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Approaches for Accommodating Demand Response in Operational Problems and Assessing its Value

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Summary (English)

This thesis deals with the development of operational models of demand response and the evaluation of this novel resource within existing frameworks for power system dispatch and market clearing.

Increasing shares of power generation from variable renewable sources, and climate change policies that discourage the use of fossil fuel intensive power plants, are among the factors that are currently driving the evolution of power systems towards greater flexibility. Activating the latent flexibility of electricity consumption through demand response can contribute towards facilitating this evolution. However, before the necessary investments can be made to establish and operate this novel resource, its value must be determined.

As with all current power system resources, if distributed demand response is deployed on a large scale it will be required to interface with the power system and market operators through established frameworks. Such frameworks are not suited to interaction with large numbers of individual flexible loads, so it is necessary to establish a representation of their aggregated flexibility that can be effectively communicated to system and market operators. In this thesis we introduce the concept of a saturation curve, which represents the flexibility offered by a broad class of flexible loads capable of providing load shifting demand response: thermal-electric loads such as refrigeration and heating. From this saturation curve we extract dispatch and market offering structures for demand response that respect the physical characteristics and constraints of the individual flexible loads within an aggregate population, while being limited in complexity to that allowable within current operational power system frameworks.

An evaluation of demand response must consider both the social welfare value it generates by reducing overall power system operation costs, and the commercial value it can accrue by participating in competitive electricity markets. Social welfare value provides an indicator of the viability of any new power system resource, but does not guarantee that the necessary investments will be made to establish and operate the resource. A positive commercial assessment will signal to investors that the resource can offer a return on their investment, and that it can thrive in a competitive environment. We consider both the social welfare and commercial value of demand response in this thesis, by simulating the deployment of our specialised operational models of demand response within power system dispatch frameworks and by developing innovative trading strategies for demand response on the day-ahead and intraday markets.

We find through the combined modelling and analysis contained in this thesis that the value offered by demand response is very low under current power system conditions, and when it is restricted to operating within existing operational frameworks. Prices and costs on the studied power systems are insufficient to allow demand response to generate significant value or revenue through energy arbitrage or load curtailment. This does not rule out that there maybe certain power systems, or sections thereof, that are currently experiencing sufficient resource scarcity to result in a favourable environment for the successful implementation of demand response. At the current time however, our research finds that the outlook for the widespread deployment of demand response is poor.

Resumé (Danish)

Denne afhandling beskæftiger sig med udvikling af operationelle modeller til *demand response* og evaluering af denne nye ressource indenfor de eksisterende *power system dispatch* frameworks og *market clearing*.

I takt med at el-produktionen fra vedvarende energikilder udbygges og en grønnere klimapolitik modvirker fossile brændstoffer, kræver el-nettet udvikling mod mere fleksibilitet. *Demand response* kan bidrage positivt til denne udvikling. Men før investeringerne følger med skal værdien af denne nye ressource bestemmes.

Hvis distribueret *demand response* skal implementeres i stor skala, skal der kommunikeres med eksisterende aktører i el-nettet i samme framework, som alle eksisterende ressourcer i el-nettet gør det i dag. Desværre er det nuværende framework ikke egnet til at håndtere så mange små fleksible ressourcer. Derfor er det nødvendig at udvikle en måde at repræsentere deres samlede fleksibilitet, der også kan fungere effektivt sammen med det nuværende framework. I denne afhandling introducerer vi konceptet *saturation curve*, som netop kan repræsentere fleksibiliteten af en lang række *demand response* ressourcer, herunder varme- og køleanlæg. Ud fra vores *saturation curve* kan vi finde nogle repræsentationer af *demand response* som inkluderer de individuelle ressourcers fysiske egenskaber og begrænsninger, og som passer ind i det nuværende framework.

En evaluering af *demand response* bør indeholde både samfundsomkostninger fra reducerede driftsomkostninger, men også den værdi, der genereres gennem deltagelse i konkurrencedygtige el-markeder. Samfundsomkostningerne indikerer levedygtigheden af en ny ressource, men garanterer ikke investeringerne til at

sætte den i drift. En positiv kommerciel vurdering er et signal til investorer om at ressourcen kan have succes i en konkurrencedygtig situation. I denne afhandling kigger vi både på samfundsomkostninger og den kommercielle værdi af *demand response*. Vi simulerer driften af *demand response* med specialiserede modeller og udvikler innovative handelsstrategier til *day-ahead* og *intraday* el-markederne.

Fra afhandlingens modellering og analyse finder vi, at værdien af *demand response* er meget lav under de nuværende forhold. Prisen og omkostningerne for systemet er ikke høje nok til at sikre en indtjening på *demand response* gennem *load curtailment* eller energi arbitrage. Derimod kan der være andre el-markeder, hvor *demand response* kan være vigtig, og kan hjælpe med at beskytte mod ressourceknapheden i el-nettet. Udrulningen af *demand response* ser dog på nuværende tidspunkt ikke lovende ud.

Preface

This thesis was prepared at the Department of Applied Mathematics and Computer Science at the Technical University of Denmark (DTU) in partial fulfilment of the requirements for acquiring a Ph.D. degree.

This thesis addresses the development of operational models of aggregated demand response to facilitate its evaluation within current power system frameworks. Methods are developed for the optimal accommodation of demand response within operational power system problems, and evaluation studies consider the social welfare and commercial value offered by this novel resource.

This thesis consists of a summary report and five research papers, detailing the research conducted over the period of January 2013 to December 2015.

Kgs. Lyngby, 31-December-2015

Niamh O'Connell

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I would like to take this opportunity to thank all those with whom I have fruitfully collaborated during my studies. Thanks to all at Danfoss and DTI, in particular Christian Heerup and Torben Green, for supplying data and teaching me all about refrigeration systems. Thanks to Juan Miguel Morales for a very rewarding collaboration and for all our discussions on trading and optimisation. Particular thanks goes to Elaine Hale and all at NREL for hosting me during my visit. My stay at NREL was highly beneficial and I learnt a lot about the modelling of power systems and demand response from working with all in the energy forecasting and modelling group, as well gaining yet more insight into the workings of refrigeration systems from those in the commercial buildings group.

Thanks also goes to all of my colleagues at DynSys (past and present). Thanks in particular to all those I have shared offices with: Marco, Javi, Jacopo and Piju. Thanks for acting as a sounding board, for all our interesting conversations (both research related and not), and for all those coffee breaks.

My family in Ireland deserve special recognition and thanks for all of their support through the years, and for accepting without question my decision to move to Denmark to work on *hard sums.*

Finally, I would like to thank Christian for his unyielding support during the highs and lows of this PhD.

List of Publications

Scientific Research Publications in this Thesis

A N. O'Connell, P. Pinson, H. Madsen, and M.J. O'Malley. "Benefits and Challenges of Electrical Demand Response: A Critical Review". *Renewable and Sustainable Energy Reviews* 39 (2014): 686-699.

B N. O'Connell, H. Madsen, P. Pinson, M.J. O'Malley, and T. Green. "Regulating Power from Supermarket Refrigeration". In *Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2014 IEEE PES*, pp. 1-6. IEEE, 2014.

C N. O'Connell, P. Pinson, H. Madsen, and M.J. O'Malley (2015). "Economic Dispatch of Demand Response Balancing through Asymmetric Block Offers". *IEEE Transactions on Power Systems* (In Press).

D N. O'Connell, E. Hale, I. Doebber, and J. Jorgensen (2015). "On the Inclusion of Energy-Shifting Demand Response in Production Cost Models: Methodology and a Case Study". *NREL Technical Report* (Golden, CO: National Renewable Energy Laboratory, 2015). NREL/TP-6A20-64465

E N. O'Connell, J.M. Morales, P. Pinson, and H. Madsen. "Trading Flexible Electricity Consumption in Spot Markets under Demand Response Uncertainty". Submitted to *IEEE Transactions on Power Systems*

Other Works Not Included in this Thesis

F N. O'Connell, H. Madsen, P. Pinson, and M.J. O'Malley (2013). "Benefits and Challenges of Demand Response: A Critical Review," In *IAEE International Energy Conference*, 2013

G N. O'Connell, H. Madsen, P. Pinson, and M.J. O'Malley (2013). "Modelling and Assessment of the Capabilities of a Supermarket Refrigeration System for the Provision of Regulating Power," DTU Technical Report 2013-24.

H N. O'Connell, H. Madsen, P. Pinson, and M.J. O'Malley (2014). "Identification of Models of Display Units in Supermarket Refrigeration Systems," DTU Technical Report 2014-02.

Contents

Part I

Summary Report

Chapter 1

Introduction

1.1 Context and Motivations

Power systems around the world are experiencing a period of rapid evolution. The long-established framework of large centralised thermal generation plants, operating within vertically integrated utilities, and serving a well-understood and forecastable load is being abandoned. In its place, we are seeing a move towards highly distributed generation [1], large shares of stochastic renewable energy sources [2], the adoption of competitive electricity markets, and a greater degree of interconnection between previously distinct power systems. Yet, these changes seem almost mundane when compared to the anticipated developments in the coming years. Micro-generation, an increase in fully or partially off-grid electricity end-users, distributed energy storage, and demand response are all predicted to play a role in the power system of the future [1, 3, 4, 5]. The increasing autonomy and flexibility of consumers has the potential to disrupt the business cases of large utilities and grid operators, and to challenge the fundamental concept of top-down power system control [6]. This major transition in the power system presents not only a power engineering challenge, but a transformation in how end-users interact with the power system, bringing about challenges across the fields of engineering, economics, psychology, and further afield.

These developments are primarily precipitated by concerns over security of energy supply, instability in the price of fossil fuels, climate change, and sustainability. These factors are unlikely to diminish, so considerable changes to the composition of the power system must be anticipated and appropriate steps must be taken to ensure that the evolution of the power system occurs optimally.

Each of these possible developments has the potential to have a profound impact on the manner in which we plan and operate the power system. It is therefore necessary to thoroughly evaluate each proposed new resource or development, and determine what measures are necessary to support its implementation if it offers a positive contribution to society, or discourage it otherwise.

