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Highlights

A bottom-up model of electricity demand response with a stochastic dynamic programming approach: application to system value of demand response in the European energy crisis.

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- A model of electricity demand response's operations under uncertainty is proposed.
- The problem is cast as a multistage stochastic program.
- An analogy with hydropower allows using stochastic dual dynamic programming for efficient solving.
- Inclusion of uncertainty and appliance-related constrained brings new insights on demand response's value.
- The modeling framework sustains multiple policy-relevant extensions.

A bottom-up model of electricity demand response with a stochastic dynamic programming approach: application to system value of demand response in the European energy crisis.

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Abstract

Demand response is anticipated as a key feature of flexibility in renewables-dominated power systems even though high-scale aggregation and integration of demand response have never been implemented. This paper proposes a model of hourly operations during a full year of power systems integrating significant shares of demand response. Attention is given to a bottom-up description of demand response as a flexibility resource. The representation is brought up to a large-scale model of power systems through a hydropower analogy, compatible with a stochastic dual dynamic programming framework. This framework surpasses traditional stochastic dynamic programming ones as it enables the capture of intertemporal arbitrage and the effect of stochastic inputs on different timescales inherent to the operation of demand response affected by social and technical limitations. Yet, such a modeling paradigm has not permeated the study of demand response. Notably, various sources of demand response from all sectors are represented. The model is used to quantify the hypothetical economic and environmental impacts of demand response on day-ahead markets in Western Europe during 2022, a particularly tense year for this power system. Apart from the model itself, a key result is the possible misalignment between a system's need for more flexibility sources and the private interest of an operator of demand response potentials. A cannibalization effect of demand response from the tertiary and the residential sector is also found due to the size of these potentials.

Keywords: OR in Energy, Stochastic Dual Dynamic Programming, Demand response, Flexibility

1. Introduction

In line with climate change mitigation efforts, future power systems will rely increasingly on renewable energy sources. The intermittent and random nature of most renewables brings about decreased flexibility on the supply side of power systems i.e., reduced capability to modify at each relevant time scale the output or consumption of energy resources controllable at this time scale. Commonly suggested solutions to manage such flexibility issues include increased interconnections,

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various forms of storage (such as batteries, pumped hydro storage, or power-to-gas), and demand response (DR).

Among these options, several reports highlighted that DR may be the key provider of flexibility in the coming decade (RTE (2023); IEA (2022)). However, DR requires the roll-out of enabling technologies, especially for residential and tertiary sector DR (Gils (2014)), and the adaptation of power markets to this new resource (Kerscher and Arboleya (2022)). To make this deployment feasible, new insights are needed on the impacts of this type of DR and on its possible remunerations in power systems facing growing uncertainty (Ringkjøb et al. (2018)).

This study focuses on modeling DR operations in power markets to contribute to these research efforts. Specifically, we assess the main attributes of DR potential – namely, specific power use in a given sector – and accommodate this bottom-up representation of each flexible power use in a wholesale energy-only power market in perfect competition. Accurately representing demand response as a flexibility provider requires handling stochasticity and stock management on different time scales (from the hours to the year). Hence, an innovative analogy with hydropower and its subsequent solving in a stochastic dual dynamic programming framework has been developed here. As a primary example, a day-ahead hourly market is represented during a whole year of operations. The contributions of this paper are twofold.

Firstly, we develop a bottom-up model of DR that leverages an analogy with the operation of hydropower resources. This model addresses the availability and social limitations of DR potentials across different timescales (annual and hourly), which implies both a fine temporal granularity (hourly), a large modeling horizon (a year), and imperfect foresight, i.e., numerous modeling timesteps in a dynamic setting. Yet, our model remains numerically tractable because it fits the framework of an efficient solution strategy for such stochastic programs, namely stochastic dual dynamic programming. The model enables assessing the sensibility of DR revenue to differences in technical or social characteristics.

Secondly, we present an application on the 2022-2023 European case. This period is marked by a rapid shift in the merit order that occurred due to rising gas prices and more stable coal prices: the comparative effects of DR can be studied in these different merit orders. We analyze the impacts of increased access to residential and tertiary sector flexible loads on the performance of the interconnected power systems in Western Europe. The focus is on the interactions between different DR potentials and with other flexibility sources such as interconnections, peak fossil-fueled generation, or pumped-hydro storage.

The case study yields several interesting results. DR has multifaceted impacts on power systems: while always leading to decreased total operation costs, technical or social constraints of DR potentials may lead to equivocal effects on system emissions or imbalances depending on the specific pre-existing merit order. Additionally, we observe a cannibalization effect where the benefits obtained by industrial DR decrease as the availability of residential and tertiary DR increases. For higher penetration levels of diffuse DR in the system, a similar saturation is faced by diffuse DR itself: from this high level, each new MW of residential or tertiary sector DR generates less revenues than the previous ones and decreases the revenues of previously existing ones.

In the simulated scenarios, a single DR potential may not systematically be beneficial, whether it is industrial DR or not. On the contrary the system benefits systematically of the operations of this potential in terms of total operation cost reductions. Therefore a misalignment between system operators and market revenues of operators of a single DR potential may arise in the present case study.

Demand response involves interactions between different types of agents and different layers

within a power system. In the DR literature, these layers have been studied with diverse intensities.

First, some studies (Gils (2014), Müller and Möst (2018)) focus on flexible electricity use to assess current and future potentials. They highlight the main technical features of specific flexible power uses, notably their availability when the system needs flexibility (Müller and Möst (2018)). A common finding is that power-intensive industrial appliances are already valued in DR schemes (Kerschler and Arboleya (2022)), even though the highest potentials and availability are in the residential and tertiary sector (Gils (2014)). These potentials remain largely untapped by power systems due to their diffuse nature.

Secondly, another line of literature focuses on connecting these diffuse flexible loads and larger power systems. In a top-down approach, numerous studies focus on the optimal operation of one flexible load in response to exogenous signals from the power system. These studies employ different approaches from operation research, often involving a representation of uncertainty and a focus on short-term operations (e.g., household-level operations by Remani et al. (2019) or Ferreira et al. (2012)). However, few operation models (a notable exception is Roos et al. (2014)) manage to keep the same technical description of flexible loads displayed in potential studies.

As to bridge power markets and individual consumers, the literature proposed multiple designs for DR triggering signals sent by networks or retailers (Silvestre Freitas Gomes et al. (2024), Astier and Léautier (2021), Lima et al. (2017), Muratori and Rizzoni (2016)), or by intermediaries called DR aggregators (Aïd et al. (2022), Chapman et al. (2016)). This requires efforts in both metering technology deployment and signal design under imperfect information. The key challenge is to find appropriate individual signals to be sent to diffuse loads to obtain a desired aggregated effect at the system level.

Then, the literature closed the business model of this intermediary layer by modeling both strategic interactions between individual consumers and the aggregator/retail level and operations of the latter on wholesale power markets (Crampes and Leautier (2012), Campaigne and Oren (2016), Okur et al. (2019)).

The previous literature ensures both the existence of flexible uses of electricity and the possibility of passing this flexibility to the system level, provided some technological (Chapman et al. (2016)), social (Verrier (2018)) or regulatory (Kerschler and Arboleya (2022)) barriers are brought down. Building on this, numerous models were proposed focusing on giving a system value to demand response or one of its characteristics (Bruninx et al. (2018)) and on studying its introduction on various power markets (Biegel et al. (2014)). Ringkjøb et al. (2018) provides an extensive literature review on demand response models at the system level. These studies mainly take the form of short-term (few hours or a single day) operations of load-shedding or shifting (Fatouros et al. (2017), Papavasiliou et al. (2018)) or very long-term (decades) expansion studies focusing on investments in DR potentials compared to networks improvements (Marañón-Ledesma and Tomasgard (2019)). As underlined by Ringkjøb et al. (2018), a research gap exists in the study of intra-year operations of DR, thus overlooking eventual intertemporal aspects of their interaction with power systems. More recently, Motta et al. (2024) points towards similar conclusions after reviewing optimization models used in operation and expansion studies dealing with demand response, acknowledging both the necessity to include stochasticity in such models and the current relative lack of literature relying on state-of-the-art stochastic programming methods at scale for DR.

Moreover, these studies consider demand-side flexibility "before the meter," meaning that they ditch bottom-up modeling of demand-side flexible resources, even though previously mentioned streams of literature highlighted how much their technical characteristics affect the whole accessible DR potential. To the best extent of our knowledge, the only bottom-up model for DR operations at the system level to be found is Verrier (2018), which integrates some technical features of DR in

its operation model - but not all relevant ones (see Section 2.1). In a review of flexibility studies, Villar et al. (2018) points out the need to better model the aftermaths of a demand response event in terms of load increases to assess the interseasonal aspect of demand response in a similar call as (Ringkjøb et al. (2018)) and to provide new insights on possible remunerations of demand response operations accounting for growing uncertainty in power systems.

The paper is organized as follows. The next section provides an overview of the relevant features for modeling demand response operating in renewable-based power systems. Section 3 first details an extended hydropower analogy (Section 3.1) and then develops a bottom-up SDDP model of an energy-only market with demand response (Section 3.2). The solution strategy, stochastic dual dynamic programming, is presented in Section 3.3. Section 4 presents our case study calibrated on North Western Europe during the recent energy crisis. Concluding remarks are made in Section 5.

2. Demand response in power systems models

The present section selects the main features to be implemented in a demand response model operating in power systems with variable renewables. A focus is first given on the modeled type of demand response and on its representation as a flexibility resource. Then, assessment strategies for stochasticity in large models are reviewed in order to set the framework prevailing in Section 3.

2.1. Describing demand response

Demand response. DR may be defined as the action for some consumers to shed or shift their power demand in response to an exogenous signal. The signal could be a market price they observe, in which case we talk about implicit demand response or direct information or order sent by another actor to the consumer, in which case we talk about explicit demand response.

Demand response is also divided into two classes depending on the destiny of the flexible load: load-shedding when the demand is purely erased and load-shifting when it is only pre- or postponed and still has to be balanced at one point.

Load-shedding is mainly found in the industrial sector with its centralized big consumers. It represents a pure loss for the consumer (e.g., steel that was not produced during the shedding event) and thus has a very high activation cost. Therefore, load-shedding is a peak mean of negative load, and recourse to it can only be limited in time and infrequent.

Load-shifting appears more frequently in temperature-related usage (cooling, heating, air conditioning) and tertiary or residential sectors. As underlined by Gils (2014) or Müller and Möst (2018), it represents a massive potential of flexible loads that remains largely untapped. With a limited duration of events, load-shifting implies less discomfort than load-shedding and is, therefore, at a quite low activation cost, so it may be activated a greater number of times.

A DR potential or deposit refers to a specific flexible use of electricity and, more specifically, to the accessible share of installed capacity associated with this use, which may be reduced or increased on a certain date. It encompasses both technically available load reduction/increase and socially acceptable ones. If activations or installation costs are accounted for, only a smaller part of a DR potential may be economically available, i.e., profitable.

In this work, we focus on modeling DR potentials, the economic relevance of which is computed ex-post. Moreover, only explicit demand response is considered. We focus on system impacts and maximum revenues gained through DR operations. With such a point of view, implicit DR appears as an imperfectly controlled explicit DR, which translates into reduced equivalent capacities of DR potentials. Thus, this choice is not too restrictive.

Negative load vs price elasticity. In recent works such as that of Chapman et al. (2016), it has been highlighted that demand response requires new types of infrastructure both in technical terms (deployment of power-related information technologies) and in terms of economic actors, particularly if it is to be expanded to the highly decentralized residential and tertiary sectors. DR programs relying on real-time pricing have only yielded mild results in these sectors as the ability of ordinary end-users to catch up with the market is limited, and so is social acceptance of such programs. Other programs relying on price signals such as time-of-use or tariff flags such as in Lima et al. (2017) can't yield as much short-term DR and flexibility as real-time pricing. Thus, the literature has also explored direct load control for flexible end-uses. A new economic actor would then emerge with demand response, a DR aggregator. A contractual relationship would link the aggregator and end-users. Designs of such contracts and optimal architecture of the control system have been studied by Chapman et al. (2016) and Aïd et al. (2022). Provided some installation efforts, this new actor seems technically realistic. That is why, in this paper, we suppose that all DR deposits evoked are controllable by such DR aggregator which interfaces the market and end-users.

