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Classifying and modelling demand response in power systems

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A B S T R A C T

Demand response (DR) is expected to play a major role in integrating large shares of variable renewable energy (VRE) sources in power systems. For example, DR can increase or decrease consumption depending on the VRE availability, and use generating and network assets more efficiently. Detailed DR models are usually very complex, hence, unsuitable for large-scale energy models, where simplicity and linearity are key elements to keep a reasonable computational performance. In contrast, aggregated DR models are usually too simplistic and therefore conclusions derived from them may be misleading. This paper focuses on classifying and modelling DR in large-scale models. The first part of the paper classifies different DR services, and provides an overview of benefits and challenges. The second part presents mathematical formulations for different types of DR ranging from curtailment and ideal shifting, to shifting including saturation and immediate load recovery. Here, we suggest a collection of linear constraints that are appropriate for large-scale power systems and integrated energy system models, but sufficiently sophisticated to capture the key effects of DR in the energy system. We also propose a mixed-integer programming formulation for load shifting that guarantees immediate load recovery, and its linear relaxation better approximates the exact solution compared with previous models.

1. Introduction

In the last years, multiple global policies and regulations have been developed in order to reduce greenhouse gas emissions. The Paris Agreement, endorsed by 195 nations in 2016, is the best example, aiming to "Hold the increase in the global average temperature to well below 2 °C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5 °C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change" [1]. More specific policies have also been developed on a continental scale. For example, in Europe, the "Roadmap for moving to a competitive low carbon economy in 2050" states that domestic emissions should be reduced by 80% by 2050 compared to 1990, with the power and industry sectors being the ones with the highest reductions needed [2]. Additionally, the Energy Roadmap, released in 2011, has targets to reduce greenhouse gas emissions to 80–95% below 1990 levels by 2050 [3].

The contribution of the power sector to these figures is considerable. In 2017, the power sector was the single largest contributor to energy related greenhouse gas emissions, with a share of around 42% of the total energy related CO^2 emissions [4]. In the future, with the probable increase of the electrification of other sectors (mainly heat and transport), this contribution is expected to be even higher. As a consequence, in power systems with increasing shares of inflexible variable renewable energy (VRE), demand-side management (DSM) has gained attention because of its potential to reduce peak generation capacity requirements, function as a reserve, and improve the utilisation of generating units and network assets. DSM is the umbrella term used for the broad range of activities aimed to modify energy consumption patterns. Of these, those unrelated to energy efficiency are labelled demand response (DR). For power systems in particular, DR can become a valuable asset by providing flexibility to the system.

This increasing attention on DR and DSM can be exemplified analysing the scientific literature. For example, Fig. 1 shows the evolution of the search results in Scopus for articles including "demand response" or "demand side management" in the title, abstract or keywords. This figure shows the number of new publications per year. Notice that before 2009 the scientific contributions related to DR were scarce, going from 11 new publications in 2001 to 130 in 2009 and to 1800+ in 2020.

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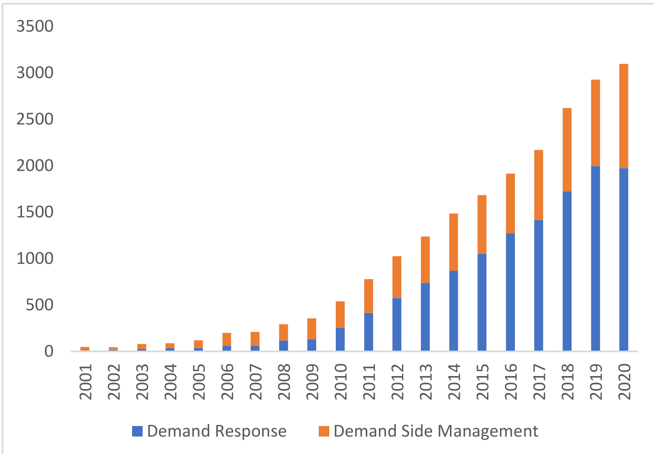


Fig. 1. Search results in Scopus for new yearly articles including “Demand Response” or “Demand Side Management” in title, abstract or keywords.

Incorporating DR in energy models is not straightforward. The first attempts to develop energy models took place in the 1950s, and different events like the ‘oil crisis’ in the 1970s, and the liberalisation of energy markets in the 1980s and 1990s incentivized research and deployment of new modelling tools [5]. During these decades the penetration of VREs was almost negligible, and thus DR and DSM were not an important part of the agenda. As a consequence of the rapid increase of VREs during the 21st century, and in order to represent the current and future energy systems, it is imperative to update these models to include DSM, and to develop new ones with it.

It is not the objective of this paper to analyse and review in detail a selection of energy models (the reader is referred to Refs. [5–10] for that purpose). However, a brief overview of relevant literature is summarized in the following lines to understand the state of the art of energy modelling. Ringkjøb et al. [6] reviewed in detail 75 energy modelling tools used for energy and electricity systems. The criterion to select these models was that they must have been used after 2012. Thus, it can be assumed that most of these models have been used to analyse systems with a certain penetration of VREs where DSM could play a relevant role. Out of these 75 models, 45 are optimisation models (60%) and only 37 (49%) include DR as an option. 46 of them (61%) include more than one energy sector, while 29 consider only electricity (39%). Within the 45 optimisation models, 30 (67%) are based on linear programming (LP), while 13 (29%) include mixed integer programming (MIP) as well.

Another study by Lopion et al. [5] reviewed 24 energy models used on a national level and including all energy sectors. 15 of these were optimisation models (63%), 7 were simulation models (29%) and 2 were a combination of both (8%). Table 1 summarizes the 13 optimisation models with publicly available information. It can be seen that 12 out of 13 include LP, and the remaining one uses nonlinear programming.

From both studies there are two key conclusions that can be inferred. First, optimisation is the most used approach in the energy models reviewed. This trend is still valid for recently developed energy models. Indeed, Lopion et al. [5] review the most common models using optimisation that were released after 2010. Second, within the optimisation models the preferred methodology is LP, especially in large-scale models, which are computationally demanding by nature due to their large size and usually computationally intractable if they are not formulated as LP problems. In the context of integrated energy system models, large-scale models

Table 1
Selection of energy models reviewed in [5].

Model name	Method	Reference
TIMES	LP	[11]
OSEMOSYS	LP	[12]
Balmorel	LP/MIP	[13]
Calliope	LP/MIP	[14]
ReMIX	LP	[15]
IKARUS	LP	[16]
OEMOF	LP/MIP	[17]
BESOM	LP	[18]
REMIND-D	NLP	[19]
MESSAGE III	LP	[20]
SCOPE	LP/MIP	[21]
Temoa	LP	[22]
TESOM	LP	[23]

include 1) broad geographical areas (usually over national scale), 2) hundreds to thousands of periods (e.g., in hours) and 3) long time spans (e.g., multiple years); they also tend to include 4) a large number of technological detail and 5) multiple sectors of the energy system to capture cross-sectoral interactions. Therefore, large-scale energy models commonly require to introduce simplifications to maintain a reasonable computational burden. These simplifications may include spatial aggregation, clustering units of the same technology, temporal aggregation (i.e., timeslices) and formulating the models as LPs.

These trends shown in the literature are crucial to consider when including DR in energy models. On the one hand, representing DR in a realistic way requires detailed equations (some of them nonlinear) and introducing large amounts of data. On the other hand, as mentioned, large-scale models require simplified equations, preferably linear and if possible in an aggregated way. Additionally, a linear formulation of DR has the advantage that it can be included in all kinds of models (either linear or nonlinear, e.g., MIP), while a nonlinear formulation can only be included in nonlinear models.

There is a substantial amount of literature on DR. O'Connell et al. [24] compiled previous works on demand response and described some benefits, challenges and some of the usual assumptions that are taken when modelling DR. Albadi and El-Saadany [25] reviewed different experiences with DR with a focus on electricity markets, including an analysis of the influence of DR in electricity prices with a case study. Strbac [26] briefly discussed the challenges and benefits of DSMin the context of the UKelectricity market, concluding that DSMmight better support security rather than back-up capacity by generation. Paterakis et al. [27] presented a comprehensive analysis of DR, pointing out benefits and challenges as well, but adding a detailed classification of DR and including practical evidence of DR use in different countries across the world. Guelpa and Verda [28] discuss about the advantages and steps for implementations for DR in thermal networks. Other relevant references providing a review of DSM and DR are Jordehi [29], Dranka and Ferreira [30].

Although this literature provides a comprehensive overview of DSM and DR, notably their main benefits and challenges, the inclusion of DSM and DR mathematical formulations in large-scale energy models is partially uncovered. Although there are plenty of models for specific appliances, e.g. Refs. [31,32], they are unnecessarily too detailed [33] and, hence, unsuitable for large-scale energy models, because they will make the resulting model computationally intractable. In contrast, the DR formulations commonly used in large-scale power systems and energy system models are too simplistic, where DR is usually represented in the form of elasticities [34,35] or ideal shifting [36,37], and both poorly represent the actual physical constraints of loads. Gils [38] and O'Connell et al. [24] argue that most flexible load processes share two key physical characteristics for load shifting: saturation and load recovery. These are precisely the two characteristics that are commonly ignored or overlooked in DR models, and cannot be represented by either elasticities or ideal shifting. A major concern about aggregated DR models [24,30] is that they are usually over-simplified and unable to capture crucial DR complexities, hence power system and energy models using these simplistic DR formulations lead to unrealistic results and misleading conclusions [39].

To overcome these drawbacks, Göransson et al. [40] proposed a model for load shifting, including saturation and load recovery. However, this model cannot guarantee the immediate recovery of load. Zerrahn and Schill [41] proposed a set of constraints to diminish the impact of undue load recovery, without solving it completely. O'Connell et al. [33] also acknowledge that it is paramount to correctly model immediate load recovery (rebound), hence they propose an MIP formulation to guarantee that load is recovered immediately after responding to a load delay or anticipation. The resulting MIP model, however, is too demanding computationally, requiring many more constraints, binary and continuous variables, hence making the formulation unsuitable for large-scale energy models.