The ongoing development of wind power is prime example of this. Novel resources often require the establishment of new assessment techniques, or adjustments to existing metrics, such as was the case with capacity value calculation methods for wind power [7]. When a favourable evaluation of a novel resource has been determined, support mechanisms, such as feed-in tariffs [8], may be required if competition in the open market is not yet feasible. Once the resource becomes competitive, it can be necessary to adjust existing market structures to accommodate its particular characteristics, such as the introduction of markets with gate closure closer to delivery time to counteract the uncertainty in wind power forecasts at long horizons [9]. Additionally, a comprehensive system of regulatory and policy measures is necessary to ensure the correct environment for the resource to succeed. All of these measures rely on an accurate evaluation of the resource at the outset.

Demand response (DR) is a broad concept encompassing any intentional alteration of the profile of electricity consumption. This can occur on a range of scales, at the level of individual appliances or over vast populations of consumers, and at the micro-second scale or over days and weeks. In this thesis, we consider DR for the provision of energy services at operational time scales. In its various guises, DR is proclaimed as a remedy to a large number of power system challenges. DR is said to facilitate high penetrations of renewable generation [10], increase power system reliability [11], alleviate distribution and transmission network congestion [12], and reduce wholesale electricity prices [13]. However, DR is an as yet unproven system resource. Its use is currently limited to demonstration projects and niche applications, and proclamations of its benefits are based on small test cases and superficial simulation-based studies. It must be assessed in the same vigorous manner as any novel resource to evaluate its contribution to the power system and determine what measures, if any, are justified to support its implementation and development.

1.2 Thesis Objectives

The objective of this thesis is to develop evaluation methods for DR that consider the physical realities of this novel resource as well as the power system and market environments in which it must operate. In the interest of narrowing the scope of this work and developing specialised methods, consideration of DR is restricted to the provision of energy services, namely load shifting and curtailment. Two central research questions are addressed in this thesis, each consisting of a number of secondary research tasks:

I. How can demand response be optimally accommodated in operational problems?

Addressing this research question necessitates consideration of the characteristics that differentiate DR from existing power system resources. A methodology must be developed to represent the physical characteristics and constraints of the flexibility offered by a broad group of loads participating in DR, from which system dispatch models and market offering structures can be extracted.

II. What operational value does demand response offer?

As an initial step it is necessary to determine the social welfare value offered by DR when restricted to operating within existing power system frameworks. However, the long-term success of DR is dependent on its ability to generate commercial revenue, not only social welfare value. The ability of DR to thrive in a commercial setting must be considered, as well as the impact that uncertainty over the achievable response might have on its ability to generate revenue in a competitive market environment.

This thesis is motivated by a lack of existing research addressing the challenge of developing operational models for DR. The general field of DR enjoys a very active research community, however the question of establishing a practically implementable representation of DR is less intensively researched. Two examples of methodologies for the representation of DR in operational models are presented by Zerrahn and Schill [14] and Mohsenian-Rad [15], however the link between their proposed representations and the physical characteristics of the flexible load is not fully elaborated. This thesis seeks to remedy this lack of research by developing methodologies for the operational representation of DR in which the physical characteristics and constraints of the underlying flexible load are intrinsically considered.

1.3 Thesis Contributions

As a motivation for this thesis, we review current DR assessment methods in Paper A. We find that these methods are largely unsuited to a detailed assessment study of DR. The current assessment methods fall broadly into two categories; overly detailed studies which facilitate the characterisation of DR at the device level, but which are too detailed for larger studies and unsuited to current market clearing and system dispatch frameworks; and overly simplified models which neglect the physical characteristics and constraints of the underlying load and assume a rational response to economic incentives intended to induce DR.

Given that DR must operate within existing power system frameworks, it is necessary to establish a representation of the resource that is both physically accurate and of low complexity. This necessitates a thorough analysis of the DR capabilities of flexible loads to determine the fundamental characteristics that differentiate them from existing power system resources. This analysis can be employed to inform the design of market products that facilitate the participation of DR in existing market structures, while respecting its physical characteristics and constraints. We have addressed this task in Paper B, in which we introduce the saturation curve concept as a novel method to graphically represent the extent of the flexibility offered by flexible loads capable of providing load shifting DR.

The generic DR representation that we have developed in Paper B can be employed to define DR products that can be dispatched for the provision of a range of power system services while respecting the physical constraints of the underlying flexible load. We develop load shifting product definitions in Papers C and D, while we present our proposal for a load curtailment product definition in Paper E. By restricting the representation of DR to a simple product definition suitable for existing power system dispatch and market clearing frameworks, we are prevented from using the full range of flexibility as to do so would necessitate a more complex representation than is allowable. In Paper C we quantify the value that is lost by not engaging the full range of flexibility available from the DR resource.

We address the social welfare value offered by DR in Papers C and D. In Paper C we investigate whether a limited representation of DR offers value by considering the problem of optimally dispatching DR alongside conventional thermal plants for the provision of regulation power. This is a small-scale proof-of-concept study that indicates the value that DR can offer and justifies further studies at a larger scale. Large-scale power system studies, often termed integration studies, are an important tool in the assessment of novel power system resources as they facilitate consideration of factors that are not visible in smaller-scale studies. Through an integration study, we can identify the source of the value that the new resource offers, for example through reducing the curtailment of renewable generation or supporting cheaper conventional generation. The impact of the new resource on other system participants can also be quantified and the effect of seasonal variations in the resource availability can be evaluated. In Paper D we address the challenge of modelling DR in an integration study by developing a method for the optimal dispatch of populations of flexible loads at reduced complexity, while also including consideration of the impact of ambient temperature on the achievable DR.

The success of a power system resource ultimately depends on the value that it offers in a commercial setting. Electricity market participants are private entities driven by the objective to maximise their revenue. A product will only be offered to the market by a market agent if it expects to generate sufficient revenue to recover its costs. Thus, to fully appreciate the viability of DR as a power system resource it is necessary to consider the value it offers to a market agent. When a market agent commits to a trade, it is obligated to fulfil it or pay an imbalance penalty for the energy volume it fails to deliver, or over-delivers. Thus, a key consideration when evaluating the commercial value of DR is the cost incurred due to its inherent uncertainty. In Paper E we assess the commercial value of DR considering uncertainty, by developing a novel trading strategy for uncertain load curtailing DR on both the day-ahead and intraday markets, and modelling the uncertainty in the delivered product.

As a final note, it should be remarked that the assessment methodologies that we have developed in this thesis only consider the *value* that is offered by DR. The *costs* associated with establishing and operating this resource are not considered, as would be required for complete assessment. To quantify those costs is a substantial task, requiring consideration of technical costs (for example communication, monitoring, and control), and social costs (rewarding customers for providing flexibility through a resource from which they already benefit through its primary purpose as an electrical appliance). Thus, a full evaluation requires a truly interdisciplinary approach spanning engineering, economics and psychology, and is beyond the scope of this thesis.

1.4 Thesis Structure

This thesis is structured as follows. Part I is a summary report outlining the main contributions of this thesis. Chapter 2 provides an overview of the concept of DR. Chapter 3 describes methodologies for the representation of DR within power system dispatch and market frameworks. Approaches for the assessment of the social welfare and commercial value of DR are presented in Chapter 4 along with selected research results from Part II. Chapter 5 provides conclusions and perspectives. An overview of the main mathematical tools employed in the analysis conducted in this thesis is presented in Appendix A.

Part II consists of the publications that contribute to this thesis.

Paper A is a journal article published in *Renewable and Sustainable Energy Reviews*. It consists of a critical review of the professed benefits and challenges of DR.

Paper B is a peer-reviewed article published in the *Proceedings of the IEEE ISGT Europe 2014*. Statistical modelling is employed in this work to establish a data-driven model of the DR capabilities of a supermarket refrigeration system.

Paper C is a journal article published in *IEEE Transactions on Power Systems* in which a method is developed to optimally dispatch DR for the provision of regulating power, and the resulting social welfare benefit is assessed.

Paper D is a peer-reviewed technical report published by the *National Renewable Energy Laboratory (NREL)*. This publication describes a methodology for the modelling of DR for power system integration studies.

Paper E has been submitted for consideration to *IEEE Transactions on Power Systems*. Optimal day-ahead and intraday trading strategies for uncertain DR are developed in this paper. They are employed to assess the commercial value of DR considering the impact of resource uncertainty on revenue.

CHAPTER 2

Demand Response

This chapter provides an introduction to the concept of demand response (DR). Section 2.1 describes the historical use of DR, and how this differs from its anticipated future use. The forms of DR that can be offered are described, as well as methods for the control of DR. Section 2.2 details some of the perceived strengths and weaknesses of DR, and Section 2.3 describes the market frameworks within which DR must operate. Finally, Section 2.4 defines the forms of DR that are considered for analysis in this thesis, and the case study that is employed.

2.1 An Introduction to Demand Response

DR can be defined as the intentional alteration of the power consumption profile by an end-user in response to an external stimulus. This stimulus often takes the form of a financial incentive or a directive to achieve a particular system state, such as a power consumption level.

DR is not a new resource to the power system. It has been employed for the provision of power system services in various forms for decades. On the Electricity Reliability Council of Texas (ERCOT) market, large industrial loads provided 1150MW of reserves in 2010, approximately 50% of the required capacity [16].

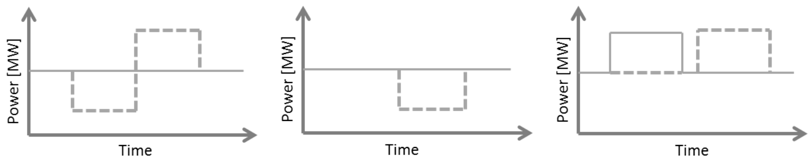
Price signals are a commonly proposed method to activate the latent flexibility of electricity consumers, with the concept first attaining notoriety in 1988 through the seminal work of Schweppe et al. [17] on spot pricing of electricity. Residential consumers have participated in DR programmes on a number of power markets, through simplistic time varying tariffs typically employed to incentivise a shift in power consumption to the night-time hours [18]. This has been implemented in France, to encourage the shift of electricity consumption to typically low load hours, supporting the operation of large inflexible nuclear plants. Critical peak pricing (CPP) is another form of tariff-based DR. It is employed on a number of US power markets to incentivise commercial and industrial consumers to reduce consumption during peak load days [19].

