System and Private Values of Demand Response: Insights for Mass Deployment

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Highlights

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- Demand response resources provide multiple services to different power systems' actors with diverse objectives, so have multiple values.
- Comparing the values of the same demand response resource gives insight into the actors' incentives to invest and operate them.
- Some flexible appliances have all-around positive values, some benefit private players but not the system, and some the opposite.
- The last two cases require different types of interventions to be deployed in a welfare-enhancing manner.

System and Private Values of Demand Response: Insights for Mass Deployment

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Abstract

Demand response is advertised by regulators, system planners, and the industry as a crucial flexibility resource for the next decade in increasingly renewable-based power systems. As of today, most demand response potentials remain untapped, notably in the diffuse residential and tertiary sectors. A massive deployment effort seems bound to happen. This paper provides insights into the values of numerous demand response potentials from the different perspectives of system planners and operators, private market actors, and consumers. To do so, a large-scale SDDP-solved bottom-up demand response model is developed and calibrated on a plausible 2035 French power system. This unique yet agile valuation framework provides insights into operation-related values of demand response, such as the system's cost or emissions reductions, and investment-related ones, such as peak generation investment deferral or mitigated renewable capacity increase. Evaluated demand response potentials originate from all types of appliances, primarily focusing on residential and tertiary sectors. Thus, multiple merit orders for demand response are obtained, depending on the merit criterion. Divergences and convergences between these merit orders enrich stakeholders' vision on which potentials should be invested first, which are riskier, and where to target eventual supports.

Keywords: Demand response, Uncertainty, Electricity markets, Stochastic Dual Dynamic Programming
JEL: C61, L94, Q41, Q42, Q48

1. Introduction

Facing the double challenge of increasing demand for electricity and massive integration of variable renewable energy sources, the power sector seeks new flexibility sources. These trends hinder the ability of power systems to follow variations of supply and demand to balance them at all relevant time scales and controlled costs. Among new flexibility sources, demand-side flexibility, also called demand response, is seen as crucial in the following decade. Regulators and system

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operators foster this flexibility option due to its lower costs compared with high-scale deployment of batteries, power-hydro storage, or with interconnections development (IEA (2022),RTE (2023)).

Even though it implies lower infrastructure costs, demand response necessitates regulatory, economic, and social efforts to be implemented significantly. In Europe, many channels are available to incentivize the development of demand-side flexibility, and numerous actors might find an interest in it (e.g.Bureau et al. (2023), recommendations 4 and 5). Therefore, an industrial plan to coordinate these efforts seems required for stakeholders to deploy demand response at the system scale (see RTE (2023) in France, DENA (2016) in Germany, DoE (2006) in the US or IEA (2022)) and benefit from this source of flexibility.

However, such coordination requires stakeholders to answer the genuine question: what is the value of a newly installed MW of demand-side flexibility from a specific power use? A relevant answer should assess simultaneously and quantitatively the specifics of the considered power use, the type of service(s) for which its flexibility is intended, but also the interest of all actors of the power system for this flexibility. Hence, large-scale deployment of demand response implies disaggregating the notion of demand response value and measuring these values. These indicators are the only way stakeholders would have access to the multifaceted impacts of demand response in both power systems and markets.

The purpose of this paper is to contribute to bridging such a gap by providing a methodology for assessing such multifaceted impacts in a unique framework. Hence, this study not only derives indicators of various impacts of unlocking some demand response from different power uses into a low-carbon power system but also ensures the comparability between the indicators. As the diverse actors of power systems are not interested by the same values of demand response, such comparability, which can not be found in the current state of the art, provides crucial insights on the difference of incentives perceived by those actors vis-à-vis the same demand response asset. To demonstrate how to use the methodology and the relevance of the resulting comparative insights, an application to a prospective 2035 French power system is provided in the paper.

The literature has extensively studied demand response. Nevertheless, it remains fragmented between studies of power use characteristics as flexibility sources, demand response revenue streams, the challenges of its integration in electricity markets, and its effects on power systems. Such state of the art is detrimental to usable policy insights as all of these aspects have to be considered in system planning. System effects are closely related to the characteristics of introduced resources and systemic flexibility needs. Resources are, in turn, only actually introduced and operated if their revenue is sufficient. Finally, such revenues depend directly on market designs, public aids, and the correspondence between the features they value and the specifics of the considered demand response potential.

Numerous academic studies or reports from the gray literature focus on inventorying flexible power uses. They describe their technical or social features as a flexibility resource (Gils (2014),

Verrier (2018)), and eventually, the cost of turning these uses flexible (ADEME (2017),IEA (2022)).

Another fruitful line of research seeks to value demand response. Such studies may take the point of view of any stakeholder: System operator (e.g., Verrier (2018),Müller and Möst (2018),Marañón-Ledesma and Tomasgard (2019)), Network operator (e.g., Nouicer et al. (2023) for the distribution level), DR aggregator (e.g., Campaigne and Oren (2016),Okur et al. (2019),Roos et al. (2014)), Supplier (e.g., Astier and Léautier (2021),Silvestre Freitas Gomes et al. (2024)), Consumer (e.g., Muratori and Rizzoni (2016),Remani et al. (2019),Siano and Sarno (2016)). These studies omit, in particular, the diversity of flexible consumptions and their characteristics, often settling for a specific use of electricity or simple "before the meter" demand reduction. Moreover, they all maximize monetary payments to the modeled actor. Thus, even if they consider several revenue streams (e.g., Roos et al. (2014)) or technical characteristics (Siano and Sarno (2016)), they only consider one type of value of demand response, its purely economic value created by operation costs reductions or savings in bills. As underlined by Kerscher and Arboleya (2022) in their literature review, only a minority of studies focus on other values of demand-side flexibility, expressed in terms of security of supply or greenhouse gas emission reduction. Recent efforts tend to recognize the need for such a multifaceted assessment of demand response value. Hence, Misconel et al. (2021) mentions the different types of values of DR. Yet, the authors only derive quantified demand response values from a system operator perspective, assessing total operation cost reductions and CO_2 emissions with different fixed levels of renewables.

Some works explicitly tackle this diversity issue but still focus on economic value by assessing revenues of demand response from different markets (Biegel et al. (2014)) or by valuing one attribute of specific electricity uses as flexibility resources (Bruninx et al. (2018)). Similar to the previous research line, they only partially inform on the values of a flexible demand. Their approach also suggests that a specific attribute of this demand may be modified to increase the measured value of this flexibility. This may not necessarily be the case for demand response, which derives directly from the concrete choices of consumption of physical persons, e.g., load-shedding from heating appliances will never be entirely available during winter because of the finiteness of the willingness to receive monetary compensation for erased heating demand.

Finally, some authors inventory in parallel the attributes of a flexible resource, the possible uses of this resource, and the properties that are valued by the different electricity markets (Bradley et al. (2013),Vicente-Pastor et al. (2018), Villar et al. (2018),Ramos et al. (2016)). However, their analysis, intended to give insights on market designs, remains mainly qualitative. Thus, the adequacy of these three aspects, sought by such insights, is not quantitatively assessed nor measured for concrete flexibility sources in actual or projected power systems.

To the best extent of our knowledge, Bradley et al. (2013) formulates the closest contribution to the present study. Yet, it is based on old data (pre-2010), not accounting for the increased uncertainty present in renewables-based power systems, and builds on exterior and different methodologies to assess DR values, thus inducing comparability issues between the resulting values. Therefore, a research gap exists (and has been underlined, e.g. in Motta et al. (2024) or Ringkjøb et al. (2018))

for a methodology to assess multifaceted demand response impacts on power systems which accounts for DR characteristics as a flexible resource and the variability of renewable generation, and allows stakeholders to compare the resulting incentives for the different actors of modern power systems.

The present study seeks to follow the ambition of the last mentioned branch of the literature while adopting a more quantitative approach. Here, the types of flexible demand, the different values and services of demand response, and, above all, measurement methods for these values are encompassed in a common framework. Hence, such measures are given for specific, flexible electricity uses with their own technical or social constraints. The main contribution of this study lies in its holistic and quantitative approach to demand response. It synthesizes possible paths for valuing making a specific power demand flexible.

Policy-wise, this study proposes methods for evaluating demand response and insights on some flexible demands to decision-makers, whatever the dimension of demand response they are interested in. The proposed framework also evaluates potential conflicts occurring in the development of DR, as some actors might have opposed valuations of the same DR potential. In other words, we build a dashboard of indicators relative to demand-side flexibilities, providing guidance on deploying demand response capacities according to stakeholders' interests.

In the EU, unlocking the potential of active consumption constitutes a focus of the current discussions on electricity market design.[3] It is notably discussed to alleviate barriers and allow demand response access to support mechanisms, such as national capacity remuneration mechanisms. Moreover, EU member states shall be allowed to create a new peak shaving product in case of an energy crisis to unlock supplementary demand-side flexibility. The sizing of such products procured by TSOs depends on assessing the potentials of demand response and their values for the system and private actors so that the new instruments target potentials that are truly additional for the system without creating windfall effects for already economical potentials. Thus, the results of the present paper may contribute to the current discussion by giving such valuations of the demand response potential in France, with a replicable methodology for other countries.

The remainder of this paper is structured as follows. Section 2.1 presents the background and reviews the attributes of a generic flexible resource. Section 2.2 recalls the main services provided by demand response to power systems and the actors responsible. We highlight how the literature focused on valuing these services rather than the resources that provide them. In Section 2.3, perspectives stemming from the meeting of services, actors, and DR resources are linked with as many DR values. For each, quantitative measurement methods with a prospective approach are proposed in Section 3. A sensitivity to the main modelling assumptions regarding DR is provided in Appendix B. Finally, in Section 4, this dashboard of values is computed for several DR appliances from all sectors in possible future French power systems with high levels of renewables.

[3]Both the general approach agreed in the Council at the end of 2023 (of the European Union (2023)) and the texts adopted at first lecture by the Parliament in April 2024 (Parliament (2024a),Parliament (2024b)) mention it.

2. From flexible uses of electricity to valued demand response

The section aims at disaggregating the notion of demand response value. From a literature review, we derive a series of indicators of DR values by bridging flexible electrical appliances, generic flexibility resources, flexibility needs of a power system, and the actors responsible for procuring these services.

2.1. A variety of power demands as flexibility resources

A flexible energy resource is an available asset that can start up and ramp sufficiently quickly to follow and adapt to varying grid or market conditions (Goutte and Vassilopoulos (2019)). This technical description does not suffice for a power system to benefit from this flexible resource. As with any energy resource, this flexibility shall be valued and paid to participate in the system. Thus, a flexible resource may also be seen as a market product and described as such. A specific electrical appliance enrolled in any demand response program is a flexibility resource and, thus, both a technical object and a market product. Each aspect assesses a resource through some of its characteristics or attributes. Villar et al. (2018) and Kerscher and Arboleya (2022) review attributes linked with technical constraints. Ramos et al. (2016) builds a list of crucial features for market products of flexibility. Their combination induces a portfolio of attributes with which a flexible resource is completely described. We extract the main attributes of a DR potential seen as a subgroup of flexible resources in Table 1.

Attribute	Description
Capacity	Installed capacity of modulation
Duration bounds	Minimum/Maximum time of activation once the resource is triggered
Ramping rate	Time required to reach a targeted level after activation. Generally infinite for DR.
Lead time	Duration between sending a triggering signal to the resource and its effective activation
Location	Grid with which the resource is connected (distribution or transport)
Availability	Temporal variations of the available share of installed capacity (Müller and Möst (2018); Verrier (2018))
Number of activations	Maximum number of activations over a predefined period, often the contract period. Reflects technical constraints (battery deterioration, nuclear flexibility) or social constraints (DR)
Recovery	Maximum time between a load reduction and the recovery of the shifted load for load-shifting (mainly for DR, eventually storage)
Cool down	Minimum time gap between the end of an event and the triggering of the following one (social constraint for DR, technical for supply-side flexibilities)
Delivery time	Time gap between contractualization and the sending of an activation signal
Predictability	If a random variable quantifies the temporal availability at a date, predictability refers to the ability of a market player to know the distribution of this variable
Controllability	Risk level of a flexible resource not following an activation signal. With predictability, it may form a unique attribute of flexibility product risk or quality (Chao et al. (2022); Schittekatte and Meeus (2020))
Objective	Service for which it is sold or market on which it is exchanged
Contract	The contract type through which the flexible resource is engaged (long-term, exchangeable...)
Remuneration	Type of settlement (pay-as-bid, pay-as-clear...)

Table 1: Attributes of a DR resource

These flexibility attributes do not possess intrinsic values, while their combination has. Here, our approach differs from that of, for example, Bruninx et al. (2018) that claims to assess the value of the controllability of demand resource. However, this study measures, in fact, this value for specific uses of electricity, which also displays a portfolio of characteristics such as installed capacities, time availability, or bounds on event duration. A fully controllable asset is irrelevant if its maximum shedding time is not over a few seconds or is never contracted.

Therefore, to assess demand response value, the focus should be placed on specific real electrical appliances seen through their unique combination of flexibility attributes. Such combinations are presented in Table (2) for the different appliances considered in this study: residential and tertiary space heating, residential and tertiary water heating, residential and tertiary air conditioning, tertiary cold storage, cement mills, paper production, pulp production, steel-making with electric furnaces, aluminum electrolysis and chlor-alkali process with membrane cell. The latter three industrial appliances are solely dedicated to load-shedding, while the others take part in load-shifting.

Installed capacity, ramping rates and availability are directly observable through these appliances' load profiles and specifications. For this study, installed capacity will be a controlled, exogenous parameter. Limits on the number or frequency of activation, duration, recovery, and minimum

downtime may depend on physical properties of the main objective of the appliance (e.g., thermal inertia in cold storage, damages to electric vehicles' battery) or on social acceptance reasons (e.g., discomfort limitation). They are derived notably from Gils (2014), Müller and Möst (2018), Alstone et al. (2017) and sectoral literature. Costs are based on Table D.1 of Bradley et al. (2013) for residential and tertiary sector appliances and on Verrier (2018) for industrial loads. Availability profiles for temperature-dependent appliances are conditioned by meteorology, which is reduced here by temperature. Profiles are adapted from Müller and Möst (2018). Hence, a DR valuation is geographically dependent, as expressed by Alstone et al. (2017). In this paper, heating and cooling demand days profiles are aggregated at the country level for France and taken from Demand.ninja (Staffell et al. (2023)) for 2022, and cooling degree days are set 5% higher in 2035. Lead time depends on the enabling technology (see Alstone et al. (2017) appendixes for a complete overview). Predictability depends on the particular chosen actor's point of view and on the installed enabling technology.

As we focus on the values of flexibility from a specific power use, controllability and predictability are supposed to be perfect. Controllability may be derived from consumer surveys. It could be expressed as a probability of failure at each hour of the year, giving the probability of a DR appliance not responding to its triggering signal at this hour. This attribute is hard to calibrate without comprehensive data on the effective consumptions at the individual scale. Even then, an estimation of this probability for a specific appliance using past consumption data may no longer be relevant in the future. For example, during the 2022-2023 winter energy crisis, France experienced a reduction in power consumption of 8-10% (see RTE or Doumèche et al. (2023)) with contributions from all sectors and a modification of consumption behavior lasting for at least six months, following intense advertising for energy savings from the government and energy suppliers. Such modification would impact our controllability attribute, and hence, for prospective studies, relying on past data to calibrate this attribute may not be relevant. That is why the parameter is supposed to be perfect in this study[4]. As a consequence, the values that are derived here are, in fact, upper bounds for the values of the considered DR potentials.