To the best of our knowledge, there is not a review in the literature covering multiple mathematical formulations for different types of DR with different levels of detail that can be effectively integrated in large-scale power systems and energy models. This paper then provides the following three main contributions:

1. We describe DR mainly from the power system perspective, including definitions and classifications of different types of DR and the products and services DR can provide for reliability or energy. In addition, we also summarize the main benefits and challenges of DR.
2. We present a collection of linear equations that represent the main types of DR and can be directly used in large-scale energy models. As demand response can be fully characterized by load shifting, curtailment or the combination of both. From the models available in the literature, we start with describing simple curtailment and ideal load shifting models, and we continue to build on them by looking at more sophisticated and realistic models, such as load shifting including saturation and load recovery.
3. We propose an MIP formulation that guarantees immediate load recovery. As an approximation, this model can be used in its LP relaxed form, and due to its tightness, it provides a much better approximation to the exact MIP solution compared with the previous model attempting to diminish the undue load recovery [41].

In this paper, we focus on classifying and modelling different types of DR rather than on different types of sectoral loads such as industrial or residential loads. To a large extent, our classification and modelling of different forms of DR can be applied to different types of sectoral loads. More specifically, the models presented in this paper are for aggregated flexible load processes that can be characterized by curtailment and/or shifting capabilities, such as those (around 30) load processes listed in Gils [38] for different sectors where their flexibility can be fully represented by shifting or curtailment.

The rest of this paper consists of two main parts, which focus on two different but related topics of classifying and modelling different types of DR in large-scale energy systems. The first part classifies different DR services in section 2, and provides an overview of benefits and challenges of DR in section 3. The second part presents the mathematical formulations for different types of DR in section 4, ranging from curtailment and ideal shifting, to shifting including saturation and immediate load recovery. Finally, some conclusions are drawn in section 5.

2. Classification of demand response

The Electric Power Research Institute (EPRI) has defined DSM as follows: DSM is the planning, implementation and monitoring of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., time pattern and magnitude of a utility's load. The changes in electricity consumption patterns can be classified as follows:

1. Energy Efficiency: these changes are typically permanent reductions of energy consumption resulting from energy efficiency investments. Where energy efficiency is the effect of producing more output per unit of energy input, resulting in reduced consumption across all hours rather than event-driven targeted load reductions. Energy efficiency is not the focus of this paper, and the reader is referred to Refs. [42,43] and references therein for further analyses and discussion on this topic.
2. Demand Response: these changes are temporal reductions or increases of energy consumption in order to support the energy system. For instance, temporal reductions can appear at times of high prices, or at times of high network loading [44]. Temporal increases can appear at times of very low or even negative prices, or at times where there is an overproduction of “free” electricity (mainly by renewable energy resources).

FERC [45] defines demand response (DR) as “changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.” In practice DR is just temporary *curtailment* or *shifting* of consumption at times when it is valuable to the electricity system, as illustrated in Fig. 2, including valley filling as a type of demand response, which is a particular case of load curtailment as discussed in section 4.1.2.

Fig. 3 illustrates a variety of demand response services, how load shifting or reductions are implemented, their dispatchability, and the type of product or service. This classification is adapted from NERC [46].

DR can be activated either by its own (i.e., self-dispatch) or by a third party.

2.1. Self-dispatch DR

Self-dispatch DR, also called price-based DR [27], where consumers voluntarily provide load shifting or reductions by responding to economic signals. The economic signals that incentivise self-dispatch decisions are time-dependent and can be mainly classified as follows [31,47]:

2.1.1. Time of use (TOU) charges

TOU chargers are clusters of prices that are set and known in advance. For example peak and off-peak prices provide incentives to an energy user to reduce consumption during peak times, or to shift it to off-peak times. Thus lowering the user's overall energy costs.

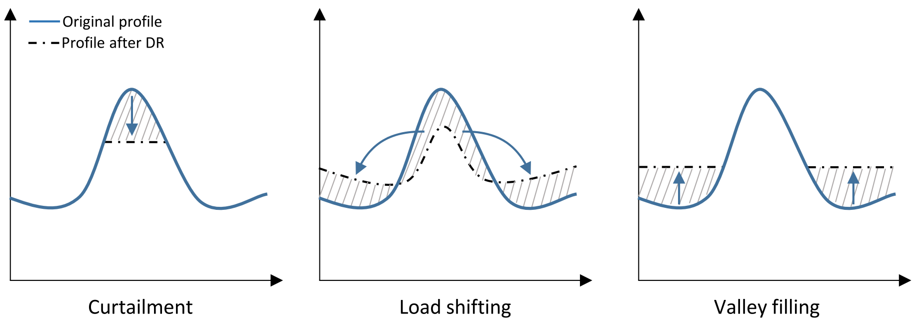


Fig. 2. Types of demand response.

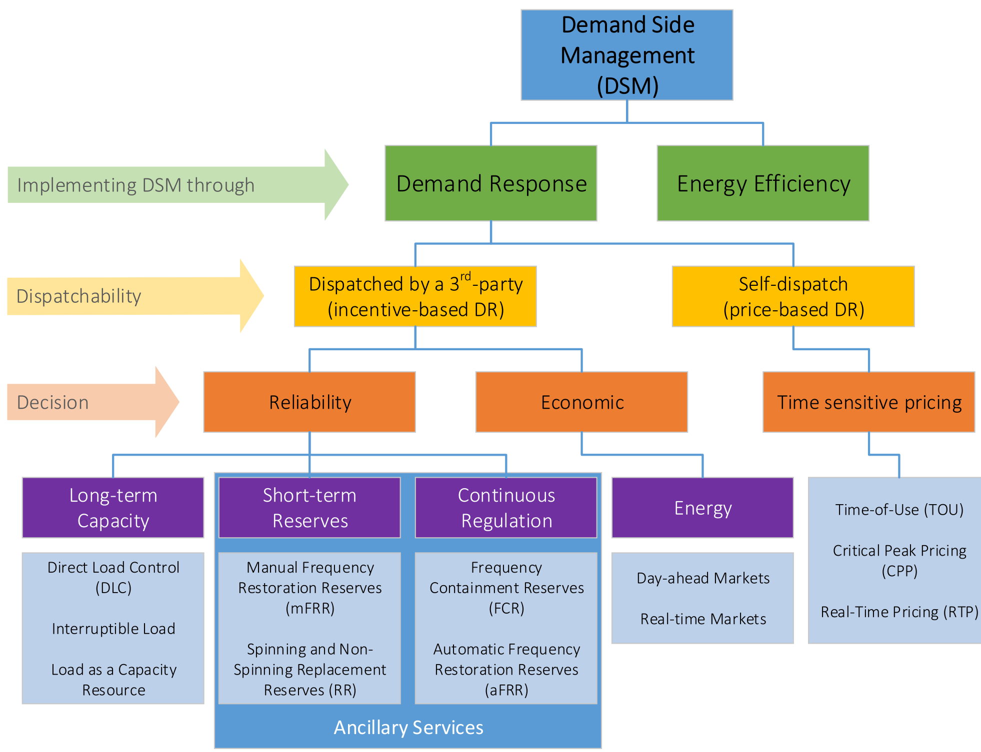


Fig. 3. Demand response categories.

2.1.2. *Critical peak pricing (CPP)*

CPP aims to capture short-term costs of periods that are critical for the power system. CPP can apply on top of TOUs and are triggered by system criteria, such as unavailability of reserves or line overloads. The utility communicates CPP events in a very short notice, from minutes to hours before the CPP rate takes place.

2.1.3. *Real-time pricing (RTP)*

RTP results from clearing very short-term markets, such as real-time or imbalance markets. These energy prices are updated in very short notice, typically every 5 or 15 min. Under RTP schemes, customers are directly exposed to the variability and volatility of wholesale power markets through single-energy prices (ignoring congestion costs), locational marginal prices (internalizing congestion costs), or zonal prices (considering congestion costs between zones, somewhere in between single- and locational-prices).

Ideally, RTP is a perfect scheme for DR to optimally respond to the system needs [47]. On the one hand, very high prices can be a signal that the system is running out of resources, then lowering consumption is the perfect way to respond, thus avoiding possible critical events. On the other hand, very low prices, or even negative prices, are a signal that the system would be better off if consumption is increased, for example increasing the use of renewable energy sources (reducing curtailment). However, the final prices of real-time markets are typically known after the actual dispatch period, hence consumers cannot know the actual price before taking the consumption decision. Therefore, consumers always take the risk of missing the right signal. This risk can be lowered or even completely avoided if consumers allow a third-party to (optimally) shift or curtail their consumption.

2.2. *DR dispatched by a third party*

There are different types of DR that are dispatched by various third parties. This case is also known as incentive-based DR, where customers are offered payments in order to deliver a specific amount of load reduction or increase over a given period. The common third parties managing DR are energy market operators (EMO) or independent/transmission system operators (ISO/TSO), distribution system operators (DSO), the retailer of the energy user or a DR aggregator. The interaction between these parties is also common, especially between aggregators and the other parties; for a thorough discussion about the importance of DR aggregators, the reader is referred to Refs. [48–50]. For example, an aggregator can participate in the energy market on behalf of many consumers and then follow the instructions resulting from the market, also an aggregator can follow the signals given by an ISO to increase or decrease the aggregated consumption.

2.2.1. Economic

In economic market participation, demand-side parties bid their resources in energy markets, which are then scheduled to supplement generation based on market conditions and market offers. By participating in energy markets, demand resources are scheduled and dispatched primarily on an economic basis. Common energy markets are day-ahead markets, and real-time or balancing markets. Unlike self-dispatch DR, consumers commit to consume the scheduled energy resulting from the market, and they can be penalized for nonperformace.

