Long-Term Electricity Investments Accounting for Demand and Supply Side Flexibility

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26 March 2019

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Abstract

Short-term Electricity Demand Response (DR) is an emerging technology in Europe's Electricity markets that will introduce a new degree of flexibility. The objective of this work is to analyze to what extent the untapped DR potential can facilitate an optimal transition to an European low emission power system. The benefits of DR consists of a reduction in peak load consumption, which leads to reduction in capacity investments, production and consumption savings, reduced congestion phases, reliable integration of intermittent renewable resources and supply and demand flexibility. The capabilities of DR are studied in the European Model for Power Investment with (High Shares of) Renewable Energy (EMPIRE), which is an electricity sector model with a time span of 30 years ending in 2050. The model is two-stage stochastic that includes uncertainty at the operational level and energy economics dynamics at a strategic level. The main contribution of this article is designing the investment-operation DR module within the EMPIRE framework. It models several classes of shiftable and curtailable loads in residential, commercial and industrial sectors, including flexibility periods, operational costs and endogenous DR investments, for 31 European countries. The results show that DR capacity substitutes partially flexible supply side capacity from peak gas plants and battery storage, in addition to enabling more solar PV production.

Keywords: Demand Response, Flexibility, Linear Stochastic Optimization, Demand Side Management, European Power System, Energy Economics

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Contents

Glossary

CCGT Closed Cycled Gas Turbines. 17, 19

CCS Carbon Capture and Storage. 17–21

DR Demand Response. 3–8, 10, 14, 18

DSM Demand Side Management. 4

GT Gas Turbine. 17

IRES Intermittent Renewable Energy Sources. 15, 19

OCGT Open Cycle Gas Turbines. 17, 19, 24

RES Renewable Energy Sources. 3–5, 9, 17

ZEB Zero Emission Buildings. 4

1. Introduction

The modernization of the European Power markets will inevitably introduce efficient mechanisms that will help in the tremendous challenge of meeting sustainability goals. This challenge can be divided into two subproblems, first, increasing the share of power capacity from renewable sources as well as their share in the energy mix, and second, operating the power system in an efficient and reliable way. Those market tools are new renewable energy market products, smart metering and ICT infrastructure, new market rules, aggregators, and finally Demand Response (DR) flexibility.

In the European Union directive on energy efficiency article 15.8 (ENTSO-e, 2015) it is indicated that *member states shall ensure the National Regulatory Agencies encourage demand side resources such as DR, to participate alongside supply in wholesale and retail markets.* In that respect, allowing the consumer side to have more decision power would increase price elasticity on the retail side and at the end on the wholesale electricity market. In that respect consumer aggregators have the responsibility of managing their clients flexibility. The European Network of Transmission System Operators for Electricity (ENTSOe) has established guidelines and recommendations to develop DR in Europe electricity markets (ENTSO-e, 2015). Six key requirements are described for unleashing the potential development of DR: *(1) price signals need to reveal the value of flexibility for the electricity system, (2) efficient use of DR based on an economic choice between the value of consumption and the market value of electricity, (3) involvement of consumers can be facilitated by automation or by a third-party company, (4) regulatory barriers regarding market agents should facilitate the development of DR, (5) subsidies to DR should remain limited and (6) reliability of DR for small consumers has to be guaranteed through proper communication and control technologies.*

DR can be used for shaving peak hour demand, avoiding the use of expensive peak generator plants, increase the reliability of the system by reducing outages, diversifying resources, integration of variable renewable resources, a more efficient system operation, as reserve capacity and giving more decision options to customers (Albadi and El-Saadany, 2008). Even more, recently the capacity of reducing CO_2 emissions through load shifting and ICT energy efficient measures has been estimated between 0.23% and 3.3% (Bastida et al., 2019). However, some of this issues can be handled by other technologies which might compete with DR. Pumped-Storage hydro power, compressed air storage, Closed Cycle Gas Turbines (CCGT) and battery storage systems can resolve high demand contingencies.

DR affects numerous agents and sectors in the electricity system, from base power and RES plants to large industrial consumers, commercial buildings and households. From this multi-agent panorama, the amount of research articles on DR is vast (Bossmann and Eser, 2016). In the last years they have filled the research gaps pointed out in (O'Connell et al., 2014) at the same time that attracting the attention of techno-social modelers (McKenna et al., 2018; Srivastava et al., 2018).

From our techno-economic system planning perspective, investments in power balancing technologies should be considered jointly in the same model. System operation conditions have to be considered in order to see which technologies are more worthwhile, at the same time that investment costs along the long-term outlook. Thereby, two main questions have to be investigated. First, in which way will DR evolve in the European power system, and second, what will the impacts be on long-term investments in a sustainable power system. To this end, the perspective adopted in this research is the electricity system perspective, assessing the system performance as a whole.

Literature review

In Lund et al. (2015) a review of flexible measures in energy systems is presented. According to them DR, can provide very short, short and intermediate flexibility in the range of 1 minute to 3 days. In Huber et al. (2014) the needs of flexibility in the operation of European power systems with over 30% of Renewable Energy Sources (RES) energy share are significant. They studied those requirements at a 1 to 12 hours time span and suggest that DR, storage, flexible power plants and interconnectors can alleviate the power ramps caused by RES. Ulbig and Andersson (2015) establishes three factors to compare flexibility of power system units: ramp, power and energy. Generators, storages and load units are quantitatively compared in those terms.

Although the literature on DR in the electricity system perspective is numerous (Bossmann and Eser, 2016), there is a lack of articles on DR on long-term investment with RES uncertainty. In Lohmann and Rebennack (2016), a short-term DR model with a long-term investment scope is described, and it is solved with a novel Benders decomposition approach. One of the characteristics of the model is the use of inter-hour electricity demand elasticities, which are theoretical parameters difficult to estimate. Instead, the EMPIRE model avoids them by modelling the clearing market condition through the power balance equation. De Jonghe et al. (2012) proposes a complementarity programming approach, a method using electricity elasticities and a piecewise linear integration of consumer value to integrate DR in a expansion model. Unfortunately the first method requires a euilibrium formulation of the problem and the other two are dependent on own and cross-price electricity elasticities.

In Ottesen and Tomasgard (2015) two flexibility management methods for a multi-energy carrier building are studied. The rolling deterministic model and the rolling stochastic model represent a prosumer optimizing its energy inputs including flexible loads: shiftable volume, shiftable profile, curtailable and interruptible loads, assuming no efficiency losses.

In a lower scale setting, in García-Garre et al. (2018) the authors present an algorithm to coordinate a prosumer's household solar PV and residential DR. Their results show that self-consumption rate raises 25% and payback lowers 20%, but without considering system effects. In another paper by Seljom et al. (2017), the system effects of Zero Emission Buildings (ZEB) were studied in fact but without including storage, DR or continental Europe.

In Ottesen et al. (2016) a bidding methodology based on stochastic optimization for aggregators with several prosumers (equipped with lossless DR) is proposed. Uncertainty in wholesale spot market prices and loads are handled with a scenario generation method. The bidding strategy is obtained in a two-stage stochastic mixed integer linear program.

A similar problem setting is presented in Sáez-Gallego et al. (2018) where a retailer buys energy in the day-ahead market for a pool of price-responsive consumers. They provide an analytic solution in the case that the retailer is not risk averse and a stochastic programming model for optimal bidding under risk aversion.

In Ottesen et al. (2018) a multi-market bidding strategy for an aggregator managing four industries is studied using a three-stage stochastic optimization approach. The technical characteristics of industrial demand response are also studied in Rodríguez-García et al. (2018). They design a methodology for standard prequalifying industrial resources and validate it at three European high-energy intensive factories. On a broad European perspective, Papadaskalopoulos et al. (2018) study the impacts of Flexible Industrial Demand (FID) on the generation and transmission mix with a capacity expansion model and a stochastic unit dispatch model. However their model does not include endogenous capacity investments in flexibility, the study is limited to 2030 and they do not include flexibility scheduling costs. Their conclusion is that FID saves capacity investments in generation, transmission and distribution grids to the order of billion euros.

In Iria et al. (2019) a two-stage stochastic optimization model is proposed for an aggregator bidding in the day-ahead and secondary reserve market, showing that the stochastic strategy is beneficial compared to an inflexible and single strategy. Another paper with an aggregator finds that EV obsolete batteries can have a second life when used by a flexible consumer to provide capacity reserves to the grid (Casals et al., 2019).

Vallés et al. (2018) give an empirical methodology to exhaustively characterize residential consumers' flexibility in response to economic incentives. Their approach consists on quantile regression to assess the probabilistic responsiveness of residential consumers, ending up with two measures called flexibility at risk and conditional flexibility at risk.

Flexible consumers can be implemented in models that look at the future European power system. In Kies et al. (2016) a simplified European power system model with Demand Side Management (DSM) as storage is presented and sheds light of the needs for demand flexibility under different transmission and RES shares scenarios for Europe in 2030.

Zerrahn and Schill (2015) suggest a DR model solving the problem of undue recovery, with time free structure and handling excessive DR units activation which is appliable to several numerical models. In Göransson et al. (2014) a simplified DSM model is used to investigate the applicability of DSM to deal with congestion management. The simplified model simulates several levels of DSM penetration in the dispatch model EPOD.

Zerrahn and Schill (2017) write a survey on generation expansion models investigating the needs of power storage in a highly renewable power system, focusing in North America and Europe. For instance the DIMENSION model (Jägemann et al., 2013), with the same time horizon as EMPIRE, supports the assessment of decarbonization pathways in the power sector. The variability of RES was limited to 4 representative days, by the time in that model version.

Zerrahn and Schill (2017) also present a green-field model, DIETER, to study the optimal storage capacity and flexibility options in 2050. They improve short-comings of existing models, with the above mentioned DR model, plus reserve capacity and multi-term variability. However the model cannot assess the system transformation since it is run on only one year. In a companion paper, Schill and Zerrahn (2018), the results of a case study for Germany are shown, representing its power system as a copper-plate (single node). They use 2013 as base year for RES in-feed time series to estimate Germany's 2050 generation and storage portfolio.

In Müller and Möst (2018) the time availability of DR is investigated. They look at the potential of DR for integrating RES generated electricity at 60% and 80% in Germany by 2035 and 2050. First they estimate the theoretical DR potentials for residential, industrial and commercial sectors taking into account weather conditions and seasonality with a single base line year, but disregarding DR operational costs. Then, by using a deterministic linear electricity market model, ELTRAMOD, the impacts of flexible loads on renewables, peak plants and storage are found to be relevant. Although the curtailment of RES generation decreases by 35-77%, DR cannot integrate large time sustained RES oversupply due to its short-term limitations. Therefore in this approach the system in-take evolution of DR is overlooked.

In Müller and Jansen (2019) a large-scale experiment with more than 300 residential heat pumps is performed. The authors make a probabilistic characterization of the aggregated heat pumps loads achieving 40-65% load reductions.

Europe's Demand Response Potential

Despite of the early implementation of DR programmes in countries like France (Albadi and El-Saadany, 2008), policy makers have been reluctant to full support DR programmes, in favour of finding the right mix of solutions for the ambitious environmental goals, and focusing on liberalizing markets (Torriti et al., 2010), mainly during the 1990s and 2000s. From the beginning, the most successful DR programmes have been applied at large industrial consumers, by means of costumer incentive based measures like Direct Load Control (DLC) and interruptible/curtailable programmes. Time of Use Tariffs (TOU) and Real Time Pricing (RTP) have been also available for residential and commercial customers, although to a lower extent due to a lack of price signals and support to DR programmes.