[4]Another justification could be that a DR aggregator could manage to achieve 1 MW from some appliance with near-perfect confidence by recruiting sufficiently many consumers from this appliance with independent probabilities of failures.

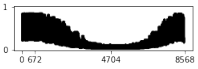
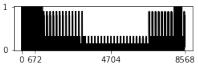
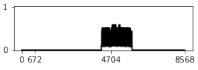
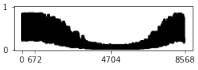
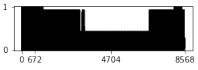
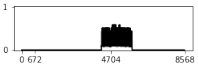
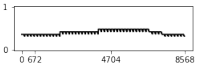
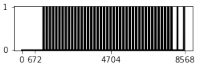
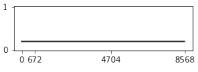
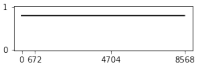
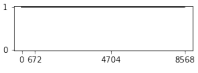
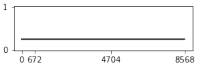
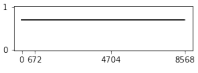
Technology	Availability	Duration	Nb of activation	Recovery time	Min. downtime	Cost (€/MWh)
Res. SH		1	1095	2	10	50.9
Res. WH		12	365	12	20	50.9
Res. AC		1	1095	2	10	50.9
Ter. SH		2	1095	4	10	26.45
Ter. WH		12	365	12	10	26.45
Ter. AC		1	1095	2	10	26.45
Ter. c. stor.		2	1095	2	23	26.45
Cement mills		3	365	20	12	10
Paper prod.		3	365	20	12	10
Pulp prod.		3	365	20	12	10
Steel-making		4	40	-	-	411
Al electrolysis		4	40	-	-	164
Chloralkali proc.		4	40	-	-	96

Table 2: Flexibility attributes of DR compatible appliances

2.2. Different flexibility services and their procurers

Flexible resources are included in power systems to provide specific services sought by precise actors. The variety of services reflects the array of flexibility needs, which are accounted for in the many definitions available for flexibility. The flexibility of a power system may refer to characteristics of the power system, to energy resources, or even to market products.

From a system point of view, flexibility relates to the ability to change production or consumption of dispatchable units at all relevant timescales. Ramos et al. (2016) specifies this definition as the ability of a system to maintain a continuous service while facing massive and rapid variations of supply or demand. Thus, flexibility is also the ability to dispatch adequate resources and to keep them available when such variations are bound to occur. The literature defines three main types of flexible resources (Villar et al. (2018) or Goutte and Vassilopoulos (2019) for the first two): up and down ramping resources that follow the rapid evolutions of balancing needs, energy-shifting

resources that smooth the meeting demand and production intertemporally, and capacity resources which are dispatchable and reservable.

References to "continuous service" or "adequate" resources link system flexibility and system performance or quality. Goutte and Vassilopoulos (2019) provide a definition of flexibility, which tends towards this perspective as it is the ability to integrate increasing uncertainty levels while keeping a satisfactory level of performance. The authors intentionally don't provide metrics of this performance reflecting the many services and points of view a stakeholder may have to define it.

From a market perspective, flexibility is defined as the ability to *efficiently* cover a variable demand (Ramos et al. (2016)). Some authors also see it as the modification of production or consumption in response to an exogenous signal (price or not) to supply balancing services or transmission constraints management services (Villar et al. (2018)). The link between resources, services, markets, and actors is made through the previous definitions of flexibility: a signal sent by responsible parties of different services links, through markets, these services to resources that could provide them. Each service's delivery may be a metric of the system's performance.

Flexibility is therefore also defined by the willingness to pay for the services of TSO, DSO, balancing responsible parties, producers, consumers, or aggregators (Ramos et al. (2016)). Among these services, Ramos et al. (2016) and Vicente-Pastor et al. (2018) highlight in particular:

- balancing, procured by TSOs, DSOs or Balance Responsible Parties,
- grid constraints mitigation (congestion, phase or voltage adjustment...), procured by TSOs and DSOs,
- portfolio optimization/imbalance penalty minimization, procured by market actors such as aggregators, BRPs, or producers,
- investment deferral, in peak capacities or the grid, procured by ISOs and TSOs but above all DSOs.

Such services may induce a categorization of demand response, as expressed in Alstone et al. (2017). This extensive assessment of DR in California divides DR into four types, reflecting the different timescales of the services for which DR resources are called. Shape DR is linked to structural changes in load profiles due to pricing schemes. It is close to the so-called implicit DR. Shift DR designates day-ahead to hourly or quarter-hourly shifts in demand but with constant total energy extracted from the grid. Shed DR acts on the same timescale as shift DR but is a load shedding that has not been recovered. Finally, Shimmy DR encompasses ancillary services that are much closer to real-time (quarter-hourly to seconds before real-time).

A limit for the value of a resource providing a flexibility service exists for each service: it is the cost of other resources able to provide the same service. That is one of the approaches used in Alstone et al. (2017) to assess the value of DR as a particular service provider for the Californian power system. For example, DR competes for congestion management with grid development and peak production units.

Moreover, as the authors state themselves (Section 5.7, second paragraph), Alstone et al. (2017) takes a system perspective that is not that of a market player or a consumer: "*Our results do not*

intend to prescribe the level of compensation for participants in any way; rather, we have described the market value to the grid- the dollar value that is cost competitive for this service type resources as compared to alternative resources in the wholesale market.". At the core of numerous bi-level studies (Okur et al. (2019), Silvestre Freitas Gomes et al. (2024)), lies the same observation that different market values may be computed for a system operator and a private asset operator for the provision of the same service. For example, Okur et al. (2019) finds that aggregators have no economic interest in balancing their own bids using some of their DR resources while system operators do.

In other words, a single resource may have different values for different services and different total values in the eyes of various actors, who have their own perceptions of the relative importance of these services.

2.3. Multiple values of a DR resource

Valuing DR by valuing services provided by DR suggests two problematic implicit assumptions. First, it supposes that all services that DR may provide and their impacts are translated into market products and prices. As Ramos et al. (2016) and Vicente-Pastor et al. (2018) underline, local grid management thanks to DR from small consumers and the associated cost of coordination between the transmission and distribution levels are yet to be explicitly accounted for in market designs. Moreover, Kerscher and Arboleya (2022) points to several market barriers preventing DR from entering traditional power markets, especially for balancing services. So, this first assumption of perfect translation from a DR resource to the valued services it provides seems optimistic.

Secondly, a higher value given to a specific flexibility service does not necessarily modify the behavior of a DR resource towards offering more of this service. As mentioned in Section 2.1, an electrical appliance enrolled in DR appears as a particular - and to some extent fixed - portfolio of attributes. These attributes may not (or should not) vary even if the offered revenues for providing a particular service increase: a household may not install a second water heater to gain more with its DR activities, so the total installed capacity for DR from residential water heating is capped.

Therefore, we depart from the service valuation and focus on the perceived valuation of the resources by a particular actor of the power system. For a single resource, multiple values are to be considered in order to reflect the different types of services they provide, whether this service is valued in a market or not. Conversely, all attributes of DR resources may contribute to all types of values. Hence, from our perspective, the value of DR doesn't come from services but from the system characteristics that the presence of DR enables.

We retain seven values of a DR resource: operation value, flexibility-investment value, private value, price-smoothing value, energy transition value, emission value, and security value.

Operation value refers to the variation in total system cost of operation during a determined period when a given DR resource is introduced. It stems from the point of view of a system operator. It should aggregate all the costs of running production or demand-side management necessary to balance load and supply at each moment of the period. Operation value is the most calculated in

the literature (e.g., 100% of the studies reviewed by Kerscher and Arboleya (2022), also Alstone et al. (2017)).

From the same system perspective, flexibility-investment value is its natural and usual counterpart accounting for the variation in grid, storage, or production investments caused by the introduction of DR at a fixed level of supply security. Numerous expansion planning studies accounting for DR exist and focus on this investment value, such as Marañón-Ledesma and Tomasgard (2019) or Misconel et al. (2021) for perfect system planners or Nouicer et al. (2023) including strategic decisions. System planners and network operators are the primarily interested actors.

As operation and investment values, private value is strongly related to market activities but now reflects the private monetary gains from the operations of a DR resource. It should account for value stacking as this resource may create different revenue streams from various markets or contracts at the same time. It represents the evaluability of the DR resource's features, i.e., converting its technical attributes into monetary revenues. It has been the concern of numerous studies with various methodologies (e.g., Goutte and Vassilopoulos (2019), Feuerriegel and Neumann (2014) or Campaigne and Oren (2016)) but has not been compared to other types of DR value in a unified framework.

Price-smoothing value focuses on the effects of introducing a DR resource on prices, their level, and their volatility. With its ability to shift load in time, DR creates an opportunity for consumers to buy low and sell high, resulting in a potential intertemporal arbitrage in power markets. This value interests primarily the intermediary layer formed by suppliers and aggregators[5] between wholesale markets and end-users. Aggregators, namely the operators of DR, generally benefit from price volatility as any flexibility resource operators (Goutte and Vassilopoulos (2019)). Suppliers have to hedge against it, above all, if retail tariffs are fixed. Depending on the level of exposure of small consumers to real-time price, i.e., depending on power tariff designs, final consumers are also directly interested in this value of DR resources.

Energy transition value accounts for the variation of the share of renewable production at fixed service quality and quantity levels when a DR resource is included. It represents the contribution of DR in mitigating renewables variability, thus fostering the energy transition without other investments. As such, it interests system operators as a proxy for public stakeholders, the whole renewables industry, and final consumers, whether they are concerned citizens or simply beneficiaries of environmental improvements.

Emission value forms with the former the environmental value of a DR resource. Emission value reflects the variations in emissions due to the operations of the power system as DR is introduced. The power mix here is kept unchanged, the emission value being like an environmental operation value, whereas the energy transition value is closer to an environmental investment value. This value is often computed as a side note from operation studies (Misconel et al. (2021),Alstone et al.

[5]As underlined by Bureau et al. (2023), the actions of suppliers and aggregators are reciprocal: the firsts buy consumption blocks at the wholesale level and sell fractions of these blocks to end-users, while the latter buy negative generation from end-users and pack it to bid at the wholesale level.

(2017)).

Finally, security value controls the variation in supply security at a fixed power mix when a DR resource is included. It highlights the balancing properties of a DR resource and the short-term effect of DR on supply security. Balance responsible parties, network, and system operators are economically and legally interested actors, but consumers might be those who value supply security the most.

All DR attributes of a specific resource contribute at least partially to each value. For example, its availability impacts the allowed operations of the resource and directly affects its operation, private, and emission values. If the resource is never available in times of stress for the system, it hinders its security and price-smoothing values. Finally, its investment and transition values depend on the correlation between its availability profile and renewable production. A similar analysis can be conducted for its event duration, bounds on activation, minimum up and down time, recovery time limit, and location. Controllability primarily affects investment-related values (investment and transition), while predictability relates more to operation-type values (operation, private, price-smoothing, emission, and security). Table 3 links the proposed set of values to power system actors and types of flexibility services as mentioned in Section 2.2.

DR values	**Interested actors**	**Related services**
Operation	System operator	Intra-bid balancing, grid constraint mitigation, system balancing
Investment	System operator, network operators	Investment deferral, system balancing
Private	Retailers, aggregators	Intra-bid balancing
Price-smoothing	Consumers, retailers, aggregators	Intra-bid balancing
Transition	System operator, consumers	System balancing, investment deferral
Emission	System operator and consumers	System and intra-bid balancing
Security	Consumers, network operators, system operator	System balancing

Table 3: Different values of a DR resource, interested actors who could bring about this value, and services provided by demand response contributing to this value.

3. Methodologies of DR valuation

This section provides measurement methods for the values proposed in the previous section. The prospective approach implies that valuation methods rely not solely on historical market, generation, and demand data analysis but more on simulation models. This choice results from the low current deployment of DR, especially in distributed sectors, and from our motivation to provide insights on future, called-for, and large-scale development of DR in renewable-based power systems.

3.1. Operation value

Operation value is estimated with the system levelized value approach of Alstone et al. (2017): the DR resource is introduced at a given level and operates at zero marginal cost in a given power mix. As the operation value reflects the point of view of a system operator, it equates to the difference in total operation costs with and without DR. It aggregates all operation expenditures from energy-only markets to meeting reserve requirements. Thus, the value is estimated from classical dispatch models with a day-ahead power balance, a balancing market power balance, and reserve constraints such as that proposed in Bruninx et al. (2018). Frequency restoration reserve and rapid reserve are considered as a whole. Reserve requirements are computed according to the French rules for calculating FRR and RR procurement levels (RTE (2018)).

This model should also account for a bottom-up description of the DR resource, displaying its particular portfolio of attributes. Thus, the previous model is completed by a module for modeling DR resources through the framework of Section 2.1, developed in Ancel and Massol (2022). The latter model also accounts for the stochasticity of renewable generation and inflexible demand. So, to derive an operation value of DR, a multistage stochastic program is considered, with reserve requirement and a linear bottom-up model of the DR resource. This paper leverages this copperplate model without transmission lines to focus on production variations and alleviate computational constraints.

For operation value, controllability and predictability of the DR resource may be considered perfect by reducing the available capacity attribute to account for such limitations: a perfect MW of the resource corresponding to several installed MW. As investment issues are not considered for this value, the operation value of a DR resource is measured by the variation in total system costs given by the SDDP bottom-up model of Ancel and Massol (2022) adapted to account for reserve requirements. The model's equations are given in Appendix A.2. A sensitivity analysis to the constraints modeling DR and activation costs' assumption is provided in Appendix B. It justifies how flexible behavior is overestimated by an order of magnitude by models not taking into account all flexibility attributes mentioned in Section 2.1.

3.2. Flexibility-investment value

For a risk-neutral system operator, the flexibility-investment value may be quantified by a simple expansion model complemented by a bottom-up module for DR for the operation phase. Such studies are numerous; refer, for example, to Marañón-Ledesma and Tomasgard (2019), Misconel et al. (2021) or Bruninx et al. (2018). The latter points out that this flexibility-investment value is null for all DR resources as soon as controllability is imperfect and the system operator is risk averse. DR competes there with costly but riskless grid investment.[6]

[6]Grid investment deferral may also be a relevant indicator of the value of a DR potential. It would be measured by adding power flow constraints - at least at the transmission level - in the operation model presented. Yet, its complete calibration would require the localization of flexible loads in the grid. Moreover, this value would physically depend, if not economically, on the location of the added flexibility on the grid. Finally, due to the absence of local

Nevertheless, we propose an estimation method for the investment value of DR resources in the common framework of this paper. Now, the model for operation value becomes the second stage of a two-stage expansion model. The first stage corresponds to investment decisions on fast peak generations at annualized investment costs. Namely, investment can be made in OCGT, representing a standard, always available but costly, fast thermal generation. The two-stage model is detailed in Appendix A.3.