2.2.2. Reliability

In this category, DR is used to supplement generation resources resolving system constraints and/or local capacity constraints. Unlike pure economic market participation, under reliability programs participation, DR must react to emergency or contingency events, not economic DR deployments, although consumers also receive economic incentives when they participate in reliability programs. These incentives then obligate them to be available over a defined period of time so they can be dispatched by the appropriate balancing authority, usually ISOs (or even DSOs). Under the reliability category, there are mainly the following three services.

2.2.2.1. Continuous regulation. Here demand resources automatically increase or decrease their consumption in response to frequency changes during a specified commitment period. Demand resources providing regulation are continuously dispatched through load frequency control (LFC) [51], where the objective is to keep the supply and load balance in real time by maintaining the system frequency on its nominal value through control strategies [52,53]. These control strategies are usually composed of [54] 1) frequency containment reserves (FCR), activated through a primary frequency control, where response is within few seconds; and 2) automatic frequency restoration reserves (aFRR), which are activated through secondary frequency control, where response is between seconds to minutes. The latter control mainly responds to smooth changes, and the former to more sudden changes of frequency. Also, FRR aims to replace the activated FCR, so FCR can be continuously available. Provision of regulation service does not correlate to DR specific constraints, like deadlines or durations.

2.2.2.2. Short-term reserves. Demand resources providing short-term reserves are obligated to increase or reduce their consumption if needed by the system operator. The total capacity availability is compensated and previously contracted with the ISOs. Under specific agreements, DR can respect their specific constraints, like deadlines or durations. These reserves types are mainly, manual frequency restoration reserves (mFRR) and replacement reserves (RR). The aim of RR is to replace the activated manual and automatic FRR. For RR, demand can either provide spinning and non-spinning reserves [55]. Spinning reserves refer to demand-side resources that are synchronised and ready to increase or decrease consumption within the first few minutes of an electric grid event. Non-spinning reserves refer to demand-side sources that are not connected to the grid but are capable of start consumption within a specified time.

2.2.2.3. Long-term capacity. This DR service only refers to lowering consumption, mainly by curtailing load. NERC [56] describes it as follows "Demand Resources that are obligated over a defined period of time to be available to provide Demand Response upon deployment by the System Operator. Capacity product is a Demand-Side Resource that displaces or augments generation for planning or operating resource adequacy." This capacity DR service is mainly implemented in three different ways:

1. Direct Load Control (DLC): This is the DR that is directly controlled by system operators. Here, system operators may directly control a specific type of appliance in the end-user premises. This service can also be compensated through critical peak pricing mechanisms, which are pre-defined high prices for use during critical peak periods triggered by system contingencies or high wholesale market prices resulting from dispatching (almost) all available generation capacity.
2. Interruptible Load: This is a service that the end-user makes available to its load-serving entity via contract or agreement for curtailment. In an interruptible load program, electric consumption is subject to curtailment under tariffs or contracts that provide a rate discount or bill credit for agreeing to reduce load during system contingencies. In some instances, the demand reduction may be affected by action of the system operator, called "remote tripping," after notice to the customer in accordance with contractual provisions.
3. Load as a Capacity Resource: Here, load commits to reduce consumption by a pre-specified amount when system contingencies arise.

Here, we differentiate between regulation, reserves and capacity because they are used in different time frames. However, they are all commonly called reserves, and every system has variations on the classification of these reserves [57], usually making them even more detailed and disaggregated, especially for continuous (regulation) and short-term supply (reserves).

Reserves and regulation are also part of ancillary services, helping to maintain electric reliability and support the transmission of electricity [58]. These services are produced and consumed in real-time, or in the very near term.

3. Benefits and challenges of demand response

Different studies have discussed in detail different benefits and challenges of DR, see for example [24–27]. Here, we summarize the main benefits for the system, for consumers, and for supporting renewable energy sources. This section also summarizes the main challenges to unlock the potential of DR.

3.1. Benefits

3.1.1. Benefits for consumers

Consumers directly benefit from lower electricity prices by curtailing energy during peak electricity prices, or by shifting it to off-peak prices. Another less direct benefit is that DR helps to mitigate market power due to increased demand elasticity [25], resulting in lower electricity bids from the generation side. These are only benefits related to energy markets.

Apart from energy, there are other products needed for the power system to operate, such as capacity, reserves and regulation (see Fig. 3). For decades, the generation side has fully profited worldwide from providing these products to the system. DR can, in some extent, replace the generation in this job and also profit from it.

A study considering just air conditioning and water heating as DR in the US showed that grid costs can be lowered by 13 billion dollars per year [59], which would translate to 10–40% bill reduction to consumers. Fig. 4 shows the proportions from where these cost reductions come from. It is interesting to highlight that 75% of the potential economic benefits come from non-energy related products, 67% from providing capacity and 8% from ancillary services. These orders of magnitude are also aligned with other studies [60].

Capacity markets provide means for system operators to procure the capacity needed to meet forecast load (or resource adequacy requirements), and to allow generators to recover part of their fixed costs [58]. These capacity payments usually benefit peak units, which are typically highly polluting. However, DR could also economically benefit from these markets providing part of the capacity resources needed to maintain bulk power system reliability requirements, while avoiding unnecessary investments in peak units.

According to Paterakis et al. [27], the largest potential of DR is in providing ancillary services. The DR characteristics and their availability qualify them for such purpose [61]. Also, Stoll et al. [62] found that in low and high DR scenarios, nearly all reserves could be provided by demand response. However, DR cannot completely displace traditional generation in providing ancillary services, since DR cannot provide some of these services like voltage support and system restoration [62]. Although DR is often cited as a cheaper and more environmentally friendly capacity resource than a combustion turbine, Cutter et al. [63] argues that, compared with a combustion turbine, DR performs poorly and provides limited flexibility.

3.1.2. Benefits for the system: increasing efficiency

Power systems are traditionally planned in a way that the total installed generation capacity must be larger than the system maximum (peak) demand. This conservative system planning attempts to guarantee the security of supply under contingencies or large demand variations. The frequency of large energy deficits is very low, because in the vast majority of cases, energy deficits are managed without significant impacts on consumers [64]. Besides, the generation, transmission and distribution assets are highly underutilised (of about 50% [26]), hence there is a significant scope for DR to contribute to increasing the efficiency of the system investment. That is, DR has the potential to decrease the need for the over-dimensioned total system capacity [65], while better utilising the resulting smaller electric infrastructure. For example, the energy crisis in California in June 2000 was caused by an energy deficit of 300 MW (~ 0.6% of the system capacity), which ultimately led to rolling blackouts [66].

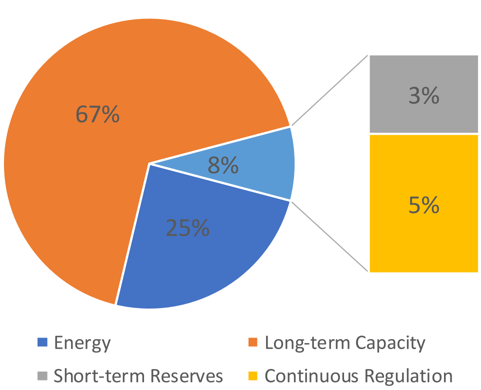


Fig. 4. Benefits proportion by providing DR to the system.

DR also produces multiple environmental benefits by reducing electric demand during peak hours. DR can save energy, reduce the dependency on fossil fuel (mainly peak) power plants, and help the penetration of renewable energy sources onto the electric grid. Besides, DR saves energy by lowering the peak demand, since heating losses are higher during high consumption: heating losses are proportional to the square of the current, that means, for example, that by reducing peak demand by 10%, losses are reduced by 19% during peak consumption. Dahlke and McFarlane [67] have shown that DR programs in MISO, which cycle residential appliances like ACs, actually decrease the overall electricity consumption. Furthermore, peak power plants are in general more inefficient and higher-emitting, hence reducing their use contributes to reduce the carbon footprint of the system; for instance, in California, the emissions during peak times can be up 33% higher compared to off-peak times [67].

3.1.3. Better integrating renewable generation

The transition towards energy systems characterised by a high share of variable renewable energy sources poses the problem of balancing the mismatch between inflexible production and inelastic demand. Current power systems have been designed to deal with demand fluctuations; however, it is questionable whether the grid can cope with both varying load and high amounts of variable generation, like wind and solar. Besides, weather-dependant variable generation cannot be perfectly forecasted, thus adding uncertainty to the already variable generation. To accommodate this uncertainty, an increased amount of reserves and regulation should be maintained [68,69], which increases needs in both power capacity and ramp capability reserve requirements [70].

DR increases the flexibility of the system, thus helping operators to cope with the variability and uncertainty of high penetrations of variable renewable resources [71,72]. For example, DR provided by certain loads such as air conditioning and electric heating are capable of adjusting their power to changes in demand or generation instantaneously [73], unlike the limited ramp rate of conventional generators. DR can also provide ancillary services, also necessary to accommodate uncertain renewable energy production.

Shifting demand to off-peak hours also helps to better use high shares of renewables. During off-peak hours, the relatively inflexible base load generators, operating near their technical minimum, together with renewable generation can exceed the low demand, hence the excess of renewables must be curtailed to maintain the balance and stability of the system. Evidently, DR offers a solution by increasing consumption in periods with excessive renewable production. This is not only beneficial to consumers, who take advantage of very low electricity prices, but also beneficial to renewable producers. Because increasing off-peak demand also increases the off-peak prices, which in turn increases profits to renewable producers by selling more at higher prices [74].

3.2. Challenges

This section summarizes the main challenges to unlock the full DR potential, which include regulatory challenges, establishing a business case, establishing the value of DR, and challenges in simulation, monitoring and prediction of behaviour. For a more detailed discussion on challenges, the reader is referred to Refs. [24,27], and references therein.