A first set of studies (e.g., Muratori and Rizzoni (2016) or Lima et al. (2017)) describes DR with the help of price elasticities in a demand function. These parameters are supposed to summarize all technical and behavioral characteristics of the flexible load. They are hard to estimate because not directly observable and may vary significantly even with a slight change in technology. Conversely, we propose a common model for all types of flexible loads, referring directly to their flexibility attributes as defined in Table 1.

A second body of work sees demand response as a negative load technology (e.g., Fatouros et al. (2017) or Marañón-Ledesma and Tomasgard (2019)). This approach is particularly adapted to models of electricity markets where the supply/demand balance constraint is written explicitly, as is the case in the present study. In such a framework, it is indeed similar to subtracting a term on the demand side of the power balance equation and adding a new power of the same amount on the production side.

This second modeling framework of DR is kept as it enables a unified representation of demand response and ordinary generation means, is adapted to explicit DR, and may be refined in order to integrate technical specifics of each DR potential.

DR as a flexibility resource. A flexible energy resource is a resource that is able to start up and ramp sufficiently quickly in order to follow and adapt to varying market/system conditions (Goutte and Vassilopoulos (2019)). This technical description does not suffice for a power system to benefit from this flexible resource. This flexibility shall indeed be valued and remunerated in order to participate in the system. Thus, a flexible resource may also be seen as a market product and described as such. The two visions exist in the literature, from which we extract the main attributes of a DR potential (Table 1), seen as a subgroup of flexible resources.

These attributes form a way of modeling quantitatively DR: a particular DR potential is characterized by a particular combination of the attributes. Depending on the modeling point of view, some attributes may become less relevant. In a system scale model of a day-ahead dispatch, the lead time for performing a DR event may be neglected as this dispatch is settled far from real-time. From a market perspective in Europe, location is irrelevant as no local flexibility market exists (Ramos et al. (2016)). Ramping rates are crucial for supply-side flexibilities (Goutte and Vassilopoulos

⁴See Villar et al. (2018); Kerscher and Arboleya (2022) for most of the technical constraints and also Ramos et al. (2016) for market ones.

Attribute	Type	Description ⁴
Capacity	Technical	Installed capacity of modulation (MW)
Duration bounds	Technical	Minimum/Maximum time of activation once the resource is triggered
Ramping rate	Technical	Time required to reach a targeted level after activation
Lead time	Technical	Duration between sending a triggering signal to the resource and its effective activation
Location	Technical	Grid with which the resource is connected (distribution or transport)
Availability	Socio-tech.	Temporal variations of the available share of installed capacity (Müller and Möst (2018); Verrier (2018))
Number of activation	Social	Maximum number of activation over a predefined period, often the period of a contract. Reflects technical constraints (battery deterioration, nuclear flexibility) or social constraints (DR)
Recovery	Technical	Maximum time between a load reduction and the recovery of the shifted load for load-shifting (mainly for DR, eventually storage)
Cool down	Technical	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	Market	Time gap between contractualization and the sending of an activation signal
Predictability	Market	If the temporal availability at a date is quantified by a random variable, predictability refers to the ability of a market player to know the distribution of this variable
Controllability	Market	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	Market	Service for which it is sold or market on which it is exchanged
Contract	Market	The contract type through which the flexible resource is engaged (long-term, exchangeable...)
Remuneration	Market	Type of settlement (pay-as-bid, pay-as-clear...)

Table 1: Attributes of a DR resource

(2019)), but less relevant for DR as the load can be dropped virtually instantaneously in residential or tertiary appliances and in the considered industrial uses of electricity. Since we model explicit demand response, predictability and controllability are also assumed to be perfect here. All other attributes will be modeled in our bottom-up representation of each DR potential.

2.2. Accounting for stochasticity

Including uncertainty in the power system model is inevitable with the rise of renewables. However, when combined with multistage programming, the basis of power system models implies a heavy computational burden. Thus, it requires particular frameworks in order to provide analysis with both wealthy system descriptions and effects of uncertainty. Wu et al. (2016) and Weber et al. (2021) review these possible frameworks outside of any consideration regarding DR - but all are used in DR studies.

Most simplistic methods consist of point-wise replacement of random variables by associated deterministic values such as their expectation or some drawn value. These models yield deterministic fixed policies, which are optimal only for the chosen realization of the noise term. Deterministic equivalent methods remain widely used in academia and the industry (Weber et al. (2021)).

Robust optimization replaces uncertainty with an uncertainty set so that the derived solution is optimal, considering the worst possible cases of noise realizations. This approach is, therefore, conservative. Dealing with demand response, it is used in (Ferreira et al. (2012)) with the idea to protect the studied individual household of power imbalances from even the worst possible hazard.

Distributionally robust optimization extends this method by optimizing on a so-called ambiguity set of probability distributions for the random variables, thus leading to less conservative policies.

Chance-constrained programming formulates optimization problems with inequality constraints imposing minimum chosen levels for the probabilities of some modeling constraints (e.g., a power balance constraint) to hold. This approach ensures a given level of reliability in the overall satisfaction of a constraint by the derived optimal policy. Regarding DR, chance-constrained programming is used in (Bruninx et al. (2018)) in order to derive a value for the controllability of DR potentials. However, this method requires assumptions on the allowed level of uncertainty.

Stochastic dynamic programming accounts for all possible realization of noise terms on a scenario tree. Thus, it yields an optimal policy (and not a single optimal solution) that adapts to the incoming state of the system and particular realizations of noise. This framework does not limit the solution by a priori statements on noise values or acceptable risk levels. Therefore, it is prioritized in the present work.

However, stochastic dynamic programming becomes intractable when the number of scenarios for the random variables and the state space size grows. Stochastic dual dynamic programming is a method published in (Pereira and Pinto (1991)) that bypasses this issue. It was primarily developed for hydropower scheduling under inflows uncertainty (Pereira and Pinto (1985) or more recently Guan et al. (2018)). But it has become a reference method in the study of power systems facing uncertain renewable production either in operations models (Fatouros et al. (2017), Papavasiliou et al. (2018), Verrier (2018)) or system expansion models (Wu et al. (2016), Lu et al. (2020), Stüber and Odersky (2020)), yet without accounting for demand response (Motta et al. (2024)). After being essentially confined to hydropower-related problems, SDDP is emerging as a relevant solving strategy in more diverse contexts, such as operation planning for dairy farms (Dowson et al. (2019)).

Recourse to SDDP imposes a relatively strict framework (see Section 3.3). It is relevant when dealing with the management of stocks directly affected by uncertainty, thus facing intertemporal opportunity costs. Following the analogy developed in Section 2.2, DR faces such challenges due to the yearly maximum energy limit for load shedding and shifting (stock limitation only captured by a temporal horizon greater than a season), daily residual demand uncertainty and hourly operations (large number of time-steps). Therefore, the choice of SDDP for our DR operation model is relevant. Yet, a SDDP compatible bottom-up description of DR potentials has not been published to the best extent of our knowledge.⁵

3. Model

The modeling framework is detailed, beginning with insights on converting the DR attributes of Section 2.1 into a tractable model. Then, the general model of the power system dispatch is given, and the solution strategy is mentioned.

3.1. Hydropower analogy for demand response

A negative load model of DR underlines the specific technical and social characteristics of the considered DR potential. Since these characteristics exhibit limitations on both the size and the number of load-shedding or shifting events, Verrier (2018) pointed out that DR behaves like hydropower stations and tried to represent some DR attributes through a hydropower analogy. Load-shedding is related to conventional hydropower, whereas load-shifting implies some intertemporal

⁵See also Motta et al. (2024) for a methodological survey on DR modeling and relevance yet lack of implementation of decomposition approaches

aspects, such as shifted load being recovered, making it closer to power-hydro storage.

Regarding load-shedding, a conventional dam with a reservoir of a size reflecting the maximum duration of an event (D), the shedding capacity (K), and the maximum number of events per year (N) seems to suffice. Each load-shedding potential is modeled by one conventional dam in the simple way of Figure 1a. A limited quantity of energy can be removed from demand throughout the year during shedding events. The shed load can't exceed the flexible part A_t of the power demanded by the consumer in a normal situation at time t . The level of this reservoir represents the quantity of energy that can still be shed during the remaining part of the year. It can only decrease as water (i.e., energy) is turbined (i.e., removed from demand or negatively generated).

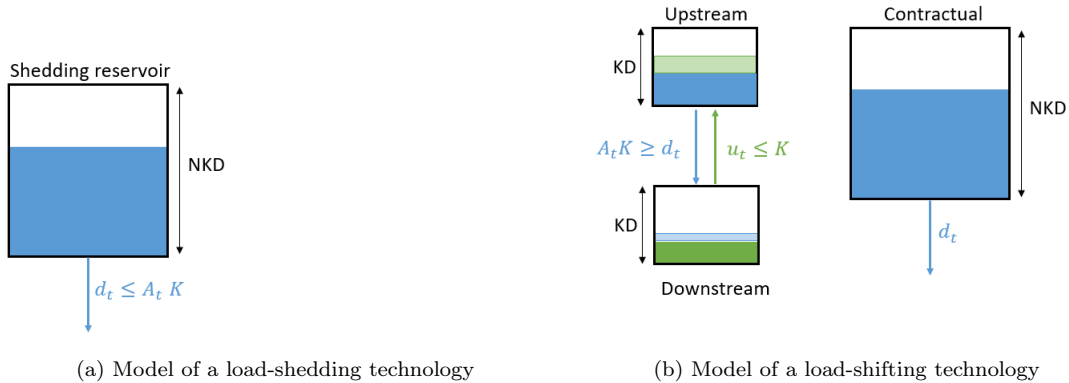


Figure 1: Initial hydropower analogy for demand response

The same analogy with a conventional dam would not be satisfactory as it can't memorize the postponed load that must be balanced. Load-shifting behaves indeed more similarly to hydropower stations equipped with pumping capacity (Figure 1b). Hence, a limited quantity of energy (water) can be postponed (turbined), thus negatively generating this energy from a system perspective. It is afterward balanced (pumped), thus increasing demand. A direct load-shifting / PHS analogy was proposed by Verrier (2018). A reservoir disconnected from the system is also considered to be bigger and serves as a non-binary counter of the shed energy. Once the contractual reservoir is emptied, the technology becomes unavailable for the remainder of the year. It encompasses the attributes of duration, number of events, and equivalent capacity, leaving aside maximum time before the recovery of the shifted energy and the minimum time between two events (downtime).⁶

The model of DR technologies presented here treats them similarly to hydropower stations. This means that the equations describing them are all linear and that the negative load from DR is naturally integrated into the production side of the power balance equation as a linear term. The inclusions in the design of reservoirs of integer parameters, such as the maximum number of activations or the memory of a postponed load to balance in the future, are crucial features of our model. It avoids integer variables in the optimization problem modeling operations of the system while keeping the constraints and objective linear. Moreover, this model explicitly represents DR deposits as stocks of flexibility that can be given a usage value in link with the abundant literature

⁶Such parameters can still be included by extending the hydropower analogy to have several downstream rolling reservoirs of size corresponding to one hour of turbinning at full capacity and rolling upstream reservoirs for minimum downtime. See Appendix A for a graphical presentation of this extended hydropower analogy for DR. For clarity, as it does not fundamentally change the modeling spirit of the present paper, these refinements are left out here.

dealing with the so-called water value in hydro-thermal scheduling (e.g., Pereira and Pinto (1991), Guan et al. (2018) or Diniz et al. (2020)).

3.2. Energy-only market model

3.2.1. Overview

We model a wholesale energy-only market for electricity with DR potentials aggregated by power use in perfect competition. As an energy-only market, resources are not paid for reservation or installed capacity. The market has to be balanced, and generation is limited by energy and capacity constraints for traditional supply means and by DR constraints derived from the analogy of the previous section.