The value of DR in terms of peak capacity investment is measured by the variation in investment for flexible peak thermal generations (here, OCGT) while targeting an exogenous level of supply security. The latter makes the systems with and without DR comparable. The level is chosen to match the proposed criterion for France by RTE. It imposes the expected cumulative imbalances over a year to be smaller than 10 GWh[7].

These DR investment values are finally benchmarked against that obtained by a new MW of CCGT capacity since both are candidate options for dispatchable flexibility.

3.3. Private value

To measure the private value of a DR resource, we consider a private operator of the resource, which is the price taker in a given power system, as what is done in Goutte and Vassilopoulos (2019) for a perfect MW of CCGT. The private value of the resource equates to the total benefits gained from the resource operation over a year.

A simple multistage stochastic program of profit maximization for this resource is solved under the operation constraints of the resource. The constraints are similar to the DR module in Appendix A.2. Operating costs of the DR resource are adapted from Gils (2014) and Alstone et al. (2017) to reflect various enabling technologies. The crux of this method lies in deriving market prices to be integrated into profit maximization as parameters. The operation model of Appendix A.2 is leveraged to do so. It produces price series for an energy-only day-ahead market and for daily reserves procurement, the system being considered here without DR.

Another approach would be to model the price series directly and exogenously control its features, such as its volatility. This is retained in Goutte and Vassilopoulos (2019) to assess the effect of increased volatility of market prices on the revenues of a flexible resource. However, it supposes a prior knowledge of how the volatility evolves, which we do not possess even though we know that price volatility varies due to the introduction of renewables. On the contrary, the present approach simulates directly the effect of introducing renewables on prices without explicitly controlling the

markets for flexibility, such local values are not easily revealed to system actors other than the T/DSOs. Thus, to contrast how different actors are incentivized, we would have to compare the economic incentive, which is non-local and permeates through the markets, with the physical and local but private incentive of system operators, making such comparison unsummarizable at the national scale. Hence, the grid-investment-related value of DR is beyond the scope of this paper, which focuses on values all actors could simply appreciate.

[7]Note that this criterion is not the currently legally enforced one, which provides that the expected number of hours with imbalances over a year should not exceed 3 hours. This new energy criterion is presented by the French TSO as more adapted to account for different depths of imbalances.

price series' volatility. That is why it is preferred. Appendix A.4 summarizes the method for DR private valuation.

3.4. Price-smoothing value

The price-smoothing value stems from variation in the volatility of hourly market prices in systems with and without DR. Hourly price series are simulated with the operation model with and without DR as in the method for the private value. For each hour of the year, price volatilities are computed as the unbiased estimator of the standard deviation of the hourly market prices over the simulations. This results in two time series of volatilities, one with DR and the other without. We then compute the dynamic time-warping distance between the two time series and the relative variations of the maximum volatilities. The former value will help compare the DR resources between them based on the distance to the base no DR case. The latter value informs on the evolution of the worst case in terms of price volatility when the studied DR resource is introduced. The dynamic time warping distance metric is chosen because it is insensible to any linear time transformation between two series. Hence, if DR only transfers volatility from one time to another or concentrates it in time without modifying its level/pattern, the metric shall not grow.

3.5. Energy transition value

In practice, the energy transition value may refer both to an investment-type value or an operation-related value. An increase in the share of renewables in consumed electricity can indeed happen if new renewable sources are invested in and installed or if existing renewables are less curtailed.

On the one hand, the energy transition investment value of a DR potential relates to how much new renewable capacity can be allowed in the system - that is, without increasing imbalances - thanks to the introduction of this DR potential. Ideally, a two stages expansion model accounting for investment in renewable capacity, for the stochasticity of renewable generation, and for an acute technical description of DR operation in a whole year would provide a measure of this transition investment value of DR. Still, such a model is hardly computationally tractable with sufficient precision to observe the marginal effect of a new MW of DR. Hence, we focus on this marginal effect in a French-inspired stylized setting by modeling the operations of 1 MW of nuclear and 1 MW of the studied DR potential against a normalized to 1 MW random demand and a similarly normalized 1 MW random wind generation. The setting is thus a marginal version of the operation model of Section Appendix A.2 with only one energy-only market. Nuclear sets the price in most off-peak hours in France while not being able to ramp up and down to follow all load gradients, thus leaving room for a complementary, flexible generation or DR.

The energy transition investment value is measured through the variation in cumulative imbalances of this reduced system with and without the DR potential. It can be interpreted as the ability of an additional MW of a DR potential to handle a supplementary MW of variable wind generation by flexibly complementing traditional low-carbon generation.

The complete description of the model can be found in Appendix A.5.

On the other hand, the operation side of the energy transition value of a DR resource is measured via the relative variation of the yearly average curtailment of existing renewables. The curtailment decisions are derived from the operation model presented above in our framework. As we only add a small (1 MW) installed capacity of the tested demand response potential, this operation version of an energy transition value is expected to be more relevant (and non-null) than the investment version.

3.6. Emission value

The emission value is measured using the same model as the operation value. Simulated operations of thermal means are converted into CO_2eq emissions through publicly available emission factors, as in Misconel et al. (2021). Emission factors are collected in Table 5. Variations in CO_2 emissions are valued according to market prices in the EU-ETS since the European power sector is included in the mechanism.[8]

3.7. Security value

Like the emission value, the security value appears to be a byproduct of the operation value method. The same model is used, but this time, the metric of interest is the volume of imbalances. Imbalances can then be economically valued at the Value of Lost Load, surveyed in France at 9k€/MWh, 33k€/MWh, and 46k€/MWh depending on the methodology with a preferred value of 33k€/MWh (CRE (2022)).

4. Assessing the multifaceted values of demand response potentials

4.1. Results of the 1 MW valuation

The previous methodology is applied to the demand response potentials identified in Table 2. A focus is set on residential and tertiary sector appliances which can be considered as load-shifting potentials. Three industrial load-shifting potentials - cement mills, paper, and pulp production - are considered for comparison. Finally, three load-shedding potentials are also evaluated because they are more contractually bounded due to fewer allowed activations but less time-constrained, as they do not require load recovery, and each activation can last longer.

4.1.1. Operation value

The relative variations in total system operation cost compared to a system without demand response are displayed for all tested potentials and a new MW of CCGT in the Operation column of Table 4. On average, all potentials induce a marginal decrease in system costs, except for paper and pulp production and the tertiary sector's AC and cold storage. In absolute value, each new MW of DR brings about an order of magnitude of 10^6€ in system cost reduction, provided this MW has no

[8] During the next decade, the EU-ETS price is expected to increase, as part of strengthened climate policies, from its current station around $80e/tCO_2$ to prices ranging between 120 and $160e/tCO_2$ in 2035 (Pahle et al. (2022)).

activation cost. Hence, a system operator would be interested in activating such potential as long as the total revenue perceived during the year for its activation by this potential does not exceed this avoided cost (or welfare gain, as demand not included in a DR potential is supposed inelastic here). It is noteworthy to compare that a new MW of CCGT induces a slight increase in total system costs on average. The latter result shall be explained by the poorer performance of the CCGT in reducing the number of imbalanced hours, notably due to its finite ramping capacity. Moreover, diffuse DR -e.g., from the residential and tertiary sectors- yields similar operation values to industrial DR, even though they operate under tighter time constraints for DR event durations and load recovery in case of load-shifting. This could point that, marginally, either such constraints have no influence on operations in general or that peak demand from these potentials coincide sufficiently with residual demand's peaks and residual demand valleys are close and deep enough so that load recovery and duration constraints of these potentials are not always binding for a sole MW of DR.

However, these average results have to be nuanced by non-negligible deviations, most of the total cost distributions being concentrated between $\pm 7.5\%$ of the average total cost without DR. This variation results from the different years of residual demand faced by the optimal policy derived by the model for each considered system. Such magnitude of deviations in the result shows that uncertainty in residual demand far surpasses what a sole MW of DR can bring about for the system regarding flexibility, thus justifying a massive deployment of new flexibilities, as found in the literature. Interestingly, this deviation can be interpreted as the risk born by a system operator that invests in the first MW of a DR potential. DR assets then compare differently if this risk is taken into account by the system operator/planner as, for example, residential space heating yields better operation value than tertiary space heating on average but with higher standard deviation. A more risk-averse planner would then opt for the latter, which is still beneficial for this value on average with fewer risks, or even ignore DR as a flexibility resource due to this risk. With such an understanding and since more flexibility (e.g., more DR) would absorb at least a part of the residual demand variability, the following installed MW would benefit from reduced investment risks, but probably also suffer from reduced operation average value up to a certain point due to cannibalization.

4.1.2. Security value

Relative variations in the yearly number of imbalanced hours compared to a system without demand response are displayed for all tested potentials and for a new MW of CCGT in the Security column of Table 4. Imbalance results exhibit similar behavior to operation value ones, with a generally positive contribution of DR potential -except for chlorine and paper production and tertiary AC - but marked with important standard deviations, i.e., risks. Once again, DR potentials seem to perform globally better on average than a MW of CCGT: according to the first two indicators, they provide more flexibility than the latter, which can be explained by their limitations in terms of ramping rates. Risks in terms of operation cost gains and security seem positively correlated, as a linear regression highlights that the variability in operation costs risks explains around 84% of the variability of the security risks (R^2), and the risks are linked with a positive coefficient ($\simeq 4.2$)

Technology	**Operation**	**Security**	**Emission**	**Curtailment**
No DR	*3.79 G€*	*40.61 h*	*1.98 $MtCO_2eq$*	*0.74 TWh*
Res. SH	-0.26 (8.02)	-4.89 (37.86)	1.36 (27.78)	0.95 (27.77)
Res. WH	-0.34 (7.56)	-1.31 (36.54)	2.64 (27.56)	-2.36 (28.18)
Res. AC	-0.44 (7.15)	-0.26 (36.10)	-0.31 (25.35)	2.11 (27.29)
Ter. SH	-0.03 (7.73)	-2.78 (36.71)	3.67 (29.04)	-3.19 (27.14)
Ter. WH	-0.16 (7.71)	-2.49 (36.48)	1.37 (27.05)	0.32 (27.11)
Ter. C. Stor.	0.48 (8.35)	-0.69 (40.95)	1.96 (27.54)	1.43 (27.15)
Ter. AC	0.12 (7.54)	1.66 (38.35)	-0.26 (25.08)	-0.36 (28.60)
Cement mills	-0.34 (7.42)	-0.37 (37.46)	1.55 (27.47)	3.04 (30.16)
Pulp prod.	0.05 (8.04)	-1.63 (40.15)	2.55 (26.96)	6.76 (30.30)
Paper prod.	1.35 (7.91)	5.39 (38.87)	9.94 (30.64)	3.51 (30.67)
Elec. arc steel	-0.25 (7.70)	-1.33 (38.52)	1.08 (27.85)	-2.89 (28.23)
Al electrolysis	-0.40 (7.36)	-0.04 (37.31)	-2.19 (26.65)	1.15 (29.05)
Chloralkali proc.	0.60 (7.99)	4.14 (39.76)	1.12 (28.96)	-1.45 (29.93)
CCGT	*0.37 (8.39)*	*7.98 (42.06)*	*1.39 (28.84)*	*-2.57 (28.21)*

Table 4: Operation related-values of a new MW of a DR potential in a system devoid of any DR. Operation, emissions, security, and curtailment values are expressed in percentage of relative variation compared to the no DR case. Average values from the simulation of the *same* 500 scenarios of demand and renewable generations are reported for each case with standard deviation in brackets.

which is meaningful (p-value $\simeq 0.00012$). A similar correlation exists between the average values. This highlights how gains in total system costs when DR is introduced mostly correlate with a reduction in imbalances valued at the VoLL. The remainder of the variability in the system's costs may be explained by how DR characteristics allow the potential to erase more costly, fast-ramping thermal production, and not only the backstop generation at the VoLL.

The case of tertiary cold storages is interesting as its average operation and security values have opposite signs, hence providing contradictory incentives for investors concerned with both values.

4.1.3. Emission value

Relative variations in the yearly GHG emissions of the system compared to a system without demand response are displayed for all tested potentials and for a new MW of CCGT in the Security column of Table 4. The emission factors used to compute the emissions from generation are taken from the French TSO and collected in Table 5.

Technology	Emission factor (tCO_2eq/MWh)
Biomass/Waste	0.494
Coal	0.986
CCGT	0.352
OCGT	0.486
Other gas	0.583
Fuel oil	0.777

Table 5: Emission factors of thermal plants from RTE's *éCO2mix* data.

Results are more contrasted regarding the emission performance of the DR potentials. Their

average value is mainly in the sense of an increase in the system's emissions, favorable contributions only brought about by residential and tertiary AC as well as aluminum production on average. Mixed results for DR in terms of lowering CO_2 emissions are also highlighted in the literature, e.g., Sousa and Soares (2023) or Ancel and Massol (2022). These studies underline how the underlying merit order affects the performance of DR in terms of emissions, notably in the presence of start-up costs and finite ramping rates. Indeed DR mainly does not contribute by moving out of the market the last called units for a short period of time, but rather by pricing out the last called units for which ramping down and eventually being called back after the DR event is less costly than maintaining a positive generation. Hence depending on the merit order - notably at the end and the relative order between gas and coal - and the continued level of residual demand after a DR event, a DR potential may either increase or decrease the production of the most polluting units. This also explains why even load-shedding may have mixed effects regarding emissions though the global yearly demand is reduced. A similar result for residential and tertiary AC, which are both mainly summer potentials, also hints towards such interpretation, as coal is absent during summer and the only emissive generation is CCGT, which is also more costly and is therefore erased in favor of the remaining means, which are all clean.

4.1.4. Private value

The private value of a new MW of each DR potential is analyzed through three indicators; a comparison is made with a new MW of CCGT. First, the expected annual revenues drawn from the operation of the potential are displayed in Table 6. As these revenues are estimated through Monte-Carlo averages, they are paired with an estimated probability of negative revenues and the standard deviations in revenues. Both reflect the estimated risk for a profit-maximizing private actor operating the potential. This risk can be price-related, the asset being non-economic in the renewable-based system at most hours, or volume-related, the energy-recovery or load-shaving duration of the DR potentials limiting its output.

Private profits are positive on average for all potentials except tertiary cold storages and significantly positive for residential and tertiary space heating, tertiary sector water heating, and all industrial potentials. Due to price arbitrage being the main source of revenues of load shifting potentials, reported average profits for the first MW introduced of the potential are but upper bounds for the following MW: notably, tertiary cold storages are in this sense unprofitable whatever the installed capacity and this is due to tight recovery constraints and availability limitations which prevent this potential from targetting relevant arbitrage opportunities.

Mixed incentives between system-oriented and private actors can arise for potentials over which revenues do not go along with system cost reductions. Such a situation may arise in the sense that a system-wise beneficial potential is not privately profitable, which happens for residential water heating and to a lesser extent for residential AC accounting for its high risk of deficit, or that a system-wise detrimental potential is privately profitable, which happens for paper, pulp and chlorine productions and to a lesser extent for tertiary AC accounting for the private risk of deficit. From a regulator point of view, the former type of misalignment leaves room for public aids supporting the

concerned potentials, up to the amount of the operation value created. On the contrary, the latter type calls for careful monitoring at least and perhaps more stringent inclusion in the markets, such as imposing coupled investment in more favorable potentials for the system or redistribution of part of the profit created by these potentials to fund the support to system-wise beneficial ones.