Nowadays, DR programmes are really diversified between countries. By 2015, the countries with open DR trading in the wholesale electricity market (explicit DR) were: UK, Ireland, France, Switzerland and Belgium. The countries with partial opening to explicit DR were Norway, Sweden, Netherlands and Austria (SEDC, 2015). As of 2019, new partially opened markets for aggregators are in Germany and Denmark. New commercially opened markets are Switzerland and Finland (SEDC Smart Energy Demand Coalition, 2017). That means 13 out of 31 European countries under this study have assessed explicit DR (i.e. DR market bidding) programs. Meanwhile the rest of the countries have explicit DR under development, have restricted participation or have not been assessed yet (East Europe).

Modeling characteristics of DR are exhaustively retrieved from surveys investigated by Gils (2016). Investment costs in flexible technologies are estimations that range from 0 to 250000€/MW. Variable operational costs estimations range from 5 to 150€/MWh for load shifting and 1000€/MWh for curtailing load. The standard load profiles for flexible end consumers are given in Gils (2015) taking into account weekdays and seasonality. Estimates for DR as reserve capacity prices in France are ranging between 65€/MWh and 500€/MWh for utilization and 12-20€/MW/year for availability as given in (SEDC Smart Energy Demand Coalition, 2017). Secondary control reserves receive 160000€/MW/year. In Norway the balancing market pays approximately 25€/MWh for down-regulation and 30€/MWh for up-regulation (SEDC Smart Energy

Demand Coalition, 2017)[1]. In Spain only power consumers with higher than 5MW have access to interruptible demand mechanisms. For 5MW blocks the payments are 127563€/MW and the utilization payments are determined in the balancing market and tertiary reserve. In Germany, payments for activations are based on bids and limited to 400€/MWh. In the United Kingdom, the Frequency Control by Demand Management pays about 4£/MW/hour. Unfortunately the balancing mechanisms are only accessible after complying with the particular regulations of each market.

As for today, global DR policy long term impacts remain to be assessed. The European DR shedding potential has been estimated on an average of 93GW in Gils (2014), which represents 18% of overall peak demand. The analysis goes further by identifying the processes and its DR potential. In another study, a linear optimization model with seven important DR processes was used to specifically estimate the DR impacts in Germany Gils (2016).

Today's DR is very limited all across Europe. According to Baker (2015) and ENTSO-e (2015) the maximum DR power assumed by each country barely reaches 5 % of the peak demand in some of the most developed. For instance this is 1.3GW, 1GW and 0.7GW for France, Spain and Great Britain respectively. The forecast for 2025 is scarcely 6% in all the countries with highest potential.

The sectors that could increase its contribution to DR are the residential and services sector; while the implementation of DR in the industrial sector is already a standard practice. For the same reason DR investments prices in industry are basically non existent. It is expected that residential DR will be greatly developed with the planned roll-out of smart metering no later than 2020. Industry consumers that may contribute with DR are steelmaking industries, paper, pulp and chloralchali process among others. In the services sector DR could be used by storage heating, retail cooling systems and ventilation systems for example. In the residential sector the appliances with reasonable potential are washing machines, tumble dryers and dishing machines, as well as air conditioning systems.

In order to assess effects of DR at a system level, the above mentioned loads can be aggregated per country. Furthermore, from a modelling perspective, these loads can be classified based on behaviour and characteristics in groups, in the same methodology proposed by Gils (2014). The potential of these DR loads have been studied in assessment studies like Gils (2016) at a country level. Still there is no consensus on DR costs. The study by Schill and Zerrahn (2018) represents 6 types of demand response is still relying in the same costs assumptions than Gils (2016) and other out-of-date German studies.

2. Demand Response Model

2.1. *Definitions*

For the purpose of clarifying the scope of the model presented in this work, some definitions will be given here. First of all, we understand by *Demand Response* (DR) the short-term changes in electricity load, by demand-side resources, responding to price variations or incentive-payments, seeking low consumption during high wholesale electricity prices or providing reserve capacity when the power system reliability is compromised. Two aspects are underlined in that definition: economic efficiency and reliability. These two general drivers have benefits both for suppliers and consumers, and imply two aspects of DR: *economic DR* and *reliability DR*. The third aspect in the definition is the short-term scope of DR, which differentiates it from broader demand side measures, here called *Demand Side Management* (DSM). It is a broader concept, including economic and reliability DR, that consists in permanent and long-term measures like ancillary services investments and electricity use changes driven mainly by electric utilities, including efficiency, storage and supply measures. The scope of this research is limited to *economic DR*.

In this context we consider a load a vector $(y_{f1}, \ldots, y_{fN}) \in (\mathbb{R}^+)^N)$ to be a non-negative vector with N components representing the demand of the corresponding hour. The *total energy* of a load is the sum of its components. A *flexible load* f, denoted by $(y_{f1}, \ldots, y_{fH})$, is a load whose hourly profile can be changed by upward or downward regulation in some of its hourly values y_{fh}[2]. A *shiftable volume load* is a flexible

[1] This depends on the market area.

[2] Shiftable and curtailable load definitions are based on Ottesen et al. (2016). More precise definitions are given in the appendix.

load such that allowed changes are those that keep the same total energy. A *shiftable profile load* is a type of shiftable volume load that can be delayed or advanced without changing its load profile. A *curtailable load* is a flexible load that whose components can be decreased but not increased. A *interruptible load* is a curtailable load which can either be left unmodified or decreased to all zero components. It is worth pointing out that shiftable profile loads and interruptible loads can only be implemented by using discrete variables.

Integrating DR into a stochastic optimization capacity expansion model presents two challenges. First, finding and adapting the right input data parameters to the optimization framework, and second, designing a DR module that keeps the problem tractable.

2.2. The EMPIRE model

The European Model for Power Investment with Renewable Energy (EMPIRE) is a stochastic capacity expansion model designed to assess the optimal investments in generation and transmission over a long-term planning horizon (Skar et al., 2016). The model makes use of a multi-horizon approach in order to avoid the curse of dimensionality. It combines short-term uncertainty in system operation decoupled from long-term investment periods. This allows the inclusion of several short-term stochastic scenarios created from uncertainty in load, solar and wind production historical data in each country. Investments are available in all kinds of power capacity, storage and transmission. The EMPIRE framework allows the introduction of new variables and constraints that enables responsive demand, in other words, price elastic electricity demand[3]

EMPIRE is a bottom-up model with an approximate representation of electric energy exchange between 31 European countries. By representing the power system through an energy transport network with 31 nodes, the model stays tractable when using multiple investment periods and short-term uncertainty. In this way, the model focus on the least-cost energy delivery and system design overseeing some power system aspects. The main principles of the model are the following: (1) Perfect competition, (2) No unit commitment and (3) Transport network. Given that, the technical aspects of DR are adapted to the characteristics of the EMPIRE model.

As a result this DR module is classified as an electricity techno-economic system perspective DR model with focus on system performance, in accordance to the classification given in Bossmann and Eser (2016) [4].

2.3. Model Scope

The DR module objective is to estimate the impacts of flexible loads on the power system design and operation. The DR module, adopting the same central planer perspective as EMPIRE, allows the unique decision maker first to invest in demand responsive loads, that is DR potential capacity, and second to shift and curtail country aggregated demand when in need. It follows, in the same way that for all the other production technologies, that the amount of DR capacity in a country is affected by its internal mix and by neighbors' mix, regardless of the individual profitability each country could get from DR. In the same way, generation companies, power consumers and DR traders act in reality with strategic behavior in the power market with regards to DR. Looking at the power market at that level of detail is an aspect that is not covered in the model. Thus, the DR module complies too with the central planer assumption. Nevertheless, the convergence towards a unified power market and coordinated international planning, makes the central planer assumption feasible.

2.4. Mathematical Model

The EMPIRE model can be sketched as shown below where DR indicates the new parts that model flexible demand. The expectation $\mathbb{E}$ is taken over the time series of load, solar power, wind power and hydropower. The module comprises new second-stage variables y^{DR}, $y^{\mathrm{DRCAP}}, y^{\mathrm{REG}}$ for the flexible loads

[3] This article focus in the DR module description, keeping Skar et al. (2016) as the reference for the complete description of the EMPIRE optimization.

[4] Aspects like behavioral operation of demand responsive loads and DR price schemes are out of the scope of this study

as well as first-stage multi-period investment variables in DR technologies x_{fi}^{DR} (i.e. endogenous expansion capacities). A summary of DR variables and parameters can be found in table 1[5].

The grid network is modelled through a transport model, avoiding thus a DC flow model that would result in an intractable problem. That means that each node has to satisfy a power balance equation, including import, export and generation. Generation and the power flow through transmission lines is constrained by capacity limits and ramping constraints. The balance equation (1) includes new DR operational variables called *load deviation* $y_{fi\omega h}^{\mathrm{REG}}$ for each flexible load $f \in \mathcal{F}$, period $i \in \mathcal{I}$, scenario $\omega \in \Omega$ and hour $h \in \mathcal{H}$. It represents the up regulation (positive) and down regulation (negative) of flexible loads. It also includes the energy loss of activating flexible loads $y_{fi\omega h}^{\mathrm{LOSS}}$ since we assume there exist DR rebound effects and operational inefficiencies, in the same way that storage and transmission have their own efficiencies $\eta_b^{\mathrm{dischrg}}$, η_b^{tran} .

The new second-stage variables are co-optimized with the network operational variables as generation $y_{gi\omega h}^{\mathrm{gen}}$, storage $y_{bi\omega h}^{\mathrm{dischrg}}$, $y_{bgi\omega h}^{\mathrm{chrg}}$, transmission $y_{ai\omega h}^{\mathrm{flow}}$ and lost load $y_{ni\omega h}^{\mathrm{ll}}$.

$$\begin{aligned}
&\underbrace{\sum_{g\in\mathcal{G}_n} y_{gi\omega h}^{\mathrm{gen}}}_{\text{Generation}} + \underbrace{\sum_{b\in\mathcal{B}_n} \eta_b^{\mathrm{dischrg}} y_{bi\omega h}^{\mathrm{dischrg}} - y_{bi\omega h}^{\mathrm{chrg}}}_{\text{Storage handling}} + \underbrace{\sum_{a\in\mathcal{A}_n^{\mathrm{in}}} \eta_a^{\mathrm{tran}} y_{ai\omega h}^{\mathrm{flow}} - \sum_{a\in\mathcal{A}_n^{\mathrm{out}}} y_{ai\omega h}^{\mathrm{flow}}}_{\text{Net import}} \\
&= \xi_{ni\omega h}^{\mathrm{load}} + \underbrace{\sum_{f\in\mathcal{F}_n} y_{fi\omega h}^{\mathrm{REG}} + y_{fi\omega h}^{\mathrm{LOSS}}}_{\text{Load Deviation}} - y_{ni\omega h}^{\mathrm{ll}} \\
&\quad n \in \mathcal{N},\, h \in \mathcal{H},\, \omega \in \Omega,\, i \in \mathcal{I}
\end{aligned} \tag{1}$$

Uncertainty in the balance equation (1) appears in the original load $\xi_{ni\omega h}^{\mathrm{load}}$, flexible loads $\mathcal{F}$ and through additional constraints (2) for the generation from variable renewable sources:

$$y_{gi\omega h}^{\mathrm{gen}} \leq \xi_{gi\omega h}^{\mathrm{gen}} \upsilon_{gi}^{\mathrm{gen}}, \quad g \in \mathcal{G},\, h \in \mathcal{H},\, \omega \in \Omega,\, i \in \mathcal{I} \tag{2}$$

where $\xi_{gi\omega h}^{\mathrm{gen}}$ is stochastic for wind, solar and hydro power, and scenario independent for the rest of technologies, while $\upsilon_{gi}^{\mathrm{gen}}$, which is scenario independent, is the first-stage variable representing capacity of generator g. Note that equations (2) link first and second-stage decisions.

