of activating demand response services to the quantification of the benefits of DR for distribution network operation and planning, based on the estimated conditional quantile functions of flexibility.
- Formulation and definition of the mechanisms and the contractual conditions that should guide the commercial relationships between DSOs, DR providers (retailers or aggregators) and consumers in the procurement/provision of DR flexibility services for an active management of distribution networks.