Technology	**Revenues (k€)**	**Negative revenue probability**
Res. SH	1788.66 (867.93)	0.070
Res. WH	0.99 (25.99)	0.956
Res. AC	605.32 (662.41)	0.000
Ter. SH	3597.13 (1745.00)	0.000
Ter. WH	5023.27 (2745.88)	0.000
Ter. Cold Sto.	-0.32 (8.25)	0.934
Ter. AC	593.89 (603.05)	0.000
Cement mills	1798.77 (811.83)	0.000
Pulp prod.	1276.74 (599.83)	0.004
Paper prod.	1492.30 (756.06)	0.000
Elec. arc steel	43.36 (30.73)	0.000
Al electrolysis	11.83 (7.83)	0.000
Chloralkali proc.	33.21 (23.56)	0.000
CCGT	53.04 (34.77)	0.000

Table 6: Private value of a new MW of a DR potential in a system devoid of DR. Average values yielded by the optimal policy tested on 500 simulated years with standard deviation in brackets.

Finally, in the model, demand response potentials can play on three different stylized markets (day-ahead, balancing, and reserve services), which differ by the resources contributing to each of the three power balances (see Appendix A.4). For each potential, Figure 1 displays the share of each of the three markets in the total activated DR energy and in the total revenues earned by the potential. Load-shifting potentials tend to contribute more than load-shedding or CCGT to balancing services and more than load-shedding to upward reserves. However, the balancing market accounts only for a few percent of the total revenues of the potential, indicating that in the models, the main arbitrage possibilities for DR are in the day-ahead market, which provides around 80% of the revenues generated by each potential. This is in line with Bruninx et al. (2018) where it is found that 70% to 75% of the value is created in the spot market for DR from heat pumps (a part of residential space heating here) or a supermarket (which contributes to cold storages, tertiary AC and space heating in our terminology). Our contribution extends such findings to more DR potentials. Policy-wise this replaces energy-only markets as the main source of revenues for DR and hence highlights how crucial allowing their participation in this market is for them to prove economic, while other places of private value creation remain only complementary.

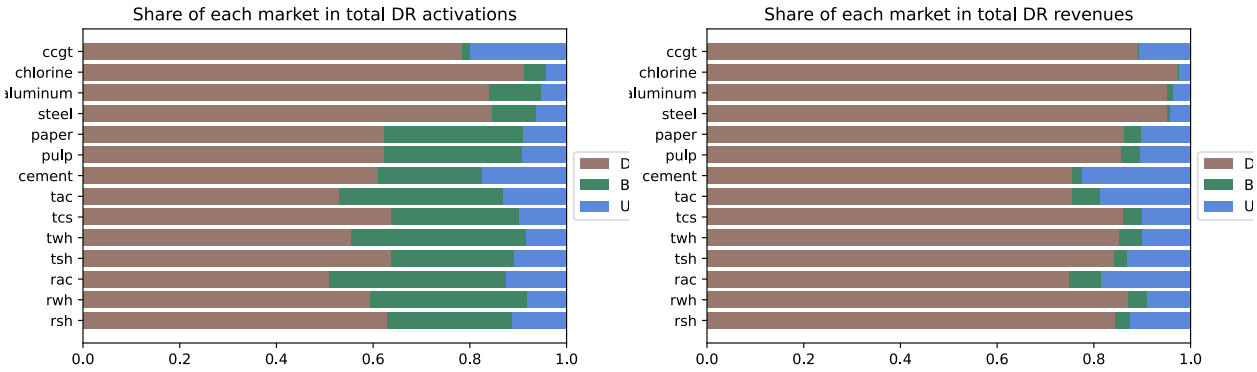
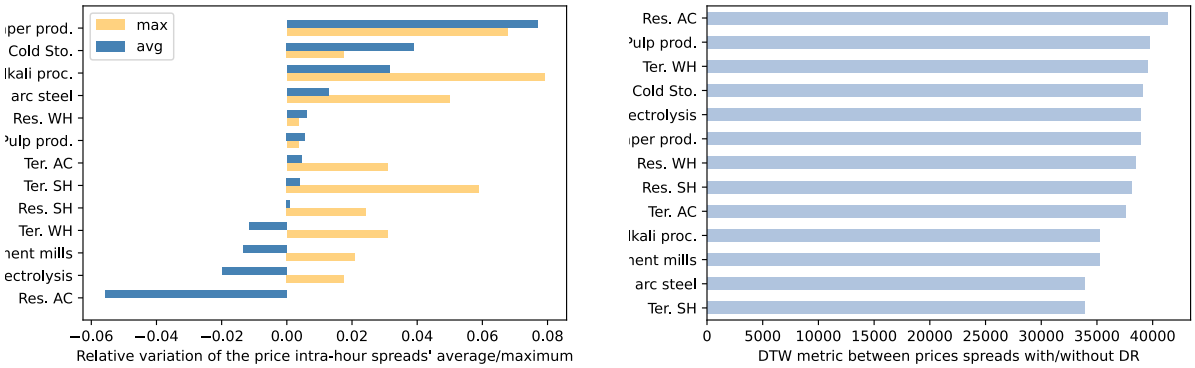


Figure 1: Average shares of the day-ahead, balancing, and reserve markets in the total load reductions and total revenues during a year for each DR potential. This share is, however not constant throughout the year.

4.1.5. Price-smoothing value

The effect of new DR potentials on the distribution of wholesale market prices is summarized in Figure 2 where results are displayed in relative variations from a system devoid of DR. Figure 2 (a) collects the variations in average and maximum price volatility during the simulated years between systems with and without DR. It reflects the smoothing of market prices induced by the presence of the new DR MW in the system. Figure 2 (b) presents the dynamic time wrapping metric between the price distributions with and without the DR potential. It measures the global resemblance of the two distributions, which are insensible to simple time shifts. For example, the DR potential of space heaters in the tertiary sector yields the most similar price distributions among all DR potentials.



(a) (b)

Figure 2: (a) Relative variation of average -blue- and maximum -orange- price spreads between a system with 1 MW of the DR potential and no DR. DR potentials are sorted by average price spreads. A price spread is the variation between simulations of price levels for the same hour of the year. Maximum and average are intended over the 8760 hours of the year. (b) DTW distance between the time series of price spreads with and without a MW of a DR potential. The larger the metric, the more distorted price spreads are by introducing DR, controlling for simple time shifts of spreads.

Price effects of the single MW of each introduced potential make the maximum and average price spreads observed throughout the year deviate by a handful of percent, only in the direction of an increase in the maximum price spread but in a mixed direction regarding the average price spread. Three classes of potentials can be found: those that induce an increase in price volatility at the most volatile hour of the year and on average over the hours of the year (paper production, tertiary cold storages, chlorine, and steel productions), those which leaves price volatilities almost unchanged (residential water and space heaters, pulp production, tertiary AC and space heaters) and those increasing volatility at the most volatile hour while decreasing it on average over the year (residential space heaters and AC, tertiary water heaters, cement mills and aluminum production).

These classes are to be compared to the three groups of potentials in terms of induced distance between price spread distributions over the year with and without DR (Figure 2b). Thus, tertiary space heating, steel, cement, and chlorine production yield the least modified price spread distributions, while residential AC and pulp production display more modifications. Since the DTW metric controls for time-shifts of the realized price-spreads, the latter potentials modify more the structure of price volatility than the first group. The two indicators provide different insights as a high modification in price spreads distribution is not equivalent to an increase of price volatility (on average nor at maximizing hour) - for example, residential AC DR modifies the distribution the most while also providing the most average spread decrease and no maximum spread modification. Notably, the indicator provided in Figure 2a interests consumers or suppliers buying on the wholesale market at each hour, potentially harmed by too high volatility of prices for the same hour of the same day from one year to the other (provided the generation mix has not evolved and the volatility is created by different realizations of residual demand). The indicator of Figure 2b may interest owners of batteries or any asset making revenues by being adapted to the current structure of price spreads, as higher values of this indicator would motivate changes in operations plans for such assets.

4.1.6. Flexibility-investment value

Induced variations in investment in peaking thermal generation between systems with and without demand response are presented in Figure 3 in front of the total unserved load during the year compared to the target of maximum unserved load, indicated by the vertical dashed line. The two figures complement each other as the optimal policy computed by SDDP arbitrages between paying for more OCGT capacity at its CAPEX and failing to reach the imbalance target by a margin penalized at the VoLL. As this policy is, in fact, only quasi-optimal (and would only be optimal with an infinite number of iterations of the algorithm), situations may occur where the quasi-optimal policy results in slightly less OCGT investment against a slightly higher total unserved load. A higher penalization of the imbalance gap would result in a more conservative policy with more OCGT in all system cases, yet that would come at the expense of the numerical stability of the model and would have to be justified since the VoLL is by definition the penalization of unacceptable unserved load.

Regarding the performance of the considered DR potentials, no one ensures a statistically significant reduction in OCGT capacity. Yet, two groups of potentials stand out. On the one hand,

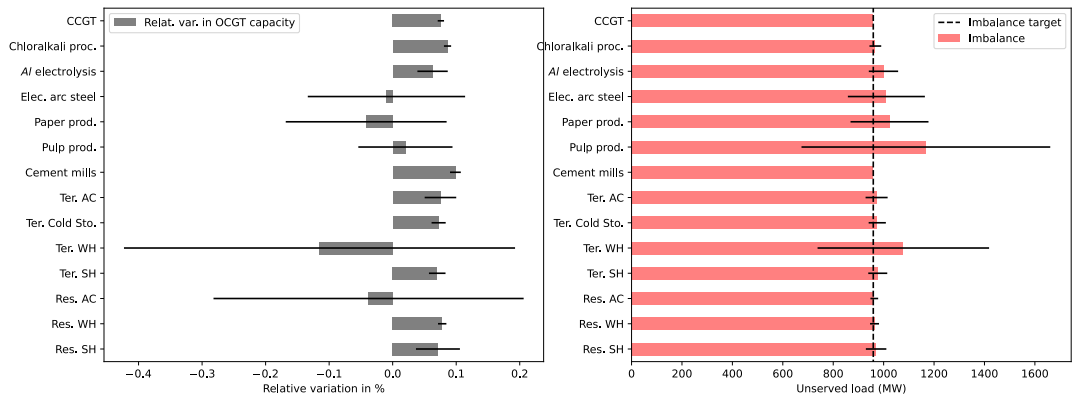


Figure 3: Investment-related value of a new MW of a DR potential in a system devoid of any DR. Reported values are average relative variation (%) in new capacity investments in OCGT compared to a system without DR.

chlorine, aluminum, and cement industrial processes, as well as tertiary AC, cold storages and space heating, and residential water and space heating imply statistically around 0.1% more installed OCGT than a system without DR but ensure a perfect respect of the imbalance constraints. Such performances are similar to that of a supplementary MW of CCGT, which has lower ramping capabilities than OCGT in the model. On the other hand, steel, paper and pulp production, tertiary water heating, and residential AC induce statistically a lesser need for OCGT investment, but with less insurance regarding the imbalance target. Apart from the caveat made above linking the imbalance gap and the investment decision in OCGT, this better performance than previous potentials or even the CCGT MW may stem from more correlation between availability periods of these potentials and peaking residual demand. This is supported, for example, by tertiary water heating being the best performer while also being the load-shifting potential with the highest event duration and load recovery limit allowed and the shortest minimum down-time.

4.1.7. Energy transition values

As reported above, the value brought about by a DR potential to the energy transition can be divided into two aspects: its ability to reduce renewables curtailment at fixed renewables capacity and its ability to mitigate the added variability by supplementary renewable capacities.

Results for the first aspect are gathered in the column Curtailment of Table 4, expressed in relative variation from the no DR case and compared with the performance of a new MW of CCGT. In this sense, residential water heating, tertiary space heating, and AC and steel and chlorine productions contribute similarly to a new CCGT to reduce the total curtailment on average by bringing more downward flexibility to the system. This contribution is, however, marked by an important risk due, as mentioned above, to the operation and security values.

The second aspect is valued according to the procedure described in Appendix A.5. Results are displayed in Figure 4 where the (average on simulations) cumulated imbalances over a year are represented for a reduced system with each DR potential. The reduction in the system's size allows

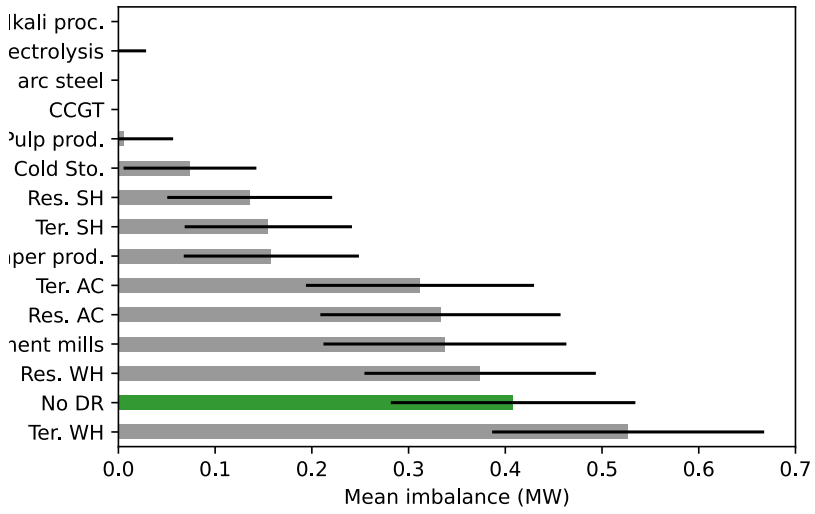


Figure 4: Cumulative system imbalances with 1 MW of each DR potential, and for comparison, without DR and with 1 MW of CCGT generation. Error bars represent the observed standard deviations over 500 simulations.

to focus on the marginal equilibrium between residual demand and supply, thus removing the outside variability of residual demand that exceeds by several orders of magnitudes the abilities of the 1 MWs introduced. The indicator provided in Figure 4 for a system without DR nor additional CCGT can be interpreted as the yearly missing supply due to the mean variability of wind generation per MW installed compared to a perfectly controllable and available MW. The contribution of the DR potential to the energy transition would be here to complement this missing supply, their capacity of doing so corresponding to the difference between the green bar in Figure 4 and the grey bars.

Here, all potentials except for tertiary water heating lead to better system balancing than in their absence. Notably, industrial DR yields similar flexibility in this sense than a new MW of CCGT; that is, they completely erase imbalances created by the added wind capacity in all scenarios of the year. Tertiary cold storage, residential and tertiary space heating, and paper production perform less than the former potentials but still significantly better than without DR, even taking the dispersion of the distribution of results into account. Finally, tertiary and residential AC, residential water heating, and cement mills provide, on average, more capability to absorb the new wind capacity than without DR, but this result may not be significant if accounting for the above-mentioned dispersion.