2.5. The Data Disaggregation

In order to disaggregate each of the DR group loads from the country load $\xi_{ni\omega fh}^{\mathrm{load}}$, equation (3) links investment and operational variables in the same way that (2) links power supply operation and capacity. Variable $y_{fi\omega h}^{\mathrm{DRCAP}}$ is called *potential load* and represents the available hourly load from flexible group f. The α_{fih} constants, taking values in $[0, 1]$, represent the share of flexible load of each DR group in a given hour h according to prefixed weekday and weekend patterns. They capture the hourly availability of each DR group and are specific for each period, group and hour of the year. Note that they depict the characteristic seasonal load demand of each group. The yearly peak load is represented by $\hat{\xi}_{ni\omega}$, which takes part into the second factor that scales the DR capacity according to the system load at time h. The goal of the second factor is to adjust the installed DR capacity, $\upsilon_{fi}^{\mathrm{DR}}$, to seasonal and yearly levels.

$$y_{fi\omega h}^{\mathrm{DRCAP}} = \alpha_{fih} \cdot \frac{\xi_{ni\omega h}^{\mathrm{load}}}{\hat{\xi}_{ni\omega}} \cdot \upsilon_{fi}^{\mathrm{DR}} \quad f \in \mathcal{F}_n \tag{3}$$

[5] First-stage variables $\mathbf{x}^{inv}$ represent capacity expansion on generation, transmission and storage. Second-stage variables $\mathbf{y}^{op}$ represent operation of generators, interconnectors and storages. For clarity of exposition their indices have been omitted at this point.

Table 1: DR module variables and parameters

Symbol	Description
Index and sets	
$f \in \mathcal{F} = \mathcal{S} \cup \mathcal{C}$	Index and set of flexible loads
$f \in \mathcal{F}_n$	Set of flexible loads that belong to node n
$f \in \mathcal{S}$	Set of shiftable loads
$f \in \mathcal{C}$	Set of curtailable loads
Independent Decision Variables	
x_{fi}^{DR}	DR capacity investment
$y_{fi\omega h}^{\mathrm{DR}}$	Actual DR load of group f
Model-Defined Decision Variables	
v_{fi}^{DR}	Total DR capacity of group f
$y_{fi\omega h}^{\mathrm{DRCAP}}$	Potential downward regulation of group f
$y_{fi\omega h}^{\mathrm{REG}}$	DR load deviation
Parameters	
c_{fi}^{DR}	DR investment cost
q_{fp}^{DR}	DR operational cost
α_{fih}	DR load profile
X_{fi}^{DR}	Maximum DR capacity investment
$U_{fi\omega h}^{\mathrm{DR}}$	Maximum upward regulation of group f
$\Upsilon_{fi}^{\mathrm{DR}}$	Maximum DR capacity of group f
t_{f}^{shift}	Maximum load time shift of group f
η_{f}^{DR}	Efficiency of flexible load f

$$
\begin{aligned}
\textbf{min}\ & \mathrm{CAPEX}\big(\mathbf{x}^{inv}\big) + \mathbb{E}\ \mathrm{OPEX}(\mathbf{y}^{op}) + \text{DR-CAPEX}\Big(x_{fi}^{\mathrm{DR}}\Big) + \mathbb{E}\ \text{DR-OPEX}\big(y^{\mathrm{DR}},\, y^{\mathrm{DRCAP}}, y^{\mathrm{REG}}\big)\\
\text{s.t.}\quad & \text{(for all scenarios } \omega)\\
& \text{Supply} = \text{Uncertain load} + \text{DR-Regulation}\\
& \text{Power Supply} \leq \text{Capacity}\\
& \text{RES Supply} \leq \text{Uncertain availability}\\
& \text{Energy Supply} \leq \text{Energy Limit}\\
& \text{Emissions} \leq \text{Emissions Cap}\\
& \text{Storage Balance} = 0\\
& \text{DR Balance} = 0\\
& \text{DR Regulation} \leq \text{DR Capacity}
\end{aligned}
$$

In order to track the amount of shifted and curtailed loads for each class, an auxiliary variable *actual load* is defined in 4. It is a load (i.e. positive values) representing the actual country aggregated load value of flexible group f.

$$y^{\mathrm{DR}}_{fi\omega h} := y^{\mathrm{DRCAP}}_{fi\omega h} + y^{\mathrm{REG}}_{fi\omega h}, \quad \omega \in \Omega,\, i \in \mathcal{I},\, f \in \mathcal{F}_n\, N \in \mathcal{N} \tag{4}$$

According to the definition the actual load in hour h is zero if $y^{\mathrm{REG}}_{fi\omega h} = -y^{\mathrm{DRCAP}}_{fi\omega h}$. It has the standard value if $y^{\mathrm{REG}}_{fi\omega h} = 0$ and upward regulation if $y^{\mathrm{REG}}_{fi\omega h} > 0$.

The DR energy loss is the extra energy needed to shift or curtail load. The DR efficiency of load f, η^{DR_f}, is defined as the ratio of the effective regulated load and the energy loss. It follows from the definition that the energy loss is

$$y^{\mathrm{LOSS}}_{fi\omega h} := \beta_f |y^{\mathrm{REG}}_{fi\omega h}| \left(\frac{1-\eta^{\mathrm{DR}}_f}{\eta^{\mathrm{DR}}_f} \right) \quad H \in \mathcal{H},\, \omega \in \Omega,\, i \in \mathcal{I},\, f \in \mathcal{F}_n\, N \in \mathcal{N} \tag{5}$$

where [6]

$$\beta_f := \begin{cases} 0.5 & f \in \mathcal{S} \\ 1 & f \in \mathcal{C} \end{cases} \tag{6}$$

The deviations from the original loads are performed under a supply cost function, included in the objective function.

$$z_{fi} = q_{fi}\left(y^{\mathrm{REG}}_{fi\omega h}\right) \tag{7}$$

With this, the main components of a general flexible load are defined. A flexible load given by

$$(y^{\mathrm{DRCAP}}_{fi\omega h_1}, \ldots, y^{\mathrm{DRCAP}}_{fi\omega h_H}) \in \left(\mathbb{R}^+\right)^H$$

is a load satisfying equations (3)-(8).

$$y^{\mathrm{DR}}_{fi\omega h} \leq U^{\mathrm{DR}}_{fi\omega h} \tag{8}$$

Specifying additional constraints and parameters, the following types of flexible loads are defined.

A *shiftable volume load* $(y^{\mathrm{DRCAP}}_{fi\omega h_1}, \ldots, y^{\mathrm{DRCAP}}_{fi\omega h_H})$ in a time window (T_{f1}, T_{fH}), indexed by $f \in \mathcal{S}$, can be replaced by a new load provided that their *total energies* are equal. In other words the new energy consumption is the same as the original, thus an equality in (9) represents this condition. A shiftable volume load satisfies equations (3)-(12). Note that for each hour h the demand variables $y^{\mathrm{DRCAP}}_{fi\omega h}$ representing the shifted load, can have a larger or lower value than the original $y^{\mathrm{DRCAP}}_{fi\omega h}$. The time window subintervals W_{fj}, $j \in \mathcal{J}$, form a partition of (T_{f1}, T_{fN}). They define the time span during which load can be shifted and their size is limited by the maximum load time shift t^{shift}_f, characteristic of each type of load. The choice of the partition is a decision variable of the problem.

$$\sum_{h \in W_{fj}} y^{\mathrm{DR}}_{fi\omega h} = \sum_{h \in W_{fj}} y^{\mathrm{DRCAP}}_{fi\omega h} \quad j \in \mathcal{J} \tag{9}$$

$$y^{\mathrm{DR}}_{fi\omega h} = y^{\mathrm{DRCAP}}_{fi\omega h} \quad h \in \mathcal{H} \setminus \cup_{j \in \mathcal{J}} W_{fj} \tag{10}$$

$$\{W_{fj}\}_{j \in \mathcal{J}} \in \wp((T_{f1}, T_{fH})), \tag{11}$$

$$|W_{fj}| < t^{\mathrm{shift}}_f,\, \omega \in \Omega,\, i \in \mathcal{I},\, f \in \mathcal{S} \tag{12}$$

[6]We model the energy loss assumming it equally distributed between the hours with load shift regulation. This sets the value 0.5 for shiftable loads to avoid double counting.

Curtailable loads $\mathcal{C}$ can be adjusted from zero to the original value in a predefined time window $(T_{f1},\, T_{fH})$, which means that they have to satisfy equations (3)-(8) and the inequalities (13)-(15) [7].

$$y^{\mathrm{DR}}_{fi\omega h} \leq y^{\mathrm{DRCAP}}_{fi\omega h},\; h \in (T_{f1},\, T_{fH}) \tag{13}$$
$$y^{\mathrm{DR}}_{fi\omega h} = y^{\mathrm{DRCAP}}_{fi\omega h},\; h \in \mathcal{H} \setminus (T_{f1},\, T_{fH}) \tag{14}$$
$$y^{\mathrm{DR}}_{fi\omega h} \geq 0,\; \omega \in \Omega,\; i \in \mathcal{I},\; f \in \mathcal{C} \tag{15}$$

Shiftable profile loads constraints can be represented through a time shift variables $t^S_f \in \mathbb{Z}$. They satisfy equations (3)-(8) and equations (16)-(18)[8].

$$y^{\mathrm{DR}}_{fi\omega}(h + t^S_f) = y^{\mathrm{DRCAP}}_{fi\omega}(h),\; h \in (T_{f1},\, T_{fH}) \tag{16}$$
$$y^{\mathrm{DR}}_{fi\omega}(h) = 0 \quad h \in \mathcal{H} \setminus (T_{f1},\, T_{fH}), \tag{17}$$
$$-t^{\mathrm{shift}}_f \leq t^S_f \leq t^{\mathrm{shift}}_f, \quad \omega \in \Omega,\; i \in \mathcal{I},\; f \in \mathcal{S} \tag{18}$$

Interruptible loads switching on or off are represented by the binary variable δ in a predefined time window $(T_{f1},\, T_{fH})$ as in equation (19). They satisfy equations (3)-(8) and equations (19)-(20).

$$y^{\mathrm{DR}}_{fi\omega h} = \delta \cdot y^{\mathrm{DRCAP}}_{fi\omega h},\; h \in (T_{f1},\, T_{fH}) \tag{19}$$
$$\delta \in \{0, 1\},\; \omega \in \Omega,\; i \in \mathcal{I},\; f \in \mathcal{C} \tag{20}$$

A fifth type of load that is useful to model is a flexible load that can be either curtailed or increased with no cost and no total energy balance. That kind of load could be an industry that increases production in times of negative electricity prices or when oversupply could destabilize the power system. This is a flexible curtailable load which fulfills constraints (3)-(8) and (21)-(22) and its costs are zero for load increase.

$$q_{fi}\left(y^{\mathrm{REG}}_{fi\omega h}\right) > 0, \text{if } y^{\mathrm{REG}}_{fi\omega h} \leq 0 \tag{21}$$
$$q_{fi}\left(y^{\mathrm{REG}}_{fi\omega h}\right) = 0, \text{if } y^{\mathrm{REG}}_{fi\omega h} > 0,\; \omega \in \Omega,\; i \in \mathcal{I},\; f \in \mathcal{C},\; h \in \mathcal{H} \tag{22}$$

3. Demand Response in EMPIRE

3.1. Piece-wise Cost Functions

The operation of flexible loads is executed at a fixed a priori cost. If a flexible load diverges at a given hour from the value of the original load, then that change is penalized by a cost (7). Therefore the load deviation y^{REG} is penalized either if it is positive or negative. In this model the costs are given by a convex piece-wise linear symmetric function, parametrized as follows. Abscissae are parametrized by $\lambda^{\mathrm{REG}}_{fi\omega ph}$, $p \in \mathcal{P}$, variables that form a Special Order Set (SOS1) and predefined ordinates μ^{REG}_{fp} as shown in equation (23)-(25), which are defined to be symmetric around the origin. Marginal costs, which are symmetric for load increase and decrease, are increased proportionally by the ratio m_{REG} on each piece (see figure 1). More specifically, the first interval has costs of operation given by input data, denoted by Q^{REG}_{fi} in the cost function. The following intervals have increased marginal costs by the factor m_{REG} (26). In this way it is more and more costly to produce a change in the load profile.[9].