We are dealing with DR in power markets. Therefore, we make the hypothesis that all DRs participating in markets do it directly or through an aggregator, which has no controllability issue with its DR pool. Namely, the DR market actor does not face uncertainty in the availability of DR potentials once it bids.

The model is copperplate. We aggregate all generations and loads as representative units. We account for interconnections, with major interconnections being endogenous to the model, whereas small capacity/less-used ones are incorporated as exogenous parameters.

3.2.2. Model

The objective is to minimize the expected system's total operation cost over a year without perfect foresight, accounting for possible supply-demand disequilibrium through slack variables (denoted μ) valued at a value of lost load (*VoLL*). Apart from the demand response part, the model is a classic dispatch problem with p_g defining traditional generations, d_j, u_j demand response decisions to curtail and recover flexible loads, *imp*, *exp* the interconnections' decisions and C denoting the constant variable costs. The slack variables μ_j^s represent the lost load in the recovery process for load-shifting assets.

$$\min_{p_1, d_1, u_1, imp_1, exp_1} IC_1 + \mathbb{E}_{\xi_2} \left[\min_{p_2, d_2, u_2, imp_2, exp_2} IC_2 + \mathbb{E}_{\xi_3} \left[\dots + \mathbb{E}_{\xi_T} \left[\min_{p_T, d_T, u_T, imp_T, exp_T} IC_T \right] \right] \right] \quad (1)$$

with non-anticipativity only denoted through the element of the stochastic process $(\xi)_t$ revealed at the corresponding stage and with the immediate cost

$$IC_t = \sum_{t=1}^T \sum_{g=1}^G C_g p_{gt} + C_{ch} d_t^{ch} + C_{ph} (d_t^{ph} + u_t^{ph}) + \sum_{e=1}^E C_e imp_{et} + \sum_{i=1}^I C_i d_{it} + \sum_{j=1}^J C_j d_{jt} + VoLL \left(\mu_t + \sum_{j=1}^J \mu_{jt}^s \right) + \alpha_{jt}$$

From a DR aggregator's point of view, these costs account for both actual technical costs and compensation for curtailed final consumers. Hence, they are modeled as volumetric and depending on the potential - compensation for the curtailment of an industrial process is related to the prevented production, while compensation for residential appliances should be more linked with comfort or basic needs. Choosing these costs to be positive can be justified by empirical studies finding a negative willingness to pay for the control of electrical usage, such as Richter and Pollitt (2018) or Broberg and Persson (2016).

This optimization is made under several classical constraints on generation and loads. First, a power balance should be maintained at all times, which is expressed through Constraint (2).

$$\forall t, \sum_{g=1}^G p_{gt} + d_t^{ch} + d_t^{ph} + \sum_{e=1}^E imp_{et} + NE_t + \sum_{i=1}^I d_{it} + \sum_{j=1}^J d_{jt} + \mu_t = L_t(\xi_q) + \sum_{j=1}^J u_{jt} + \sum_{e=1}^E exp_{et} + u_t^{ph} \quad (2)$$

Random variable.. Stochasticity is accounted for in the model through residual demand $L_t(\xi_q)$, the total demand before any DR event minus the output of non-dispatchable renewables - wind, solar and run-of-water. The residual demand at all 24 hours of a day is observed at the beginning of this day, meaning decisions for this day are made with perfect information on this day but no knowledge of future days.

Two major assumptions are taken on the random variable. On the one hand, it is supposed independent between stages. This is not true for real residual demand. However, some tricks exist to model the time dependency of residual demand while keeping time independence of the noise term: scenarios or linear models describing residual demand such as AR(n) ones (Fatouros et al. (2017)). Here, we rely on the first option, drawing scenarios that convey themselves the necessary time dependency of residual demand, while the picking of one scenario may remain time independent, following Verrier (2018) for example. Thus, the second assumption is that the space of possible values for our random variable is supposed to be finite, with only several scenarios of residual demand being allowed. This number may, however, be extremely big as it grows exponentially with the number of scenarios at each stage.

Capacity limits K , are imposed on all productions and interconnections, traditional generations' capacity being affected by an exogenous availability factor A_g . Water balance constraints are provided for hydropower stations with reservoir levels denoted by X^{ch} , X^{ph} . for reservoir hydropower and pumped hydro storages (which possess an upstream and a downstream reservoir), respectively.

$$\forall g, t, 0 \leq p_{gt} \leq A_{gt} K_g \quad (3)$$

$$\forall e, t, 0 \leq imp_{et}, exp_{et}, t \leq K_e \quad (4)$$

$$\forall t, 0 \leq d_t^{ch} \leq \eta K_{ch} \quad (5)$$

$$\forall t, X_t^{ch} = X_{t-1}^{ch} - d_t^{ch} \text{ with } X_0^{ch} \text{ given} \quad (6)$$

$$\forall t, 0 \leq d_t^{ph} \leq \eta K_{ph} \quad (7)$$

$$\forall t, 0 \leq u_t^{ph} \leq K_{ph}/\eta \quad (8)$$

$$\forall t, X_t^{phu} = X_{t-1}^{phu} - d_t^{ph} + u_t^{ph} \text{ with } X_0^{phu} \text{ given} \quad (9)$$

$$\forall t, X_t^{phd} = X_{t-1}^{phd} + d_t^{ph} - u_t^{ph} \text{ with } X_0^{phd} = 0. \quad (10)$$

Demand response.. Finally, constraints on DR are built according to modeling choices mentioned in Section 2.1. Making profit of the hydropower analogy of Section 3.1, we model capacity limits on shedding/shifting decisions (11,12,13), availability of the flexibility of each power use (11,12), maximum duration of a DR event (14), and a maximum amount of shifted/shed energy per year contracted with end users (15,16). Thus, we give a detailed bottom-up description of each flexible power use. Notations are directly related to that for hydropower according to the analogy developed in the previous section.

$$\forall i, t, 0 \leq d_{it} \leq A_{it}K_i \quad (11)$$

$$\forall j, t, 0 \leq d_{jt} \leq A_{jt}K_j \quad (12)$$

$$\forall j, t, 0 \leq u_{jt} \leq K_j \quad (13)$$

$$\forall j, t, 0 \leq X_{jt}^{shift} = X_{jt-1}^{shift} - d_{jt} + u_{jt} \leq K_j D_j = X_{j0}^{shift} \quad (14)$$

$$\forall j, t, 0 \leq X_{jt}^{contr} = X_{jt-1}^{contr} - d_{jt} \text{ with } X_{j0}^{contr} = N_j K_j D_j \quad (15)$$

$$\forall i, t, 0 \leq X_{it}^{contr} = X_{it-1}^{contr} - d_{it} \text{ with } X_{i0}^{shed} = N_i K_i D_i \quad (16)$$

Note that the double inequality around X_{jt}^{shift} in Constraint (14) means that a load reduction event may not concern more energy than what can be reduced at maximum capacity during D_j hours and that a load increase event may not concern more energy than what can be increased at maximum capacity during D_j hours. Hence, taking up the fruitful power-hydro storage analogy for load-shifting developed in Verrier (2018), Constraint (14) models both an upstream reservoir with storage $K_j D_j$ through the positivity inequality and a downstream reservoir with similar storage through the maximum size inequality.

The present model describes the operations of DR potentials in a wholesale energy-only perfect market. The potentials are described in a bottom-up manner. Constraints (11) to (16) are indeed directly linked with the most crucial DR attributes listed in Section 2.2.

Yet, we do not forget that the potentials and individual consumptions of one type are aggregated to enter the market: aggregator has access to multiple end-users with the same power use. Consequently, the aggregator can activate simultaneously a load reduction and a load increase for a given load shifting potential, which is also possible in our model. Practically, a non-convex constraint of type $u \times d = 0$ is avoided.

3.3. Solution strategy

3.3.1. Dynamic programming expression and resolution

Problem (1) under constraints (2) to (16) belongs to the class of stochastic dynamic programming as the noise term ξ is supposed to be independent between each period P . This multistage stochastic linear program with linear constraints may thus be represented as a stochastic dynamic program with T/P stages and each stage k being described as

$$\min_{y_k \in \mathcal{U}(x_{k-1}, \xi_k), x_k = F_k(x_{k-1})} IC_k(y_k, x_k) + V_{k+1}(x_k, (\xi)_{l \geq k+1}) \quad (17)$$

with $\mathcal{U}(x_{k-1}, \xi_k)$ a convex, non-empty⁷ set defined by aforementioned constraints on decision variables, F_k a transition function defined by the above state transition equations, IC_k an immediate cost corresponding to the sum in the objective function (1) truncated for $t \in \{k, \dots, k + P - 1\}$. The function V_{k+1} is our Bellman function, representing the cost-to-go to temporal horizon T/P beginning a trajectory at state x_k .

Problem (1) under Constraints (2) to (16) fits the assumptions of SDDP. Notably, it guarantees relatively complete recourse by adding slack variables to Constraint (2), penalized at the value of lost load.

⁷This property means that there always exist possible decisions whatever the in-coming state of the system or the realization of the stochastic variable may be. It is also called relatively complete recourse.

Note that V_{k+1} is the expected cost-to-go as it accounts for all possible future values of the random variable ξ . A coherent risk measure other than the expectation could have been chosen in order to model, e.g., a risk-averse planner. Our choice means that all residual demand scenarios are weighted the same in the eyes of market players.

The wholesale energy-only market model encompasses numerous state variables and time steps. Hence, as a dynamic program, its resolution is computationally tedious. Fortunately, the convexity and time-independence of the stochastic variable hypothesis enables recourse to the efficient SDDP class of solving methods, provided that the stochastic variable is realized in a finite space.

3.3.2. SDDP

A succinct description of the class of algorithms coined SDDP is given here, with more details on the algorithm termination in Appendix B. More technical material may be found in Shapiro (2011), or for a more practical approach in the documentation Dowson and Kapelevich (2021). This section relies also on Leclère (2017). The employed implementation for our application is based on Dowson and Kapelevich (2021).

SDDP solves large-scale multistage stochastic optimization problems under a specific hypothesis: state and control variables are continuous (actually, SDDP also works with integer variables but requires some type of convex relaxation, which is costly and will be avoided here); these variables must belong to convex compact sets of finite dimensional spaces, the stage objective functions must be convex, and dynamics linear. Most of all, the noise must take values in a finite set and be a white noise, i.e., noises of two distinct stages are independent. The latter hypothesis enables it to fit into a dynamic programming framework. Note that, it can always be obtained at the cost of expanding the dimension of the state variable (Shapiro (2011)).

Under these hypotheses, SDDP yields an optimal solution of a dynamic programming problem with piece-wise linear Bellman functions approximating the Bellman functions of the true problem. Estimating these linear forms at some stage and some state relies on the computation of the dual variable associated with a slightly modified subproblem, determining the true Bellman function at this stage.

Convergence towards the optimal policy is guaranteed (Shapiro (2011)), yet the convergence rate remains an open question. Hence, a termination criterion has to be designed from the natural bounds of the optimal policy yielded by the procedure. We use the criterion developed by Shapiro (2011). Details on this rule and how it compares with others are given in Appendix B.

Finally, SDDP avoids the complete enumeration of all possible scenarios for the noise, which alleviates a bounding computational constraint in the scenario-based method. However, note that it does not prevent the curse of dimensionality arising with high dimensional state variables (which increases when the state space has been expanded to fit the white noise assumption). This source of complexity affects the resolution of all subproblems. In a sense, SDDP handles better stochasticity than its counterpart but is still bounded by curses inherent to a dynamic programming framework.

4. Case study: 2023 North Western Europe

As a short illustration of its usability, the previous general model is applied to 2023 North Western Europe (NWE) – Belgium, France, Germany, Luxembourg and the Netherlands– marked by increasing CO₂ prices, very high prices of gas and a non-negligible share of variable renewables. Some details on calibration and the envisioned scenarios are given in the following paragraph. Then we analyze the results of our simulations.