3.2.1. Regulatory challenges

According to Cappers et al. [75], power system service definitions need to be updated because they explicitly or effectively exclude DR participation in ancillary services. Moreover, minimum resource bid sizes are present in many markets, excluding smaller DR participants. If the market does not allow for aggregation of multiple small consumers, this could exclude smaller DR service providers from participating in electricity markets. Most DR resources are connected to the distribution network and so collaboration between DSOs and ISOs is important to exploit DR resources [27]. However, ISOs can view DR as a source of flexibility to the system, whereas DSOs might use DR to avoid congestion. This can result in a conflict of interest and is a challenge to building the regulatory framework. For example, low price signals from ISOs can cause an increase of demand, which in turn can result in congestion in the distribution grid. O'Connell et al. [24] mentions current market mechanisms are not designed for a market where DR plays a large role. DR is employed primarily for the provision of emergency contingency support and ancillary services, with limited participation in the day-ahead market. Day-ahead participation of DR by direct market bidding or contracts between individual market stakeholders requires a long time to plan ahead this participation, which prevents effective market participation [61]. A further challenge with the current regulatory framework is the tariff structure. If (particularly residential) consumers are to respond to a price signal, they first need to see it. However, real-time pricing solutions have challenges of their own. Responsibility for system security may shift partially to the consumer, who might be exploited by being exposed to very highly fluctuating energy prices, although some authors have found this effect to be small or have suggested solutions [76].

3.2.2. Establishing a business case

Paterakis et al. [27] identifies three main business models for DR: aggregating small consumers, real-time pricing schemes, and direct contracts with the ISO. Direct contracts with the ISO are only possible for some large industrial consumers, and thus exclude a large share of DR resources. Aggregation of small consumers meanwhile may compromise real-time pricing schemes, as discussed in the previous section. O'Connell et al. [24] mentions that if a wind plant owner operates a DR resource it will benefit from the balancing services that demand can provide. Simultaneously transmission or distribution capacity will be used more efficiently, benefiting the ISO. The DR benefits are thus not distributed in a way that incentivises the use of DR maximally. Even if price signals are included in real time, the reduced variability in prices as a result of some demand response will result in less incentives for additional demand response [77].

3.2.3. Valuation of DR

DR could be perceived as a complicating factor for predicting and modelling the energy system [27]. In a system with potentially high shares of renewables, the preference could be given to proven OCGTs instead of DR from a system analysis perspective if DR is too hard to model correctly. Another issue is the value of not supplying energy by DR. If the DR resource gets paid for the consumption reduction in the wholesale market, and also gets a premium for the DR service, it could get paid double. This could be construed as unfair. At the same time DR has environmental and economic benefits due to its efficiency, for which it does not get a premium. If the capacity value of DR is large, peak plant owners will see reduced profits. Potentially, DR will cause a diminished number of peak hours per year, but will still require flexible generation for the remaining peak hours. The most significant factor determining the value of demand response is the inflexibility of the existing generators [26].

3.2.4. End-user behaviour

Another challenge is creating the right tools to evaluate and measure DR actions. A flawed methodology presents the risk of consumers gaming their baseline in order to increase their payment. DR by small consumers might behave irrationally, especially when it is not automated, and it is thus hard to predict their behaviour. For example, various types of consumers require different contracts based on their consumption profiles and requirements. Faced with too many contract options, consumers might make poorer decisions. DR applied in ancillary services would require more frequent and shorter interruptions. These would need to be regulated and automated. The costs of installing capable equipment might be prohibitively high [78–80].

4. Demand response models

Aggregated DR formulations are paramount to correctly model the optimal planning and operation of power and energy systems (including markets). Although there are many detailed models for DR for specific appliances, there are very few aggregated models that consider realistic DR constraints at a system level. Detailed models for specific appliances, which correctly model for instance realistic non-ideal shifting, are very difficult to aggregate on a city or country level, because they require many detailed parameters that are very specific to a given technology and environment. For example, in the case of thermostatically controlled loads, some of the parameters needed are outside temperature, isolation characteristics and thermal inertia of the building [81,82]. And even with some level of aggregation (few buildings) these aggregated parameters are still needed [83,84]. Many of these detailed models for specific appliances are listed in Refs. [31,85,86] and references therein.

On the other hand, aggregated DR models commonly used for system analyses are usually oversimplified. Estimating the benefits of DR are dependent on these simplifications and accurate evaluation still needs to be achieved [39]. The most common oversimplification is that all demand behaves in a completely economical rational way: DR can be completely described by a linear demand function based on own-elasticity [34] and cross-elasticity values [87], where own-elasticity dictates curtailment capabilities and cross-elasticities dictates the shifting capabilities [88].

DR is very poorly represented in the form of elasticity values and more detailed modelling is required to realistically represent its capabilities, which are ruled by physical constraints.

Gils [38] shows that most of flexible load processes share two key physical characteristics for load shifting, namely, saturation and load recovery, and these are precisely the two characteristics that are commonly ignored or overlooked in DR models, and elasticities cannot represent either of these physical characteristics. For example, elasticities cannot represent load recovery or load rebound: in the case of thermostatic controlled loads, consumption can be initially reduced, but its local (comfort) constraints avoid that the temperature falls below a given threshold, at this point the local control will recover the load by forcing consumption to restart [33].

Another phenomenon that is not represented by elasticity values is the response to saturation. Continuing with the example of thermostatic controlled loads, in case that electricity prices are very low for prolonged periods of time, elasticities will dictate sustained very high (or maximum possible) consumption; however, the local constraints will avoid that the temperature exceeds a maximum threshold by stopping consumption, thus saturating (limiting) the maximum sustained high consumption of the appliance.

Due to these simplifications, O'Connell et al. [24] and Zerrahn and Schill [41] argue that although the basic aggregated models are useful to find high level conclusions about the contribution of DR on a system level, these models are flawed and the conclusions reached may be misleading. These problems arising as a consequence of oversimplified DR models were already envisioned more than a decade ago in previous studies [39]. Therefore, there is a lack of investigation on aggregated models with a more accurate representation of the actual demand capabilities, for example, through load shifting including saturation and immediate load recovery.

In this section, we present models for aggregated flexible load processes that can be characterized by curtailment and/or shifting capabilities. Gils [38] lists around 30 different load processes for three different sectors where their flexibility can be fully represented by shifting or curtailment. Such load processes include, for example, cement mills and paper production in the industry sector, pumps in water supply and cold storages in the services (tertiary) sector, heating through heat pumps and cooling by air conditioners in the residential sector. Demand response through sector coupling, on the other hand, may need tailored models to represent their aggregated flexibility, for example, power-2-mobility can be modelled using electric vehicles and their shifting flexibility through smart charging and vehicle-2-grid (see section 4.2.7), and power-2-hydrogen can be modelled using the specific sector coupling technologies, e.g., electrolyzers, H_2-fired power plants, and their flexibility, including H_2 storage [89].

4.1. DR through curtailment

Load curtailment or shedding mainly appears in two different forms: to provide capacity or energy. The difference between these two is the price that consumers are willing to pay, the former being very high and the latter being relatively low.

4.1.1. Load curtailment to provide capacity

Curtailment for capacity has always been an emergency measure used by ISOs to guarantee the correct functioning of power systems. By curtailing part of the load, ISOs can avoid catastrophic (complete blackout) events [90,91]. To include curtailment for capacity, energy models include the option of non-supply energy, which is highly (linearly) penalized in the objective function. The value of this penalization is known as the value of lost of load (VoLL), which is traditionally defined as the value attributed by consumers to unsupplied energy. VoLL is an estimation of the maximum electricity price that consumers are willing to pay to avoid an outage, and it is very high (e.g., 10,000+€/MWh). This high non-supply energy penalization makes this type of curtailment the last emergency measure to balance demand and supply. That is, when the generation capacity, under specific circumstances, is not enough to cover peak demand, demand itself can provide capacity by curtailing, thus lowering the capacity requirements.

The general total consumption d_t^{DR} including curtailment as DR is then mathematically expressed as

$$d_t^{\mathrm{DR}} = D_t^0 - d_t^{\mathrm{NSE}} \qquad \forall t \tag{1}$$

$$d_t^{\mathrm{DR}}, d_t^{\mathrm{NSE}} \geq 0 \qquad \forall t \tag{2}$$

where t is the index for time periods, D_t^0 is the inflexible base load, and d_t^{NSE} is the non-supplied energy. Equation (1) obtains the total consumption as the base load minus curtailment, and (2) are the non-negative constraints for the decision variables.

4.1.2. Load curtailment to provide energy

DR participating in pure energy markets reacts to price variations according with its bids and constraints. DR appears in the form of curtailment in processes with very high utilisation rates, common in energy-intensive industries [38]. In this way DR "provides energy" by reducing demand [92,93]. This DR is commonly modelled as a flexible demand that is energy limited [94], that is, they can only reduce consumption by a certain amount of energy in a given period, e.g., a day:

$$d_t^{\mathrm{DR}} = D_t^0 - d_t^- \qquad \forall t \tag{3}$$

$$\sum\nolimits_{t=1}^{T} d_t^- \leq D^{\max} \tag{4}$$

$$d_t^- \leq \overline{D}_t^- \leq D_t^0 \qquad \forall t \tag{5}$$

$$d_t^{\mathrm{DR}}, d_t^- \geq 0 \qquad \forall t \tag{6}$$

where d_t^- is the amount of energy to be curtailed, $D^{\max}$ is the maximum reduction of load within the optimisation time span T, and $\overline{D}_t^-$ is the maximum reduction of load each period. In case there is no limit for the total energy to be curtailed $D^{\max}$, constraint (4) must be omitted.

DR as curtailment also appears in industrial or commercial premises which have on-site generation [94]. In this case, the production costs of the on-site generation are used as bidding price (or cost) for curtailment, this bidding price will then multiply d_t^- in the objective function of the optimisation problem. That is, if the electricity price in a given period is lower than the on-site generating costs, then the demand is supplied by the grid; on the other hand, electrical curtailment from the grid will be scheduled if the electricity price is higher than the on-site generation costs, since it is cheaper to provide the demand with the on-site unit.