[7]Note that shiftable loads are allowed to be higher than the original load, but curtailable loads are constrained by the potential load in (13). As both types of actual shiftable load and actual curtailable loads are required to be non-negative, the downward regulation can be as low as $-y^{\mathrm{DRCAP}}_{fi\omega h}$.

[8]The time index is in parenthesis to highlight the use of the variable t_S.

[9]Note that curtailable loads, since they can only be decreased, do not need variables $\lambda^{\mathrm{REG}}_{fi\omega ph}$ on the positive axis, or equivalently, $q^{\mathrm{DR}}_{fp} = 0$, $p \in \mathcal{P}^+$.

$$y^{\mathrm{REG}}_{fi\omega h} = \sum_{p\in\mathcal{P}} \mu^{\mathrm{REG}}_{fp} \lambda^{\mathrm{REG}}_{fi\omega ph} \tag{23}$$

$$\mu^{\mathrm{REG}}_{f(-p)} = -\mu^{\mathrm{REG}}_{fp},\ y^{\mathrm{REG}}_{0f} = 0, \quad p = 1\ldots, |\mathcal{P}|/2 \tag{24}$$

$$\sum_{p\in\mathcal{P}} \lambda^{\mathrm{REG}}_{fi\omega ph} = 1\ \forall\omega,\ i,\ f \in \mathcal{S}\cup\mathcal{C} \tag{25}$$

$$q^{\mathrm{REG}}_{fp+1} = q^{\mathrm{REG}}_{fp} + \beta_f m^p_{\mathrm{REG}} Q^{\mathrm{DR}}_{fi} \cdot \left(\mu^{\mathrm{REG}}_{fp+1} - \mu^{\mathrm{REG}}_{fp}\right) \tag{26}$$

$$q^{\mathrm{REG}}_{f(-p)} = q^{\mathrm{REG}}_{fp} \quad p = 0, \ldots, |\mathcal{P}|/2,\ f \in \mathcal{S} \tag{27}$$

$$q^{\mathrm{REG}}_{f0} = 0 \tag{28}$$

$$\beta_f = \begin{cases} 0.5 & f \in \mathcal{S} \\ 1 & f \in \mathcal{C} \end{cases} \tag{29}$$

3.2. DR Upper Bounds

It follows from equation (9) that the flexible variables for the shiftable groups are upper bounded by $\sum_{h\in W_{fj}} y^{\mathrm{DRCAP}}_{fi\omega h}$ (which is the right hand side in the shiftable load balance in that equation). However this limit can be extremely high and would suppose an infeasible upward regulation. For that reason it is necessary to fix an upper limit to shiftable loads. The upper-bound should have the following two characteristics: 1. Allowing at least the same upward regulation than downward regulation and 2. allowing extra upward regulation during off-peak hours proportionally higher than in peak hours. In other words, it allows load valley filling and restricts upward regulation at peak hours. The upper bound, denoted by $U^{DR}_{fi\omega h}$, are defined in detail in 7 and are specific for each year, scenario and flexible group.

$$y^{\mathrm{DR}}_{fi\omega h} \le U^{DR}_{fi\omega h} \quad \omega \in \Omega,\ i \in \mathcal{I},\ f \in \mathcal{S} \tag{30}$$

In addition to DR operation upper bounds, there are DR investment and capacity upper bounds. The upper bound capacity $\Upsilon^{\mathrm{DR}}_{fi}$ is set as an exogenous. The maximum investment in DR capacity in year i for load $f \in \mathcal{F}$ is denoted by X^{DR}_{fi}. If $\upsilon^{\mathrm{DR}}_{fi}$ denotes the total DR capacity of load f in period i, x^{DR}_{fi} denotes the power investment in load f and DRL is the DR investment operational life in number of investment periods, then the constraints that must be satisfied are

$$x^{DR}_{fi} \le X^{DR}_{fi} \tag{31}$$

$$\upsilon^{\mathrm{DR}}_{fi} = \upsilon^{\mathrm{DR}}_{f0} \cdot \chi(DRL - i) + \sum_{\substack{j=0,\\ j<i}}^{DRL} x^{DR}_{fi-j}, \tag{32}$$

$$\upsilon^{\mathrm{DR}}_{fi} \le \Upsilon^{DR}_{fi} \quad i \in \mathcal{I},\ f \in \mathcal{S}\cup\mathcal{C} \tag{33}$$

$$\chi(x) = \begin{cases} 0 & x \le 0 \\ 1 & x > 0 \end{cases} \tag{34}$$

3.3. The Objective Function

The objective function is extended with two new terms: the investments in DR capacity and the cost of operation of flexible loads. The marginal costs q^{REG}_{fp} are calculated through equations (26)-(29). u is the

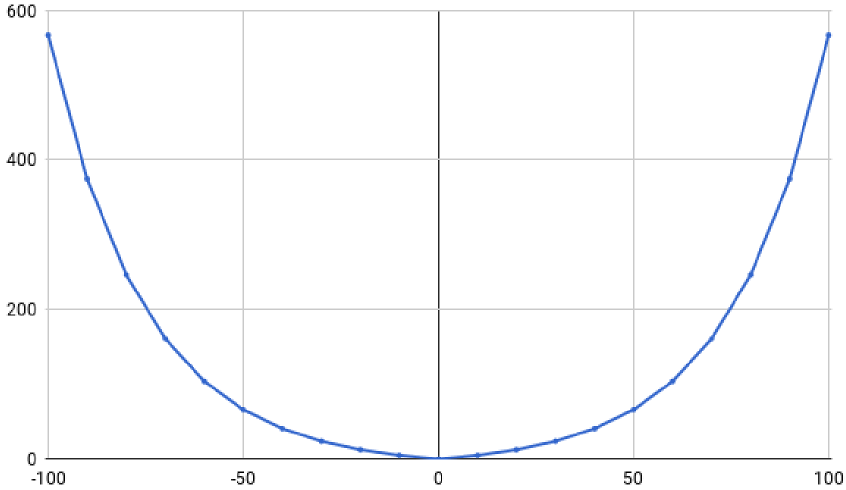

Figure 1: Piece-Wise Linear Cost Function. The abscissa represent percentage of upward and downward capacity and the ordinates represent the percentage cost of deviation.

number of years between each investment period i and ϑ[10] is a recovery factor to count the present value of each year within the investment period.

$$\min z = \sum_{i \in \mathcal{I}} (1+r)^{-u(i-1)} \times$$
$$\underbrace{\left\{ \sum_{g \in \mathcal{G}} c^{\text{gen}}_{gi} x^{\text{gen}}_{gi} + \sum_{l \in \mathcal{L}} c^{\text{tran}}_{li} x^{\text{tran}}_{li} + \sum_{f \in \mathcal{F}} c^{\text{DR}}_{fi} x^{\text{DR}}_{fi} + \sum_{b \in \mathcal{B}} c^{\text{storPW}}_{bi} x^{\text{storPW}}_{bi} + c^{\text{storEN}}_{bi} x^{\text{storEN}}_{bi} \right.}_{\text{Investment cost for generation, transmission, DR and storage capacity, period i}} \tag{35}$$
$$\left. + \vartheta \sum_{\omega \in \Omega} \pi_\omega \sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \underbrace{\sum_{n \in \mathcal{N}} \left[\sum_{g \in \mathcal{G}_n} \left(q^{\text{gen}}_{gi} y^{\text{gen}}_{ghi\omega} \right) + \sum_{f \in \mathcal{F}_n, p \in \mathcal{P}} q^{\text{REG}}_{fp} \lambda^{\text{REG}}_{fi\omega ph} + q^{\text{ll}}_{ni} y^{\text{ll}}_{nhi\omega} \right]}_{\substack{\text{System operation cost (all nodes } n\text{),} \\ \text{generation + cost of DR operation + value of lost load,} \\ \text{period } i \text{ scenario } \omega\text{, season } s\text{, hour } h}} \right\}$$

10
$$\sum_{j=0}^{u-1} (1+r)^j = \frac{(1+r)^u - 1}{r(1+r)^{u-1}}$$

4. Demand Response Baseline Case

A significant amount of input data regarding DR potentials is needed in order to run the model. The data compilation has been based in two sources. In first place, the global assessment of the DR potential in Europe presented in Gils (2014) is unique in terms of spatial, seasonal and end-consumer representation[11]. The study is thorough in putting together previous assessments of particular flexible load sectors across Europe. For that reason, it is the main source for defining the model parameters described in table 1. Additionally to that study, the same author's reference Gils (2015) provides hourly and seasonal variations for DR loads, and Gils (2016) contains investment and operation prices for each DR technology.

In second place, the need for initial DR potentials requires the use of data from Baker (2015) where current European flexible potentials are assessed. According to that source the countries with highest DR potential are Belgium, Germany, Spain, France, Great Britain, Ireland, Netherlands, Poland Slovenia and Sweden [12]

The DR technologies that represent flexible demand in the model are aggregated in the following 7 groups. Heating and air conditioning (AC) in all sectors are flexible since they can be controlled according to the network and weather conditions. Heating Ventilation and AC (HVAC) are specific of large industries and commercial centers. Cooling and water group includes all industrial and commercial appliances aimed to manage large food cooling systems or water supply systems. The process shift group includes the following industrial processes: pulp, paper, recycling paper and cement. All of them allow to hourly shift production. Washing appliances comprises only household appliances. Heat storage consists of appliances and installations that allow thermal storage and releasing it at need. And finally, process shedding are industrial processes that can be partially stopped: aluminium, copper, zinc, chlorine and steel Gils (2014). In the appendix the potentials of each group by country are showed in table .7.

Load series by country are obtained from Open System Power Data Data (2017); Wiese et al. (2019), which is one of the most exhaustive public available data bases. Wind and solar series are provided by the Renewables Ninja dataset (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016; Renewables Ninja, 2017), based in rigorous assessment of weather data[13].

With a database consisting of 7 years of hourly wind, solar and load data, the scenario generation routine based on moment matching creates the scenario tree representing the short-term uncertainty. The scenario generation routine is based in Seljom and Tomasgard (2015) and consists in finding the best scenario tree that matches the mean, variance, skewness and kurtosis of the historical data. Each scenario consists of 4 seasons with 168 consecutive hours each for load, wind, solar and hydro, at the same moment in time across all countries in order to preserve internal correlation between series. In addition, there are 24 extra hours for two extreme operating conditions: 1. Day with single highest peak net load and 2. Day with lowest global IRES energy generation. That makes 672 hours per scenario, that is, 6720 hours in 10 scenarios per period (in total 900 scenarios)[14].

The DR costs are summarized in table 2 compared with other technology costs. Note that investment costs plus fixed OM costs in DR technologies, which most probably affect the optimal solution, are lower than the cheapest technology (OCGT). However investment costs are not the only criteria to choose these technologies, because variable OM costs and capacity availability have also an impact. Industrial DR investment costs are non-existent because DR is an inherent feature of industry operation, to different degrees according to each industry sector. The span of hours where the load can be shifted is limited for each group by the maximum load time shift parameter t_f^{shift} in the last column in table 2. The group with largest load shifting time is the industrial shifting with 24 hours, characteristic of a medium-term planning process. The second largest is heat storage with 12 hours, as thermal energy storage technologies allow that time span.