The future vision of DR differs significantly from existing DR. Current DR programmes are typically only open to larger consumers who are required to provide a response infrequently. Going forward, it is envisaged that DR will be provided by large numbers of smaller, distributed consumers offering flexibility on a continuous basis. Time varying electricity tariffs will evolve from known day/night price changes to highly variable price variations at resolutions down to five minutes. The purpose of inducing such substantial flexibility is to support the operation of a future power system where flexibility is essential. Large penetrations of renewable generation, limited conventional generation and transmission capacity, and expensive peaking power plants all necessitate flexibility to ensure that power delivery can occur in the most economically efficient manner possible.

2.1.1 Forms of Demand Response

DR on operational time scales can be divided into three main categories; load shifting, load curtailment and load deferral. An illustrative example of each is shown in Fig. 2.1.

Load shifting is provided by flexible loads that can increase or decrease their power consumption without causing a detrimental effect on the end-use service that they provide. Such flexible loads resemble conventional power system storage technologies, in that any load that is curtailed at one instance must be recovered at another. Thus, this form of DR is typically net zero energy, though it can be net positive or negative depending on the load considered. Suitable loads for the provision of this form of DR include heating, cooling, and refrigeration, as their end-use service is a temperature which operates within an acceptable temperature range. Furthermore, thermal mass on such systems acts as an energy storage, slowing the change in temperature relative to the change in power consumption.



(a) Load Shifting **(b)** Load Curtailment **(c)** Load Deferral

Figure 2.1: Types of operational DR. Solid lines indicate the original load profile, dashed lines indicate the load profile under DR.

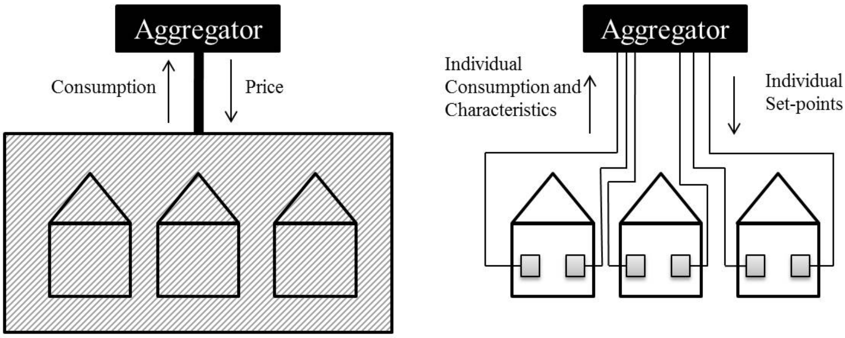
Load curtailment is achieved when flexible loads reduce their power consumption temporarily and do not require any recovery of the energy consumption avoided during the curtailment event, resulting in a net reduction in demand. This can be provided by discretionary loads such as lighting, or by on-site generation which results in the appearance of reduced load from the site as a whole.

Load deferral occurs when flexible loads delay or advance power consumption. This is typically a net zero energy service that is provided by consumers operating batch processes, such as pharmaceutical plants. In residential settings, a typical example of a deferrable load is a washing machine, which needs to consume a certain amount of power over a fixed duration to achieve its task, but the timing of the start of the process can be flexible.

2.1.2 Control of Demand Response

In a deregulated power system, participants must offer their services through a competitive market structure. Rather than allowing individual flexible consumers to directly participate in the market, it is envisaged that they will be aggregated under a representative market agent, often termed an aggregator. The aggregator participates in the market on their behalf, offering the combined flexibility of the population of responsive loads. In this manner, they can be considered to form a virtual power plant. The aggregator is responsible for ensuring that any flexibility that has been accepted by the market can be achieved by the population of flexible loads. There are two main approaches to achieving the required response; direct control and indirect control.

Direct control involves the aggregator having a detailed knowledge of the system under control, through intensive monitoring, control and communication infrastructure. Under direct control, the aggregator will issue directives to individual flexible appliances to achieve the required power consumption level.



(a) Indirect control

(b) Direct control

Figure 2.2: Control frameworks for DR [Paper A].

Indirect control is a price based control framework, where the aggregator issues a price signal to the population of flexible appliances, expecting a particular response. Under this framework, the aggregator has limited information about the population of flexible devices under control and must estimate the price-demand relationship. This estimation can be done in real-time or can be based on historical data.

Fig. 2.2 shows a conceptual comparison of the two forms of control. There are advantages and disadvantages to each control framework. Indirect control has a reduced control and communications burden, and the use of time varying prices is said to increase the social welfare of the system [17]. Direct control allows for a more precise response, due to the ability to issue distinct power consumption directives to individual appliances, and is therefore often considered more appropriate for the provision of power system services closer to real time, when reliability is essential [20]. However, direct control often calls for some form of state estimation in order to understand the system under control and to facilitate the issuance of power consumption directives that are appropriate and which can be achieved. There is no clear choice between indirect and direct control, and it is likely that both control frameworks will be present to some degree if DR is implemented at a large scale. Further details on both direct and indirect control can be found in [21].

2.2 Strengths and Weaknesses of Demand Response

DR is expected to be a highly valuable participant in the future power system. The activation of the demand side through DR is said to bring about a number of benefits for the planning and operation of the power system.

DR is said to be a key mechanism for achieving high penetrations of variable renewable generation. System operation costs are increased at high penetrations of variable renewables due to the need for additional reserves to balance the frequent fluctuations in power output from variable renewable generation. By allowing DR to provide these reserves in place of conventional generators, increased penetrations can be tolerated and the cost of their integration can be reduced [10, 22]. In addition to replacing conventional generation for the provision of reserves, DR is said to offer greater reliability [11] and a larger effective ramping rate [23] than thermal generators, indicating that DR will be capable of competing with conventional power system resources from a technical standpoint.

Demand side flexibility can also be harnessed to reduce load at times when the power system is stressed, through a shortfall in either generation or transmission capacity. Employing DR in this manner optimises the use of available power system resources, avoiding or delaying costly upgrades and reinforcements on transmission and distribution networks [24], reducing reliance on expensive peaking generation plant, and potentially reducing generation capacity requirements in the long-run [25]. The resulting cost savings may translate to substantial social welfare gains for the power system.

Social welfare gains are also expected through the introduction of time varying retail electricity tariffs as part of the transition to large-scale DR. Varying electricity tariffs will contribute towards reducing supplier market power [26], the wholesale cost of electricity, as well as volatility in wholesale prices [13].

Taken together, these benefits of DR translate to an increase in social welfare. However, DR faces a number of challenges before it can be considered a viable power system resource. Chief amongst these is the difficulty in capturing the social welfare benefits in a profitable business case. This difficulty stems from the distribution of social welfare benefits across a large and diverse group of power system stakeholders, including consumers, producers and system operators [12].

Consumers themselves represent a significant barrier towards to development of DR, as their interaction with electricity consumption will introduce uncertainty into the flexibility that can be achieved. Consumers have a complex and diverse set of priorities, and ensuring that their electricity consumption is optimal is unlikely to be a key consideration for most. While the introduction of time varying tariffs is said to bring about social welfare benefits, these benefits may not translate to significant value for the consumer. One empirical study [27] has shown that consumers subject to hourly varying electricity tariffs have a saving of just $10 a year, while another [28] demonstrated that the introduction of time varying prices had no statistically significant effect on either average daily consumption or peak consumption. While these empirical studies are focussed on particular cases, their results indicate that the general introduction of time varying electricity prices may have a very limited impact on energy consumption. Furthermore, if those consumers who do respond to time varying prices find low savings on the order of those found in [27], they are likely to become insensitive to variations in the electricity price and stop responding, thus exhibiting the response fatigue described in [29].

Other barriers to DR include a lack of appropriate market mechanisms. Many markets that currently accept DR impose excessive restrictions, such as requiring aggregators to plan DR with multiple hour lead times, essentially eliminating the benefit of rapidly deployable flexibility [30]. Furthermore, the development of DR may experience resistance from existing generation asset owners who might see a reduction in capacity value as a result of DR [31].

The lack of clarity over the true value that DR offers is a key motivating factor for this thesis. Much of this uncertainty stems from a lack of experience, as most understanding of advanced DR comes from relatively small-scale demonstration projects [32, 33]. Aside from these empirical studies, most analyses of DR depend on simulation studies. These simulation studies generally adopt one of two approaches; assuming that DR exhibits perfectly economically rational behaviour [10, 34, 35], or that the power system operator has perfect information and control of the individual flexible loads [36, 37]. The former approach is inadequate and potentially leads to misleading results as it overlooks the complexity introduced through interaction with end-users, as well as the impact of the physical characteristics and constraints of the underlying load. The latter approach has merit if the objective is to explore the full range of flexibility offered by DR, however it is unrealistic to assume that a system or market operator has such an extensive knowledge and control of each flexible load, and furthermore that it is capable of scheduling each load optimally. The computations necessary for such an optimisation are likely beyond current computational capabilities and at best have computation times far exceeding those allowable at the operational timescales on the power system. Assessments resulting from this approach likely overestimate the benefit of DR, as they do not account for the value that is lost when the complexity of the resource representation is reduced to a level that is suitable for current system dispatch and market clearing frameworks. A third approach that is sometimes taken is to represent DR in the form of a negative generator, using constraints such as maximum capacity, ramping rates, and minimum up times [31, 14]. This is a promising approach that can result in an evaluation of the realisable value of DR. To be successful, this approach requires the development of tailored constraints reflecting the DR offered by a population of flexible loads, rather than being restricted to established thermal generator constraints. Furthermore, accurate parameter values and the impact of external stimuli must be identified.