4.2. Sensibility to pre-existing levels of demand response

In the above, we added one megawatt of demand response potential to a system devoid of any other demand flexibility or from batteries. However, there is no assurance that the values obtained for this megawatt do not change with the initial level of this potential or others. The purpose of this section is to assess this cumulative effect. Therefore, we compute the same evaluations first with an existing level of 1 gigawatt for the evaluated potential only and then with this same level

fixed for all other potentials as well. In the latter case, the gigawatts of demand response compete based on their marginal cost (cf Table 2). However, the new megawatt is still considered free so it has a priority for activation in the merit order. This does not assume that it will be activated as soon as it is available, as its constraints on the recovery time of the erased load or on the minimal gap between two load reductions can make it less attractive than another less restrictive flexibility. Indeed, each of these constraints adds an opportunity cost to the simple activation cost to form the marginal cost of the potential.

One can consider that the measured values for the lone megawatt represent the upper bounds of what a new demand response megawatt can capture as value. When active, this megawatt earns income from the existing variability in prices/availability of other means of production. In other words, it captures a share of the variability associated with renewables. However, at a fixed capacity of renewables, the variability "to be filled" remains the same whether this megawatt is alone or other sources of flexibility are available. Thus, in the second case, the other sources available simultaneously with the new demand response megawatt compete with it to fill the variability gap. Consequently, this new megawatt acts, at most, as if it were the only source of flexibility available and, therefore, is generally less valued. Hence, the values obtained for the lone megawatt represent the upper bounds for the values of this demand response potential in a system where other flexibilities available over the same period are implemented.

5. Conclusion

In this paper, a unified methodology for the assessment of demand response multiple values is proposed. It is based on variations around a stochastic programming approach fitting in the theoretical framework of stochastic dual dynamic programming, which serves as solution technique. This tool is adapted to provide indicators for seven values of a DR potential, values selected based on the coupling of insights from the literature regarding the relevant characteristics of a flexibility source, the services provided by a flexibility source such as a demand response potential, and the types of actors interested by such services. Hence, indicators are derived on how the introduction of a potential affects the total system's costs, emissions, security, or the structure of wholesale market prices, generates profit, and contributes to the inclusion of more renewables in the system with less recourse to thermal speakers. The unity of the framework they are derived from provides a supplement of comparability between such values, which is necessary to anticipate misaligned incentives for different actors and a proper regulation and industrial deployment of such assets, but is generally lacking in the current literature with each study generally focusing on one value, service or characteristic of the considered resource.

The methodology is then applied to 14 demand response potentials identified in the literature evolving in the French power system of 2035. Such a case study is motivated by the relatively good understanding of what will the generation mix at this date, the identified need for additional flexibilities, and current discussions at the EU level on the design of new support mechanisms for better inclusion of demand-side flexibilities. As the latter could notably take the form of an

additional auction for new DR capacities in case of system tightness, the present study contributes to understanding which potentials would need supplementary revenues to become economic while being beneficial for the system, depending on the sought system effect (e.g., cost, emission or imbalances reduction or price smoothing or decreased need for thermal flexibility). Finally, the comparison of the different values provided in Section 4 for the same potential underlines eventually mixed contributions from several potentials to different services (such as DR as a way to reduce the system's emissions directly) and even misalignment of incentives which calls for careful regulations.

Public support also manifests through capacity payments, which are increasingly open to demand-side flexibility. Thus, following the same motivation as in this study, a limit of this work and a new axis for research could include such capacity payments in DR revenue. This poses, however, the daunting question of the definition in advance and the guarantee of a DR capacity, notably for diffuse potentials.

Acknowledgements

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Appendix A. Appendix - Models specification for valuing DR

Appendix A.1. Generation of scenarios for random demands and renewable production

Wind and solar generation. . Capacity factors for wind and solar generations are derived at the country level from renewables.ninja (Pfenninger and Staffell (2016) and Staffell and Pfenninger (2016)). Twenty scenarios of years of capacity factors are sampled directly from 2000 to 2019 in the datasets. For 2023, offshore and onshore wind are disaggregated. For 2035, the 'long-term fleet' dataset is used so that aggregated national capacity factors are provided. Overall, due to the planned deployment of offshore wind in France, aggregated capacity factors are higher in 2035 than in 2023. The same dataset is used for solar generation over the two periods.

Demand. . Twenty scenarios of years of demand are derived with a similar method to Verrier (2018) and data from the ENTSO-E transparency platform. We use seven historical years (2016-2022) of actual loads. Only 51 weeks of historical data are kept in order to align the beginning of the scenarios to 1 am on the first Monday of the year. From these seven years, the dataset is tripled by also considering each year the scenarios where demand is shifted one day forward and backward. Demand is shifted so that a weekday is shifted to a weekday and a week-end day to a week-end day. Namely, the demand on Friday in a forward-shifted year amounts to that of the next Monday in the normal year. Similarly, the demand on Saturday in a backward-shifted year amounts to that of the previous Sunday in the normal year. This procedure yields 21 different years of demand.

Then, twenty scenarios of demand are built by the following sampling procedure. For each of the 51 weeks of the year, a tuple formed by a historical year and a shift (forward, null, or backward) is drawn uniformly with replacement among the 21 choices. The scenario is formed by aligning these 51 sampled weeks. The procedure is repeated twenty times to produce twenty scenarios of demand.

The same sampled tuples of years and shifts are applied on the day-ahead forecast loads. This yields twenty scenarios of day-ahead forecasts corresponding to the sampled actual loads. Thus, scenarios of day-ahead forecast errors are produced and used for modeling the balancing market.

Finally, reserve requirements are computed from the twenty day-ahead forecast scenarios. As in Bruninx et al. (2018), the three types of reserves are aggregated. Upward and downward requirements are derived from the rules established by the French TSO (RTE (2018)). However, we notably ignore the minimum activation time and minimum up-time requirements. The upward reserve should cover the loss of the biggest generation mean at all times, which is a 900 MW nuclear reactor in France. So, the upward reserve has a fixed component of 1 GW at all hours. Upward reserve is completed by a dynamic component which writes, in MW,

$$UR_{dyn} = \begin{cases} \max(500, \sqrt{10D_h + 22500} - 150) & \text{if } D_h - D_{h-1} \leq 12000 \\ \max(500, \frac{D_h - D_{h-1}}{6}) & \text{otherwise.} \end{cases}$$

Downward reserve is less regulated. A mandatory minimum downward reserve of 500 MW is procured at all times. However, this reserve decreases generation and is procured only from symmetrical reserve bids. This constraint is applied in this paper as it might limit the revenues gathered by a flexibility source from reserve auctions.

Run-of-river. . The same method for demand is used to derive twenty scenarios of years of run-of-river and poundage hydro-power generation from ENTSO-E data (2016-2022).

Appendix A.2. Operation model from system view

The model used for deriving a system operation value for DR is written as a multistage stochastic programming problem. It fits an SDDP framework: convex costs, linear constraints, independent noise terms, and a finite number of scenarios. The scenarios and random variables are described in the previous section.

The model describes hourly operations on day-ahead, reserve, and balancing markets along a "year" of 357 days (51 complete weeks). Its objective is to minimize the expected total cost of operations. Random variables representing intermittent renewable generations, day-ahead demand forecast, forecast errors, and reserve requirements are drawn at the beginning of each day.

At stage $t \in \{1, ..., 357\}$, the subproblem (in the sense of Pereira and Pinto (1991)) to be solved minimizes

$$\sum_{h=1}^{24} \sum_{g \in G \cup H} C_g(g_h^{DA} + g_h^{Bal} + g_h^{UR}) + PC(\mu^{DA} + \mu^{Bal} + \mu^{UR} + \mu^{DR}) \tag{A.1}$$

where PC denotes the value of lost load/the market price cap, μ^M the imbalance in market M, and g_h^M the generation of thermal (G) or hydro-power (H) mean g sold in market M at hour h at marginal cost C_g. In the following, the subscript h for hours is not written for clarity.

The four markets should be balanced for all hours h, even though all means can't participate in all markets - day-ahead (Constraint (A.2)), balancing (Constraint (A.3)), upward reserve (Constraint (A.4)) and downward reserve (Constraint (A.5)),

$$D^{DA} = \sum_{g \in G} g^{DA} + lh^{DA} + 0.8(phs_{turb}^{DA} - phs_{pump}^{DA}) + PV + WIND + RoR + d^{DA} - u^{DA} + \mu^{DA} \tag{A.2}$$

$$D - D^{DA} = \sum_{g \in G \setminus \{Nuclear\}} g^{Bal} + lh^{Bal} + 0.8(phs_{turb}^{Bal} - phs_{pump}^{Bal}) + d^{Bal} - u^{Bal} + \mu^{Bal} \tag{A.3}$$

$$D^{UR} = \sum_{g \in G} g^{UR} + lh^{UR} + 0.8 * phs_{turb}^{UR} + d^{UR} + \mu^{UR} \tag{A.4}$$

$$D^{DR} = 0.8 * phs_{pump}^{DR} + u^{DR} + \mu^{DR} \tag{A.5}$$

Namely, in this framework, only pump-hydro storage and load increase can provide a downward reserve, and nuclear can't contribute to forecast error balancing. d denotes the decrease of load, and u its increase thanks to DR. The latter variable disappears if the DR potential under study is load-shedding. D_h represent the true demand at hour h, D_h^{DA} its day-ahead forecast and D_h^{UR}, D_h^{DR} the associated upward and downward reserve requirements.

Operating constraints for traditional thermal generations limit their outputs and their ramp rates,

$$\forall g \in G, g^{DA}, g^{Bal}, g^{UR} \geq 0 \tag{A.6}$$

$$\forall g \in G, g^{DA} + g^{Bal} + g^{UR} \leq A_{g,h} K_g \tag{A.7}$$

$$\forall g \in G, \forall h > 1, -r_g K_g \leq g_h^{DA} + g_h^{Bal} - g_h^{DA} - g_h^{Bal} \leq r_g K_g \tag{A.8}$$

where $A_{g,h}$ is an availability factor of the installed capacity K_g (always one except for nuclear plants, derived from the historical mean availability of the French nuclear fleet).

Hydro-power productions - lake hydro (Constraints (A.9) to (A.12)) and PHS (Constraints

(A.13) to (A.18)) - are capacity, ramp and energy-constrained

$$0 \leq lh^{DA}, lh^{Bal}, lh^{UR} \tag{A.9}$$

$$lh^{DA} + lh^{Bal} + lh^{UR} \leq K_{lh} \tag{A.10}$$

$$-r_{lh}K_{lh} \leq lh_h^{DA} + lh_h^{Bal} - lh_{h-1}^{DA} - lh_{h-1}^{Bal} \leq r_{lh}K_{lh} \tag{A.11}$$

$$0 \leq L_h = L_{h-1} - lh_h^{DA} - lh_h^{Bal} - lh_h^{UR} \tag{A.12}$$

$$0 \leq phs_{turb}^{DA}, phs_{pump}^{DA}, phs_{turb}^{Bal}, phs_{pump}^{Bal}, phs_{turb}^{UR}, phs_{pump}^{DR} \tag{A.13}$$

$$phs_{turb}^{DA} + phs_{turb}^{Bal} + phs_{turb}^{UR} \leq K_{phs} \tag{A.14}$$

$$phs_{pump}^{DA} + phs_{pump}^{Bal} + phs_{pump}^{DR} \leq K_{phs} \tag{A.15}$$

$$-r_{phs}K_{phs} \leq phs_{turb,h}^{DA} + phs_{turb,h}^{Bal} - phs_{turb,h-1}^{DA} - phs_{turb,h-1}^{Bal} \leq r_{phs}K_{phs} \tag{A.16}$$

$$-r_{phs}K_{phs} \leq phs_{pump,h}^{DA} + phs_{pump,h}^{Bal} - phs_{pump,h-1}^{DA} - phs_{pump,h-1}^{Bal} \leq r_{phs}K_{phs} \tag{A.17}$$

$$\begin{aligned} 0 \leq L\_phs_h^{upstream} = L\_phs_{h-1}^{upstream} &- phs_{turb,h}^{DA} - phs_{turb,h}^{Bal} - phs_{turb,h}^{UR} \\ &+ phs_{pump,h}^{DA} + phs_{pump,h}^{Bal} + phs_{pump,h}^{UR} \end{aligned} \tag{A.18}$$

with L_0 set to 75% of the energy capacity installed for lake hydro-power and L_phs_0 to 50% of the energy capacity of PHS.

Finally, the problem accounts for a bottom-up model for the DR technology under scrutiny (Constraints (A.21), (A.22) and (A.24) only for load-shifting ones)

$$0 \leq d^{DA}, d^{Bal}, d^{UR}, u^{DA}, u^{Bal}, u^{DR} \tag{A.19}$$

$$d^{DA} + d^{Bal} + d^{UR} \leq (A_{dr,h}K_{dr} - \sum_{k=1}^{\nu}\sum_{m} d_{h-k}^{m})_+ \tag{A.20}$$

$$u^{DA} + u^{Bal} + u^{DR} \leq K_{dr} \tag{A.21}$$

$$\sum_{m} d_{h-\Delta}^{m} \leq \sum_{k=0}^{\Delta-1}\sum_{m} u_{h-k}^{m} \tag{A.22}$$

$$X_h^{cont} = X_{h-1}^{cont} - d^{DA} - d^{Bal} - d^{UR} \tag{A.23}$$

$$X_h^{up} = X_{h-1}^{up} - d^{DA} - d^{Bal} - d^{UR} + u^{DA} + u^{Bal} + u^{DR} \tag{A.24}$$

with $X_0^{cont} = NK_{dr}D_{dr}$ and $X_0^{up} = K_{dr}D_{dr}$ where N is the maximum number of activations per year, K_{dr} the installed capacity, and D_{dr} the maximum duration of a DR event of the studied DR potential. Δ is the maximum delay for load recovery. ν is the minimum down time. The markets are indexed by m.

The two power mixes considered to calibrate the model are summarized in Tables A.7 and A.8.

[9]Capacity and reservoir sizes are from the French national register of power production units, publicly available through the Open Data Réseaux Energie platform. Reservoir capacity is set at the maximum stored energy in the period 2015-2023. Operating costs are adapted from Pietzcker et al. (2021) and account for a carbon price.

Technology	Capacity (GW, GWh)	Ramp rate (%)	Cost (€/MWh)
Biomass/Waste	2.272	80	67.12
Coal	1.816	55	95.68
CCGT	9.669	60	56.64
OCGT	2.015	75	66.36
Other gas	2.420	80	74.12
Fuel oil	2.566	80	112.68
Nuclear	61.370	30	7.88
Lake hydro-power	8.787, 3100	45	1
Pumped hydro storage	5.051 , 32	85	2
Run-of-river	11.940	-	0
Wind (On-Offshore)	20.842-0.494	-	0
Solar	14.639	-	0

Table A.7: Assumptions on installed capacity and costs for 2023 French power system.[9]

Technology	Capacity (GW, GWh)	Ramp rate up-down(%)	Cost (€/MWh)
Biomass/Waste	3	80	118.36
CCGT	9.669	60	80.64
OCGT	2.015	75	98.40
Other gas	2.420	80	111.98
Fuel oil	2.566	80	170.82
Nuclear	63	30	9.32
Lake hydropower	9.487 , 3100	45	1
Pumped hydro storage	6.051 , 35	85	2
Run-of-river	12.159	-	0
Wind (On-Offshore)	39-18	-	0
Solar	65	-	0

Table A.8: Assumptions on installed capacity and costs for 2035 French power system.[10]

This model is solved with SDDP in order to produce a near-optimal policy for dispatching all the available means during a year. 500 simulations are then computed from this policy facing 500 years of random variables drawn in our sample of 20^{357} possible years. In the main results section, these 500 years are the same for all cases to ensure comparability and are drawn randomly from the sample. The SDDP algorithm used is that implemented by Dowson and Kapelevich (2021), modified to comprise with the termination rule proposed in Shapiro (2011).