The wholesale energy-only market chosen for this case study is the day-ahead hourly market, which gathers indeed the most players while facing supply uncertainty from renewables and demand variation at an hourly granularity. Moreover, this market is being made increasingly accessible to active consumers, aggregated or not, in the European Union.⁸ This case study seeks to demonstrate possible uses of the presented DR model. As it has been shown in the literature (e.g., Biegel et al. (2014)), the day-ahead market is not the sole or even the primary source of revenue for DR aggregators. Future work is set to analyze various revenue streams for DR and combine them in the present model.

4.1. Context

The context of 2023 NWE amid a gas crisis, which translated into a power crisis, presents the unique combination of gas being less competitive than other dirtier fuels such as lignite in systems still highly relying on carbonized production means, risks of power shortages due to unplanned outages and increasing share of variable renewables.

Coal and lignite plants are still competitive due to high gas prices, even though the carbon price tends to move them out of the market. Thermal means are subject to a carbon price set at 80€/tCO₂ in this study. Their unitary costs take it into account along with their average carbon content, their average efficiency⁹ and their average fuel price.¹⁰ The merit order of the thermal technologies is profoundly modified when going from "low" gas prices pre-dating the current surge to average 2022 gas prices.

In a context of high gas prices, some of NWE's neighbors, such as the UK and, to a lesser extent, Spain, have access to cheaper gas, already saturate their internal use of gas, and may use power interconnections with NWE to export this cheaper gas transformed into power and benefit from this price difference. Figure 2 shows the change in power exchange habits between France and the UK. Scandinavian countries also produce cheap electricity thanks to massive hydropower capacities. They are also quite well interconnected with NWE.

The price at which power is exchanged in these interconnections - constant in our model - reflects the 2022/2023 situation where the UK and Spain tend to export gas-based power at a lower price than that of internal CCGT or GT production, and Scandinavia relies on hydropower surplus.

Austria, Poland, and Switzerland are the three countries most connected to NWE. However, exchanges are often one-way and no particularity of generation mix or gas prices would justify a modification of the traditional pattern of exchanges between NWE and these countries. So we chose to model these exchanges as fixed parameters, not decision variables.

4.2. Calibration and data

Demand. Residual demand encompasses aggregated non-flexible electricity demand and the production of solar panels, wind turbines and run-of-water hydroelectric means. Data is taken from ENTSO-E for all NWE countries from years 2016 to 2021, excluding 2020 due to the effects of Covid-19 on power demand. Twenty residual demand scenarios are built for each day of the modeled year as in Verrier (2018) from this historical data, resulting 20³⁶⁵ possible years of residual demand. Examples of such scenarios are displayed in Appendix C.1 (Figure C.7).

⁸See Directive 2019/944, Regulation 2019/943 or Commission (2023)

⁹DIW data

¹⁰Average of ARA prices in 2022 T2 for coal and gas.

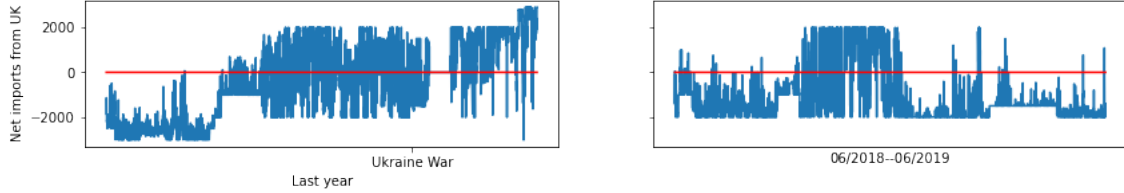


Figure 2: French net power imports from the UK during the last year marked by increased gas prices in NWE above all since the beginning of the Ukraine war and from June 2017 to June 2018, a more representative year. France was structurally an exporter of power during spring and, since the high gas prices period, has become an importer. Data: ENTSO-E

Thermal and nuclear means.. Nuclear and thermal productions are aggregated respectively into one representative nuclear power plant, four representative thermal power plants, a peak gas mean (gas turbine), a base gas mean (CCGT plant), a lignite plant as it's still important in Germany and a traditional coal plant. Their capacities sum up to the installed capacities of the modeled means in the underlying real system (ENTSO-E data). Installed capacities and marginal costs of each technology used in the following simulations are displayed in Appendix C.1. Two sets of costs are chosen, LP and HP, reflecting low and high fossil fuel prices, respectively.

Ramping time is neglected. This means that the modeled system is more responsive than the real one. This would a priori reduce the recourse to DR technologies but we will see that, even in this pessimistic context, a need for demand-side flexibility still exists. Thermal means are considered always available at full capacity, whereas the installed nuclear capacity is weighted by an availability factor $A_{gt} \in [0, 1]$. It is calibrated on 2022 data from the French TSO to reflect the availability shortage which occurred at the time and fostered the energy crisis. For example, a lot of maintenance on nuclear power plants takes place during the summer rendering up to 40% of the installed capacity unavailable. Note that, in 2023, all German nuclear plants will have been decommissioned.

Hydroelectric production.. Three main types of hydroelectric means exist run-of-water, which is not controllable and included in the residual demand in our model; conventional hydroelectricity, which can turbine water from some reservoir in a controlled way; and hydroelectricity with pumping capacity, which can additionally store energy by pumping water. A representative station is modeled for each of the last two types. Generation is done at unitary constant costs, pumping is supposed free.

A traditional focus point of hydroelectric means modeling is to account for the random filling of water reservoirs by the meteorological water cycle. It requires the construction of representative inflow scenarios, generally obtained from historical data at the station level and the addition of supplementary state variables i.e. a significant increase in computational effort. In our copperplate model, we could not assess the diversity of climates faced by the real hydropower stations since we only model a representative dam. Moreover, our objective is to model the operations of DR deposits, not a perfect hydropower scheduling. Therefore, the filling of the reservoir is not modeled explicitly and our representative stations are given a fixed and finite reservoir size. We choose to set these sizes to the average energy production of each mean -conventional or PHS- in 2016-2019. As they are the first two means to be called, this equates to reproducing the last year's total consumption. The fact that water in hydropower stations should not know a period of scarcity means that the marginal cost of turbinning water through these stations does not include an opportunity cost and renders our model rather optimistic about hydroelectricity production. However, this eventual flaw will be present in our analysis of systems with and without DR, thus not impacting the comparison.

Demand response. DR is included according to the framework developed in Section 2.2. Three load-shedding potentials are considered, all industrial: steel-making with electric furnaces, the electrolysis step of aluminum production and chlorine electrolysis. Two industrial load-shifting deposits include cement mills and paper and pulp production. Load-shifting in the tertiary sector is aggregated in two deposits: tertiary cooling (cold storage, air conditioning) and tertiary heating (space and water heaters). The same division applies to the residential sector with residential cooling (AC) and heating (space and water heaters).

Equivalent installed capacities are derived from sectoral/grey sources for industrial loads (Atmaca and Atmaca (2016), CNI (2021), EuroChlor (2023), COPACEL (2023), Chimie and de France (2023)) and tertiary or residential loads (ADEME (2016), ADEME (2021)). Methods for deriving availability profiles and heating/cooling days for each country are taken from (Gils (2014)). Maximum number of DR events and recovery limits are arbitrary decisions from the authors, informed notably by Gils (2014), RTE (2023) or Leducq et al. (2019). All calibration data for DR is displayed in Appendix C.2.

4.3. Results

The model calibrated as stated above is run 10 times so that our SDDP model yields optimal policies when marginal costs of thermal means are high (HP) or low (LP) and when the system has access to 0, 25, 50, 75 or 100% of the tertiary and residential DR potentials. An optimal policy in a given setting is then tested against 500 simulations of a full year of operation in this setting. Results are analyzed from a system point of view and a DR operator perspective.

4.3.1. System effects of DR

Our simulations confirm a property often given to DR in the literature: its ability to reduce total operation costs of the system by smoothing over time the demand curve and shaving peaks. The observed distributions of operation costs are indeed drifted left as DR is integrated into the system in both fuel price scenarios (Figure 3). The reduction is, however, of a few percent and seems to be non-linearly related to the level of tertiary and residential DR integration in both fuel price scenarios. In Figure 4 (A), the marginal effect of DR capacity in total cost reduction seems to decrease with the level of penetration of DR, whatever the gas prices are (i.e., whatever the upper part of the merit order of generation looks like). Systems costs are reduced in our framework either by reduced imbalances or by decreased recourse to peak productions.

The average (over the simulations) amount of emissions of the system during the year reflects the use of thermal means. As DR should compete with peak means at lower costs, it should move a part of these generations out of the market and hence reduce systems costs but also emissions since polluting thermal means are the most costly.

In Figure 4 (B), it appears that emissions follow such a pattern of decrease but with lesser intensity than cost decrease, especially in the case of high gas prices. The lower decrease in emissions in high gas prices should have been expected as, in such a scenario, gas-fueled plants have higher variable costs than coal-fueled plants and thus form the peak generations. They also have higher capacity so that the introduction of DR only causes some gas plants to be priced out of the market, but not all gas plants so that the generation from coal remains largely unaffected by DR operations. Since gas plants are significantly lesser emitters than their coal counterpart, the decrease in emission is thus lower when peak plants are gas-fueled. This is in fact simply a merit order effect.

The more general observation of cost decrease being higher than emissions decrease whatever gas prices may be explainable either by demand response characteristics or by an end-of-merit-order effect. Regarding DR characteristics, the previous analysis holds indeed in the load reduction phase

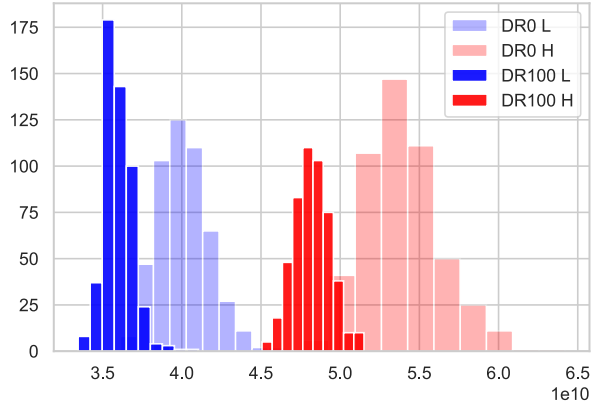


Figure 3: Total operation costs distributions over 500 simulations of systems with and without DR at full capacity, with low (L) or high (H) fuel prices.

of a DR event, it may hold no more in the mandatory load recovery phase if residual demand during this phase is still high. Should that happen, peak means would be called back in order to cover this second phase of DR events. Thus, recovery constraints may be too harsh for DR to bridge between peak and off-peak hours in certain periods of the year. Therefore a trade-off of emissions/imbalances may appear when DR is introduced depending on the merit order it integrates.

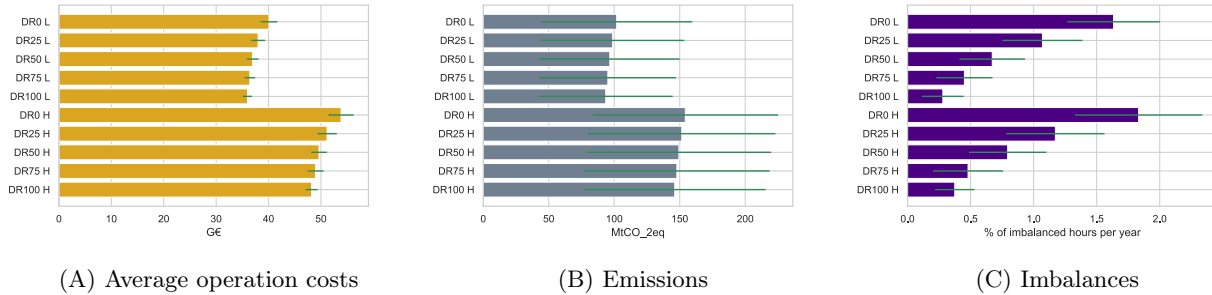


Figure 4: Performance of the simulated systems in low fuel prices (first five bars) and high fuel prices case (last five bars). Average costs are expressed in G€, emissions in MtCO_2eq and imbalances in percentage of hours in a year that lose load (i.e., slack variables of Section 3.2 are non-null).