[11] Throughout the rest of the article *DR potential* refers to the estimated DR capacity in Gils (2014). This DR potential denoted by Υ_{fi}^{DR} is in fact constant along the strategic time frame i.

[12] This potential is measured by the ratio between the DR potential and the country's peak demand.

[13] Both data from load and IRES have been preprocessed to correct data measure errors and synchronize historical data in the period from 2010 to 2016.

[14] The simulations performed with the input data show that the solutions are stable with respect to the scenario trees.

Table 2: DR technology costs for the 7 groups considered in the model and other technology costs for comparison. Sectors: 1. Residential, 2. Industrial, 3. Commercial, DR source: Gils (2016),

Technology	Sector	Investment Cost (k€/MW)	Fixed OM (€/MW) pr. yr.	Variable OM (€/MWh)	Efficiency η_f^{DR}	Max. Time Shift (h)
Heating & AC	All	250	7500	10	0.97	2
HVAC	2, 3	10	300	5	0.97	2
Cooling & Water	2, 3	5	150	20	0.98	6
Process Shift	2	0	0	150	0.99	24
Washing appliances	1	30	900	50	1.00	6
Heat Storage	1, 3	20	600	10	0.98	12
Process Shedding	2	0	0	1000	1.00	-
Gas OCGT		400	1950	0,45	-	
Battery Storage (Zn)		588			0.75	
Battery Storage (Li-ion)		400			0.88	
Pumped Storage Hydro		1000			0.80	

Given the level of aggregation in the model, the flexible loads suitable for the model are shiftable loads and curtailable loads. Therefore the DR groups are meant to be shiftable volume loads, except the last one which is a curtailable load. In a market modelling setting where each single load needs to be modelled, it would make sense to represent shiftable profile and interruptible loads. In addition, the problem size in the European model would make it intractable with flexible loads that require binary variables.

4.1. DR in Europe

Two factors impact the DR development: the initial DR capacity and the bounds on total DR capacity. The model should allow investments to reach at least the theoretical DR potential. Therefore the upper bound for the DR baseline case is set exactly at the DR potential of each DR group in each country[15].

As mentioned in section 1, the initial DR capacities are below 1.3GW in each country. That is a substantial low flexibility utilization compared to what the results show in figure 2. There are considerable DR capacity increases in most countries during the investment period. The DR-to-peak ratio (DR capacity divided by peak demand) and the DR to IRES ratio (DR capacity divided by total Intermittent Renewable Energy Sources (IRES) generation capacity) give insight of the DR intake. From a system perspective, in the final period (2050) the DR-to-peak ratio amounts to a total of 34.5% of European peak demand on the winter season, while the initial DR-to-peak ratio is 0.8%. However there are varied ratios along the countries with highest DR capacities, as shown in table 3, from the lowest ratio in the United Kingdom (5.4%) to the highest in Hungary (40.8%). When it comes to the global DR to IRES ratio, its variation goes from 0.4% to 5.8% along the optimization horizon. The top 10 countries show a moderate DR to IRES ratio ranging from 4.8% to 11.7%. The top-10 countries have a 6.9% DR to IRES ratio and accumulate the 81% of European installed flexible loads.

4.2. DR Operation

The first DR impact is on the hourly load profile. It can be easily observed in all lands during all stages that DR capacity allows load upward regulation when the inter-hour price difference is higher than the cost of flexible load arbitrage. This can be easily seen in the net load profile, which is defined as load minus IRES

[15] It is worth mentioning that the real consumer potential is affected by multiple factors as national TSO policies or geographic and weather conditions. Anyhow, if a significant amount of the above mentioned loads fall into DR programmes, then DR would have a role in the optimal power system design and shares as promising as 10% of peak load with flexible loads could be reached in the coming decades. Later in the sensitivity analysis section we will investigate what happens when this limit is varied between 0.5 and 1.5 times the DR potential

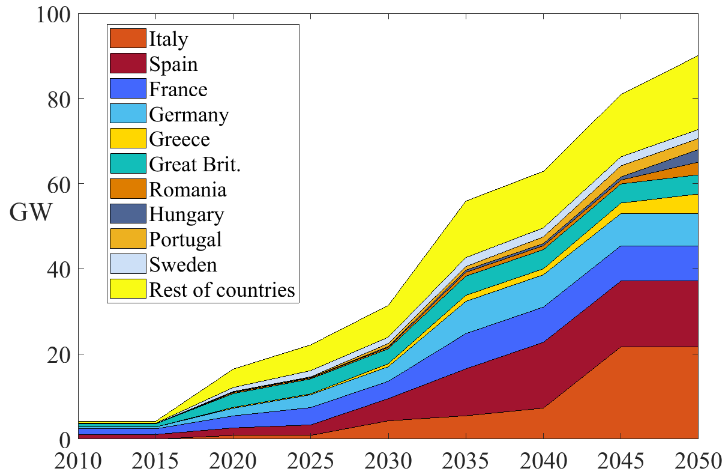

Figure 2: Total DR Capacity Evolution from 2010 to 2050 of top DR countries in GW.

Table 3: 10 highest DR capacities in 2050 and initial DR capacity in 2015 together with other ratios.

Country	DR Capacity (GW)	Initial DR Capacity (GW)	DR to peak ratio (%)	DR to IRES ratio (%)	IRES Capacity (GW)	Total capacity (GW)
Italy	21.7	0.0	31.0	11.2	194.2	219.6
Spain	15.6	1.1	29.6	4.8	322.3	343.7
France	8.5	1.3	6.8	5.0	168.8	242.3
Germany	7.6	0.4	6.5	8.0	95.3	221.6
Greece	4.6	0.0	38.6	9.0	51.0	58.2
Great Britain	4.5	0.7	5.4	5.9	76.7	117.2
Romania	3.0	0.0	25.2	7.4	40.8	56.2
Hungary	3.0	0.0	40.8	5.4	54.5	55.1
Portugal	2.6	0.0	27.1	11.7	22.6	28.5
Sweden	2.2	0.1	6.6	6.5	33.2	50.0
Europe	91.0	4.2	14.5	5.8	1575.1	2059.4

production (fig. 3). When the IRES production is quite variable it creates peaks and valleys in the net load. The valleys, when there is high IRES production, can be used for upward regulation and thus downward regulation during the peaks. The effect is specially stressed in countries with high solar capacity as Spain as shown in figure 3. The 48 hours load sample with DR events is shown with changes in the original load profile making it flatter and achieving peak shavings in the order of 10GW in Spain and 3GW in France in the load profile during the winter season. The DR regulation events depend strongly on the daily solar peak production since this is the kind of production that creates substantial electricity price differentials, as opposed to wind power which is more stable throughout. A second factor is the power mix of each specific country. For instance a system mainly dominated by dispatchable power plants has less price volatility.

4.3. DR and System Capacities

In 2050, the global DR changes amounts to 95.8TWh, which is 2.4% of the yearly net generation and 22% of total available flexible energy. Across the long-term planning horizon a total of 295TWh have been changed by DR loads, while 1274TWh keep the original hourly pattern.

The major investment in DR capacity occurs in the sixth period (27GW). The DR groups in descending order of capacity are 6, 2, 4, 7, 3, 5 and 1 with 41GW, 23GW, 10GW, 8GW, 8GW, 1GW and 0.3GW

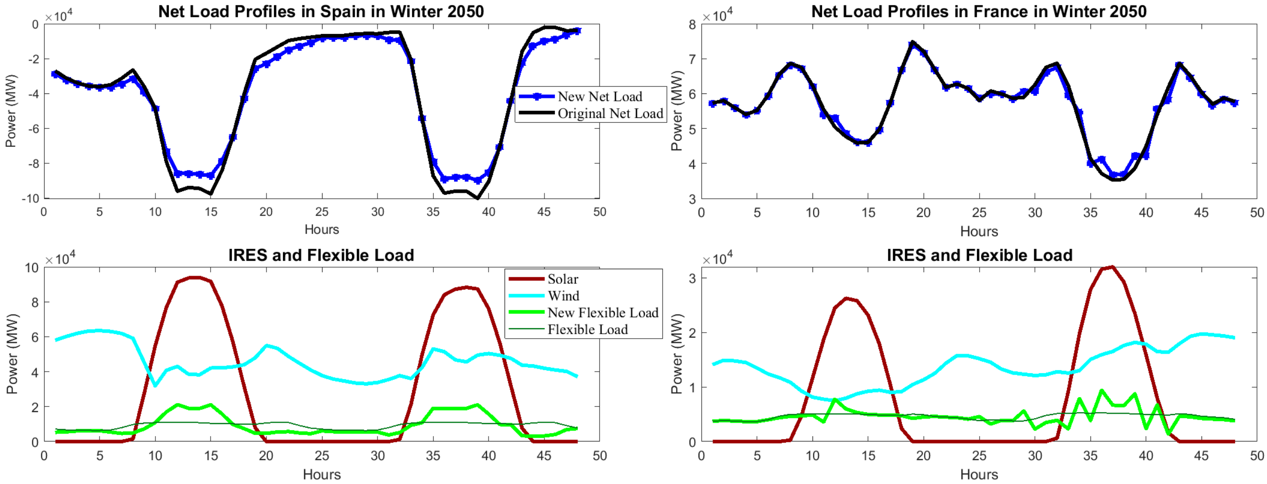

Figure 3: Sample load profiles in Spain and France in 2050. Net load refers to total load minus IRES production. The term 'new' refers to the profile with active DR.

respectively. The reasons that groups 6, 2 and 4 have largest capacities are diverse: 1) Group 6 has the 2nd largest shifting time, 2) group 2 has the lowest variable cost and 3) group 4 has largest time window even though its variable cost is the second largest[16]. The 3 largest total investments are lead by the same groups 6, 2 and 4 with 38GW, 22GW and 10GW, respectively. There is no investments in groups 1 and 5 for two reasons. The former has high investment cost. The latter has characteristics inferior to class 2. Investments in groups 3 and 7 represent only 18% of all DR investments, leaving main share, 82%, for groups 2, 4 and 6. On country average, the capacity of groups 2 and 3 reaches full potential in period 4, while the groups 1, 5 and 6 do not reach the capacity's upper theoretical potential at the end of the horizon.

At the final period, 7 out of 10 countries with high installed RES capacities[17] are among the 10 highest regarding DR installed capacities. The 10 countries with highest DR capacity in 2050 concentrate a total of 80% of global DR capacity, 67% of IRES installed capacity and 68% of total installed capacity.

The renewable that receives the most investments globally is solar, with an accumulated increase from 2010 to 2050 of 748GW, followed by onshore wind with 718GW. The main investment in solar happens in 2035 with 234GW. This is corresponds to an annual equivalent rate of 17% with respect to solar capacity in 2030. On the other side, offshore wind has no capacity in the final period since its energy contribution is not worth the high investment costs. Nevertheless, considering all the renewable technologies, there are 9 countries with more than 90% RES share in 2050 (of which only Spain and Hungary are also in the previous top-10). Europe's RES share amounts to 76%.

Regarding technologies that can compete with DR by providing generation flexibility to the system, ramping capacity and peak supply, it is interesting to see the changes in the following technologies. In the first group, fossil fuel technologies with high ramping rates, which can supply during residual peak demand periods. That is, existing Gas Turbine (GT), Open Cycle Gas Turbines (OCGT), Closed Cycled Gas Turbines (CCGT) and gas with Carbon Capture and Storage (CCS). In the second group, technologies that can store energy for periods with scarcity of supply like: regulated hydro power, hydro pump storage and battery storage.

The first group has an increase of 35% caused by the increase of gas CCGT power mainly and investments in CCS from 2040. At that point, backup capacity from CCS substitutes the already abated nuclear power.