The cost of curtailment or the value penalizing curtailment can be modelled in a step- [95] or piece-wise fashion [96], which leads to linear or quadratic penalizations on the curtailment value in the objective function, respectively. These penalization models are analogous to own-elasticity functions [35,71]. For the case of DR as capacity, non-supplied energy is usually linearly penalized using VoLL [97].

4.1.2.1. Valley filling. Although all types of DR can be fully characterized as either load shifting or curtailment or the combination of both, it is also common to find "valley filling" as an extra classic form of DR [98,99]. Here, we will show how valley filling is a particular case of load curtailment to provide energy, by using the model presented above. The model (3), (5) and (6) can be rewritten only in terms of the variable d_t^{DR} by replacing the variable d_t^- from (3) into (5) and (6):

$$\underline{D}_t \leq d_t^{\mathrm{DR}} \leq \overline{D}_t \qquad \forall t \tag{7}$$

where $\underline{D}_t$ and $\overline{D}_t$ are the minimum and maximum limits for demand consumption, respectively. Notice that, from (3) in (5) and (6), $\overline{D}_t = D_t^0$ and $\underline{D}_t = D_t^0 - \overline{D}_t^-$, and if the maximum load reduction is allowed, then $\underline{D}_t = 0$. Now the bidding price (or cost) for curtailment which was previously multiplying d_t^- in the objective function, will now multiply $-d_t^{\mathrm{DR}}$, which is obtained by replacing d_t^- in terms of $-d_t^{\mathrm{DR}}$ from (3).

Therefore, the resulting model (7) can be interpreted as a valley filling DR which will consume ($d_t^{\mathrm{DR}} \neq 0$) as long as the electricity price is lower than the bidding price, thus filling demand (low price) valleys. This type of valley filling DR is commonly considered and modelled as a negative generator (due to the negative sign in the objective function, as discussed above) [100], hence usually involving a binary variable (u_t) that takes the value of 1 if the demand is committed to consume within $[\underline{D}_t, \overline{D}_t]$, or 0 if consumption is zero, and (7) would then become $\underline{D}_t u_t \leq d_t^{\mathrm{DR}} \leq \overline{D}_t u_t, \ \forall t$, which would be typical constraints of industrial electrical boilers [101]. The model can be further extended to include more constraints [96], commonly used for generating units to include, for example, startup and shutdown decisions [102,103], which may be useful to limit the quantity of startups in a given period, e.g., a day.

4.1.3. Limiting the number of interventions and duration of load curtailment

To limit the number of interventions and duration of load curtailment, Zerrahn and Schill [104] proposed the linear constraint (8), complementing the load curtailment model (3), (5) and (6). In this model, the load can be curtailed once every T^{OFF} hours for a duration of maximum T^{DUR} hours:

$$\sum_{i=0}^{T^{\mathrm{OFF}}} d_{t+i}^{-} \leq \overline{D}^{0} T^{\mathrm{DUR}} \qquad \forall t \tag{8}$$

where $\overline{D}^0$ is the maximum load that can be curtailed in a single period.

However, this constraint cannot actually enforce that the load curtailment lasts a maximum of T^{DUR}, it just ensures that the total load curtailed during $T^{\mathrm{OFF}}+1$ h does not exceed $\overline{D}^0 T^{\mathrm{DUR}}$. For example, for a $T^{\mathrm{OFF}}=20$ and $T^{\mathrm{DUR}}=2$, (8) allows a load curtailment of $0.1\overline{D}^0$ for 20 consecutive periods, clearly violating the maximum duration of the curtailment of $T^{\mathrm{DUR}}=2$.

Guaranteeing a maximum number of interventions and duration of load curtailment. Here, we present an MIP model that guarantees a maximum number of interventions and maximum duration of the load curtailment:

$$d_t^{-} \leq \overline{D}_t^{-} \sum_{t=0}^{T^{\mathrm{DUR}}-1} \delta_{t-i} \qquad \forall t \tag{9}$$

$$\sum_{t=1}^{T} \delta_t \leq N \tag{10}$$

$$\sum_{t=0}^{T^{\mathrm{OFF}}-1} \delta_{t-i} \leq 1 \qquad \forall t \tag{11}$$

$$\delta_t \in \{0,1\} \qquad \forall t \tag{12}$$

where the binary variable δ_t indicates if there is an intervention ($\delta_t=1$) or not ($\delta_t=0$). Constraint (10) allows a maximum of N interventions during the time span T. Constraint (11) enforces that there is only one intervention in T^{OFF} consecutive hours. Once there is a curtailment intervention, (9) ensures that the curtailment can last a maximum of T^{DUR} hours. Notice that by definition $T^{\mathrm{OFF}} \geq T^{\mathrm{DUR}}$, which makes that the summation in (9) cannot be greater than one.

To indicate when the curtailment starts and after how many periods it should end, the model in Ottesen and Tomasgard [105] introduces two sets of binary variables. This type of constraints are similar to those used in unit commitment models to impose minimum up and down times [102,103].

A simpler and more general formulation for curtailment in aggregated DR models would be to only limit the number of interventions to a maximum number N in the time span T:

$$d_t^{-} \leq \delta_t \overline{D}_t^{-} \qquad \forall t \tag{13}$$

$$\sum_{t=1}^{T} \delta_t \leq N \tag{14}$$

Adding binary variables can also help to impose a fixed level of curtailment. For example, Marañón-Ledesma and Tomasgard [106] differentiate between curtailable and interruptible load, where the curtailable load d_t^- can be continuously adjusted from 0 to a predefined maximum $\overline{D}_t^-$, as modelled through this paper. In contrast, the interruptible load switches on or off [107], which can be achieved by replacing the inequality (13) by an equality, thus forcing the interruptible load d_t^- to be either 0 or $\overline{D}_t^-$.

The constraints to limit the number of interventions and duration of load curtailment make the model more specific to a given device/appliance [108]. However, if these MIP models are used in their LP relaxed form, i.e., $0 \leq \delta_t \leq 1$, then δ_t can represent a portion of demand that provides DR. Thus the LP relaxed formulations 1) make the model more suitable to represent aggregated demand in large-scale energy models, and also 2) make the models computationally more efficient, since they require solving an LP instead of an MIP.

4.2. DR through load shifting

Load shifting or deferral is the most common type of demand response. For example, Gils [38] lists more than 20 different processes that can be characterized by its ability to delay or anticipate consumption by a given time. Load can be shifted typically because it can: store heat or cold [44] (e.g., space heating, air conditioning), demand flexibility (e.g., washing, ventilation) [109], or physical storage (e.g., fresh water supply, hydrogen production) [32]. Load shifting is mainly limited by technical constraints, and also process requirements and availability of unutilized plant capacity [38].

From the system point of view, load shifting provides the same functionality as conventional storage units. That is, by shifting, load can "produce" energy by reducing demand when electricity prices are high, and consume energy by increasing demand when prices are low. Although DR shifting and storage work very similar in practice, and the equations are also similar, the primary difference is that storage as demand response, such as that of EVs, must supply a demand (e.g., enough energy to drive EVs) so there is always a given consumption, but that is not the case for pure storage units, which consumes and produces only if they can get a benefit from energy markets.

In this section, we present four different aggregated models for load shifting: 1) ideal shifting, 2) shifting including saturation, 3) shifting including saturation and load recovery, and 4) EVs which have a specific type of shifting.

4.2.1. Ideal shifting

The most common and simplistic way to model shifting is by supplying a given demand in a given time window [36,94,106,110], e.g., a day, a week, a year:

$$d_t^{\mathrm{DR}} = D_t^0 + d_t^{+} - d_t^{-} \qquad \forall t \tag{15}$$

$$\sum_{t=1}^{T} d_t^{+} = \sum_{t=1}^{T} d_t^{-} \tag{16}$$

$$d_t^{+} + D_t^0 \leq \overline{D}_t \qquad \forall t \tag{17}$$

$$d_t^- \le \overline{D}_t^- \le D_t^0 \qquad \forall t \tag{18}$$

$$d_t^{\mathrm{DR}}, d_t^+, d_t^- \ge 0 \qquad \forall t \tag{19}$$

where T is the number of periods in the time span, d_t^+ and d_t^- are the increment and reduction of demand consumption over the base demand D_t^0, respectively. To not change the overall consumption, (16) imposes that increments and reductions are balanced over the time span. That is, if energy consumption is reduced (increased) in one period, it has to be recovered by increasing (decreasing) demand in other period(s). Constraint (17) guarantees that the base demand plus the demand increment do not exceed the maximum capacity limit for demand consumption. The demand reduction is limited by (18). And (19) are the non-negative constraints for all decision variables.

The inconvenience of shifting the demand is expressed with a transaction cost in the objective function for demand increments d_t^+ or reductions d_t^- [111]. If these transaction costs are disregarded, the final demand profile with the ideal shifting will become completely independent from the base demand profile D_t^0. This makes the shifting model even more ideal as shown below.