Appendix A.3. Investment model

The investment model is built on the modeling framework of Appendix A.2 and calibrated for the 2035 French power system (Table A.8, except for OCGT, which is endogenous). A stage is added before the first day of the year to make investment decisions. Investment is available for one

[10]Capacity and reservoir sizes are adapted from French official energy planning and prospective studies by the French TSO (RTE (2023),RTE (2021)). Operating costs are adapted from Pietzcker et al. (2021) and account for a carbon price.

flexibility source other than DR, namely fast thermal units, represented here as OCGT. Associated investment costs in thermal fast generation - a proxy for all fast ramping means - are annualized with a 4% interest rate and a 30-year lifespan. OCGT data comes from Fraunholz et al. (2021) and induces an investment cost of 23132 €/MW. The latter decisions set the capacity and energy upper bounds of these means in the operation phase. The sketch of the investment model is

$$\min IC_{ocgt} * k_{ocgt} + \mathbb{E}\left[OPEX(k_{ocgt}, Imb)\right] \tag{A.25}$$

$$\text{s.t.} \tag{A.26}$$

$$\text{Demand}_t = \text{ Supply}_t + \mu_t \tag{A.27}$$

$$\text{Supply } \leq \text{ Inst. Capacity}(k_{ocgt}, k_{phs}, K_g) \tag{A.28}$$

$$\text{Hydro-power transition equations (A.12) and (A.18)} \tag{A.29}$$

$$\text{If DR is present, DR constraints (A.19) to (A.24)} \tag{A.30}$$

where IC designates investment costs and lowercase letter decision variables. In practice, the problem is reformulated in a dynamic programming framework, and state variables are used to make investment decisions and percolate through the operation stages. The whole is solved using SDDP.

Imb represents the cumulative yearly imbalance target constraint serving as security of supply criterium. This constraint is softly implemented in the model by adding a quadratic term in the last subproblem's objective, keeping it convex and thus suitable for the SDDP framework. The quadratic term penalizes the gap between the cumulative imbalance over the year and the target level. It is also penalized at two times the level of the VoLL. This term is written with our notations $VoLL(\sum_t \mu_t - Imb)^2$.

Moreover, the operation phase is simplified compared to Appendix A.2 to alleviate the computational burden of the algorithm and cope with the supplementary step, which requires more iterations of SDDP for end-of-the-year decisions to back-propagate on the investment decision. Only one day-ahead hourly decision is taken by each generation, which means that reserve requirements and forecast error balancing are not considered. Also, only five representative weeks for the year are considered for the same reason. The weeks are the same as those selected for the energy transition investment value and are chosen to reflect each season plus the winter - and thus tight situations for the system - occurring on both ends of the year. The maximum annual number of activations of DR potentials and the maximum imbalance criterium are reduced proportionally to the year's size.

The optimal investment decision is based on the computed expected OPEX for a year. The latter quantity is a piecewise linear function of the invested OCGT capacity computed by SDDP according to the visited scenarios of random variables. Hence, it is still random, even though it accounts for billions of year scenarios. Moreover, the investment stage has a linear objective, so the investment decision can be very sensitive to the OPEX function's uncertainty. So, the whole

problem is run 10 times in order to mitigate this effect, which also motivates the reduction in model size compared with the operation value model of Appendix A.2. The flexibility investment value is then given by the variation in the averaged-among-runs invested OCGT capacity with and without the studied DR potential.

Appendix A.4. Private operation model

The private valuation of a DR resource is done through a multistage stochastic program which maximizes the expected total revenues of a price-taker operator of the resource acting on all available markets for DR. Contrarily to the previous models, the power system and its uncertainty are only displayed through four sets of price series. The prices are obtained by running the operation model of Appendix A.2 without DR and saving the dual variables of the equilibrium constraints (A.2) to (A.4).

To keep the intraday structure of the prices, noted $\lambda^{DA}, \lambda^{Bal}, \lambda^{UR}, \lambda^{DR}$, the random variables are revealed for the whole day at the beginning of each day. Moreover, as for demands in Appendix A.2, the four prices are drawn from the same scenario - i.e., the simulation result of the operation model. The scenarios are considered equiprobable.

Then, the private operator problem is solved by SDDP and stated as follows

$$\max_{d,u,\mu \geq 0} \mathbb{E}\left[PC_1 + \mathbb{E}\left[PC_2 + \mathbb{E}\left[... + \mathbb{E}\left[PC_T\right]\right]\right]\right]$$

s.t.

$$d_t^{DA} + d_t^{Bal} + d_t^{UR} \leq A_t K \tag{A.32}$$

$$u_t^{DA} + u_t^{Bal} + u_t^{DR} \leq K \tag{A.33}$$

$$0 \leq X_t^{cont} = X_{t-1}^{cont} - \sum_m d_t^m, \quad X_0^{cont} = NKD \tag{A.34}$$

$$0 \leq X_t^{up} = X_{t-1}^{up} - \sum_m d_t^m + \sum_m u_t^m \leq KD, \quad X_0^{cont} = KD \tag{A.35}$$

$$\sum_m d_{t-\Delta}^m \leq \sum_{k=0}^{\Delta-1} \sum_m u_{t-k}^m + \mu_t \tag{A.36}$$

with

$$PC_t = (\lambda_t^{DA} - AC) d_t^{DA} - \lambda_t^{DA} u_t^{DA} + \sum_{t=1}^{T} (\lambda_t^{Bal} - AC) d_t^{Bal} - \lambda_t^{Bal} u_t^{Bal} + (\lambda_t^{UR} - AC) d_t^{UR} + \lambda_t^{DR} u_t^{DR} - VoLL\mu_t \tag{A.37}$$

where the first four terms in (A.37) reflect the four sources of revenues, a day-ahead market, balancing market, upward and downward reserves, and the last, the penalty for load recovery failures, set at the value of lost load.

Appendix A.5. Energy transition model

The energy transition model is an operation model similar to that of Appendix A.2 but with normalized yet still random demand and wind generation and without any other generation except 1 MW of nuclear and DR. To increase the number of iterations of the SDDP solving method in order to ensure confidence intervals for the optimal solution at least two orders of magnitudes smaller than that of the solution, the year is only represented by five weeks (the 2nd, 14th, 30th, 40th and last one). Beginning-of-the-year and end-of-the-year winter weeks are present because these periods are that of higher and more volatile demand with possibly absent wind, making them prompt to induce imbalances.

Existing assets in the reduced models have similar calibration as in the operation model (Appendix A.2), except for the maximum number of activations per year of DR potential, which is proportionally reduced by 35/365 to match with the representative weeks.

The optimal policy is then generated by SDDP and tested against 500 random years scenarios. We compare cumulative imbalances - i.e., the sum through a year of all slack variables associated with the supply-demand balance of Appendix A.2.

Appendix B. Sensitivity to the DR modeling constraints

Here, we test the sensitivity of our proposed model for demand response valuations to the inclusion of constraints limiting the load-shifting time window, the frequency of load-shifting activations, the modeling of multiple markets (day-ahead, balancing, and tertiary reserve), and the level of activation cost (energy cost). It highlights that overlooking time constraints -linked to comfort considerations, thermal properties of buildings, or technical aspects of underlying electricity usages- leads to almost continuous activations for time arbitrage and profits up to 4 times higher than when considering such constraints. Considering only the DA markets does not modify the resulting activation pattern much compared to the full model. Still, it considerably reduces the upper distribution of annual profits for the flexible demand. Sensitivity to activation costs is less surprising, with reduced activations and profits as these costs increase to the point of no participation in the market for energy costs higher than $100€/MWh$.

To do so, we consider the model of Appendix A.2 calibrated on a reduced version of the year based on four representative weeks (the 2nd, 15th, 30th and 49th of the year). Uncertainty regarding demands and renewable generation is revealed at the beginning of each day, drawn from 20 scenarios built as in the complete year calibration of Appendix A.1. For this sensitivity analysis, we always consider DR provided by residential heating appliances for which we keep similar flexibility attributes as in the complete case, except for the total number of allowed activations per year, which is multiplied by 672/8760 and the installed capacity, which is kept to $1MW$. The subsequent multistage stochastic program is then solved using SDDP (Pereira and Pinto (1991), implemented with a slightly modified Dowson and Kapelevich (2021)) and Shapiro (2011)'s stopping rule after 2100 iterations of backward and upward phases. Finally, the resulting optimal policy faces 500

realizations of the four representative weeks, drawn from the $20^2 8$ years in the sample and kept the same for all tested models. Resulting metrics (erased energy, system costs) are displayed scaled back to a 8760 hours year.

On this basis, tested models for sensitivity to load-shifting modeling choices are the full model as in Appendix A.2 (called hereafter "Full_DR"), the same without load recovery time constraint ("No_Delta"), without minimum time between two DR events ("No_Nu"), without both ("No_Nu_No_Delta"), and the full model which would only consider the day-ahead market ("DA_DR"), thus excluding balancing and reserve procurement. For sensitivity to the activation cost, we consider the "No_Nu_No_Delta" model because it removes DR activation barriers the most, making clearer the role of prices in such activation, and set the value for the activation cost AC at $0, 10, 50, 100$ and 150 €$/MWh$, the models being named accordingly.

To measure the sensitivity of the solution, we assess both the effect on the behavior (pattern of upward and downward movements, cumulated erased energy) and profits (distributions) of the DR asset under study and the global effect on the system costs and day-ahead prices.

Appendix B.1. Sensitivity to the inclusion of the time-related constraints

Figure B.5 shows that the absence of a minimum downtime ("No_Nu") leads to a total amount of erased energy increased around 4 times compared to the cases with this downtime, independently of the presence of a load-recovery time limit. However, the recovery limit induces different behaviors for depleting the total number of allowed activations per year. With this limit, all activations can not be used at the end of the year to postpone some load indefinitely and thus implies a flatter pattern of activation across the year with the choice of using the asset more in the first winter period while keeping some activations for the end of the year. Moreover, it appears in Figure B.5 that, in our model, the absence of other markets than the day-ahead one or the absence of recovery time limit reduce only marginally the total amount of erased energy (see also Table B.9) and do not affect the cumulative pattern throughout the year. Regarding the time limit, it was expected that this constraint concerns only recovered energy and not the erased one, so the influence of this constraint is seen more in the comparison of Figures B.7 and B.8. Regarding the marginal difference in erased energy when considering multiple markets or only the day-ahead one, it could be explained by the fact that all markets present similar opportunities of time arbitrage (for the DA and balancing ones) or modulation needs, so as the marginal cost of DR is supposed null here, there is no (massively[11]) new incentive when considering several markets. More realistically, some DR would have a non-zero marginal cost. Thus, other markets than the DA with a more limited number of service providers would, in fact, create new activation incentives, but not more than the incentive perceived by the zero marginal cost DR, here modeled, with equality if and only if the non-zero marginal cost DR is

[11]The bulk of this incentive comes from the variability brought about in the system by renewable generation and structural load pattern. Additional incentives could only come from forecasting errors uncorrelated with the above elements in the balancing market and sudden, similarly uncorrelated load variations in the reserve one as we do not account for contingencies.

	DA	Balancing	Reserve	Total
Full_DR	248.42 (13.85)	14.99 (5.91)	55.08 (11.76)	318.50 (6.94)
No_Delta	241.40 (13.65)	13.82 (6.62)	52.40 (12.05)	307.62 (2.44)
No_Nu	884.88 (49.32)	37.36 (17.63)	156.17 (35.67)	1078.41 (36.05)
No_Nu_No_Delta	971.77 (38.13)	20.55 (15.01)	102.68 (31.43)	1095.00 (0.00)
DA_DR	307.60 (2.28)	-	-	307.60 (2.28)

Table B.9: Average annually erased energy (MWh) per market in each model for the 500 simulated years.

always infra-marginal.

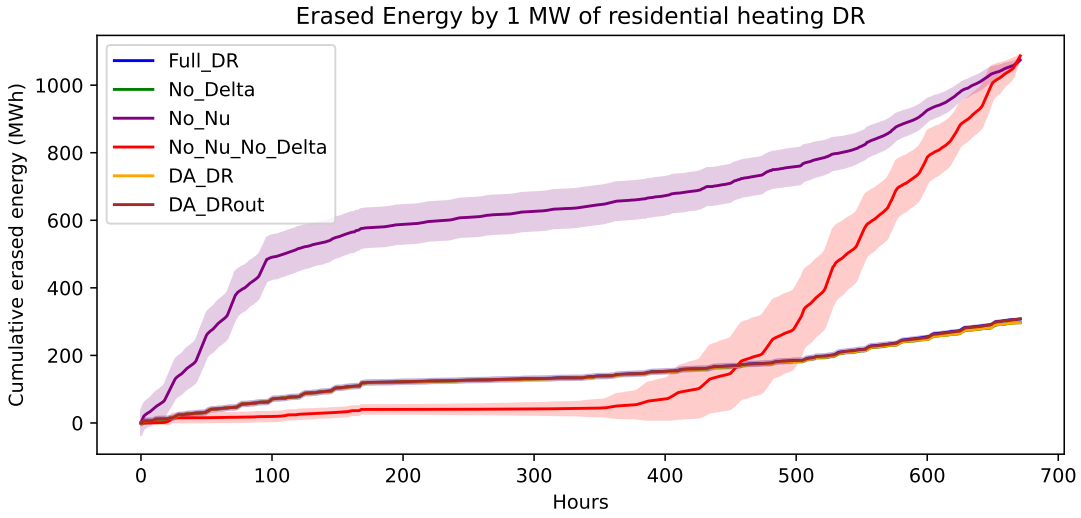

Figure B.5: Cumulative erased energy over the four representative weeks in the different demand response models. Solid lines are average over the 500 simulations, shades associated with standard deviation.

The distribution of profits realized by operating the MW of DR over the year reflects the above conclusion regarding its usage patterns, with added information regarding the effect of the recovery time limit. As displayed in Figure B.6, profits are increased on average by 67% when no recovery limit applies and by 126% when no minimum downtime applies. Still, those increases do not add linearly as removing both limits leads to an increase of 128% of the profits on average. These increases are driven by the new possibility of extremely favorable years more than by a movement of the bulk of the distribution as shown by the relative constant median (black triangles in Figure B.6) of profits across cases. Moreover, Figure B.6 highlights that most of the profitability of the load-shifting appliance and most of the variability of the profits come from participation in balancing and reserve mechanisms, even though we saw above that most DR volume is dedicated to the day-ahead market. Notably, with only the day-ahead market revenues, the MW of DR earns 0.72 k€/year on average and a median of 0.67 €/year which is well below the often cited 20-100k€/MW/year for demand response costs (RTE (2023), chap. 9), while when considering the full but time constrained model we get 6.12 k€/year and 1.59 k€/year on average and median respectively for the sole

modeled MW of DR, still below the cost range and of the same order of magnitude of revenues found in RTE (2023) (Table B.10).