[16]Since the investment cost of groups 4 and 7 are zero their capacity is adjusted a posteriori to their actual maximum operational values in each country

[17]RES are onshore wind, offshore wind and solar.

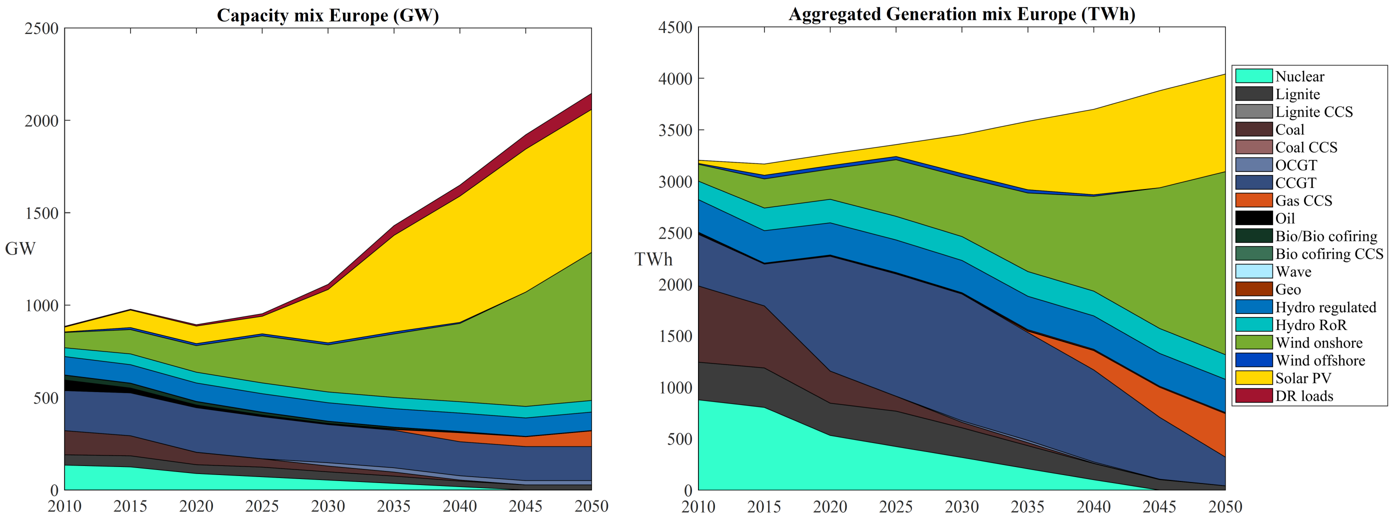

Figure 4: Europe's Generation Capacity (GW) and Energy Generation (TWh)

The second group has a slight increase of 21% in power capacity. Regulated hydro power and hydro pumped storage have moderate increases at around 16%. Meanwhile, the new technology that is integrated into the system is battery storage, which becomes cost-effective exactly when the solar capacity starts the large investments by 2030-2040. The degree at which those investments are caused (or causing) by DR capacity is analysed in next section. Meanwhile, DR capacity increases more than 22 times its initial capacity.

Transmission capacity sums up to 501GW by 2050, with the major investments happening when solar capacity reaches system dominance. This represents a significant increase of 700% interconnector capacity and means that half of the interconnectors would rise by more than 80% capacity. The most reinforced transmission corridors are Spain-France, France-Great Britain, Poland-Germany, Poland-Lithuania, Poland-Czech Republic and Italy-France with total capacities in 2050 of 83GW, 52GW, 30GW, 13GW, 13GW and 12GW respectively. The countries with highest aggregated transmission capacity in 2050 are France (179GW), Germany (104GW) and Spain (89GW).

The emission constraint imposing a 90% reduction by 2050 (EU aggregated) is binding in all periods. The carbon price[18] decreases from 4€/EUA in 2020 to 3€/EUA in 2030. From there carbon price increases steadily to 9€/EUA[19] in 2050. These values are far from the actual market carbon price, 24€/EUA, because the emissions in the ETS from other sectors are not accounted here. The carbon prices here show that any carbon price above those mentioned before, would impose into the electricity system a more stringent emission cap. There are many countries that decrease their emissions by 100% in 2050: Norway, Sweden, Finland and Austria (although they might be dependent on imports). In total there are 14 countries with reductions of more than 98%.

Average electricity cost increases from 42.0 €/MWh by 2020 to 53.2 €/MWh by 2050. The increase is caused mainly by the increase on investment costs, despite that non-polluting technologies have decreasing costs. Part of the increase is caused by high costs of CCS technologies, which are necessary to cover the demand. The investments in CCS start in year 2035 with 4GW total installed, then a 10 fold increase in 2040, reaching at the final period a capacity of 85GW in total.

[18] Given as the shadow price of the emission constraint
[19] One European Allowance or EUA is equivalent to $1tCO_2$

4.4. No DR Case

In order to analyse the impact of DR in the European power system, the model outcomes with disabled DR operation are compared to the reference case. There are five main differences, explained in this section, between the two cases as can be seen in table 4: 1) IRES capacity is higher in DRB, 2) IRES curtailment is higher in DRB, 3) peak plants capacity (OCGT, CCGT and Gas CCS) is higher in DR0 and 4) storage capacity is much more higher in DR0.

The first difference is caused by a higher solar capacity in DRB than in DR0, which is a consequence of the availability of shifting load to high solar production periods. Unfortunately that brings a 7.8% higher IRES curtailment in DRB than in DR0, which is explained by the fact that in certain days the solar production is high but not high enough to make a significant price difference that can be economically efficient for load shifting. Neither the solar surplus is transmitted on cross-country interconnections nor charging storage units. This is surplus electricity that could be used in other sectors.

Regarding point 4 storage power capacity shows the highest of the deviations with 86% more in DR0 than in DRB. The difference on battery energy capacity is incredibly 18 times higher in DR0. In this case, it is clear that the availability of flexible loads reduces the needs of investments in storage infrastructure. However, the DR loads cannot substitute all the storage power and energy capacity.

In accordance to difference number 3, flexible loads allow savings on peak plants because the net demand peaks are reduced. The generation portfolios are further analysed in the rest of this section, starting with the energy mixes (fig. 5). Despite the high curtailment difference in 2050, the IRES annual generations are approximately the same until 2035, period in which DRB shows more production from IRES and less from peak plants (by 2050 in DRB there is only 1.8% more production). If we look into wind and solar separately, DRB has more generation of both from 2030 to 2050 except only for 2040 (when a high investment in solar capacity causes a change in sign of production). In conclusion, flexible loads allow taking advantage from solar production, which, although it is intermittent, has 75% lower investment costs than onshore wind.

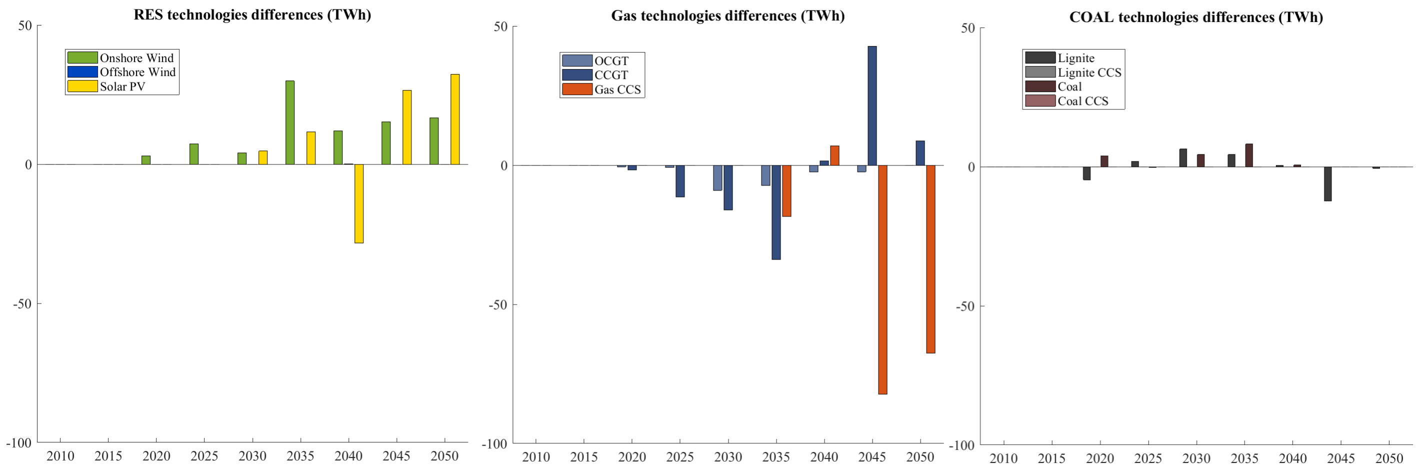

Figure 5: Europe's Generation Difference between DR0 and DRB by period. Positive y-axis indicates larger energy generation in DRB than in DR0 and viceversa.

When it comes to generation from the peak power plants, there are low differences in 2020 and 2025 when solar still has low shares in the energy mix. In 2035 the electricity generated from peak plants is higher in DR0 than in DRB. From next period there is a trend switch: in DRB there is more generation from CCGT and less from CCS than in DR0. Therefore, only in peak plants, the DRB's energy mix has higher emission intensity (which is compensated by a major IRES electricity production). The main differences in generation in 2050 comes from CCS, onshore wind and solar with -68TWh, +17TWh and +32TWh respectively.

The overall average electricity price without DR technologies follows the same evolution as in DRB but are 2% higher from 2035 due to a lower IRES integration and the need of gas CCS. The CCS capacities in

Table 4: Main differences between cases DR0 and DRB in 2050.

Metric	DRB	DR0	Difference %
Electricity Generation (TWh)	4019.30	4023.30	-0.10
IRES capacity (GW)	1575.10	1537.70	2.37
Solar PV (GW)	773.90	744.90	3.75
IRES generation (TWh)	2726.60	2677.70	1.79
IRES curtailment (TWh)	118.80	109.50	7.83
Total Installed Capacity (GW)	2059.40	2053.40	0.29
Transmission Capacity (GW)	501.10	499.40	0.34
Emissions (MtCO2) 2010-2050	6399.00	6401.00	-0.03
Peak Plants (GW)	293.00	324.00	-10.58
Electricity Price (€/MWh)	53.20	54.50	-2.44
Storage Capacity (GW)	59.80	111.40	-86.29

DR0 are two times higher than in DRB in 2035, and decrease until 2050 when they set at 16%.

As expected the differences in energy generation have its reflection on the capacity portfolio (and viceversa). Total generation investments are in fact very similar in both cases. If we include storage power capacity and transmission capacity in the mix then DR0 needs in fact 50GW more than DRB. These 50GW are compensated in DRB by the virtual infrastructure (or IT capacity) of flexible consumers, with 91GW.

It is interesting to analyse the capacity mix in 2035 because by then there is a huge investment in DR capacity of 25GW, in solar capacity and current fossil fuel plants are about to be decommissioned. In DRB there is more onshore wind capacity and solar capacity, while in DR0 there is more peak capacity (fig. 6). That is the moment when both cases start to diverge. 2040 is a moment when both mixes even out. From 2045 to 2050, DRB's supply is based in solar and DR flexible loads, while DR0 case has to make use of gas CCS, onshore wind, and solar production through storage[20].