4.2.1.1. Ideal shifting without a base demand profile. The set of constraints (15)–(19) can be further simplified if transaction costs are disregarded, that is, neither d_t^+ nor d_t^- appear in the objective function. To show this, let us introduce the free variable $\Delta_t = d_t^+ - d_t^-$, which can take either positive or negative values, and replace it into (15)–(18), we then obtain the following constraints [36]:

$$d_t^{\mathrm{DR}} = D_t^0 + \Delta_t \qquad \forall t \tag{20}$$

$$\sum_{t=1}^T \Delta_t = 0 \tag{21}$$

$$\Delta_t + D_t^0 \le \overline{D}_t \qquad \forall t \tag{22}$$

$$\Delta_t + D_t^0 \ge \underline{D}_t \qquad \forall t \tag{23}$$

where $\underline{D}_t = D_t^0 - \overline{D}_t^-$. Now, by replacing Δ_t from (20) into (21)-(23), the model (20)–(23) can be written as

$$\sum_{t=1}^T d_t^{\mathrm{DR}} = D^{\mathrm{Total}} \tag{24}$$

$$\underline{D}_t \le d_t^{\mathrm{DR}} \le \overline{D}_t \qquad \forall t \tag{25}$$

where $D^{\mathrm{Total}} = \sum_{t=1}^T D_t^0$. The resulting model will then ensure that there is a total energy consumption D^{Total} during the time span (24), distributing the flexible (variable) part of the demand to the periods with lowest prices while respecting the demand capacity limits (25). Therefore ideal shifting without a base demand profile will result if transaction costs are disregarded, even if the set of constraints (15)–(18) is used for including a base demand profile. However, not all shifting models need an underlying hourly demand profile, for example, a demand for hydrogen can be daily, weekly or monthly [112], leaving the DR model free to choose the cheapest hourly periods to consume electricity as far as the total demand for a given time period, e.g., weekly, is satisfied (24) within the technical demand capacity limits (25).

4.2.1.2. Ideal shifting with curtailment. Ideal shifting can be combined with curtailment, for example, in the case of a hybrid technology that can shift demand in time and also shift it from electricity to another source (e.g., gas), like the on-site generation example mentioned in section 4.1.2. The common practice to add curtailment is by allowing curtailment in (15):

$$d_t^{\mathrm{DR}} = D_t^0 + d_t^+ - d_t^- - \rho_t \qquad \forall t \tag{26}$$

where ρ_t is the positive variable representing the demand to be curtailed in each time period. However, if the curtailment bidding price is the same for all time periods, only one time-independent curtailment variable (ν) is really needed, unlike ρ_t that adds T extra variables to the formulation. The new formulation adding curtailment only requires modifying (16), now allowing demand reductions to be higher than demand increments:

$$\sum_{t=1}^T d_t^+ + \nu = \sum_{t=1}^T d_t^- \tag{27}$$

where ν is the positive (no time-dependent) variable representing the overall curtailment in the time span, and it is penalized by a cost reflecting the (no time-dependent) demand willingness to curtail. Also d_t^- has a new component representing curtailment.

In the case of ideal shifting without base demand, (24) then becomes

$$\sum_{t=1}^T d_t^{\mathrm{DR}} = D^{\mathrm{Total}} - \nu. \tag{28}$$

Notice that d_t^{DR} will remain within its limits as long as it is bounded by (25).

4.2.2. Shifting including saturation

The previous ideal shifting model can be extended to include saturation. For the sake of completeness, here the complete new model:

$$d_t^{\mathrm{DR}} = D_t^0 + d_t^+ - d_t^- \qquad \forall t \tag{29}$$

$$e_t = e_{t-1} + d_t^- - d_t^+ \qquad \forall t \tag{30}$$

$$\underline{E} \le e_t \le \overline{E} \qquad \forall t \tag{31}$$

$$e_0 = e_T = E^0 \tag{32}$$

$$d_t^+ + D_t^0 \le \overline{D}_t \qquad \forall t \tag{33}$$

$$d_t^- \le \overline{D}_t^- \le D_t^0 \qquad \forall t \tag{34}$$

$$d_t^{\mathrm{DR}}, d_t^+, d_t^- \ge 0 \qquad \forall t \tag{35}$$

where (29) and (33)–(35) are the same as those constraints of ideal shifting in section 4.2.2. The new constraints (30)–(32) involve the free variable e_t representing a storage level, where (30) tracks its state of charge. Constraint (31) imposes a maximum and a minimum storage capacity. And (32) ensures that the storage level returns to its initial value at the end of the time span, thus guaranteeing that demand can be shifted, but the total overall energy consumption will remain the same, similarly to (16).

The load saturation effect is then modelled by giving a maximum and minimum capacity to the storage level [113,114]. That is, (31) will not allow an unlimited load overconsumption (over-curtailment) during many consecutive periods because the storage will reach its maximum (minimum) level [115]. Notice that if (31) is disregarded, the set of constraints (29), (30) and (32)–(35)

is equivalent to the ideal shifting model presented in section 4.2.1.

Also, this shifting model including saturation can be modified to allow curtailment, by replacing (32) with:

$$e_0 = E^0 \tag{36}$$

$$e_T = E^0 - \nu. \tag{37}$$

where, basically, these constraints allow demand reductions to be higher than demand increments (similarly to (27)). In case the demand willingness to curtail is time-dependent, a time-dependent variable for curtailment ρ_t should be used instead, and replace (29) by (26).

4.2.3. Shifting including saturation and load recovery

Previous shifting models presented in sections 4.2.1 and 4.2.2 do not model load recovery nor do they take into account the delay time of some DR appliances. Although the formulation presented in section 4.2.2 models saturation, it does not limit the maximum time that the DR appliance takes to be saturated, which is known as anticipate (advance) or delay (defer) time. Also, the models in sections 4.2.1 and 4.2.2 do not ensure load recovery in due time, also known as load rebound, which is usually immediately after a delay (load decrease) or anticipate (load increase) of load takes action [50]. These delay and load-recovery times are the most common parameters used to characterise shiftable loads [38]. To solve this issue Göransson et al. [40] proposed a linear shifting model including these delay recovery load times, the complete formulation is as follows:

$$d_t^{\mathrm{DR}} = D_t^0 + d_t^+ - d_t^- \qquad \forall t \tag{38}$$

$$e_t = e_{t-1} + d_t^- - d_t^+ \qquad \forall t \tag{39}$$

$$e_t \le \sum\nolimits_{l=0}^{L-1} d_{t-l}^- \qquad \forall t \tag{40}$$

$$e_t \le \sum\nolimits_{l=1}^{L} d_{t+l}^+ \qquad \forall t \tag{41}$$

$$d_t^+ \le \overline{D}_t^+ = \overline{D}_t - D_t^0 \qquad \forall t \tag{42}$$

$$d_t^- \le \overline{D}_t^- \le D_t^0 \qquad \forall t \tag{43}$$

$$d_t^{\mathrm{DR}}, d_t^+, d_t^- \ge 0 \qquad \forall t \tag{44}$$

where L is the delay and recovery time of the DR process. These constraints are very similar to those presented in section 4.2.2, but now the constraints on the storage e_t (31) and (32) are replaced by (40) and (41). Here, (40) ensures the storage level e_t to be lower than the sum of the downward shift d_t^- over previous *L-1* periods. Similarly, (41) enforces the storage level e_t to be lower than the sum of the upward shift d_t^+ over future L periods.

Adding anticipate shifting. The formulation (38)–(44) just models load delay and not load anticipation, as highlighted in Zerrahn and Schill [41]. Notice that (40)-(41) model load delay by imposing upper bounds to e_t; similarly, we model load anticipation by imposing lower bounds to e_t:

$$e_t \ge -\sum\nolimits_{l=1}^{L} d_{t+l}^- \qquad \forall t \tag{45}$$

$$e_t \ge -\sum\nolimits_{l=0}^{L-1} d_{t-l}^+ \qquad \forall t \tag{46}$$

In short, (38)–(44) together with (45) and (46) model load shifting (delay and anticipation) and load recovery.

4.2.4. Trying to guarantee immediate load recovery

A major drawback of the formulation above is that it allows for undue recovery of load shifts, that is, it cannot really guarantee an immediate load recovery, as widely discussed in Zerrahn and Schill [41]. To tackle this issue, Zerrahn and Schill [41] propose to add the following constraint:

$$d_t^+ + d_t^- \le \max\{\overline{D}_t^+, \overline{D}_t^-\} \qquad \forall t \tag{47}$$

thus limiting the amount of load that is shifted up and down simultaneously, which is the reason why the formulation above fails to guarantee immediate load recovery [41].

To also allow load delay and anticipation, Zerrahn and Schill [41] suggest an alternative formulation by substituting the variables d_t^+ and d_t^- for DSM_t^{up} and $DSM_{t,tt}^{do}$. With the double time index of $DSM_{t,tt}^{do}$ it is possible to connect every downward shift in hour tt to an upward shift in hour t. Therefore, it could be possible to start with a downward shift and later compensate it with an upward adjustment, that is, the formulation allows delay and anticipate shifting. The final formulation is written as follows:

$$d_t^{\mathrm{DR}} = D_t^0 + DSM_t^{up} - \sum\nolimits_{tt=t-L}^{t+L} DSM_{tt,t}^{do} \qquad \forall t \tag{48}$$

$$DSM_t^{up} = \sum\nolimits_{tt=t-L}^{t+L} DSM_{t,tt}^{do} \qquad \forall t \tag{49}$$

$$DSM_t^{up} \le \overline{D}_t^+ \qquad \forall t \tag{50}$$

$$\sum\nolimits_{t=tt-L}^{tt+L} DSM_{t,tt}^{do} \le \overline{D}_{tt}^- \qquad \forall tt \tag{51}$$

$$DSM_{tt}^{up} + \sum\nolimits_{t=tt-L}^{tt+L} DSM_{t,tt}^{do} \le \max\{\overline{D}_{tt}^+, \overline{D}_{tt}^-\} \quad \forall tt \tag{52}$$

$$d_t^{\mathrm{DR}}, DSM_t^{up} \ge 0 \qquad \forall t \tag{53}$$

$$DSM_{t,tt}^{do} \ge 0 \qquad \forall t, tt \tag{54}$$

It is important to remark that, this formulation still allows simultaneous up and down shifting. The authors in Ref. [41] highlight the importance of immediate load recovery, so they propose the constraint (52) to lower the effect of undue recovery of load.

4.2.5. Shifting including saturation and guaranteed load recovery

Load shifting models including load recovery must guarantee the immediate load recovery, as this is required by many shiftable loads [41]. O'Connell et al. [33] also acknowledge that the need to recover load is paramount, they then propose an MIP formulation to guarantee that load is recovered immediately after responding to a load delay or anticipation. The model, however, is not LP and much larger: it requires many more binary and continuous variables (per period), and many Big-M constraints, hence making the formulation unsuitable for large-scale energy models since it will make the resulting model computationally intractable.