An end-of-merit-order effect is also plausible, that is total system costs are also affected by the number of imbalanced hours as such imbalances are valued at the value of lost load, i.e. 3000 €/MWh here which is one order of magnitude higher than the most expensive generation. A decrease in the average number of such hours is found, independently of the gas prices. Figure 4 (C) displays the percentage of hours of the year experimenting imbalances depending on the gas prices and residential and tertiary DR integration. If the effect on diffuse demand response on imbalances is approximated to a linear effect, which seems reasonable according to Figure 4 (C), an increase of one percent in diffuse DR capacity reduces by 1.1 hour the number of imbalanced hours. With high gas prices, since emissions variations show that costly coal generation is not priced out of the market as it is no longer the peak generation, the total system cost reduction may be primarily driven by the decrease in imbalance rather than the suppression of expensive generations.

4.3.2. DR usage and revenues

Apart from system performance, the introduction of DR in the simulated power systems can be analyzed potential by potential, one of the main features of our model. Two aspects are crucial: the availability (timing constraint) and relevance (economic constraint) of demand response at times of need for the system and the ability of DR to generate revenues from its operations.

Availability and usage of DR. . The relevance of demand response potential vis-à-vis system status is indicated by the possibility of activating them in times of particularly high residual demand - for load reduction - or low residual demand - for load increase. As a metric to evaluate the system relevance of each demand response potential, we compute the average share of load reductions/increases during the 20% highest/lowest residual demand hours over the total load reduction/increase (see Figure 5 for the case of low gas prices and maximum DR capacity). Note that such share is considered null either because there is no activation during the hours of interest (it is the case for chlorine in Figure 5) or because the potential is never activated during the year (aluminum and steel in our example).

PHS provides an interesting benchmark for DR potentials. PHS and load-shifting are indeed two flexibility means that provide both downward and upward services while being limited by energy constraints. That is why load-shifting was modeled in Section 3 through a hydropower analogy. Conversely, PHS could be considered as a load-shifting potential with low variable cost, high installed capacity and a flat, always available, load profile. From this perspective, a load-shifting potential outperforming the relevance metric of PHS implies good relevance for the system.

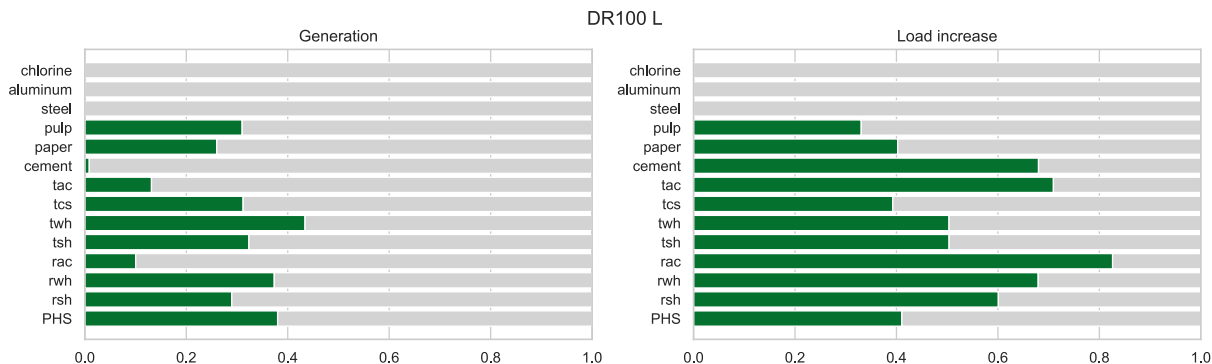


Figure 5: Left: Share of load reduction (resp. turbinning) happening during the hours of top 20% residual demand over all load reductions during the year. Right: Share of load increase (resp. pumping) happening during the hours of bottom 20% residual demand overall load increases during the year. Average on 500 simulations of the system with low gas prices and maximum DR capacity. The bottom lines are decisions of turbinning/pumping for power-hydro storage. [Example: On average, around 25% of load reductions from the paper industry happen during the hours when residual demand is among the 20% highest residual demand of the year. Around 40% of load increases from paper production happen during the 20% lowest residual demand hours.]

Results among our simulations with different shares of DR and higher gas prices are quite similar to that of Figure 5: industrial load-shedding appears irrelevant to the system as they are almost never activated (see also Figure Figure D.8), most load-shifting potentials are outperformed by PHS in terms of load reduction except tertiary and residential water heating, but most load-shifting potentials from all sectors are by far more accurately present during valley hours in order to increase load. A notable result deals with residential and tertiary air conditioning, as these potentials contribute poorly to the mitigation of peak residual demand but are strong load increaser during valleys of residual demand. This result is driven not by economic features such as the variable costs of these potentials but rather by comfort/physical features as AC is primarily used during summer

making it available only during this period of relatively low residual demand. This can also be seen on Figures D.11 and D.12 which depict the average operations of these potentials for each hour of each day of the year: AC is primarily decreased around 7 p.m. and increased around 10 a.m. during summer weeks.

Moreover, Figures D.8 to D.12 display that there seems to be no strategic timing to activate demand response at the scale of the year as load reductions are spread quite smoothly among hours when the potential is available and the system can be expected to experience high prices, meaning that the calibrated maximal number of activation is not binding in our simulations. This goes with the notable exception of the load-shedding from chlorine electrolysis, the only load-shedding potential to be economically relevant, which depletes during the peaking hours of the very end of the year, while not appearing during the other tense hours.

Finally, the general pattern of PHS operations (Figure D.9) seems to be respected by most load-shifting potentials *provided they are available*. This induces competition between PHS and the available potentials, highlighted by the reduction of total PHS generation between the DR100 and DR0 cases (Figure D.9). The competition is clear for potentials with high availability such as that from the paper and pulp industry (see the exact same pattern of operation as PHS in Figure D.10). However, the competition turns out more as a complementarity for potentials available mostly during hours when PHS operations would have been less beneficial (i.e., bridging not-so-peaking hours with not-so-empty hours). They take indeed a part of the production of PHS during these hours saving PHS energy capacities for more "intense" PHS operations during interesting hours. Cement mills (Figure D.10)), tertiary and residential AC (Figures D.11, D.12), residential water and space heating (Figure D.12) belong to such complementary DR potentials.

Operation revenues of DR. Moving from system relevance, each DR potential can also be seen as a private asset playing on the energy market in order to generate revenues, independently of system needs for flexibility. Market revenues R_j of a single DR potential j over the whole year may be computed ex-post from the point of view of an operator of this sole potential as

$$R_j = \sum_{t=1}^T (\lambda_t - C_j) d_{jt} - \begin{cases} \sum_{t=1}^T \lambda_t u_{jt} & \text{if load-shifting} \\ 0 & \text{if load-shedding} \end{cases}$$

where λ_t is the market price at time t , computed as the dual variable of Constraint (2). Distributions of market revenues for different mixes and DR integration are computed from 500 simulations of the decisions determined by the optimal policy facing a random residual demand year and are displayed in Appendix E.

Among industrial load-shedding potentials (Figure E.13), we already saw that only chlorine is activated, the other having therefore null revenues from energy market operations. Chlorine generates revenues with a positive distribution. This distribution remains globally unchanged as more diffuse DR is incorporated in the system suggesting no competition between chlorine electrolysis load shedding and diffuse DR. Higher gas prices provide slightly higher revenues which is well explained by the increase in peak prices but not in base prices it entails. Note that private DR actors would therefore benefit from higher market prices during peak times and from a system with more greenhouse gas emissions, which goes against more independent/system operator's interests.

Industrial load-shifting potentials (Figure E.14) display similar features of separation between high and low gas price regimes. They are all active and profitable in all cases and simulations, but on different scales as paper and pulp potentials are between 2 and 4 times more profitable on average than the cement potential (but with higher variance nonetheless) despite relatively similar installed capacities. The difference hence comes from the differing availabilities of these potentials.

Tertiary load-shifting potentials (Figure E.15) yields also higher revenues when peak market prices are higher (high gas prices). With their capacity being increased, in both gas price regimes, all these potentials show a saturation in revenues as revenues obtained grow then decrease with capacity, the turning point being somewhere between 75% and 100% of the maximum potential. Space heating and water heating are significantly more profitable than tertiary AC which is to be linked to remarks made above on the availability during the summer only of this potential. Tertiary AC and tertiary cold storage, especially with low gas prices, may even be non-profitable in some simulated years, even though their revenue distribution belongs mostly to the positive part of the graph.

Residential load-shifting potentials (Figure E.16) also present a saturation. Residential AC has a higher chance of being non-profitable than any other DR potential, yet we saw that it played an important system role in compensating for very low residual demand. Residential water heating appears as the more profitable DR potential, but it displays saturation for lower levels of integration (between 25 and 50% of the maximum potential) and greater revenue variance than any other DR means.

Globally, diffuse demand response may cannibalize itself as some of its potentials are activated during the same hours, and the same range of prices and create revenues from the same variability of the residual demand. Once this variability is absorbed, any new MW in a diffuse DR potential decreases the revenue caught by each MW of DR of the same type. However, as this happens for massive integration of DR in the system, such an effect can be neglected for the most part of DR deployment as diffuse DR levels in North Western Europe are low compared to the cannibalization threshold.

Finally, the difference in revenues among potentials and the decrease in revenue of diffuse DR in case of significant integration would play against the system relevance of the same potentials. Hence, the question of economic incentives for investing in and operating diffuse demand response should be investigated in detail in order to mitigate the possible misalignment of private and system interests we highlight here.

5. Discussion

Future renewables-based power systems are in great need of flexibility. Demand response is seen by academia, industrials and regulators as one of the most promising options for providing flexibility in the next decade. Yet, the effects of demand response on power systems and markets, in terms of power prices or competition with other flexibility resources, remain insufficiently studied to ensure that its deployment is safe and swift. Its main features also have to be accounted for in large-scale models as they greatly influence the impacts of a DR potential on power systems and the revenues it is able to capture by limiting its possible operations.

In the long run, only the correspondence between market product attributes and technical features of a flexible resource guarantees that the latter is properly valued in the different power markets. This correspondence reflects the power system's ability to efficiently procure flexible resources at the right time and on sufficient levels. Establishing adequacy is a hot policy topic (Kerscher and Arboleya (2022)), notably in Europe through reflections on future market design (Commission (2023)). The present paper presents a model giving insights on such adequacy as it can be adapted to various mixes or markets while keeping a relevant description of DR resources.

This paper proposes a bottom-up model for the operations of demand response in power markets during a full year. Building from flexibility attributes pointed out as crucial by the literature,

the model bridges demand response as flexibility provider modeling and power system operation planning under uncertainty, which was still too scarce in the literature yet crucial for the analysis of demand response’s contributions in modern power systems Motta et al. (2024). As such, it is designed to be compatible with a powerful method for solving multistage stochastic convex-linear optimization problems, SDDP. This resolution method is chosen in order to account for stochasticity in the model while allowing for numerous state variables describing DR attributes.

Model features are explained through a hydropower analogy in reference to previous DR models, to DR and hydropower’s common nature of flexibility means, and to historical applications of stochastic programming in power systems. This model’s point is the study of modern and future power systems encompassing more intermittent renewable energy sources, storage capacities and demand-side management.

As, to the best extent of our knowledge, no bottom-up model of DR in an SDDP framework exists, a concise review of the method is provided. We highlight its ability to handle large sets of accessible values for random variables at each stage because the complexity of the method grows only with the sum on all stages of the size of these sets. Traditional scenario-based approaches have growing complexity with the product of these sizes. SDDP has been historically designed for (water) stock management problems. Opportunity costs¹¹ of depleting these stocks at some stage, given the state of the system, are natural outputs of the method. As our hydropower analogy underlines, these outputs are also relevant for other flexibility means, such as DR, and the present model enables their computation.