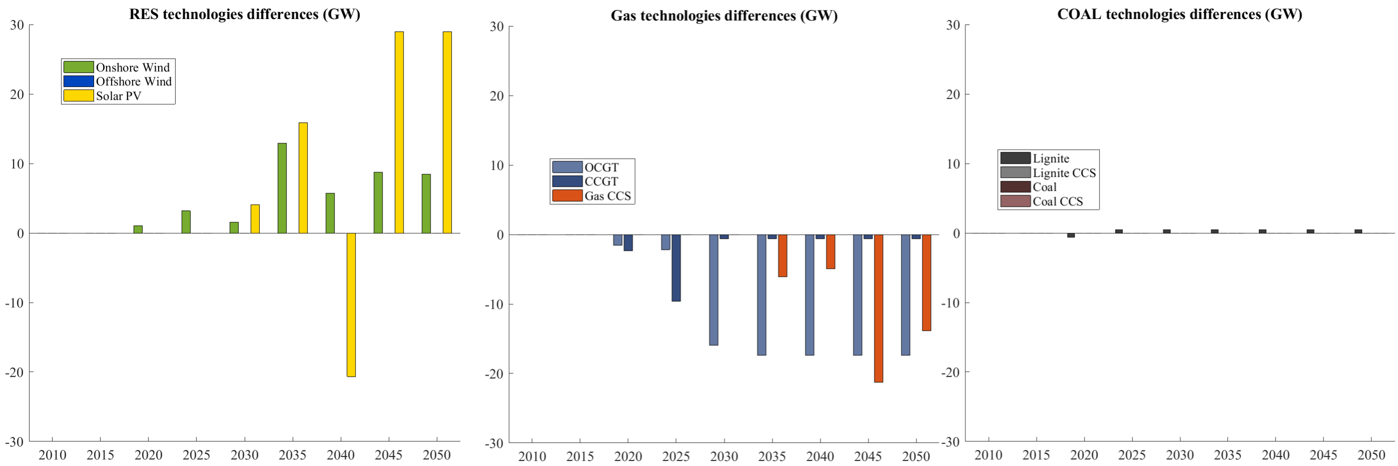

Figure 6: Europe's Capacity Difference between DR0 and DRB by year. Positive y-axis indicates larger capacity in DRB than in DR0 and the negative side less capacity.

[20]The portfolio of lignite and coal plants remains the same until 2050 in both cases with minor differences in generation

5. Sensitivity Analysis

5.1. Capacity Sensitivity

The amount of DR capacity that is permitted in the system is a key parameter. Therefore a sensitivity analysis is performed on the total DR capacity of each country. The upper limit is specified for each country relatively to the theoretical DR potential in the reference case (that is DRB) by using the following scaling factors: 0.5, 0.75, 1.25 and 1.5 (indexed from case DR1 to DR4 respectively). Factor 1 is considered to be the baseline case, DRB, which allows full development of the DR potential. Cases 1 and 2 take a conservative approach to the assessed theoretical potential, while cases 3 and 4 have a optimistic view of how far DR can be developed. This translates in the model into relaxing or tightening constraint 33.

Table 5: Relative differences of each sensitivity case in percentage with respect to the reference case DRB (%).

Metric	DR0	DR1	DR2	DR3	DR4
DR Capacity	-100.0	-41.8	-17.2	27.0	46.8
CAPEX	1.3	0.1	0.0	0.0	-0.1
OPEX	2.0	0.7	0.4	-0.4	-0.7
Net Generation	0.1	0.0	0.0	0.0	0.0
iRES cap	-2.4	-1.4	-0.6	0.7	1.4
Solar cap	-3.7	-2.9	-1.3	1.6	3.1
iRES generation	-1.8	-1.0	-0.5	0.5	0.9
Curtailed generation	-7.8	-2.1	-1.3	1.1	2.1
Total capacity	-0.3	-0.8	-0.3	0.4	0.8
Transmission Capacity	-0.3	-0.6	-0.2	0.1	0.1
Emissions 2010-2050	0.0	0.0	0.0	0.0	0.0
Storage power capacity	86.3	13.7	7.0	-3.5	-5.4
Storage energy capacity	3.8	0.7	0.3	-0.1	-0.2
Average electricity cost	2.4	1.1	0.6	-0.4	-0.8
Peak plants	10.7	2.3	1.0	-0.9	-1.8
of which Gas CCS	16.2	5.9	2.5	-2.6	-4.9

Table 5 shows the percentage variation with respect to the reference case DRB. We see that relaxing the DR total capacity constraint (DR3 and DR4) allows more DR capacity into the system, more solar capacity, more IRES curtailment, less peak plants capacity globally and less gas CCS. Note that the sequence of cases shows around 20% change in DR capacity while solar capacity changes by 1% and storage power capacity by 2-6%.

The groups with highest DR capacity in all the cases are groups 6 (heat storage), 2 (HVAC) and 5 (washing appliances), except in DR4 where group 3 takes group 5's third position. In particular in DR4 their capacities are 234GW, 30GW and 11.7GW respectively, which added to the rest of the groups sums up to 315GW. Investment in group 1 is not affordable.

5.2. Costs Sensitivity

In order to analyse how investment and operation costs affect the intake of DR capacity, results with different costs levels have been obtained. The cost sensitivity cases consisted in scaling both the investment and operational costs of all the DR groups at the same time with the following factors: 0.25, 0.5, 2, 4 and 8. That is halving and doubling the costs in each case, which are labelled from DRC1, DRC2 for the cheaper cases and DRC3 to DRC5 for the more expensive.

In table 6 the main differences between cases are represented. As expected the amount of DR capacity diminishes with increasing costs. There is less IRES, solar capacity and generation when less DR capacity available. IRES curtailment is higher in DRC1 and DRC2 than in DRB becuase they have higher solar capacity. High costs of DR make solar capacity inefficient as can be observed in cases DRC3 to DRC5, which have a similar solar capacity. The reason behind this is that operational costs in DRC1 and DRC2 make efficient to shift a bit more energy to the IRES production hours. While in DRC4 and DRC5 the curtailment is lower than in DRB since there is less RES hourly surplus during the normal and low demand seasons.

Storage capacity differences are significant (fig. 6). It increases with less DR capacity from -9% to 38% in DRC5. In other words, storage and DR capacity are substitute technologies.

Although total installed capacity decreases with increasing DR costs (due to solar capacity), the capacity of peak plants (+11%) and in particular gas CCS (+20%) increase. Electricity price are down to -8% cheaper in DRC1 and stay stable at +3% in DRC3 to DRC5.

Table 6: DR costs sensitivity analysis outcomes' percentage variation respect to DRB (%)

Metric	DRC1	DRC2	DRC3	DRC4	DRC5
DR Capacity	205.4	124.1	-39.8	-76.9	-76.9
CAPEX	-1.6	-0.6	0.5	0.6	0.7
OPEX	-10.7	-5.9	2.0	2.6	-6.4
Net Generation	-1.6	-0.5	0.1	0.1	0.1
iRES cap	11.9	10.2	-3.7	-3.8	-3.6
Solar cap	29.7	23.2	-6.8	-7.2	-6.8
iRES generation	6.3	5.6	-2.8	-2.8	-2.7
Curtailed generation	11.2	17.9	-7.4	-7.1	-7.1
Total capacity	6.2	5.7	-1.7	-1.4	-1.2
Intercon. cap	6.2	3.3	0.8	0.5	0.5
Emissions	0.0	0.0	0.0	0.0	0.0
Storage power cap	-9.0	-10.2	20.1	22.9	37.5
Storage energy cap	-0.2	-0.2	0.8	0.9	1.6
Average electricity cost	-7.5	-5.6	2.8	3.2	3.0
Peak plants	-22.7	-15.1	7.7	10.9	10.8
Of which Gas CCS	-52.9	-40.1	20.2	20.2	19.6

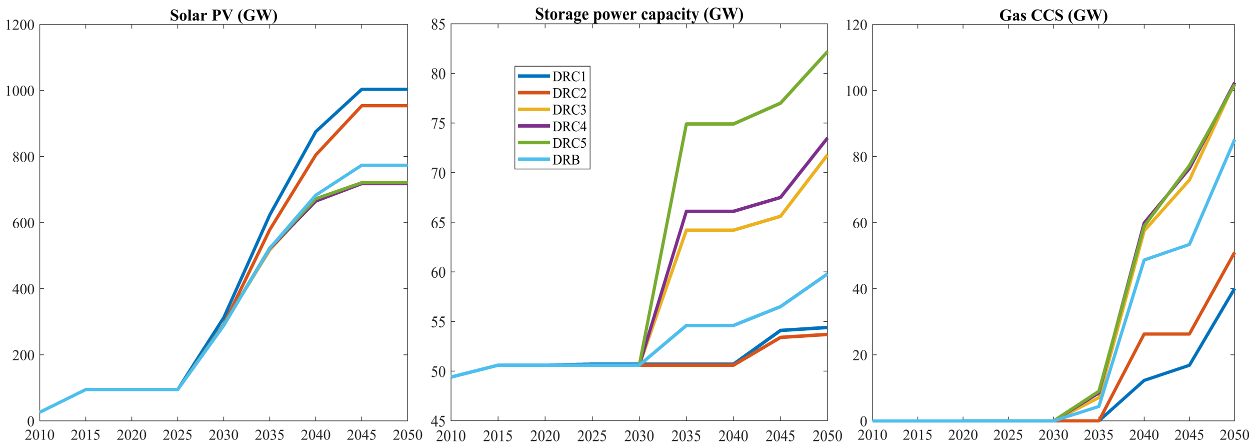

Figure 7: Europe's Capacity Development by year between DRB and DRC1-5 cases.

6. Discussion

The long-term capacity expansion model EMPIRE has been upgraded to allow investments in demand responsive loads. In this way, the central planer can arbitrage a limited amount of flexible load in order to meet the energy demand. While in reality DR provides local benefits to the grid, the model has assumed a homogeneous distribution of flexible loads within each country. That should not be a limitation of the model as long as a correct assessment of the capabilities of flexible loads within each country is made, and as long as their operation is fairly represented. A higher spatial resolution would divide DR potential in smaller demand regions, which at the end would yield a lower total aggregated flexible loads. The same consideration is valid for the supply side. It should not be seen as a different problem as increasing the spatial resolution of the model application.

The results might incur an underestimation of DR potential as in the model only energy based markets are considered. That is, this study assesses *economic DR*. A model that incorporates DR capacity reserves, would probably require slightly higher capacities than the ones in the results. The system perspective plays a role in that sense. In any case the DR has been properly assessed by reasonably limiting its capacity and operation. The model could be easily extended to include capacity reserves at the current time resolution by properly introducing slack capacity constraints. Further on, if the time resolution increases to the scale of minutes, DR operating reserves could be assessed as primary, secondary and tertiary reserves. That is, the operation of DR could be viewed both as economic DR and *contingency DR*.

Investments in DR capacities happen because flexible loads provide a more efficient way to take profit from wind and solar energy instead of curtailing it. This was an expected result. It has been seen that the countries with highest IRES capacities have also the highest DR capacities. Also, when solar power investments become at the same price as onshore wind, the southern countries with high solar potential would take more profit of investing in solar than in onshore wind. It has to be taken into account that IRES capacities depend on multiple factors besides DR capacities as for example, most directly, country specific IRES profiles, CO_2 prices and IRES technology costs.

Besides the great DR potentials seen in the results, electricity markets will have to evolve further to technically integrate larger and larger amounts of DR and operate those resources efficiently. European electricity markets are going in that direction but there is still a long way to reach the desired level of consumer participation. This development obviously cannot happen in less than 5 years, and in fact it goes hand in hand with the gradual digitalization and transformation of the power system into a zero emission system.

The DR potentials in Europe have been assessed in Gils (2014) by using a single period optimization. In this study, by including endogenous DR investments into a stochastic capacity expansion model, the development of DR capacities has been co-optimized together with all other available generation technologies. Unfortunately the transport sector could not be included in the study case as load profiles for charging electric vehicles (EVs) were not available. The total energy demand by EVs is included in the study as yearly demand. On one side, EVs demand could cause higher peak loads that would require higher generation capacities. On the other side, EVs demand on a standard basis happen during off-peak hours. In addition the effect of EVs on country load profiles in the coming 5 years would be insignificant, while for longer horizons when the fleet of EVs grows, most probably the charging periods will be adapted to the shape of the future load profiles.