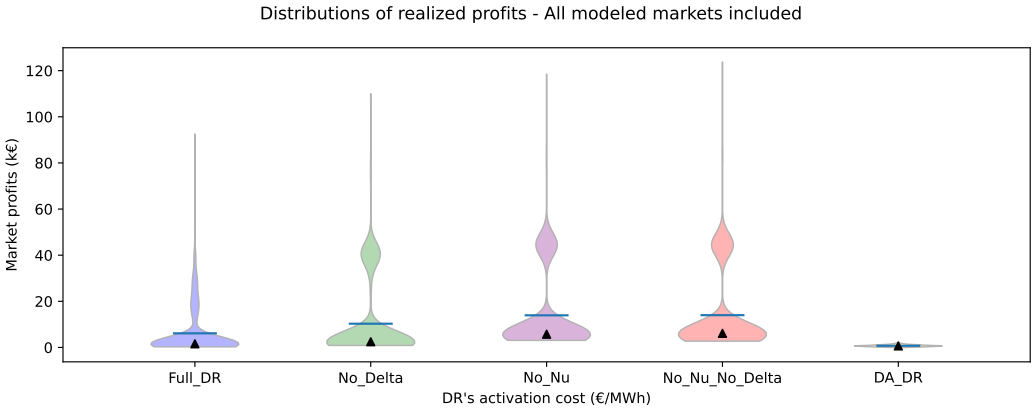

Figure B.6: Distributions of the profits realized by the flexible demand in the different models of DR.

	Full_DR	No_Delta	No_Nu	No_Nu_No_Delta	DA_DR
Avg. profits (k€/MW/y)	6.12	10.29	13.93	14.00	0.72
Median profits (k€/MW/y)	1.59	2.49	5.76	6.13	0.67

Table B.10: Average and median yearly profits in the different models of DR.

Examining the DR asset's upward and downward activations in each model case clarifies how more full capacity and consecutive activations are set when no time limits are accounted for. Moreover, it appears that most of the value for upward modulation is found outside the day-ahead market, as day-ahead upward DR exists almost only in the case "DA_DR" (compare the bottom left heatmap of Figures B.7 to B.10 and of Figure B.11). Obviously, deleting the recovery time limit reduces the frequency of upward regulations in total (Figure B.7 vs. Figure B.8) and therefore results in stronger peaks of upward modulation. This highlights that maximum load recovery time reduces the opportunities for time arbitrage and forces the DR asset to recover in not necessarily low-price enough hours, which explains reduced profits, especially in less volatile years.

Removing a minimum downtime also increases the frequency of upward modulations, but simply due to the massive increase in downward modulations due to the load recovery limit. Therefore, both constraints are necessary for modeling the possible activations and, hence, the business case of a specific appliance as a DR resource. If different appliances are aggregated and play as such in the markets, these constraints can be explicitly translated by combining the flexibility attributes of the underlying assets to derive an equivalent availability pattern, minimum downtime, and maximum recovery time for the bundled asset. Or, the difference of activation levels and frequency observed when comparing the full and "No_Nu_No_Delta" models could be translated into a reduction of the nameplate capacity of the bundled asset: if an underlying asset with capacity of 1 MW can be activated only every ν timesteps and has to recover load in Δ timesteps, then it can provide downward modulation of $1/\nu$ MW at every timestep and an upward modulation of $1/(\Delta\nu)$ MW at

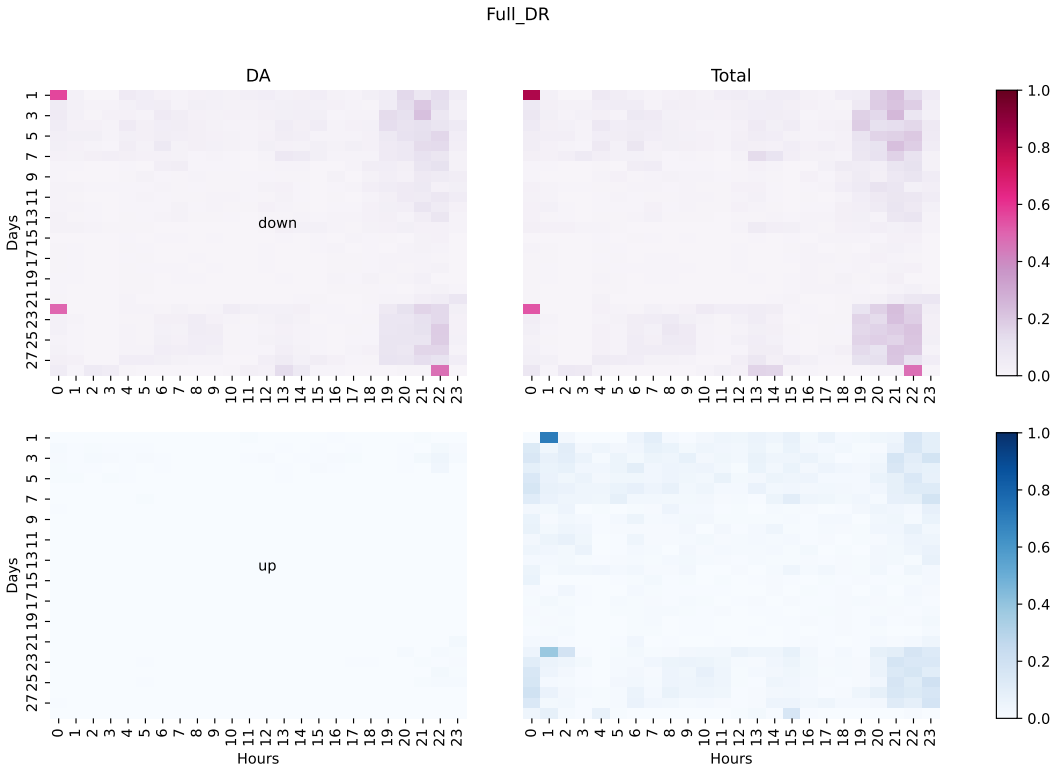

Figure B.7: Average downward (top) and upward (bottom) modulations of the flexible demand in the complete model ("Full_DR").

every timestep+1, so that the 1 MW underlying asset could contribute as a perfect $1/\nu$MW to the bundled asset in the day-ahead market and as a perfect $1/(\Delta\nu)$ MW to the bundled asset in the balancing or reserve markets, the two offers being coupled.

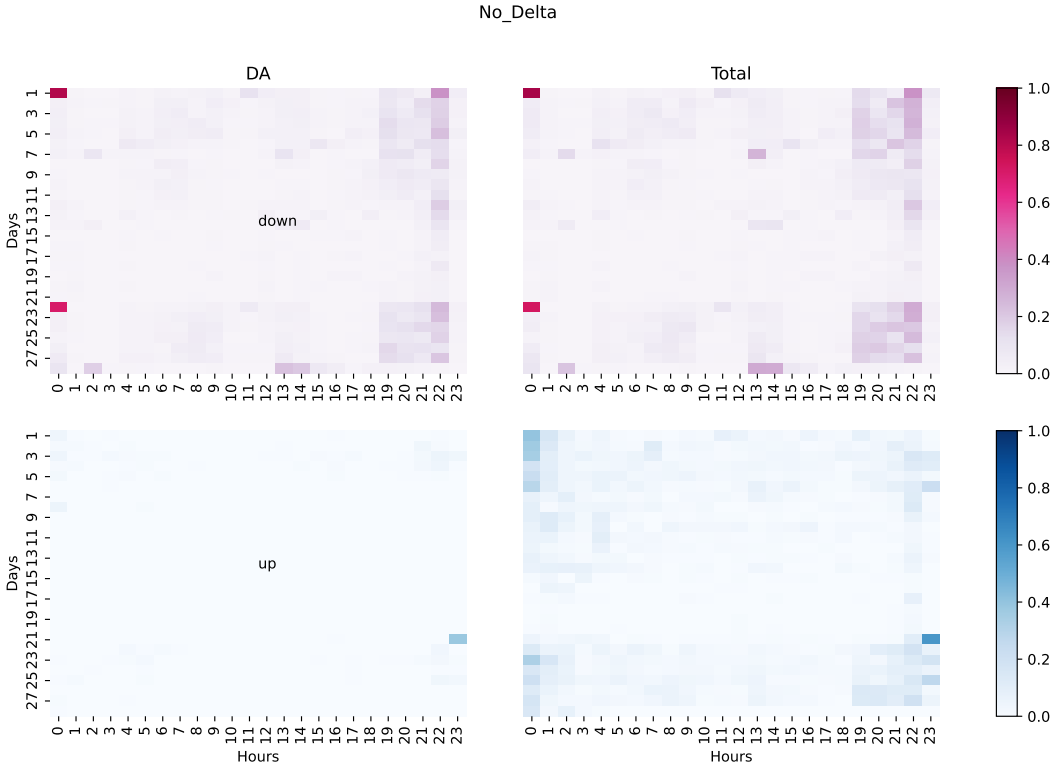

Figure B.8: Average downward (top) and upward (bottom) modulations of the flexible demand in the model without maximum recovery time ("No_Delta").

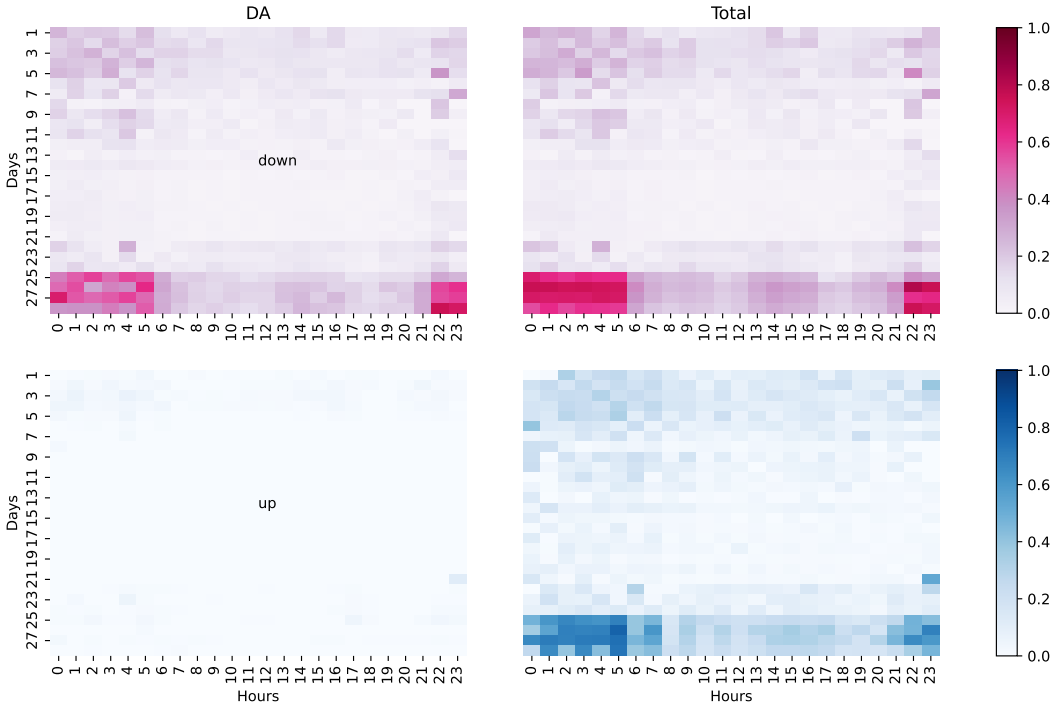

Figure B.9: Average downward (top) and upward (bottom) modulations of the flexible demand in the model without minimum downtime ("No_Nu").

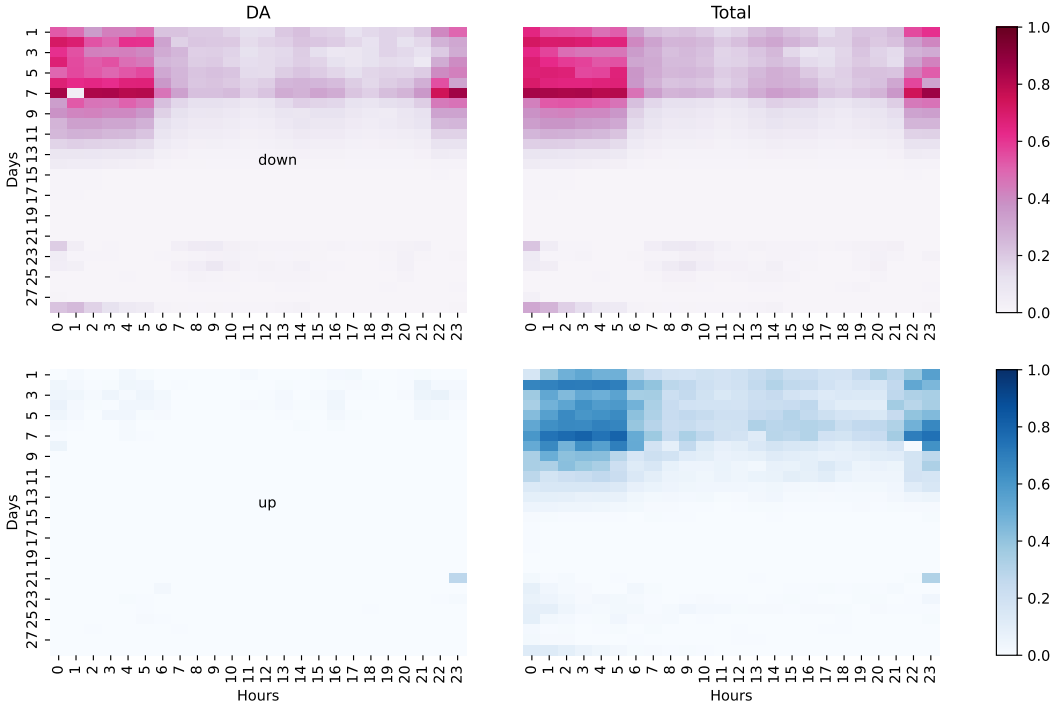

Figure B.10: Average downward (top) and upward (bottom) modulations of the flexible demand in the model without minimum downtime and maximum recovery time ("No_Nu_No_Delta").