2.3 Market Participation of Demand Response

Competitive electricity markets consist of a number of trading platforms onto which DR market agents can offer their flexibility resource. They can broadly chose to offer energy products on forward markets, or capacity products on ancillary services markets.

Here we take the Nordic electricity exchange, Nord Pool Spot, as an exemplar market structure [38]. Nord Pool is similar to a number of markets across Europe, thus the details provided below are applicable in a broader setting that just the Nordic region.

Forward markets differ by their lead time to energy delivery, liquidity, and auction type.

The **Day-Ahead Market**, Elspot, is a forward energy market that is cleared daily at noon through a single-price auction process. Market participants submit their bids prior to market clearing for energy delivery the following day. Bids consist of a price, volume and delivery hour. Accepted bids are binding in terms of the volume offered, and rewarded at the market clearing price. If there is congestion on the transmission lines connecting market regions, the single market price will be adjusted to reflect the cost of congestion in each region, resulting in zonal prices.

The day-ahead market has energy delivery lead times between 12 and 36 hours, as its original purpose was to facilitate the scheduling of large inflexible thermal generators with long turn-on times and slow ramping rates. These long lead times may render this market impractical for DR as it necessitates an accurate forecast of the flexibility far in advance of it being exercised, which may be difficult to ascertain. Additionally, by scheduling so far in advance one of the key benefits of DR, the ability to provide a response rapidly and with limited forewarning, is eliminated.

The **Intraday Market**, Elbas, is a continuous trade energy market that operates in a bilateral manner. Trades for the sale and purchase of energy are matched and cleared through an exchange. Trade on this market is open until one hour before energy delivery. As with the day-ahead market, trades comprise a volume, price and delivery hour. Participation on this trading floor can occur independently of trades on the day-ahead market, however one of the benefits of Elbas is the ability to rectify deviations from planned production from Elspot without resorting to the regulating market, where prices may be less favourable.

The proximity to delivery time offers advantages for DR, as the burden of ensuring an accurate forecast of the achievable response is reduced. The main drawback of this market is its historically low liquidity, meaning that there may not always be attractive trades available to DR. As of late 2010, the average hourly trade on Elbas was approximately 300MW, compared to the average hourly Elspot trade of 30GW. This liquidity has however been increasing in recent years, and is expected to continue rising as the share of variable renewable generation grows [39].

Deviations from planned energy production or consumption at real-time are settled through the **regulating power market**. This is a market for manual reserves, which can be activated at any time and must be capable of fully activating within 15 minutes. This market is operated by the transmission system operator within each market region. Reserves are activated in turn according to a merit order bidding list, which is sorted in increasing order (for up-regulation) or decreasing order (for down-regulation). On some systems, suppliers of regulating power may receive a capacity payment for participating on this market. This mechanism ensures that there is sufficient capacity to balance real-time imbalance. Production balance responsible (PBR) parties are subject to two-price settlement on the Nordic market, where any excess generation is sold at the down-regulation price and shortfalls are purchased at the up-regulation price. Load balance responsible (LBR) parties are subject to one-price settlement where their individual imbalance (either positive or negative) is settled at the price of the overall system imbalance.

As the regulating market is the closest to real-time, it is ideally suited to benefit from the rapid response abilities of DR resources. However, for DR to participate on the regulating power market, it must have a proven ability to adhere to strict reliability requirements. This ability will naturally vary according to the flexible load providing DR, and will need to be evaluated on a case-by-case basis. Some markets in the U.S. currently allow DR to provide reserves, notably the ERCOT market [16], however this is primarily served by large industrial loads rather than many small distributed loads.

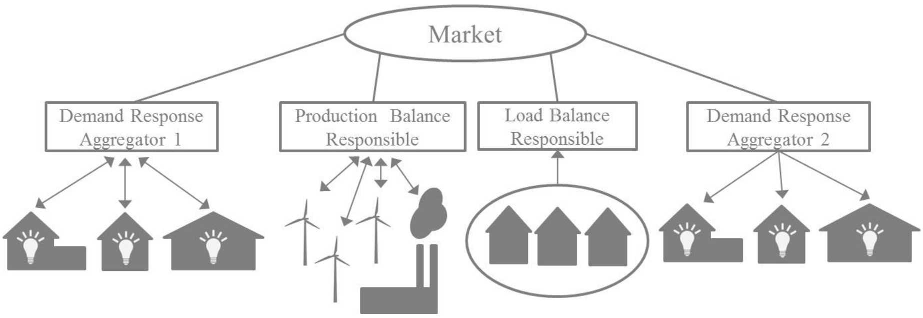


Figure 2.3: Market framework.

2.4 Focus of Demand Response Analysis

There are clearly a vast number of approaches that can be taken when evaluating DR. To extract meaningful results it is necessary to narrow the scope of analysis.

Fig. 2.3 illustrates the conceptual relationships between electricity market participants. It is assumed that DR agents, or aggregators, assume a role similar to that of a load or production balance responsible. DR agents interface directly with the market and are obligated to ensure that the DR resources under their control achieve the aggregate flexibility profile that the market has accepted. DR agents could also adopt the role of load balance responsible or retailer and represent the inflexible load of their flexible consumers in the market. In this thesis we assume that the DR agent only considers the flexible load, while inflexible load is managed by a separate retailer. This assumption is made as the inflexible load has no bearing on the value of the DR resource.

The analysis that we have conducted in this thesis focusses on the interface between the DR agent and the market. The relationship between the agent and the individual flexible loads in its portfolio is not considered. This has been the topic of a large volume of research. The interested reader is directed to references [40, 41, 42] for detailed discussion and investigation of methods for optimal control of populations of flexible loads. It is assumed that the agent has put in place sufficient mechanisms to ensure that its population of flexible loads can achieve the flexibility profile that has been accepted by the markets, either by direct control (as DR Aggregator 1 in Fig. 2.3) or indirect control (as DR Aggregator 2 in the same figure). This assumption is subject to the constraint that the agent can only offer physically feasible flexibility to the market. The identification of representations of DR that consider the physical constraints of a population of flexible loads is a key contribution of this thesis.

As a result of this focus on the higher level interface between the DR agent and the market, the interaction with the consumer is neglected. The advent of DR represents a paradigm shift for the power system, as consumers transition from being passive participants to active suppliers of power system services. As consumers are by their very nature irrational beings, this introduces a great degree of uncertainty over the response that will be achievable if consumers directly control flexible loads. The complications associated with direct human interaction with DR programs are detailed in [27, 29] which discuss the results of empirical DR studies. In this thesis, we assume that DR will be automated, eliminating much of the uncertainty associated with human interaction. Additionally, the DR services are considered to come from industrial and commercial loads rather than residential loads, further reducing the impact of individual end-user interaction.

We evaluate DR here for its operational benefits. Potential planning benefits such as reducing long-run generation capacity requirements are not considered, though it has been indicated that this is a potentially significant benefit of DR [25]. Among the large number of operational power system services that DR can offer, the focus here is placed on the use of load shifting and curtailment for the provision of energy services. Day-ahead, intraday, and regulating power markets are considered, though payments for the provision of DR capacity are not. This potentially reduces the evaluated benefit of DR, however as there are currently no clear regulations on the use of DR for capacity provision it seems premature to consider this potential market in an evaluation.

2.5 Case Study

In order to develop appropriate methodologies and attain valid results, it is necessary consider a sample DR resource as a case study. This facilitates the development of a DR model that reflects the true characteristics of the flexibility of a given resource. In this thesis the sample DR resource adopted is supermarket refrigeration. This choice was made partly due the suitability of refrigeration for DR, and partly due to the ready availability of data describing its flexibility. Supermarket refrigeration is an ideal candidate for early uptake of DR for three key reasons:

Ability
: The thermal mass of foodstuff in refrigeration systems acts as an energy storage, allowing the alteration of power consumption while keeping the food temperature within a suitable range.

Incentive

Supermarkets typically operate at a low profit margin, thus any opportunity to reduce costs is inviting. DR may offer substantial energy cost savings if consumption can be optimised with respect to a real-time price, or if a contract can be established with an aggregator to use the flexibility not currently being used by the supermarket itself. The economically rational nature of a profit-driven enterprise is also beneficial as it eliminates much of the irrationality and uncertainty associated with interactions with domestic end-users.

Scale

Supermarkets typically operate as part of a large chain. This structure naturally lends itself to the formation of a large population of flexible resources, and the supermarket chain operator could potentially adopt the role of a DR market agent. Individual supermarkets are typically considered to be large commercial loads, however the flexibility offered by a single supermarket is most likely below the threshold for participation in an electricity market. This necessitates aggregation with other supermarkets to combine their flexibility and offer it to the market as a single product.

The availability of data was also a key consideration when selecting the case study. As high frequency and distributed DR is in its infancy, there is a lack of historical data available for analysis. Any data that is available results from demonstration projects that typically consider residential DR [32, 33].

The models developed in this thesis are data-driven, using data from a refrigeration test centre. However, the dataset employed is limited in scope. This has necessitated the use of simulation methods to investigate the behaviour of the refrigeration systems under conditions not present in the data. Consequently the numerical results of the studies contained herein are subject to the limitations of the available data and resulting models. The methodologies that we have developed are not subject to this limitation, and will retain their relevance and applicability as more data becomes available. Any data that becomes available in the future can be employed within the developed frameworks to inform more accurate numerical results.

Finally, the singular focus on supermarket refrigeration as a case study should not be interpreted as a limitation on the methodologies that we have developed. They have been developed in a generic manner so that they can equally be applied to any flexible load capable of shifting or curtailing load.

Chapter 3

Accommodating Demand Response in Operational Models and Markets

In this chapter, we present methodologies for the implementation of DR within existing market clearing and power system dispatch frameworks. We identify the key characteristics of load shifting DR, and describe models for its dispatch and market participation. The models are limited in complexity to that allowable in existing frameworks, while ensuring that the physical constraints of the underlying flexible load are respected.