A short application of the model is proposed, focusing with crude details on a simplified day-ahead market for North Western Europe under particular circumstances of high gas prices and competitive use of power interconnections by neighboring countries. It follows that DR has multifaceted impacts on power systems: while always leading to a decrease in total operation costs, system emissions or imbalances, technical or social constraints of DR potentials may lead to equivocal effects on the market revenues of DR depending on the specific pre-existing merit order. Moreover, a cannibalization effect is highlighted, with diffuse DR displaying decreased benefits as its capacity rises above some (high) threshold.

A single DR potential may not be systematically beneficial in the simulated scenarios. On the contrary, the system benefits systematically from the operations of this potential in terms of total operation cost reductions. Therefore, a misalignment between system operators and market revenues of operators with a single DR potential may arise in the present case study.

Finally, a natural extension of the model is its spatial disaggregation at the transmission level or to account for the location of DR resources in the system. Building from usual linear approximations of Kirchhoff’s laws, e.g., with power transfer distribution factors, our copper-plate model transforms easily to an optimal power flow model only through some additional linear constraints and decision variables. This type of model would be useful when dealing with the value of demand response as a way to defer network investments.

One of the main limitations of our model, as stated here, is that it captures only one stream of revenue for demand-side flexibility. Thus not all attributes of DR as a flexibility source are modeled and valued, hindering our analysis of DR deployment in power systems. Therefore, future research may seek to integrate additional markets, such as intraday ones or reservation payments in the model for DR, which may be exchanged in reserve auctions or operated directly on energy markets

¹¹In fact, approximations of these costs with controlled quality.

if not reserved.

Finally, the modeling framework presented in this paper can be easily adapted to assess other types of values of demand response, such that from the point of view of a private price-taker aggregator (here, the stochastic variables would be the market clearing prices) or, even, test the effect of demand response on investment decisions under uncertainty. For example, one could add an initial investment stage in supply-side flexibilities and softly set a yearly imbalance target in energy (e.g., a convex penalization of the gap to target in the last solving step), the whole model still being in line with the SDDP assumptions - and notably the relatively complete recourse. Such avenues of modeling are testimonies of the multiple variations our modeling approach allows.

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Appendix A. Extension of the hydropower analogy

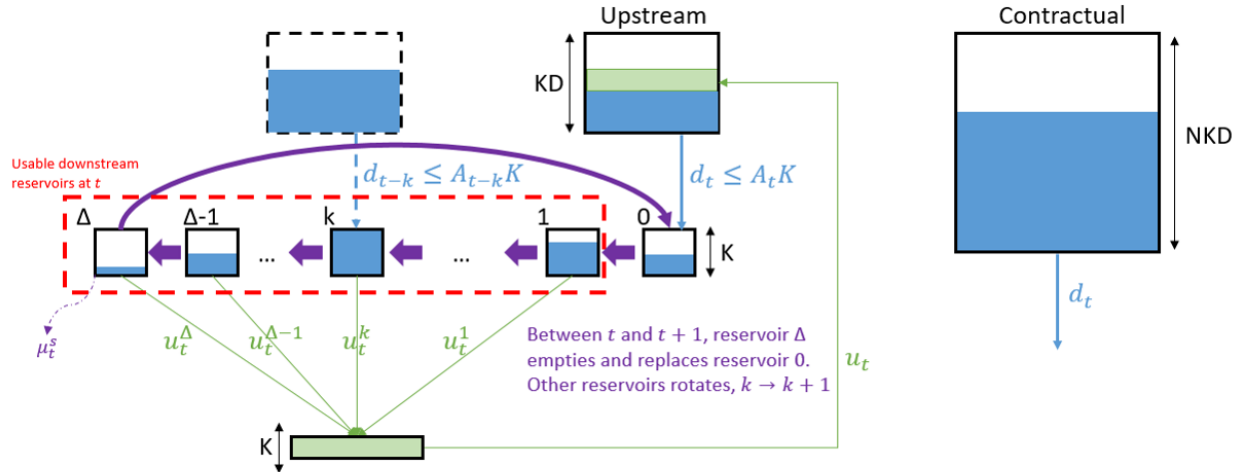


Figure A.6: Extended hydropower analogy to include the time limit for load recovery Δ . To include a minimum downtime ν , a set of $\nu + 1$ rolling upstream reservoirs of size the asset capacity should be added similarly. Note that the model of DR remains devoid of binary variables and linear; hence, it is in line with our solving strategy for the system's scale dispatch problem.

Appendix B. Stochastic Dual Dynamic Programming

Let's consider an archetypal problem solvable with SDDP, with finite horizon T yielding some decision rule π :

$$\begin{aligned} & \min_{\pi} \mathbb{E} \left[\sum_{t=0}^{T-1} C_t(X_t, U_t, \mathbf{W}_t) + K(X_T) \right] \\ \text{s. t. } & X_{t+1} = f_t(X_t, U_t, W_t) \\ & U_t = \pi_t(X_t, W_t) \end{aligned} \quad (\text{B.1})$$

where C_t is an instantaneous convex cost, K a convex final cost, $X_t \in \mathbb{X}$ a state variable at stage t , f_t the linear state transition dynamic from stage t to $t + 1$, π_t the decision rule at stage t , $U_t \in \mathbb{U}$ the decision(s) taken at t and \mathbf{W}_t the random variable representing some noise existing between stage t and stage $t + 1$ (excluded) with values in the finite set \mathbb{W}_t . Note that, if \mathbb{W}_t is not finite, it may be possible to reduce it to a finite set by methods such as sample average approximation. In general, it seems reasonable to enumerate \mathbb{W}_t – which is done in SDDP – but not the whole scenario tree $\mathbb{W}_1 \times \dots \times \mathbb{W}_T$ – which is not done in SDDP but would if one wanted to discretize the whole state space. The process $(\mathbf{W}_t)_{t \in \{1, \dots, T\}}$ is supposed to be a white noise so that there is stage-wise independence. Sets \mathbb{X} et \mathbb{U} are compact. Problem 1 under Constraints (2) to (16) presented in Section 3.1 is an instance of such a problem.

With these hypotheses, Problem B.1 may be formulated in a dynamic programming framework by introducing a Bellman function V_t at each time step. This approach enables to decompose the resolution of the complete problem into that of a backward in time series of subproblems associated with each stage and the system state at this stage. The Bellman function, also called the cost-to-go, represents the expected future cost when starting from a given state. It is defined for $x \in \mathbb{X}$, $w \in \mathbb{W}$ by

$$V_T(x) = K(x) \tag{B.2}$$

$$\hat{V}_t(x, w) = \min_{u_t \in \mathbb{U}} C_t(x, u_t, w) + V_{t+1} \circ f_t(x, u_t, w) \text{ if } t < T \tag{B.3}$$

$$V_t(x) = \mathbb{E} \left[\hat{V}_t(x, \mathbf{W}_t) \right] \text{ if } t < T. \tag{B.4}$$

The goal of SDDP is to approximate by inferior values the functions V_t with a supremum of affine functions relying heavily on the convexity of the V_t . These affine functions for stage t are obtained from the subproblem defining V_t in the classical dynamic programming framework where V_{t+1} is replaced by its approximation \tilde{V}_{t+1} computed at the previous step (we begin with $t = T$ and final cost K is supposedly known). For a realization w of \mathbf{W}_t and a given state x_t at stage t , this subproblem writes

$$\begin{aligned} \hat{\beta}_t(w) = & \min_{x, u} C_t(x, u, w) + \tilde{V}_{t+1} \circ f_t(x, u, w) \\ \text{s. t. } & x = x_t [\hat{\lambda}_t(w)] \end{aligned} \tag{B.5}$$

The dual variable $\hat{\lambda}_t(w)$ is associated with the state constraint of the previous subproblem. By definition of $\hat{\lambda}_t(w)$, we have the following inequalities for all realizations w and all states x

$$\hat{\beta}_t(w) + \langle \hat{\lambda}_t(w), x - x_t \rangle \leq \hat{\beta}_t(w) \leq \hat{V}_t(x, w) \tag{B.6}$$

since $\tilde{V}_{t+1} \leq \hat{V}_{t+1}(\cdot, w)$. An approximation by inferior values of the function V_t in the neighborhood of x_t is then given by the affine function, also called cut,

$$\beta_t + \langle \lambda_t, \cdot - x_t \rangle := \mathbb{E} \left[\hat{\beta}_t(w) \right] + \langle \mathbb{E} \left[\hat{\lambda}_t(w) \right], \cdot - x_t \rangle. \tag{B.7}$$

Here, only the backward phase of SDDP yielding new cuts for approximating the true value functions has been described. This phase relies notably on the drawing of relevant trajectories $(x_t)_{t \leq T}$ for the state variables. Indeed, the cuts are only good approximations of the value functions near these points. The choice of relevant state for computation is also encountered in traditional stochastic dynamic programming and the selected approach is to grid all the state space which may be extraordinarily costly in high dimensional systems. In SDDP, computations are made only

at "relevant" states i.e. those taken by the system when it follows an optimal path according to some drawn trajectory of noises. Actually, to compute this optimal path, knowledge of true value functions is required. So, these value functions are replaced by their approximates built in a previous backward phase. This describes the forward phase of SDDP. Backward and forward phases depend on each other and mutually strengthen their results. Thus SDDP alternates between forward and backward phases numerous times until some stopping condition is met.

Under the hypothesis taken here, the convergence of the approximate after k iterations of forward and backward phases $\tilde{V}_t^{(k)}$ to V_t is guaranteed when k goes to infinity (see Pereira and Pinto (1991) or Shapiro (2011)). Thus the resulting policy also converges towards the true optimal policy as the algorithm iterates. At each step (k) (composed of a forward and a backward phase), an exact inferior bound of the value of the true problem is given by $\underline{v}^{(k)} = \tilde{V}_0^{(k)}(x_0)$ (note that the initial state x_0 is supposed to be known and set) and an exact upper bound by $\bar{V}^{(k)} = \mathbb{E} \left[\sum_{t=0}^{T-1} C_t(X_t^{(k)}, U_t^{(k)}, \mathbf{W}_t) + K(X_T^{(k)}) \right]$. The latter bound may not exactly be computed and must be estimated by a Monte-Carlo method: several samples of realizations of \mathbf{W} are drawn which yields as many trajectories for X and U , then the mean on samples of the total cost $\bar{v}^{(k)}$ is computed. A confidence interval for the value of the upper bound, $[\bar{v}_{l,\alpha}^{(k)}, \bar{v}_{h,\alpha}^{(k)}]$, may be derived. Noting v^* the true optimal value, we have the following inequalities after step (k) with some confidence level $1 - \alpha$,

$$\underline{v}^{(k)} \leq v^* \leq \bar{V}^{(k)} \in [\bar{v}_{l,\alpha}^{(k)}, \bar{v}_{h,\alpha}^{(k)}]. \quad (\text{B.8})$$

Several stopping rules exist and are primarily based on inequalities B.8. As we mentioned, the inequality gets tighter as k grows so a simple stopping rule is to set a number of iterations for the algorithm but this gives no guarantee of the quality of the approximation. The original criterion proposed by Pereira and Pinto (1991) relies on the above inequalities. Setting a priori some confidence level $1 - \alpha$, the algorithm should stop after step (k) if $\underline{v}^{(k)} \geq \bar{v}_{l,\alpha}^{(k)}$. However, as pointed out by Shapiro (2011), this condition may be met very early if the confidence interval around the upper bound is very large i.e. the estimation of the upper bound is of poor quality, and no optimality guarantee may be obtained. He proposes then the following stopping rule, which is used for the resolution of Section 3 model. It states that algorithm should stop after iteration (k) if $|1 - \bar{v}_{h,\alpha}^{(k)}/\underline{v}^{(k)}| \leq \epsilon$ with a confidence level $1 - \alpha$ and some precision $\epsilon > 0$ set a priori. This stopping rule guarantees that the policy yielded by SDDP is ϵ -optimal for the true problem with probability $1 - \alpha/2$. Note that these results suppose that the distribution of the upper bound is normal.