The models above allow for undue load recovery because the formulations allow simultaneous up and down shifting [41]. Although (47) and (52) attempt to limit the amount of load that is shifted up and down simultaneously, they still fail to guarantee immediate load recovery. To overcome this drawback, we add to the previous formulation (38)–(46) the binary variable δ_t, and to guarantee immediate load recovery, the proposed formulation enforces that the load cannot be shifted up and down simultaneously. For the sake of completeness, here we write the full resulting MIP formulation for load shifting (delay and anticipation) and guaranteed load recovery:

$$d_t^{DR} = D_t^0 + d_t^+ - d_t^- \qquad \forall t \tag{55}$$

$$e_t = e_{t-1} + d_t^+ - d_t^- \qquad \forall t \tag{56}$$

$$e_t \le \sum_{l=1}^{L} d_{t+l}^+ \qquad \forall t \tag{57}$$

$$e_t \le \sum_{l=0}^{L-1} d_{t-l}^- \qquad \forall t \tag{58}$$

$$e_t \ge -\sum_{l=1}^{L} d_{t+l}^- \qquad \forall t \tag{59}$$

$$e_t \ge -\sum_{l=0}^{L-1} d_{t-l}^+ \qquad \forall t \tag{60}$$

$$d_t^+ \le \overline{D}_t^+ \delta_t \qquad \forall t \tag{61}$$

$$d_t^- \le \overline{D}_t^- (1-\delta_t) \qquad \forall t \tag{62}$$

$$\delta_t \in \{0,1\} \qquad \forall t \tag{63}$$

$$d_t^{DR}, d_t^+, d_t^- \ge 0 \qquad \forall t \tag{64}$$

Notice that the binary variable δ_t in (61) and (62) guarantees that load cannot be shifted up and down simultaneously by imposing that variables d_t^+ and d_t^- are mutually exclusive.

Similarly, we can modify the model (48)–(54) to guarantee immediate load recovery by introducing the binary variable δ_t and replacing (50)–(52) by

$$DSM_t^{up} \le \overline{D}_t^+ \delta_t \qquad \forall t \tag{65}$$

$$\sum_{t=tt-L}^{tt+L} DSM_{t,tt}^{do} \le \overline{D}_t^- (1-\delta_t) \qquad \forall tt \tag{66}$$

$$\delta_t \in \{0,1\} \qquad \forall t \tag{67}$$

4.2.6. LP approximation for immediate load recovery

Although the model above guarantees immediate load recovery, it requires solving an MIP, which is computationally more demanding than solving an LP. For a large variety of problems, this would not be a barrier, but for many large-scale energy models solving MIP problems is intractable, hence an LP equivalent or approximation is preferable.

For the LP approximation, the MIP model (55)–(64) can be relaxed by making the variable δ_t continuous $0 \le \delta_t \le 1$. The quality of this approximation depends on the tightness of the model [102,103,116], and solving the LP relaxation of the ideal tightest possible model (convex hull) provides the exact MIP solution. The tightness of the model then defines how near the solution of the LP relaxation is from the exact MIP solution, and the tighter the model is, the nearer its relaxed solution is to the MIP solution. Apart from being a better approximation of the MIP problem, a tight formulation also speeds up the MIP solving times [102,103].

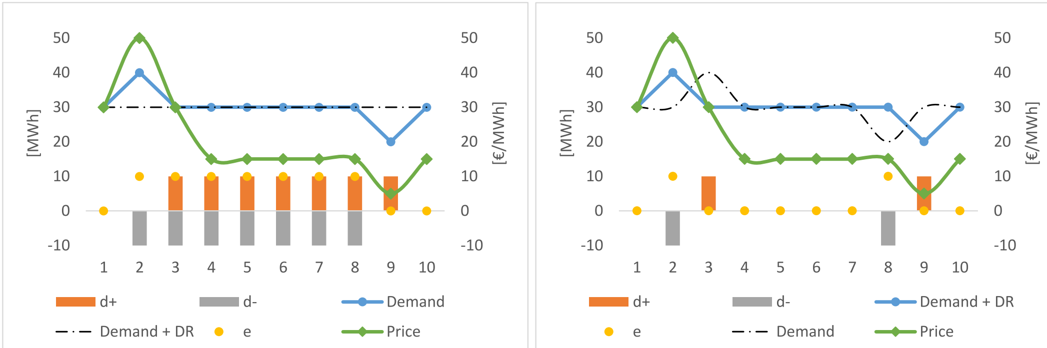
Now, in the following example we will illustrate how the proposed model extension (61)–(63), in its relaxed form, better lowers the effect of undue load recovery compared to the model extension (47) proposed by Zerrahn and Schill [41]. Let us consider the demand profile depicted in Fig. 5 (solid blue line with circles) and a maximum shifting time of one period ($L = 1$), also let us define the maximum possible values for d_t^+ and d_t^- as $\overline{D}_t^+ = 10$ and $\overline{D}_t^- = 20$, respectively. The resulting demand after DR then optimally reacts to the energy prices (solid green line with diamond markers) in order to lower energy costs. The initial demand profile without DR is facing a total cost of 6600€.[1] Fig. 5(a) shows the resulting demand profile after DR (dashed black line) as a feasible solution of the model extension (47), lowering the total costs to 6150€. The model extension (47) allows to shift 10 MW from the most expensive period (2) to the cheapest period (9), resulting in 7 periods shifting, thus clearly violating the allowed shifting time of one period ($L = 1$). This is a consequence of (47) imposing $d_t^+ + d_t^- \le \max\{10, 20\}$, which allows $d_t^+ = 10$ and $d_t^- = 10$ from period 3 onwards, making an unlimited shifting time possible, resulting in an ideal shifting similar to the one described in section 4.2.2.

On the contrary, the proposed model extension (61)–(63) in its relaxed form avoids this unlimited shifting completely, as illustrated in Fig. 5(b): once $d_3^+ = 10$, (61) forces $\delta_3 = 1$ and (62) forces mutual exclusivity, i.e., $d_3^- = 0$, which is the only feasible solution (instead of $d_t^- = 10$ allowed by (47)), thus allowing shifting for a maximum of one period. In order to lower costs, the proposed model only allows to shift 10 MWh from the most expensive period (2) to the next period, since the maximum shifting time is one period ($L = 1$), and again the model can shift 10 MWh from period 8 to the next to take advantage of the cheapest price on period 8. The minimum possible energy cost after DR is then 6300€, unlike the 2.4% underestimation (6150€) produced by the model extension (47) which resulted in an unrealistic and overestimated DR flexibility.

The previous example shows how the proposed formulation (61)–(63) could impose mutual exclusivity because the shifting took place at maximum capacity ($d^+ = 10 \le 10$); however, this is not always the case as illustrated in the following second example. Let us consider the parameters and demand profile of the previous example but now the maximum possible values for d_t^+ and d_t^- are defined as $\overline{D}_t^+ = 12$ and $\overline{D}_t^- = 24$, respectively, and the minimum load after DR for period 2 is limited to 100 MWh (imposed by a constraint like (25)). Fig. 6(a) shows the optimal solution produced by the model extension (47), which presents a total costs to 6100€. Now to keep the minimum load of 100 MWh in period 2, a maximum of 10 MW can be shifted from the most expensive period (2) and are shifted to the cheapest period (9), resulting again in 7 periods shifting, and 2 MWh from the second most expensive period (3) shifted 6 periods to the cheapest period (9), thus increasing the load on the cheapest period by a total of 12 MWh. As in the previous example, (47) imposes $d_t^+ + d_t^- \le \max\{12, 24\}$, which allows $d_t^+ = 12$ and $d_t^- = 12$ from period 4 onwards.

Fig. 6(b) shows the possible optimal shifting resulting from the proposed model extension (61)–(63) in its relaxed form: once $d_3^+ = 10$, (61) makes $\delta_3 \ge 0.833$ and (62) imposes $d_3^- \le 24(1-\delta_3)$ allowing $d_3^- = 4$, which results in an imposed shifting of at least

[1] 30 MWh at 30€/MWh on periods 1 and 3, 40 MWh at 50€/MWh on period 2, 30 MWh at 15€/MWh on periods 4 to 8 and 10, and 20 MWh at 5€/MWh on period 9.



(a) Approximation from (47) (b) Approximation from the relaxed (61)-(63)

Fig. 5. Comparison of undue load recovery for different model approximations for the case when there is shifting (delay) to the maximum possible ($d^+ = 10 \leq 10$). The right axis is for d+, d-, e, Demand and Demand + DR, and the left axis is for energy prices.

6 MWh (d_3^+-d_3^-) for one period and the other 4 MW are allowed to shift to the cheapest period (9). Also, to lower costs 8 MWh are allowed to shift one period from period 8 to period 9. Thus resulting in a total energy cost of 6220€. Notice how in this second example, although the proposed model presented an underestimated cost of 1.3%, the resulting demand profile after DR is very similar to the exact feasible solution (see Fig. 5(b)); unlike the model extension (47) which presented an underestimated error cost of 3.2% (2.5 times higher) and a very different profile compared with the exact feasible solution. The larger the difference between the exact feasible profile after DR and the profile from the model approximation, the larger the impact to the system since the system will expect an over-flexible load, to balance VRE for example, which is far from feasible in practice leading to misleading conclusions about the potential and expectations of DR.