Section 3.1 presents a model based methodology for the characterisation of load shifting DR. The saturation curve concept is introduced in Section 3.2 as a method of characterising flexibility. Finally, three different methods of representing DR in system dispatch and market clearing frameworks are presented in Section 3.3.

3.1 Model-Based Approaches for the Characterisation of Demand Response

Establishing a representation of DR that captures its key characteristics at an appropriate level of detail is one of the central objectives of Papers B and C.

Ideally, historical data of actual flexible loads participating in DR programmes would be used to inform this characterisation of DR, however the extent of the available data is insufficient to construct a complete characterisation. Instead, we have used data from DR experiments at a refrigeration test centre to build a time series (ARMAX) model of the system. We then employed model predictive control, as described in Appendix A, to simulate the behaviour of the refrigeration system when providing load shifting DR.

Our simulations reveal that DR in refrigeration systems exhibits two key characteristics that distinguish it from other power system resources; saturation and rebound. These characteristics are shared by all flexible thermal-electric loads, including water heating and air conditioning, as they all operate within limited operating constraints which restricts the duration and magnitude of any adjustment in power consumption that occurs during a DR event.

Saturation occurs when a change in power consumption is imposed for an excessive duration, causing an operating constraint to become binding. In refrigeration, this occurs when a food temperature reaches a maximum or minimum allowed level. As the primary function of a flexible appliance is to supply the end-user with a given service, rather than to provide DR, the operating constraints have priority over a call for DR. Thus, reaching a maximum or minimum allowable temperature causes the response to cease. Once the response has saturated in this manner, the flexible device can either remain at the temperature bound or it can correct the temperature deviation that occurred during the response through energy recovery or rebound.

Rebound occurs when a flexible device attempts to correct the actions that occurred during the response. This can be either a rapid increase or decrease in power consumption. The combination of response and rebound form a load-shifting DR event, as the flexible device should have returned to its original operating conditions at the conclusion of the event.

Fig. 3.1 illustrates both saturation and rebound on a refrigeration system. The system is initially requested to reduce power consumption to a level indicated by the dashed green line in the upper plot, which it successfully achieves for a brief period before the maximum allowable temperature is reached, as indicated

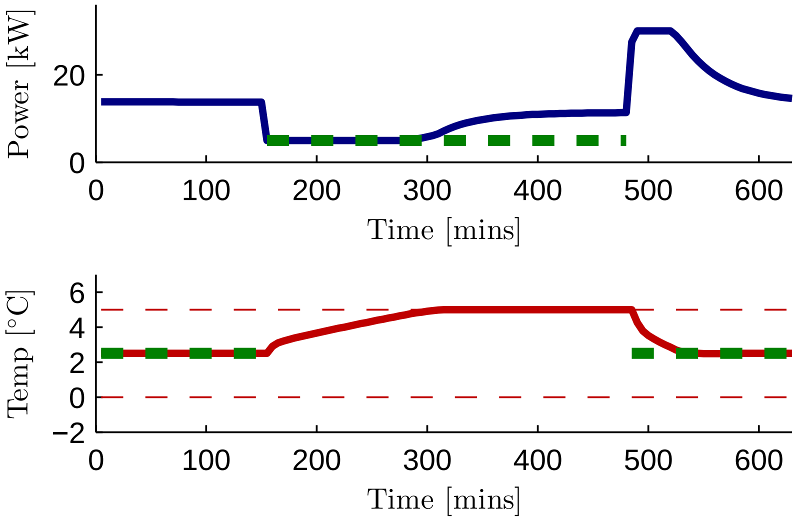


Figure 3.1: Power consumption and temperature of a refrigeration system when a reduction of power consumption to 5kW is requested. The heavy dashed lines indicate the temperature/power references to be tracked. Temperature bounds are indiciated by the dashed red lines [Paper C].

in the lower plot. At that point, the response saturates. Once the system is released from providing the response it attempts to return to its normal operating temperature, as indicated by the dashed green line in the lower plot, causing a rapid rebound. During rebound the power consumption increases to the maximum capacity of the system. In this simulation, and the illustrative simulations that follow, it is assumed that under normal operating conditions the supermarket operates the refrigeration system according to its own objectives, here assumed to be maintaining the average of the temperature constraints. When the aggregator or DR market agent requests a response, it issues a power reference which the supermarket must strive to follow.

Both saturation and rebound are undesirable traits of load-shifting DR. Saturation prevents a DR resource from providing a reliable power product over an extended duration, while an uncontrolled rebound may render the benefits of the prior response null. If DR is employed to stabilise the operation of an unstable power system, a sudden rebound following a response may further destabilise the system rather than support it.

It is imperative that saturation and rebound are considered in any representation of DR, so that they can be handled appropriately within system dispatch or market clearing.

3.2 Representing Flexibility through Saturation Curves

The power consumption, P_t, at a given time, t, on a flexible refrigeration system can be described in a simplified form as

$$P_t = P^{\mathrm{Base}} + P_t^{DR} \tag{3.1}$$

where

$$0 \leq P_t \leq P^{\max} \tag{3.2}$$

P_t^{DR} is a free variable and P^{Base} is constant. The baseline consumption, P^{Base}, is that required to maintain standard operating conditions. The DR provided, P_t^{DR}, is the difference between the actual consumption and the baseline consumption. It can be positive or negative and is only non-zero during DR events. In order to offer DR reliably, allowable magnitudes and durations for P_t^{DR} must be identified.

We introduce the concept of a saturation curve in Paper B. A saturation curve defines the relationship between P_t^{DR} and the maximum duration for which it can be reliably maintained before reaching the saturation point. We conducted model based simulations in Paper B which reveal a non-linear relationship, as is illustrated for the case of a flexible refrigeration system in Fig. 3.2. It can be seen that large magnitude changes to power consumption can only be reliably maintained for a short duration, whereas smaller adjustments are tolerable for significant periods.

A load shifting DR event consists of both a response and recovery, where the response can consist of a curtailment ($P^{DR} < 0$) or an increase in consumption ($P^{DR} > 0$). The recovery will adjust power consumption in the opposite direction to return the system to its original operating state.

The maximum duration of the response component is found directly from the saturation curve, but if the subsequent recovery is not controlled (in magnitude and duration) it can result in an undesirable and potentially destabilising conclusion to the DR event. The recovery, or rebound, can be controlled by selecting a power magnitude and corresponding duration from the opposite side

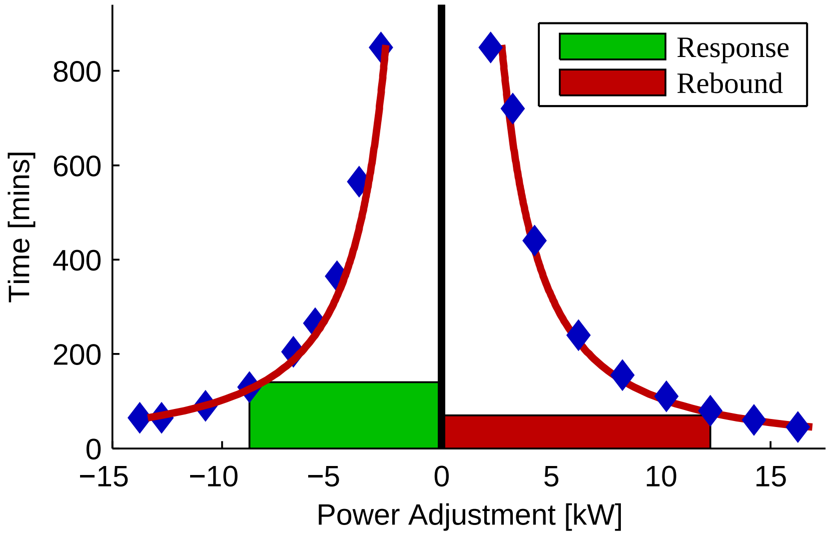


Figure 3.2: Relationship between adjustment in power consumption and the maximum allowable duration. Simulation based results are indicated by points, which are joined by the closest fit curve. Possible response and recovery definitions are indicated [Paper C].

of the saturation curve. This will facilitate the controlled return of the flexible load to its standard operating conditions.

A possible combination of response and rebound are illustrated in Fig. 3.2, where an extended reduction in consumption by 8kW is coupled with a rapid rebound at 12kW, where both power adjustments are relative to a baseline consumption. By controlling both components of a load-shifting event in this manner, the negative aspects of saturation and rebound can be avoided.

The characteristics represented by the saturation curve, saturation and rebound, are common to all flexible thermal-electric loads, ensuring its applicability beyond the sample case of refrigeration. Similar curves can be found for flexible air-conditioning or heating loads, with different parameter values. Consequently, the saturation curve offers an easily understood method of comparing the flexibility of candidate flexible loads.

In addition to representing the flexibility of individual flexible loads, saturation curves can be employed to represent large populations of loads, using simple summation along the power axis. Consider a population of 1000 identical super-

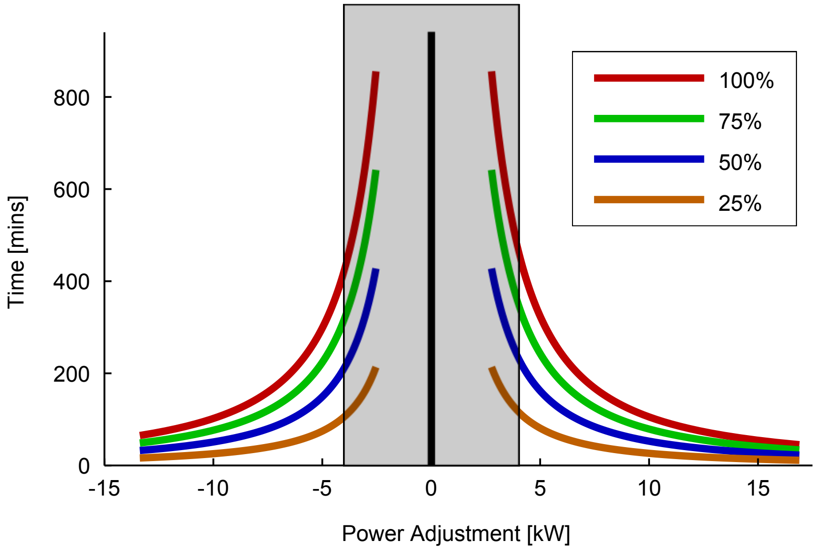


Figure 3.3: Partial saturation curves, where the shaded region indicates prohibited power adjustments as the partial saturation cannot be reliably defined [Paper C].

markets, with the flexibility of each represented as in Fig. 3.2. Their combined flexibility can be represented similarly to Fig. 3.2, with the power axis scaled in megawatts (MW) rather than kilowatts (kW). Inhomogeneous populations will result in a non-continuous saturation curve, due to differing power capacities of individual loads.