Appendix C. Case study - Calibration Data

Appendix C.1. Power system

Technology	Installed capacity (MW)	Carbon content (tCO ₂ /MWh)	Cost (LP-HP) (€/MWh)
Lignite	6240	0.428	95.1
Anthracite	13731.6	0.342	165.1
CCGT	40109.8	0.202	91.7-171.7
GT	3081.8	0.202	128.3-240.4
Nuclear	77907	0	23
Hydro Conv.	10554.4	0	7.53
PHS	14276 (+) / 12486 (-)	0	9.54
Interco. UK	3780	0	95-150
Interco. Spain	3000	0	96-160
Interco. Scand.	4609	0	15
Run-of-water	29826	0	0
Wind	186274	0	0
PV	173259	0	0

Table C.2: Installed capacity by country (MW), carbon content (tCO₂/MWh) and Variable cost (€/MWh) in the modeled NWE power system. For thermal means, we suppose a carbon price is set at 80€/tCO₂ in line with the 2023 EU-ETS projections. Their efficiency is taken into account in installed capacity numbers.

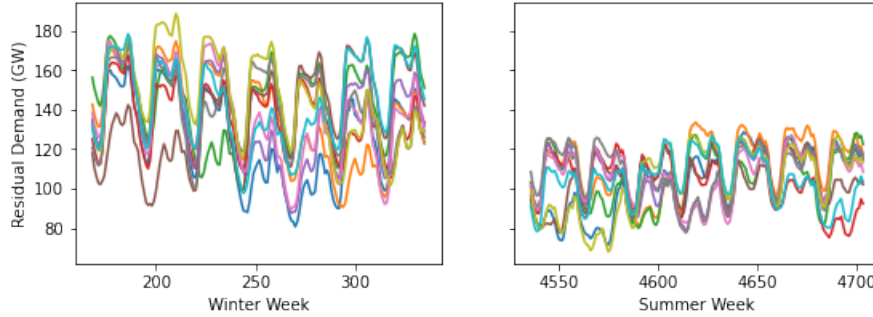


Figure C.7: Ten scenarios of residual demand in NWE for a winter week and a summer week. The structural cyclicity of demand is affected by intermittent RES production – particularly in Germany due to higher RES integration.

Appendix C.2. Demand response potentials

Technology	Installed capacity (GW)	Mean available capacity (GW)	Cost (€/MWh)	Event duration (h)	Nb of events	Availability variation
<i>Steel electric furnace</i>	1.6	1.15	411	4	40	No
<i>Aluminum electrolysis</i>	0.35	0.25	164	4	40	No
<i>Chlorine electrolysis</i>	1.4	1.1	96	4	40	No
Cement mills	1.1	0.3	10	3	365	E
Paper	1	0.2	10	3	365	E
Pulp	1.3	1.0	10	3	365	E
Res. space heating	30	7.2	50.9	1	1095	Th E
Res. water heating	40	5.2	50.9	12	365	Th E
Res. AC	15	0.6	50.9	1	1095	Th E
Ter. space heating	15	2.6	26.45	2	1095	Th E
Ter. water heating	5	1.1	26.45	12	365	Th E
Ter. AC	11	0.5	26.45	1	1095	Th E
Ter. cold stor.	10	4.1	26.45	1	1095	Th E

Table C.3: Characteristics of modeled demand response means. Economic availability variations (E) are related to opening days of businesses, business hours and seasonal variations in business activity. Thermal availability variations (Th) are linked with the thermal sensitivity of the specific electricity use.

Appendix D. Case study - Demand response activations

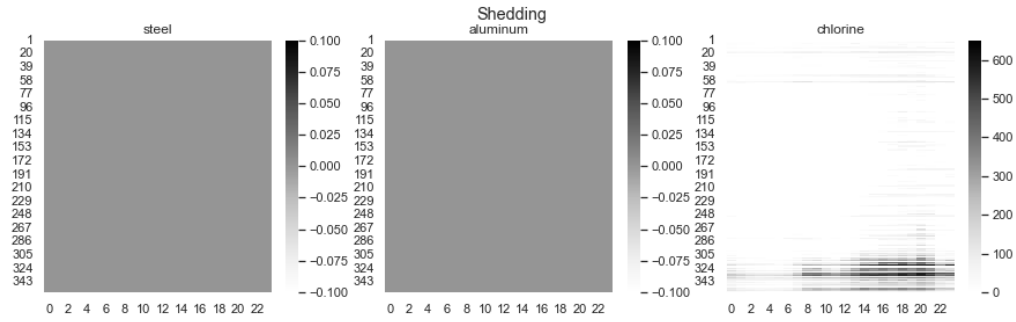


Figure D.8: Load-shedding operations in the DR100 low gas prices case. Left: load reduction. Right: load increase. [Each row is a day of the year, each column is an hour of the day, and color reflects the energy shed during this hour of this day.]

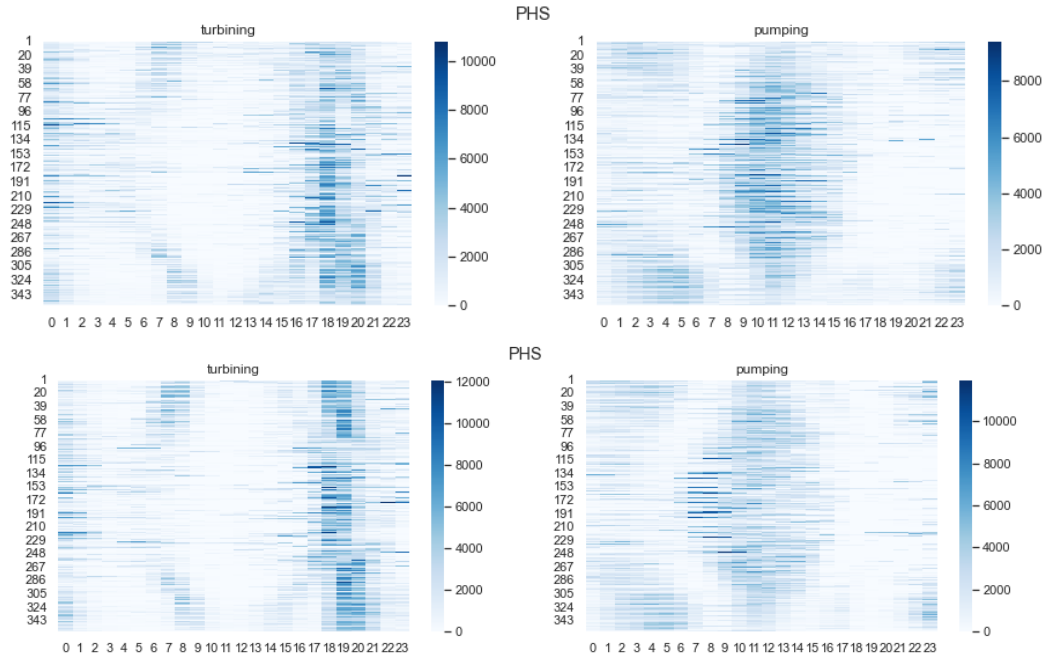


Figure D.9: PHS operations in the DR100 (upper line) and DR0 (bottom line) low gas prices case. Left: turbining. Right: pumping.

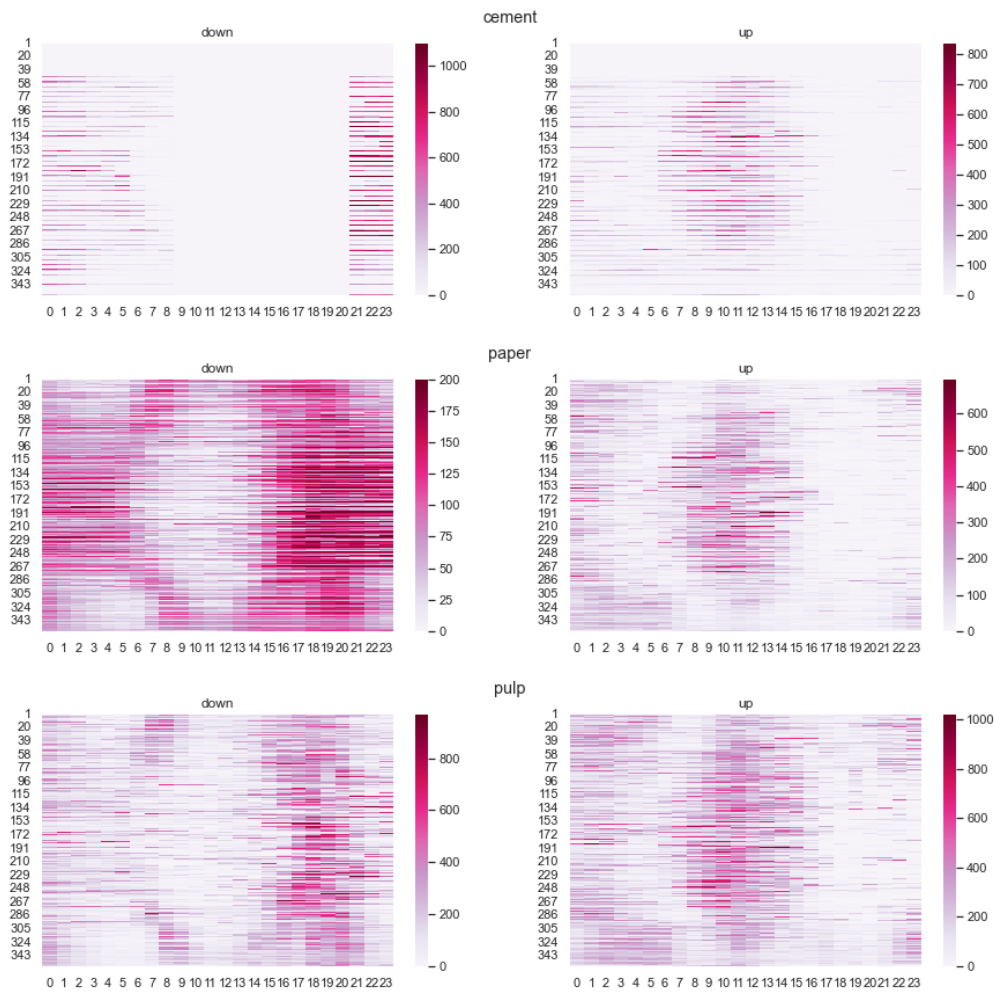


Figure D.10: Industrial load-shifting operations in the DR100 low gas prices case