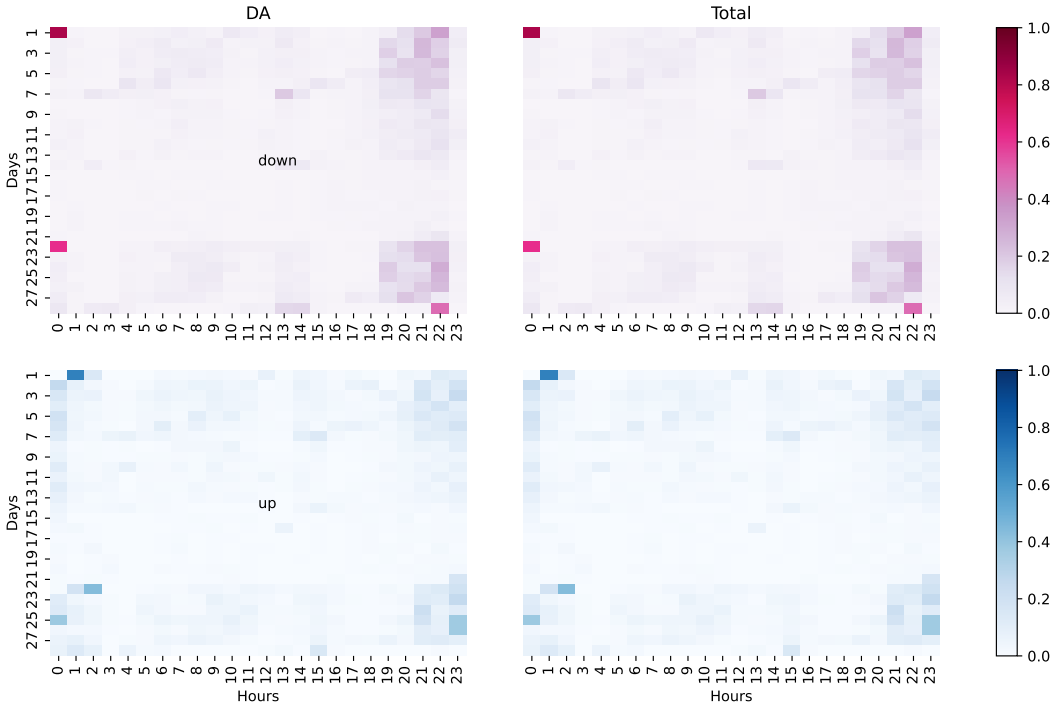

Figure B.11: Average downward (top) and upward (bottom) modulations of the flexible demand in the model with only the DA market ("DA_DR").

Regarding the system's costs and day-ahead prices, the hypothesis modifying the behavior of the DR asset has no perceived impact at this system scale due to the small installed DR capacity (approx. $1/10^5$ of the total system's capacity). However, the existence of the asset contributes to reducing the occurrence of high system cost scenarios solely through its role at the margin. This can be perceived both in total costs (Figure B.13) and in prices where price peaks are mitigated (Figure B.12). Prices in the day-ahead market remain of the same order of magnitude in all cases (Figure B.12), but the distribution of system costs is shifted to the left when only the day-ahead market is considered (Figure B.13). This is because, in the latter case, balancing and reserve are not considered at all. Keeping those requirements and removing the possibility for DR to participate in these mechanisms (case "DA_DRout") brings back the system cost distribution close to that of the full model (Figure B.13).

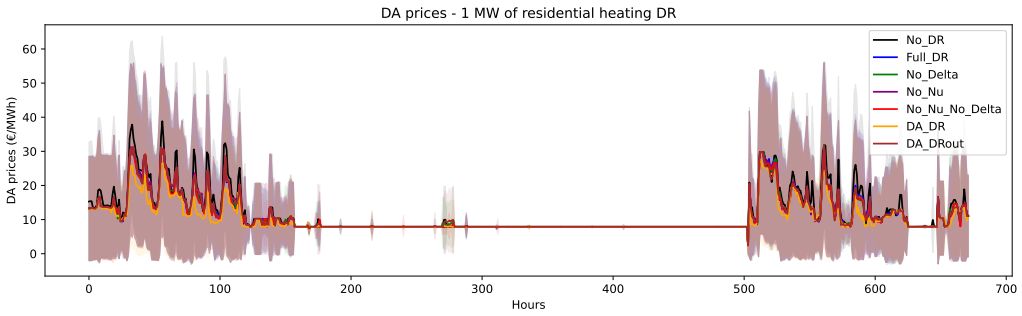

Figure B.12: Average day-ahead prices (spreads in shading) during the four representative weeks depending on the model of demand response

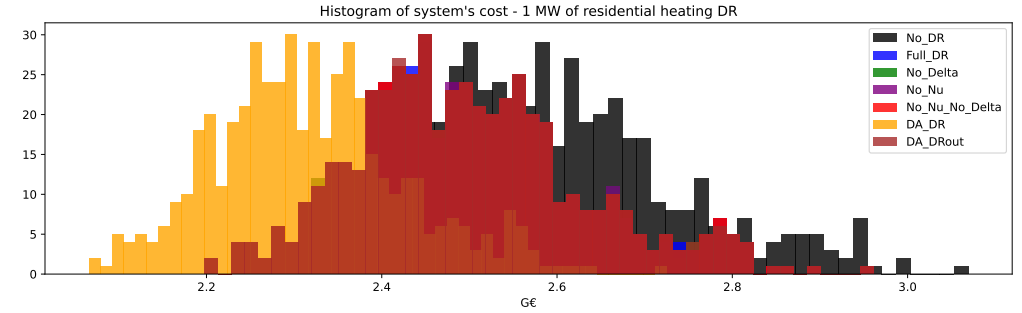

Figure B.13: Distributions of the system's costs during the four representative weeks depending on the model of demand response

Appendix B.2. Sensitivity to the activation cost of DR

The effect of non-zero activation costs on DR bids being accepted in the markets manifests strongly even at low energy prices. In Figure B.14, the total amount of erased energy over the year decreases by approx. 78% already when the activation cost of DR goes from 0€/MWh to 10€/MWh. After this impressive start, additional increases in costs affect erased energy proportionally less up to activation costs of the order of 100€/MWh, after which DR is almost no longer called. Hence,

cost hypotheses are increasingly crucial as low or negative prices become more frequent for longer periods of time (i.e., exceeding load-recovery limits of the DR appliance) in the markets since they could price out the DR, which could arbitrage on them. In actual systems, this would create a negative feedback scheme where long periods of negative prices occur due to a lack of flexibility in the system, preventing additional flexibility from entering the market and being activated for the system and, in turn, reinforcing the initial flexibility issue.

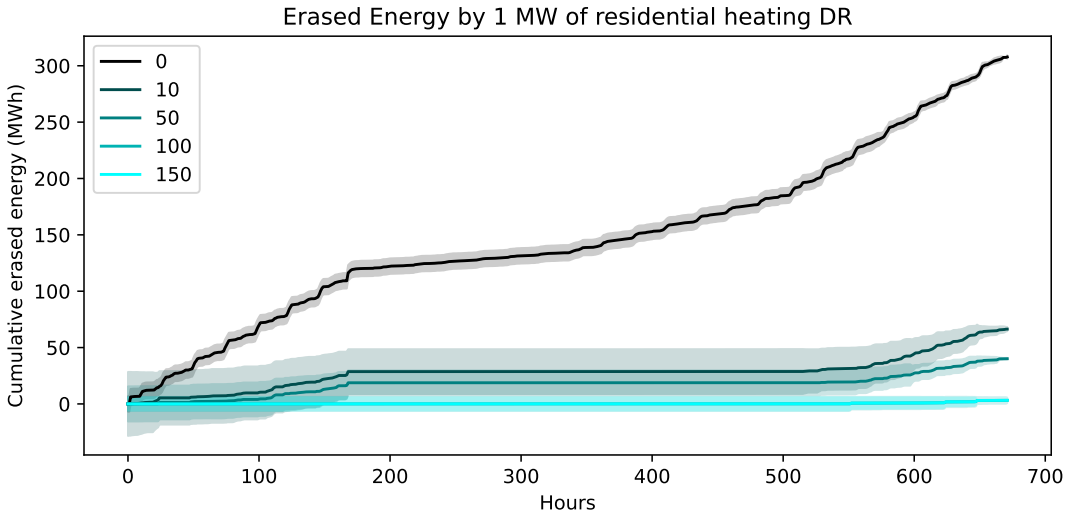

Figure B.14: Cumulative erased energy over the course of the four representative weeks for different activation costs

Profits vary as expected once costs are positive: they decrease strictly as activation costs increase. However, it may seem surprising that average and median profits increase when moving from null activation costs to positive costs (Table B.11). This may be explained by the nature of the solution of the multistage stochastic dynamic program of the dispatch, which is that of a policy and not a usage pattern. Thus, the optimal policy with no activation costs could be to activate as soon as even the slightest intertemporal arbitrage has a high probability of occurring. In contrast, with low but positive costs, the optimal policy is more selective and requires a higher probability of positive time arbitrage to dictate an activation of a DR event. Facing a given realization year, the former policy may well result in some activations being not profitable, while the latter avoids such traps, hence the higher profits when activation costs become positive. Usage patterns, as displayed in Figures B.16 and B.17, support such explanation through more selective activations. Once activation costs increase again, the DR asset arbitrage opportunities become increasingly rare until the asset is priced out of the market in most years, hence the approx. 0^- median (Table B.11) compensated on average by disproportionally profitable years (upper distributions in Figure B.15).

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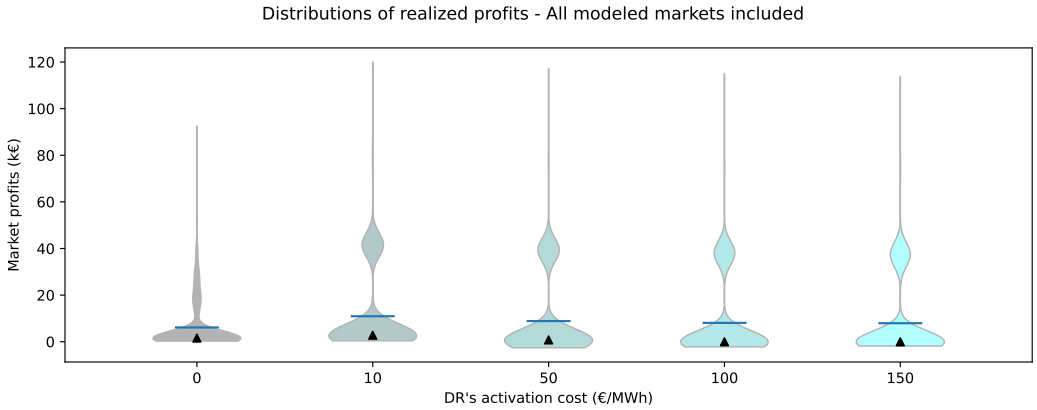

Figure B.15: Distributions of the profits realized by the flexible demand for different activation costs

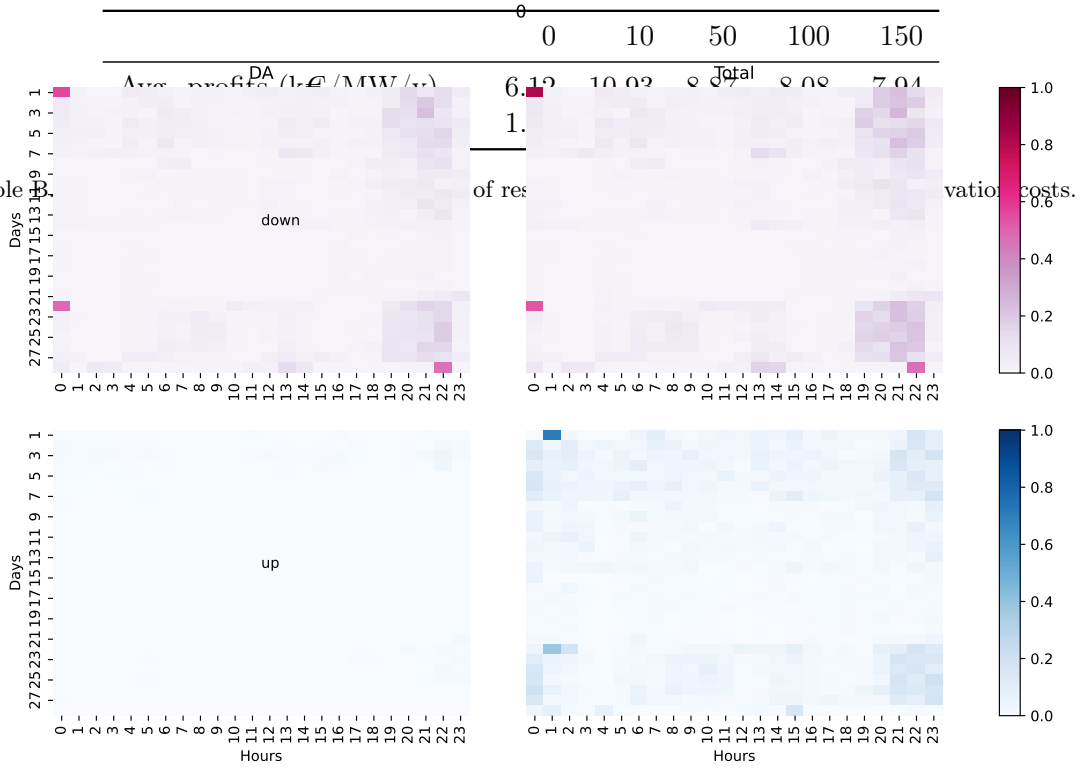

Figure B.16: Average downward (top) and upward (bottom) modulations of the flexible demand with an activation cost of 0 €/MWh

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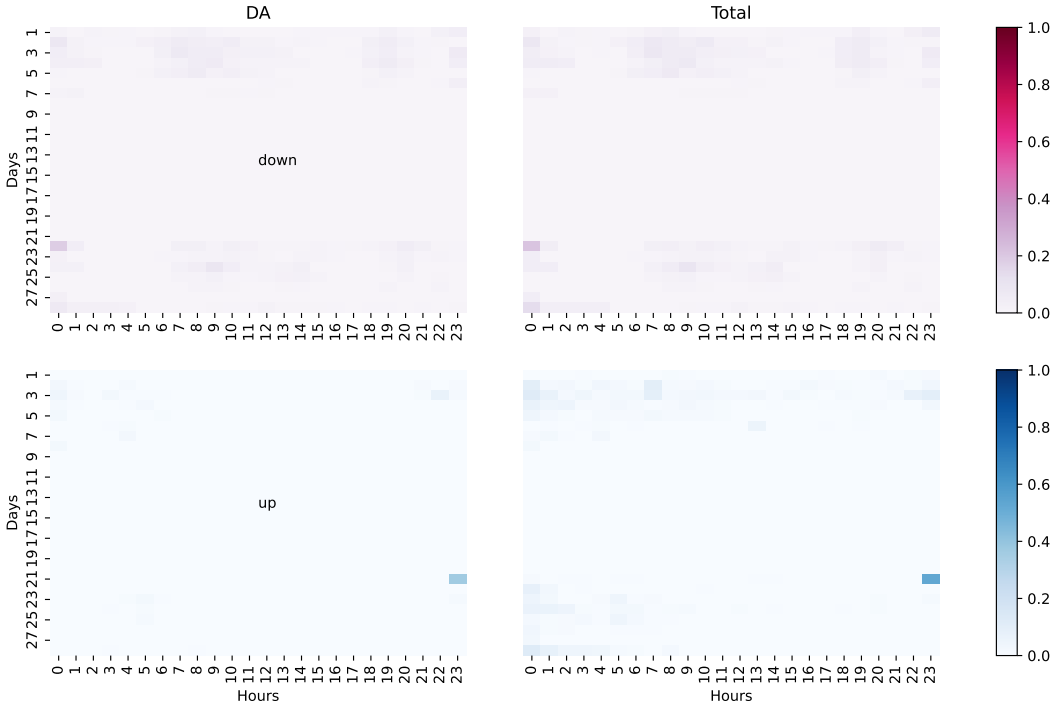

Figure B.17: Average downward (top) and upward (bottom) modulations of the flexible demand with an activation cost of 10 €/MWh

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