The saturation curve illustrated in Fig. 3.2 describes the full extent of the flexibility offered by the refrigeration system. Scheduling DR events according the these limitations will result in refrigeration temperatures being driven to their absolute maximum or minimum allowable level prior to returning to a normal operating point. This may not be desirable for all flexible loads, as it exposes the system to greater risk of breaching operating limitations in the case of unforeseen events on the system. To reduce this risk, it may be preferable to schedule DR events within a given proportion, for example 50%, of the available flexibility. To facilitate this, partial saturation curves can be defined, where both the response and recovery portions of a load shifting DR event are defined within the allowable flexibility range.

Typically, temperatures in refrigeration systems exhibit an exponential relationship with time [43]. However, for large adjustments to power consumption over short durations the relationship between temperature and time can be approximated as linear. Within this linear region, the saturation curve for a change in temperature that occupies $X\%$ of the full temperature range can be found by scaling the saturation time (y-axis) by $X\%$. Fig. 3.3 illustrates partial saturation curves, where the shaded region indicates the power adjustments that result in non-linear temperature trajectories. Within this region partial saturation curves cannot be reliably defined.

3.3 Establishing a Representation of Demand Response Suitable for Existing Frameworks

The saturation curve concept offers an easily understood representation of the flexibility bounds of a DR resource, but it cannot be used directly to offer DR to the power system. Unit commitment and economic dispatch methods of scheduling resources on the power system rely on linear or piece-wise linear constraints which cannot be used to describe the saturation curve. Market operators clear the market subject to offers submitted by participants, consisting of a price and power magnitude. As with system dispatch, the saturation curve cannot be directly integrated into existing market frameworks. Instead, it is necessary to discretise the saturation curve into a subset of DR products that can be offered to a system or market operator in a similar, or identical, manner to existing power system resources.

We suggest three different methods of representing DR on existing markets here. All three of our proposed representations result from discretisations of the saturation curve, and as such restrict the DR abilities that can be scheduled. This reduces the value that can be extracted from DR but ensures that the value that is assessed is realistically accessible.

3.3.1 Asymmetric Block Offers

Our proposal for the ready accommodation of DR within market clearing frameworks is an asymmetric block offer. In an asymmetric block offer, flexibility is offered through a set of response-rebound combinations, where the power magnitude and duration of each are defined from the saturation curve. An example of the blocks that comprise an asymmetric block offer is illustrated in Fig. 3.2. The constraints defining these offers are similar to those that define traditional block products, a power supply level and duration, but consist of both power supply (load curtailment) and consumption (recovery) as seen from the power system perspective. This similarity facilitates the inclusion of this novel DR product type into power system dispatch frameworks alongside conventional resources.

Asymmetric block offers are *all-or-nothing* offers, and cannot be partially accepted as this would result in an unknown system state (for example temperature) at the conclusion of the DR event. This would introduce uncertainty into the ability of a device, or population of devices, to fulfil subsequent DR requests.

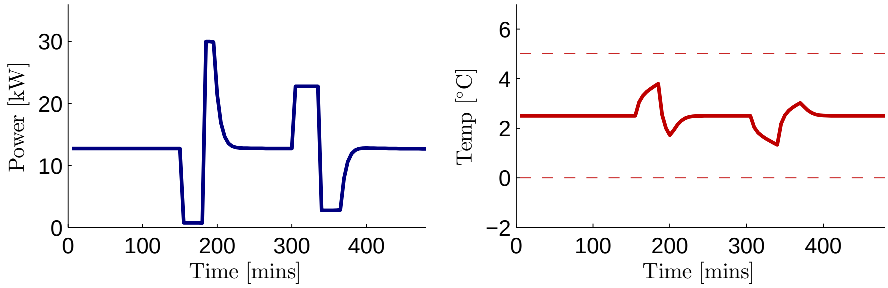
A key characteristic of an asymmetric block offer is that the response and recovery are adjacent, there is no delay allowable between the two components of the DR event. This is because the power consumption that would occur during this intermediate period between response and recovery is undefined. Under normal operating conditions, the flexible loads consume power at a known and forecastable level which is sufficient to maintain a standard operating point. This is considered to be the baseline consumption. After a response, a new operating point is reached and the power consumption necessary to maintain this new operating point is distinct from the baseline consumption. If we are to allow the separation of response and recovery, this new power consumption level must be defined as part of the DR event to ensure that all of the DR behaviour, defined as any deviation in power consumption away from the baseline, is expected by the market or power system operator.

Fig. 3.4 provides an illustration of the simulated power consumption and temperature changes that occur on a single refrigeration system as it fulfils two different asymmetric block offers. In the first case the event commences with a reduction in consumption whereas the second event commences with an increase in consumption, where the refrigeration system is pre-cooled. The blocks are defined from the 50% saturation curve, and it can been seen that the temperature change that occurs during the response portion of the event brings the temperature approximately 50% of the way to the absolute temperature limits, indicated by dashed red lines.

Our concept of an asymmetric block offer and its use in a dispatch framework for the provision of regulating power are fully elaborated in Paper C.

3.3.2 Simplified Models for Large-Scale Studies

The asymmetric block offer presents a valid method of offering DR on a competitive electricity markets, however optimisation studies to assess the value or revenue that can be achieved through market participation in this manner are computationally expensive. This is due to the all-or-nothing structure of these offers, which necessitates a mixed integer programming approach employing bi-



(a) Power Consumption **(b)** Temperature

Figure 3.4: Power consumption and refrigeration temperature of single refrigeration system providing DR through asymmetric block offers.

nary variables. An overview of mixed integer programming methods is presented in Appendix A.

This complexity renders the block offer structure inappropriate for large-scale power system studies. Instead, it is necessary to derive a relaxed formulation that is less computationally burdensome, while respecting as far as possible the need to observe the physical characteristics and constraints of the underlying flexible loads providing DR.

In Paper D, we exploit the similarities between load shifting DR and traditional energy storage technologies to define a set of DR behaviours that can be scheduled in the same manner as hydroelectric or battery energy storage. Using the saturation curve, we can define a DR load shifting product with a defined duration, within which the net energy adjustment must be zero. This definition assumes that the load shifting event is 100% energy efficient, which is not true in all cases. We provide detailed discussion on the complexity of ascertaining the efficiency of a load shifting event in Paper D, where we show that the efficiency depends on the magnitude of the power adjustment during the response and recovery phases. We also note that external conditions may also affect the efficiency, though data is not available to confirm this hypothesis. Fig. 3.5 illustrates four possible load shifting products that can be offered, as defined by their balancing duration and magnitudes for load reduction and increase.

This relaxed formulation introduces increased risk of violating an operating constraint, however measures can be taken to alleviate this risk. A partial saturation curve can be employed to define the DR product definitions (magnitude and duration), so that even if the full extent of the allowable flexibility is employed, as defined by the partial saturation curve, the operating constraints will not be violated. Furthermore, uncertainty over the final operating state at the

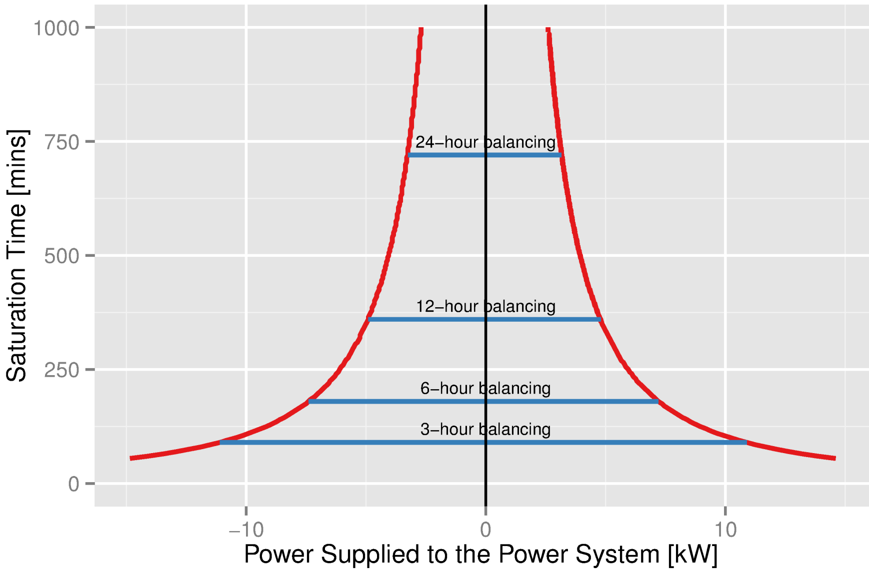
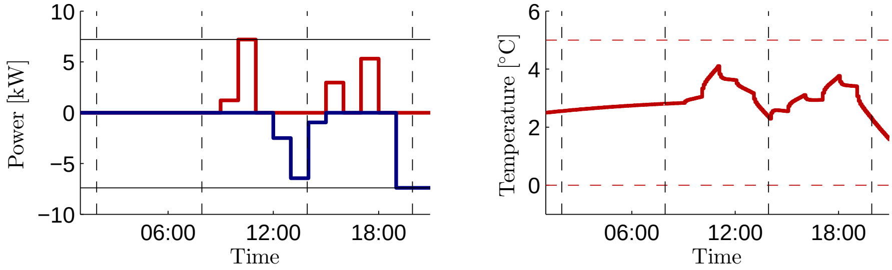


Figure 3.5: Demand response products as defined by balance time. Note that in this figure the power adjustment is seen from the perspective of the power system rather than the flexible load. An increase in power supplied to the power system corresponds to a reduction in consumption at the appliance level [Paper D].

conclusion of the DR event is introduced due to the possible inaccuracy of the event efficiency. Consequently, the ability to achieve subsequent DR events is uncertain. This can be relieved by limiting the number of DR events that are requested within a given period.