The DR development in Europe has been assessed for seven different end consumer groups, inside a capacity expansion stochastic optimization model. In this way the study sheds light on what are the most affordable DR loads. Clearly, the results show that the main contributor by energy volume to load shifting is heat storage end uses, followed by industrial process shifting. These are expected results because these are the groups that offer a more flexible time frame. The type of DR group aggregation allows the modelling to be done with linear second-stage variables, which keeps the model computationally tractable, because modelling shiftable profile loads or interruptible loads requires binary variables.

The approach for modelling flexible demand consists of variables representing the demand regulation given a cost of operation. This approach relies on the assumptions on DR operation costs, which express the willingness of each consumer to shift demand into the less expensive hours. In the literature other approaches have been proposed as for example modelling responsive loads in a second level optimization problem, which would require to transform the model into a equilibrium model. The approach using inter-hour elasticities of demand would require major assumptions on price elasticities, as those are not available for all sectors and countries.

The availability of flexible loads is modelled through deterministic profiles. Despite of that, the amount of available flexible capacity becomes uncertain because it is proportional to the system load, which is uncertain. However, consumer behaviour from any economic sector has capacities dependent on weather conditions, peak demand and the type of electricity contract. To upgrade the study case in that sense, uncertainty in DR group availability could be represented in the load profiles α_{nifh}. Unfortunately, that would imply increasing the computational complexity in terms of short-term scenarios.

In this study it was chosen to use homogeneous data regarding DR costs among the countries. On one side that is suitable for analyzing how DR technologies can spread through European countries considering a common European market. On the other side, there can be cost differences and varied electricity market's mechanisms from country to country that make the situation quite diverse. When it comes to costs, it would be interesting to see the results considering a decreasing cost trend.

7. Conclusions

Flexible demand can be modelled in a capacity expansion model with short-term dynamics. From a large scale perspective, flexible demand can be aggregated in groups of end consumers that share similar time of use, investment and operative costs. Two types of flexible loads have been used in the study case, shiftable volume loads and curtailable loads. The two types can be modelled with linear variables. Basically the model for demand responsive loads is like a storage without the need of a physical infrastructure.

The optimal solution is the one that reallocates flexible loads during valley net load hours, that is at moments of highest IRES production. The load arbitrage in the optimization model EMPIRE, responds to a system perspective least-cost criteria.

The adoption of demand responsive loads into a large scale power system capacity expansion model will have positive impacts on the system. Specially relevant is the fact that gas power plants supplying flexible energy during peak events are partially substituted by the flexibility offered by DR loads. On one side DR introduces more degrees of freedom into the model. It allows more IRES integration into the system, less IRES curtailment, and less investments in peak plants. On the other side, unexpectedly, investments in polluting plants are affordable (OCGT) when flexible demand reduces emissions from other parts of the system. In that sense, DR is not a technology that would allow a significant reduction of CO_2 emissions. Without policies that limit total emissions, DR has no effect on global emissions.

Speaking globally, solar PV and onshore wind capacities follow similar paths because the former is more efficient in southern countries while the latter is efficient in Nordic countries and British Islands. By 2050 their installed capacities are 774GW and 802GW respectively. Countries with highest installed DR capacities are the ones with highest solar capacity.

The sensitivity analysis on maximum DR capacity has shown that larger DR availability can underline its benefits. More DR capacity means, mainly, that fewer peak plant investments are needed. However, the more DR capacity, the more IRES curtailment.

The impacts into the power system are not extreme in the sense of turning around the capacity mix. DR capacities act as a support technology, integrating 2% more IRES, and therefore facilitating the transition towards a system with high shares of renewables.

Acknowledgements

The research of this paper has been conducted on the Center for Sustainable Energy Studies (CenSES) from the The Research Council of Norway with project number 209697. The authors thank the support from the European Union's Horizon 2020 project "SET-Nav" (No. 691843).

Appendices

Load Definitions

In this context, we can define a *load* as a step function f with domain a discrete interval whose image, representing load values along the time domain, is a subset of a given feasible set X_f. The *total energy* of a load is the integral of f over the interval. A *load transform* of a load f, denoted by $\tilde{f}$, is any composition $\tilde{f} = h \circ f \circ g$ such that g is a bijective function representing the time shift, h is a function representing the load regulation and $\tilde{f}$ is a load. A *flexible load* is a load f that can be replaced by any load transform $\tilde{f}$ with image $X_{\tilde{f}}$. Considering different types of transforms we can define two subsets of flexible loads: shiftable and curtailable loads Ottesen et al. (2016). A *shiftable volume load* f is a flexible load that can be replaced by a transform $\tilde{f}$ whose total energy is the same as the total energy of f. In particular a *shiftable profile load* is a shiftable volume load such that the available transforms satisfy $h = \mathrm{id}$ and g is a translation in the time domain. A *curtailable load* is a flexible load such that the available transforms satisfy $g = \mathrm{id}$ and $\tilde{f} \leq f$. A *interruptible load* is a curtailable load such that either $\tilde{f} = f$ or $\tilde{f} = 0$. Given the discrete nature of a load, its image on a bounded interval can be represented by a finite sequence denoted by y_h, $h = 1, \ldots, N$ which we call its *discrete representation*. It is worth pointing out that shiftable profile loads and interruptible loads can only be implemented by using discrete variables.

Upper bound mathematical definition

The objective of the upper bounds is to limit load shifting and allow sufficient valley filling.

Given a load $(\bar{y}^{\text{load}}_{ni\omega f1}, \ldots, \bar{y}^{\text{load}}_{ni\omega fN})$ and a constant A, the scaled load is the component-wise scaling $(A\bar{y}^{\text{load}}_{ni\omega f1}, \ldots, A\bar{y}^{\text{load}}_{ni\omega fN})$

The load ramps are defined as the consecutive hour differences of the scaled load

$$r_{fi\omega h} := A\bar{y}^{\text{DR}}_{fi\omega h+1} - A\bar{y}^{\text{DR}}_{fi\omega h} \tag{.1}$$

Ramp selection consists of defining the positive and negative ramps as follows.

$$\begin{aligned} r^{+}_{fi\omega h} &:= \max\{r_{fi\omega h}, 0\} \\ r^{-}_{fi\omega h} &:= \max\{-r_{fi\omega h}, 0\} \end{aligned} \tag{.2}$$

The ramps $r^{+}_{fi\omega h}$ and $r^{-}_{fi\omega h}$ contain the absolute values of the positive and negative ramps separately.

Given an hour h, the load $\bar{y}^{\text{load}}_{fi\omega h}$ is: 1. a local minimum if the corresponding ramps $r^{+}_{fi\omega h}$ and $r^{-}_{fi\omega h-1}$ are positive (equivalently $r^{+}_{ni\omega fh-1} = r^{-}_{fi\omega h} = 0$), 2. a local maximum if the ramps $r^{+}_{fi\omega h-1}, r^{-}_{fi\omega h} > 0$ (equivalently $r^{+}_{fi\omega h} = r^{-}_{fi\omega h-1} = 0$), 3. in descending slope if $r^{-}_{fi\omega h} > 0$ and $r^{+}_{fi\omega h-1} = 0$ and 4. ascending slope if $r^{-}_{fi\omega h-1} = 0$ and $r^{+}_{ni\omega fh} > 0$. The principle to add up neighboring ramps in a given hour is basically to add up all upcoming positive ramps and all previous negative ramps. In this way a local minimum load accumulates all the neighbouring ramps and proportionally takes more slack increase than the peaks.

The ramp time window parameter h_0 selects the neighboring ramps that define the upper bound. The mathematical formula for the upper bound is as follows.

$$U^{DR}_{ni\omega fh} := A\bar{y}^{\text{DR}}_{fi\omega h} + \sum_{t=h}^{h-1+h_0} r^{+}_{ni\omega ft} + \sum_{t=h-h_0}^{h-1} r^{-}_{ni\omega ft} \tag{.3}$$

Note that in the definition if $\bar{y}^{\text{load}}_{fi\omega h}$ is a local maximum $(h - h_0, h + h_0)$, then the corresponding ramps are 0 [21], the two summations in the definition are zero and the upper bound is just the first term $A\bar{y}^{\text{DR}}_{fi\omega h}$.

The upper bound depends on the choice of the constant A. As the input data for each load group specifies that each hour load is the potential for both upward regulation and downward regulation, it is logical to choose $A = 2$. That means each hour load has a range to decrease and increase by at least 100%.

[21] Unless there are consecutive local minimum and maximum within $(h - h_0, h + h_0)$

Theoretical DR Potential by Country and Class

Table .7: DR potentials in GW. Adapted from Gils (2016).

Country	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total
Europe	23.2	22.7	7.8	9.5	63.4	156.1	8.8	291.5
France	3.0	3.6	1.3	1.6	8.1	26.0	0.8	44.3
Germany	4.2	3.1	1.1	1.4	13.1	17.8	1.7	42.5
Great Brit.	2.7	2.3	0.8	0.5	9.1	21.5	0.3	37.1
Italy	2.7	2.6	0.8	0.9	6.8	16.2	1.3	31.4
Spain	2.2	2.8	0.8	0.8	4.1	9.6	1.2	21.5
Poland	1.2	1.0	0.4	0.3	2.8	8.5	0.3	14.5
Sweden	0.5	0.8	0.3	0.8	1.6	8.7	0.2	12.8
Norway	0.2	0.7	0.2	0.3	0.8	6.8	0.5	9.6
Netherlands	0.7	0.8	0.3	0.2	3.0	3.6	0.1	8.8
Finland	0.2	0.4	0.2	1.0	0.8	5.4	0.2	8.1
Romania	0.6	0.2	0.1	0.2	1.1	4.0	0.4	6.5
Belgium	0.5	0.5	0.2	0.2	1.7	2.8	0.3	6.3
Greece	0.6	0.6	0.2	0.2	0.9	3.2	0.5	6.2
Austria	0.4	0.3	0.1	0.2	1.3	2.5	0.1	4.9
Czech R	0.4	0.3	0.1	0.1	0.9	2.5	0.1	4.4
Switzerland	0.4	0.4	0.1	0.1	1.2	2.0	0.1	4.2
Hungary	0.4	0.3	0.1	0.1	0.7	2.4	0.1	4.1
Portugal	0.4	0.4	0.1	0.2	1.1	1.8	0.1	4.1
Denmark	0.3	0.2	0.1	0.1	1.1	1.6	0.0	3.4
Slovakia	0.2	0.2	0.1	0.1	0.5	1.6	0.1	2.7
Bulgaria	0.3	0.2	0.1	0.1	0.4	1.4	0.1	2.5
Ireland	0.2	0.2	0.1	0.1	0.6	1.3	0.0	2.4
Serbia	0.2	0.1	0.0	0.1	0.4	1.1	0.0	2.0
Croatia	0.2	0.1	0.0	0.1	0.3	0.6	0.0	1.4
Lithuania	0.1	0.1	0.0	0.0	0.3	0.8	0.0	1.3
Slovenia	0.1	0.1	0.0	0.0	0.3	0.6	0.1	1.1
Latvia	0.1	0.1	0.0	0.0	0.1	0.7	0.0	0.9
Bosnia H	0.1	0.0	0.0	0.0	0.1	0.5	0.1	0.8
Estonia	0.1	0.1	0.0	0.0	0.1	0.4	0.0	0.7
Luxemb.	0.0	0.0	0.0	0.0	0.1	0.1	0.2	0.5
Macedonia	0.0	0.0	0.0	0.0	0.1	0.3	0.0	0.5

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