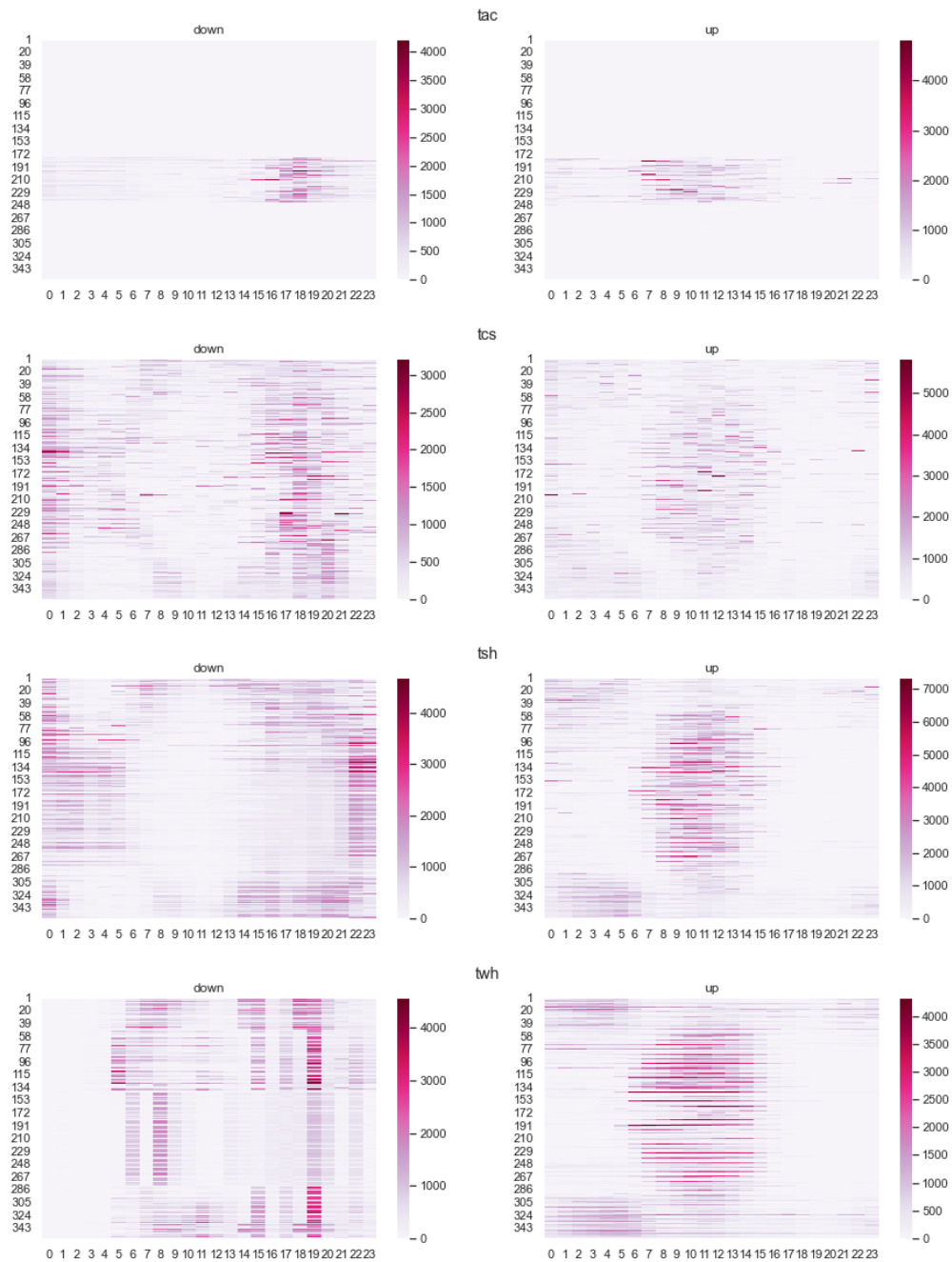


Figure D.11: Tertiary load-shifting operations in the DR100 low gas prices case

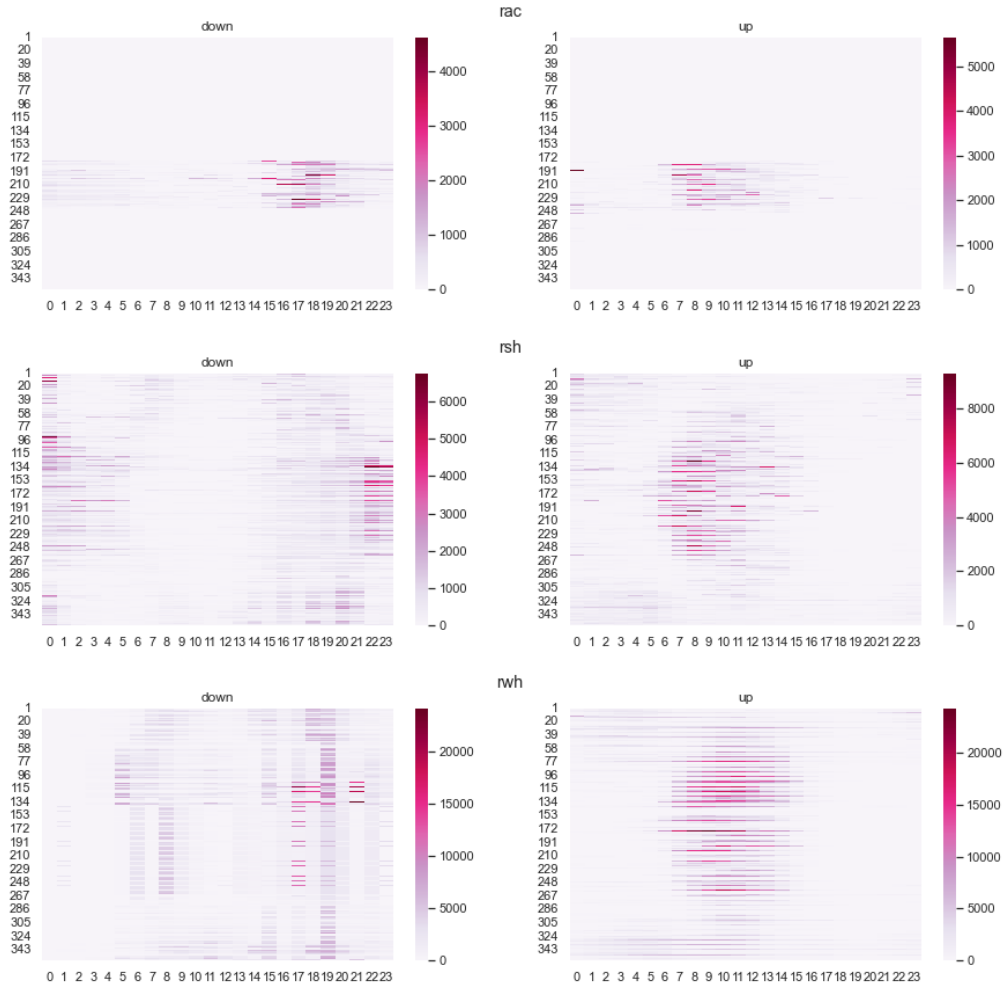


Figure D.12: Residential load-shifting operations in the DR100 low gas prices case

Appendix E. Case study - Demand response market revenues in different power mix

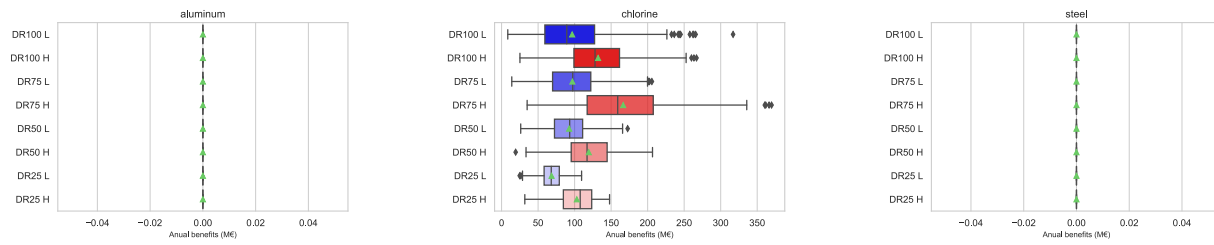


Figure E.13: Distributions of market revenues from the operations of load-shedding potentials in power mix with high (red) or low (blue) gas prices and 25, 50, 75 and 100% of residential and tertiary DR available capacity (transparency).

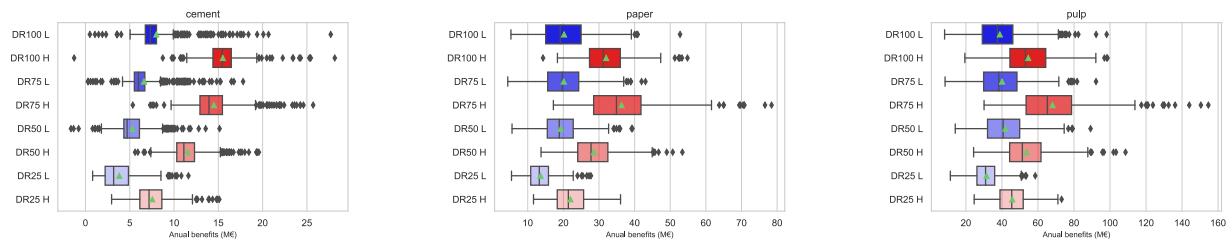


Figure E.14: Distributions of market revenues from the operations of industrial load-shifting in power mix with high or low gas prices and 25, 50, 75 and 100% of residential and tertiary DR available capacity.

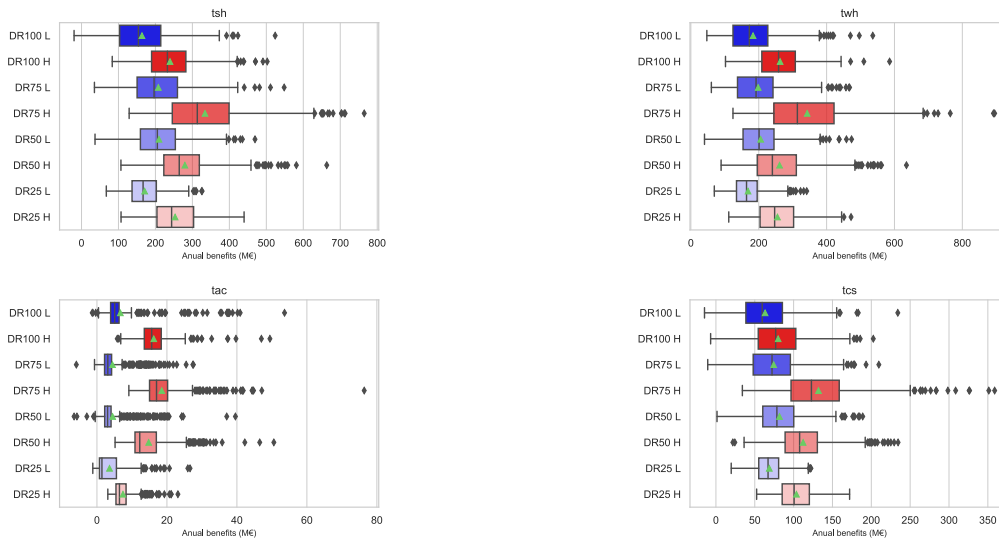


Figure E.15: Distributions of market revenues from the operations of tertiary sector load-shifting in power mix with high or low gas prices and 25, 50, 75 and 100% of residential and tertiary DR available capacity.

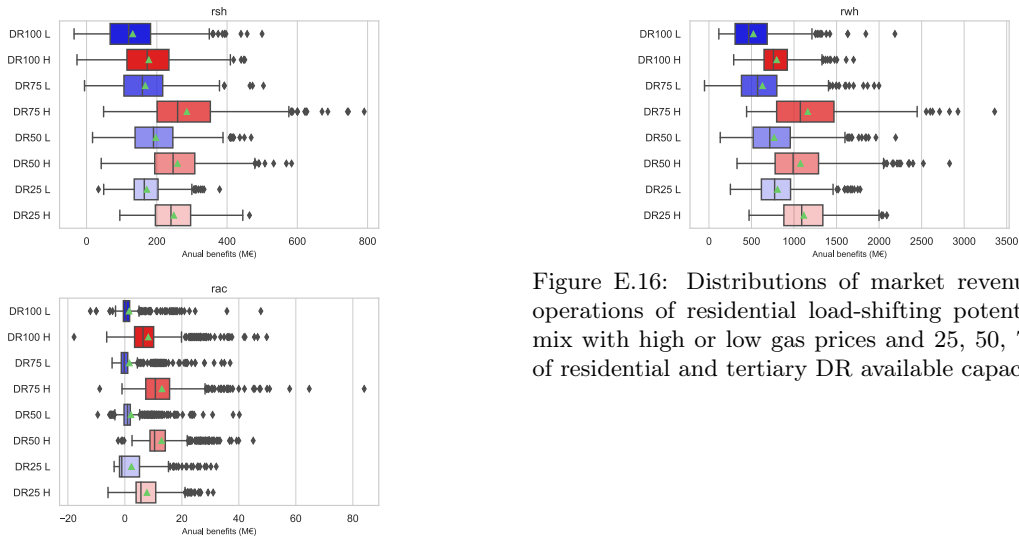


Figure E.16: Distributions of market revenues from the operations of residential load-shifting potential in power mix with high or low gas prices and 25, 50, 75 and 100% of residential and tertiary DR available capacity.

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