An illustrative example is provided in Fig. 3.6 which shows the scheduled DR and resulting temperature behaviour of a single refrigeration system when scheduled according to the relaxed formulation to serve a regulating power profile alongside conventional generators (not shown). The scheduled DR product is the 6-hour balancing product shown in Fig. 3.5, where the maximum adjustments to power are shown by the solid horizontal black lines in Fig. 3.6a. The vertical dashed lines indicate the 6-hour windows within which the upwards and downwards power adjustments must balance. Note that the adjustment to power is seen from the perspective of the power system here, such that an increase (in red) corresponds to the provision of up-regulation, or load curtailment. It can be seen by comparing Fig. 3.6a and Fig. 3.6b that the provision of up-regulation results in an increase of temperature on the refrigeration system. It is seen from



(a) Power Adjustment (System Perspective)

(b) Temperature

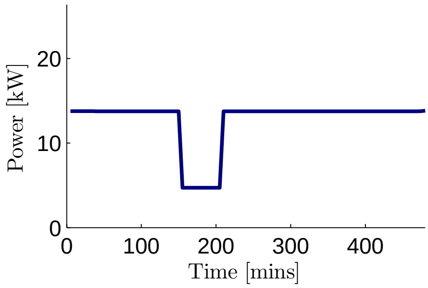
Figure 3.6: Power consumption and refrigeration temperature of a single refrigeration system providing DR as scheduled using the relaxed DR product definition.

Fig. 3.6b that the temperature doesn't violate its bounds (indicated by the dashed red lines), and that despite the simplified assumption of 100% efficiency, the temperature at the conclusion of each event (at the vertical dashed lines) is very close to the temperature at the start of the event. This is a simple demonstration of the efficacy of the simplified formulation, and does not rule out the possibility of constraint violations under certain circumstances.

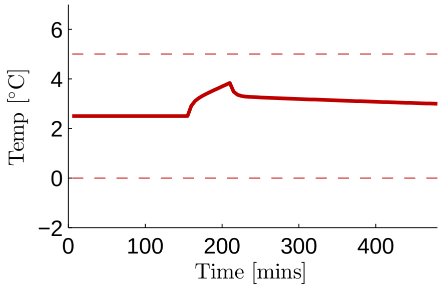
3.3.3 Load Curtailment

Curtailment is the simplest DR product to represent within existing market and system dispatch frameworks, as it can be defined using constraints commonly employed in the scheduling of thermal generators, namely, capacity restrictions, maximum up-time, and minimum down-time. Curtailment products do not allow for any significant recovery of energy following the event and consequently the curtailment that occurs must not cause a substantial change in the operating state of the flexible load. This restricts the duration and magnitude of the curtailment event. A minimum rest time is necessary following a curtailment to facilitate the gradual return to the initial operating point of the system. We have defined curtailment products using the saturation curve, ensuring that the duration of a given curtailment event is significantly less than the saturation time.

Fig. 3.7 illustrates the power consumption and temperature behaviour of a single refrigeration system during a simulated curtailment event. The duration of the event has been extended to emphasise the effect of load curtailment on



(a) Power Consumption



(b) Temperature

Figure 3.7: Power consumption and refrigeration temperature of a single refrigeration system during a curtailment event.

the operating temperature. It can be seen that there is no energy recovery following the curtailment, and consequently the temperature of the refrigeration system at the conclusion of the event is distinct from that at the start of the event. The temperature gradually returns to the initial temperature as the power consumption following the event is the same as prior to the event, which is that necessary to maintain the initial steady state temperature.

The need to avoid energy recovery and maintain acceptable operating conditions restricts the ability of thermal-electric loads to offer curtailment. Such loads are more naturally suited to providing load shifting DR products, which facilitate the return to normal operating conditions immediately following the DR event. Discretionary loads, such as lighting, are more suited to the provision of load curtailment as they do not require energy recovery.

We consider curtailment products, as defined using the saturation curve, in the DR trading strategies that we have developed in Paper E.

Chapter 4

Assessing the Value of Demand Response

We have employed the models described in Chapter 3 in the research presented in Part II of this thesis, to assess the value offered by DR in existing market clearing and system dispatch frameworks. In this chapter, we introduce these studies and selected results are presented. Section 4.1 describes our assessment of the social welfare value offered by DR, both in a small-scale proof-of-concept study, and a large-scale power system integration study. We address the revenue generating potential of DR on competitive electricity markets in Section 4.2.

4.1 Assessing the Social Welfare Value of Demand Response

Determining the social welfare value offered by DR is a necessary first step in any evaluation. The social welfare value represents the total value that DR offers through cost reductions in power system operations. A social welfare assessment assumes that all power system resources operate within a perfectly competitive market, and that the system is optimally dispatched to minimise the cost of serving the load. This is not a realistic framework, as it does not consider the strategic bidding behaviour of market participants. Furthermore, this analysis assumes that the central structures of the power system remain in place as DR is rolled out. Fundamentally altering the architecture of the power system through the introduction of DR has the potential to transform investment strategies for generation and transmission assets, and to result in considerable changes to the generation portfolio, as detailed in Paper A and references therein. Even more dramatic changes are possible, such as the shift away from marginal cost based trading, as renewable generation technologies with very low marginal costs and DR with indeterminate marginal costs become dominant market participants. Such changes will naturally affect the value offered by DR, however the extent and nature of these changes cannot be reliably forecast at present.

Despite these shortcomings, a social welfare evaluation is an invaluable tool, as it provides a first iteration estimate of the value that DR can offer to the overall power system. Once social welfare feasibility has been shown, analysis can continue to consider the value that DR can offer to a market agent operating within a realistic electricity market, or markets.

We address the social welfare value of DR in Papers C and D. Our assessment initially considers a small test case, in which the value of employing load shifting DR for the provision of regulating power is explored. This is followed by a large-scale study in which it is considered that DR can be employed for load shifting close to real-time. This large-scale study covers a large geographical area and a duration of one year. It consequently facilitates an analysis of the value of DR, its impact on other system participants, and the seasonal variations in the resource. We address a number of key research questions in both of these works, which we discuss in detail below.

4.1.1 Assessing Demand Response in a Proof-of-Concept Study

The ability of DR to provide a rapid response indicates its suitability for the provision of close to real-time power products such as regulating power [23]. Here we consider the value offered by DR when dispatched for the provision of regulating power using the asymmetric block offer structure described in Section 3.3.1. Full details of this study are presented in Paper C.

The asymmetric block offer imposes a fixed response-recovery structure on the DR resource offered. The need to recover energy immediately following the provision of a response may result in cases where the service provided by DR may be exacerbating rather than aiding system imbalance, and the value offered by DR may consequently be negatively affected.

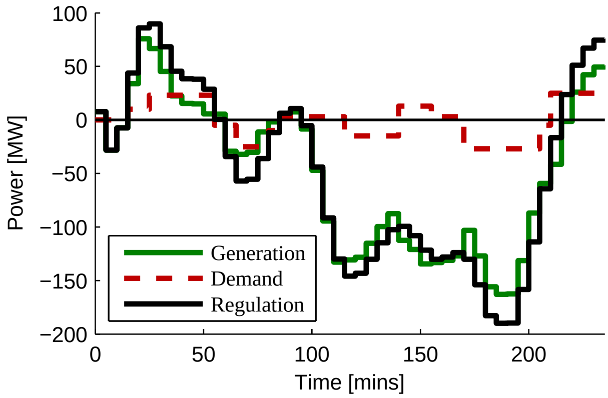


Figure 4.1: System dispatch of conventional generation and DR units for the provision of regulating power - Case B1 [Paper C].

We examine the value of DR when offered in the form of asymmetric blocks by optimally dispatching DR alongside thermal generators such that the cost of providing regulating power is minimised. This optimal dispatch framework employs mixed integer programming, as detailed in Appendix A. The DR resource is offered as a set of mutually exclusive asymmetric block offers which are priced such that they are first in the merit order and are consequently dispatched ahead of thermal generators. Determining an accurate marginal cost of DR is a substantial task that is beyond the scope of this thesis.

We find that cost savings of up to 26% can be achieved through the introduction of DR, depending on the case considered. Fig. 4.1 illustrates a sample dispatch of conventional generation and load shifting DR for the provision of regulating power. It can be observed that the load shifting DR switches between providing and consuming power (response and recovery), while the generation resource consistently tracks the regulating power profile. As expected, this leads to occasions where the DR resource is exacerbating the system imbalance, and the conventional generation resources are required to provide excess regulation to compensate. This can be observed around the 150$^{\text{th}}$ minute of the simulation. Thus, while DR can be seen to reduce costs under current cost assumptions, it necessitates additional capacity requirements from conventional resources.

The results of our study indicate that DR offers an appreciable value, in spite of the need to recover energy as part of a load shifting product. However, the limitations of this small-scale study mean that it should be treated as a proof-of-concept study rather than one that provides a general conclusion on the benefit of DR. A more detailed study is required before such a conclusion can be made.

4.1.1.1 Assessing the Value Lost through a Restricted Demand Response Description

The block offer structures that we introduced previously and employed in Paper C represent a subset of the flexibility that is available from a given DR resource. This limits the value that is offered by DR, but ensures that the value that is assessed can be accessed using existing frameworks for system dispatch and market clearing. When making such a restriction, it is important to evaluate the consequent impact on the assessed value of DR. We conduct this assessment in Paper C by comparing the performance of the DR resource when represented by an increasing number of block offers to its performance when the full range of flexibility is accessible. The latter is determined by assuming that the system operator has perfect knowledge and full control of each individual flexible load, as simulated using the time series model from which the saturation curve and block offers are found.