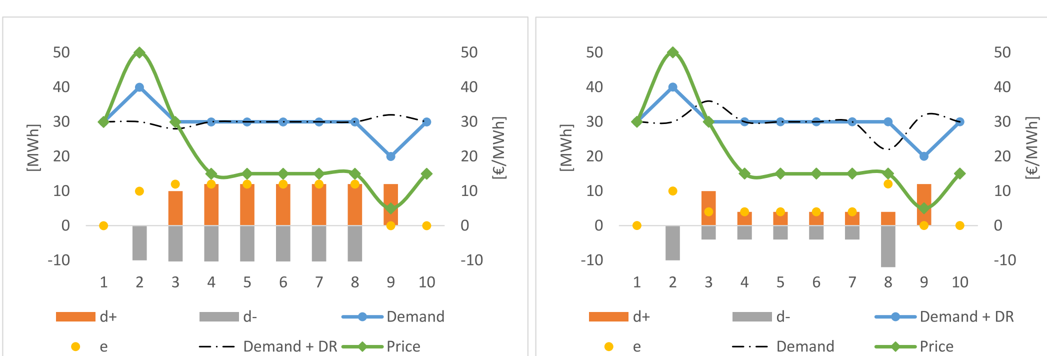
For the second example, in Fig. 6, the proposed formulation could not guarantee the shifting for only one period, but the solution was a much better approximation than the completely ideal shifting allowed by the formulation (47) by Zerrahn and Schill [41]. As mentioned above, this error appears because the models allow both variables d_t^- and d_t^+ to take values different than zero in the same period, as also widely discussed in Zerrahn and Schill [41]. This problem is completely solved by defining δ_t as a binary variable in the proposed formulation (61)–(63), thus imposing mutual exclusivity, but the model would become an MIP, which is computationally more demanding than the LP relaxation. That is why here we also propose the relaxation of (61)-(63) as an alternative approximation to keep the model as an LP.

In short, although the proposed formulation extension (61)–(63), in its relaxed LP form, cannot guarantee that variables d_t^+ and d_t^- are mutually exclusive at all times, it provides feasible solutions that are much more nearer to mutual exclusivity (of d_t^+ and d_t^-) than the solution that can be obtained with (47). This results as a natural consequence of the proposed model being tighter, that is, the feasible solutions resulting from the formulation (47) are not feasible for the proposed model (61)–(63) [116], as shown in the previous two examples.

In case that the shifting model with load recovery is always used in its LP relaxed form, where δ_t is always treated as a continuous variable $0 \leq \delta_t \leq 1$, we can reduce the dimension of the problem by eliminating the δ_t variable: we now apply the Fourier-Motzkin elimination procedure to variable δ_t, then the relaxed form of (61)-(63) can be replaced by its exact equivalent:

$$\frac{d_t^+}{\overline{D}_t^+} + \frac{d_t^-}{\overline{D}_t} \leq 1 \qquad \forall t \tag{68}$$

Similarly, we could eliminate δ_t from (65)-(67) by applying the Fourier-Motzkin elimination procedure. Therefore, the relaxed form of (65)-(67) can be replaced by its exact equivalent:



(a) Approximation from (47) (b) Approximation from the relaxed (61)-(63)

Fig. 6. Comparison of undue load recovery for different model approximations for the case when there is shifting (delay) but not to the maximum possible ($d^+ = 8 \leq 10$). The right axis is for d+, d-, e, Demand and Demand + DR, and the left axis is for energy prices.

$$\frac{DSM_{tt}^{up}}{\overline{D}_{tt}^{+}} + \frac{\sum_{t=tt-L}^{tt+L} DSM_{t,tt}^{do}}{\overline{D}_{tt}^{-}} \leq 1 \quad \forall tt \tag{69}$$

Notice that in the model (48)–(54), the proposed constraint (69) can replace the three sets of constraints (50)–(52), resulting in a tighter and more compact model (lower number of constraints and non-zeros), which apart from potentially solving faster, due to being more compact, it will produce more precise results, due to its tightness [103].

4.2.7. Electric vehicles (EV)

Demand response by EVs is perhaps the most widely researched type of DR. Here we present a formulation for aggregated EVs that is commonly used in the literature, for further details about EV models the reader is referred to Refs. [85,117–120], and for comparison of different EV models to Ref. [121].

To represent EVs in power system models, many formulations rely on generic or qualitative mobility patterns, in which average connected and available capacities range from 80 to 90% at all times. Some formulations do not even explicitly take mobility patterns into account [122]. Similarly to the shifting models presented so far, an energy balance or inventory for EV batteries is needed. Rarely, an explicit energy balance is omitted [123]. The total EV energy inventory is then commonly modelled as

$$e_t = e_{t-1} + p_t^{\text{G2V}}\eta^{\text{G2V}} - \frac{p_t^{\text{V2G}}}{\eta^{\text{V2G}}} - E_t^{\text{drive}} \quad \forall t \tag{70}$$

where p_t^{G2V} and p_t^{V2G} are the power consumed and provided by the EVs, respectively, and η^{G2V} and $\eta^{\text{V2G}}$are their respective efficiencies. E_t^{drive} is the total electric consumption by all EVs while driving.

The storage energy capacity, as well as the charging and discharging capacity are limited by

$$\underline{E}N^{\text{plugged}} \leq e_t \leq \overline{E}N^{\text{plugged}} \qquad \forall t \tag{71}$$

$$0 \leq p_t^{\text{G2V}} \leq \overline{P}_t^{\text{G2V}} N^{\text{plugged}} \qquad \forall t \tag{72}$$

$$0 \leq p_t^{\text{V2G}} \leq \overline{P}_t^{\text{V2G}} N^{\text{plugged}} \qquad \forall t \tag{73}$$

where N^{plugged} is the total number of EVs connected to the system, $\underline{E}$ and $\overline{E}$ are the minimum and maximum energy storage capacity per vehicle, respectively, and $\overline{P}_t^{\text{G2V}}$ and $\overline{P}_t^{\text{G2V}}$ are the maximum charging and discharging capacity of the EVs, respectively.

For the sake of brevity and clarity, this section presented the key components of the DR models, but these models can be easily extended to include further details, such as:

- Including period duration: this is paramount to differentiate between power (charge/discharge) and energy (storage) units when the model has period durations different than an hour [85,124].
- Representing that just a percentage of the load is controllable: it is straightforward to include a parameter representing the percentage of the load that is responsive, this parameter should multiply the capacity limits of the variables that allow DR.
- Modelling losses: if any specific process presents significant losses (or dissatisfaction) when activating DR, an efficiency (or penalization) parameter can be added to the storage inventory equations (or objective function) to represent this effect, similar to the case of EVs in (70), and other cases of DR with losses or dissatisfaction penalization are shown in Refs. [41,125].
- Including reserves: all these models can be extended to include reserves. This model extension is less evident and may require addition of binary variables to avoid double-counting reserves when the DR is activated up and down. For further details on reserve modelling, the reader is referred to the EVs cases in Refs. [121,124,126] or storage in general in Ref. [127].

Finally, the mathematical formulations presented in this section could also be integrated into market clearing models. Energy markets already allow the participation of DR through curtailment (see section 4.1.2) where large-scale and aggregated demand can bid their willingness to pay. Aggregated DR through shifting could also participate in the market using parametrized aggregated storage models (similar to those in section 4.2), as proposed by some ISOs (e.g., ERCOT [128]) and mandated by FERC [129] to open up the US wholesale energy markets to distributed energy resources (DERs), including demand response.

5. Conclusions

In future energy systems with large penetrations of variable renewable energy sources, demand side management and demand response (DR) are expected to play a crucial role due to their potential to provide flexibility, reduce peak generation capacity requirements and function as reserve providers, among others. It is therefore desirable that energy models include DR as an option when analysing future energy systems. Most of the basic aggregated demand response models found in the literature are oversimplified, and although they can be useful on a system level, conclusions based on them can be mistaken. Moreover, integrated energy models, in which usually many different energy sectors are included, are commonly designed as linear programming (LP) problems. Therefore, when modelling DR it is desirable to write the mathematical problem in a linear and aggregated way, while ensuring that the quality of the results is sufficient. Balancing this tradeoff is not straightforward. Before this paper, there was not in the literature any review of a collection of linear and aggregated DR formulations that can be implemented in large-scale power systems or integrated energy system models. We have filled this gap by suggesting mathematical models that are linear, i.e., simple enough to keep a low computational burden, but sufficient to capture the key effects of DR in the energy system.

This paper consisted of two main parts, which focused on two different but related topics of classifying and modelling different types of demand response. The first part presented a literature review including a classification of demand side management categories, with a particular focus on DR from the power system perspective. In this paper, we identified different benefits and challenges of implementing DR analysed in previous studies. Benefits include reduction of electricity prices, mitigation of market power, a potential increase of the overall system efficiency, and finally a better integration of large shares of variable renewable energy sources. A major challenge of implementing DR in practice is the regulatory framework, since current markets are not designed for systems where DR plays a major role. On top of that, establishing a feasible business case, properly valuing DR in order to define its revenues, and taking into account the behaviour of end-use consumers are also relevant challenges.

The second part of this paper presented a collection of linear and aggregated mathematical formulations that can be used to implement DR in large-scale integrated energy models. These formulations consist of sets of linear inequalities for different types of DR, thus these inequalities can be directly incorporated into any energy system model or power system model. The different DR models presented in this paper include formulations for load curtailment to provide capacity, for curtailment to provide energy, for valley filling (which is a case of curtailment to provide energy), for ideal load shifting, for load shifting including saturation, for load shifting including saturation and load recovery, and for electric vehicles. It is important to remark that future research is needed to improve DR formulations for load recovery, since current linear models cannot guarantee immediate recovery of load, which can lead to unrealistic results.

Since previous linear models cannot guarantee immediate load recovery, leading to unrealistic results, we then propose a mixed-integer programming (MIP) formulation to solve this undue load recovery problem. As an approximation, this model can be used in its LP relaxed form, and due to its tightness, it provides a much better approximation to the exact MIP solution compared with the previous formulations attempting to diminish the undue load recovery. Apart from using the different models, presented in this paper, in studies exploiting DR, an interesting subject for future research is to compare the impact on flexibility to harness renewables of the different models approximations using large-scale integrated energy system models.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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