Table 4.1 presents the cost savings that are achieved in three sample cases. Each case corresponds to a different profile of required regulating power. In each case, the same DR resource is represented by a number of distinct asymmetric blocks, where each block consists of a different combination of response and recovery achievable by the DR resource. As the number of blocks increases, the accessible DR behaviour approaches the full range of flexibility that can be achieved with a fully modelled and controlled system. An infinite number of blocks offers the same flexibility as the fully modelled system. It can be seen from Table 4.1 that there is a clear reduction in cost savings when DR is represented using block offers, however the reduction is not overly large. The difference between the value offered by the fully modelled resource and that which can be accessed using block offers represents the maximum amount that should be invested into

Table 4.1: Regulating power provision cost reduction with DR as represented in the form of block offers or as fully modelled and controlled individual flexible load. Results shown correspond to three different regulating power profiles, B1, B2, and B3. Table adapted from Paper C.

	B1	B2	B3
2 DR Block Offers	9.54%	18.10%	19.70%
3 DR Block Offers	17.10%	23.42%	21.25%
4 DR Block Offers	20.81%	23.42%	25.13%
5 DR Block Offers	21.23%	23.43%	25.13%
6 DR Block Offers	21.43%	23.63%	26.00%
Fully Modelled Demand	24.45%	28.72%	34.22%

establishing the control and communications infrastructure that is necessary to achieve this level of control. The relatively small additional benefit that can be accessed by a fully modelled resource indicates that such significant infrastructure investment may not be warranted. Furthermore, it can be seen that representing the resource using only four block offers rather than six does not significantly reduce the cost benefits that are achieved. This indicates that only a very simplistic representation of DR is necessary to access significant benefits.

4.1.2 Assessing Demand Response in a Large Scale Power System Study

Following the proof-of-concept study that is presented in Paper C, it is necessary to see how the value of DR scales, in a study that covers a large geographic area over a long study duration. We present such an analysis in Paper D, in which we develop methods to model DR in a large-scale social welfare study and assess the impact of DR on a realistic power system.

4.1.2.1 Considerations when Modelling Demand Response in a Large-Scale Power System Study

A number of particular considerations are required when modelling DR for a large-scale power system study. Chief amongst these is the impact of external factors on the seasonal resource availability. Renewable generation resources such as wind and solar generation exhibit significant seasonal variations, which affect the value that they offer to the power system. On some systems load and renewable generation share a coincidental peak, such as in Ireland [44], while on other systems renewable generation and load may have opposing peaks, such as in Texas [45]. The ability of any resource to provide a power system service when it is needed, be it generation or DR, is a determining factor in its value and suitability for a particular power system.

For thermal-electric flexible loads, including the case study of supermarket refrigeration, the external factor with the greatest impact is ambient temperature. The load shifting abilities of thermal-electric flexible loads are defined by three quantities; baseline power consumption, maximum power consumption, and efficiency. All three quantities are temperature dependent. Baseline power consumption is that required to maintain the normal operating conditions, and represents the maximum load curtailment that can be achieved under normal operating conditions. The difference between the baseline and maximum power

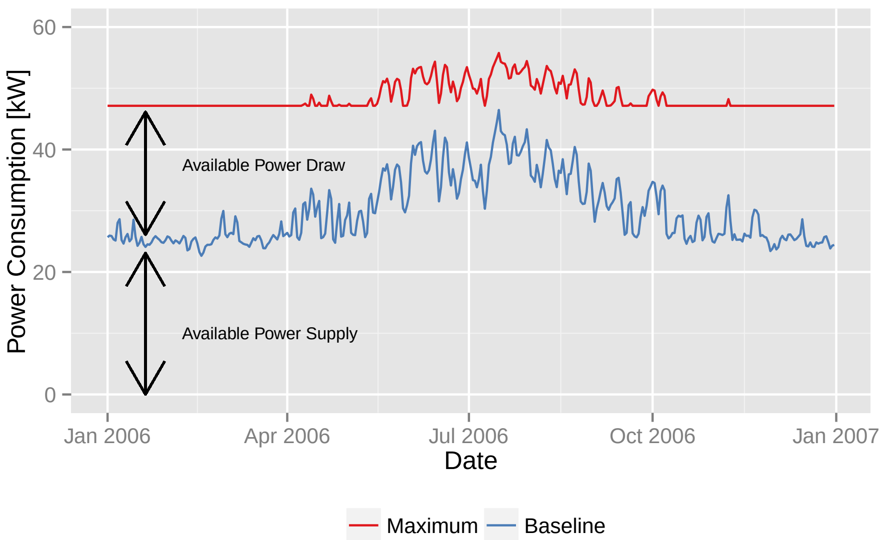


Figure 4.2: Available DR resource for effective supply and draw of power from a single supermarket refrigeration system over a year. Power is supplied to the power system through load curtailment, while power is drawn from the power system to recover from load curtailment [Paper D].

consumption represents the amount of power available to recover energy lost during a period of reduced power consumption. Fig. 4.2 illustrates the variations in baseline and maximum power consumption in a single supermarket refrigeration system over a year. It can be seen that power consumption is highest during the warm summer months, which indicates that the available load curtailment is greatest then. However, the available power for energy recovery is lowest during the same period. This limits the DR that can be achieved during those month as it is necessary to balance any load curtailment with an equal amount of energy recovery. During the cold winter months the load shifting resource is greater as there is capacity available for both load curtailment and energy recovery. We considered the temperature variations in the baseline and maximum power consumption, as well as efficiency, when defining the DR products that are offered in our simulation studies presented in Paper D. A further consideration that is necessary in large-scale system studies is the computational burden of simulating the optimal dispatch of DR. For this reason, we employed the relaxed definition of load shifting DR services presented in Section 3.3.2 in this study.

4.1.2.2 Assessing the Value offered by Demand Response and its Impact on Power System Stakeholders

Large-scale power system integration studies facilitate an analysis of the impact of introducing a new resource to an existing power system. Integration studies provide valuable insights into the value that can be accrued by a given resource, how it varies geographically and temporally, as well as its effect on existing system resources; which resources are supported and which are displaced. Sensitivity studies also facilitate the analysis of how the value may evolve as, for example, the penetration of renewable generation increases, or as the amount of DR increases. Integration studies have been previously employed to assess wind power, solar power, and storage [46, 47], and we present an integration study for load shifting DR in Paper D. Our study considers a load shifting DR resource with a maximum load curtailment capacity of 63.5 MW which is integrated into a test system that closely resembles the power system in Colorado, USA. We optimally dispatch the system to maximise social welfare every day for a year, with an additional hourly dispatch to correct for forecast errors that appear at real-time.

Fig. 4.3 shows the monthly variations in the cost reductions offered by DR. The annual cost reductions amount to $2.089 million, or $32.85/kW-year, though it is clear from Fig. 4.3 that this value varies seasonally, as expected due to the seasonal variations in the DR resource. As anticipated, the value is lowest during the summer months when the flexibility of the refrigeration units is restricted due to their limited ability to recover energy. The seasonal variations are not overly significant however, which is a favourable indicator for the suitability of this form of DR on systems with a range of seasonal trends. The Colorado test system is summer load peaking and has peak wind generation during the winter.

Sensitivity studies on the installed DR capacity provide insight into the possible trajectory of DR value as the resource is developed and further deployed. Our sensitivity studies consider a naïve resource expansion, in which the base population of flexible devices is simply multiplied by 5, 10, and 25. This expansion does not consider the increase in resource diversity that would occur as other end-users activate their flexibility. Consequently, the projected trajectory should be considered as an indicator of direction only, not a definitive result. Fig. 4.4 indicates that the marginal value of DR will suffer a significant reduction as the installed capacity increases. Though not shown here, the revenue for DR operators suffers similarly. This indicates that early-adopters of DR represent significant additional benefit to the power system, however as more flexible loads provide DR their marginal value drops. Considering that the DR capacity of the average *large* supermarket is approximately 150 kW, the annual value offered by each large supermarket at the lowest considered DR resource

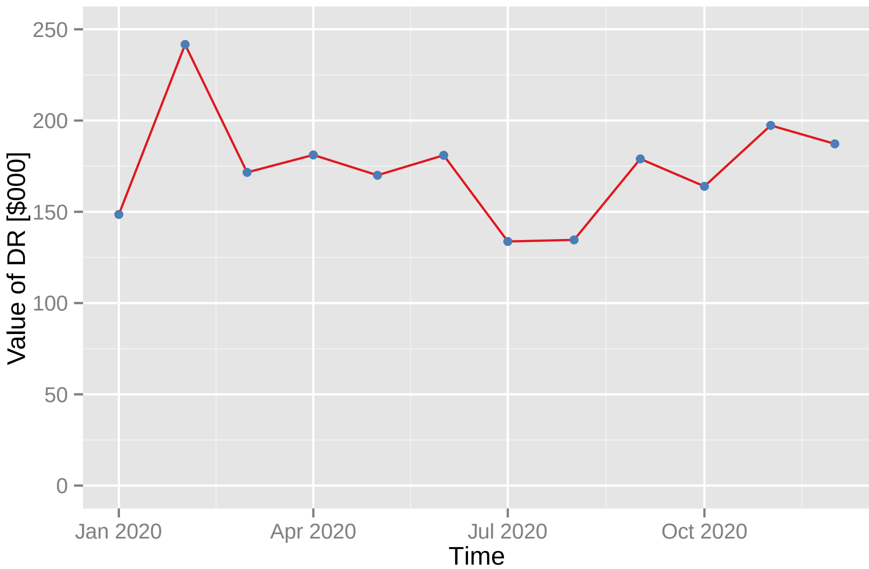


Figure 4.3: Operational cost savings achieved through the use of DR, per month over a year [Paper D].

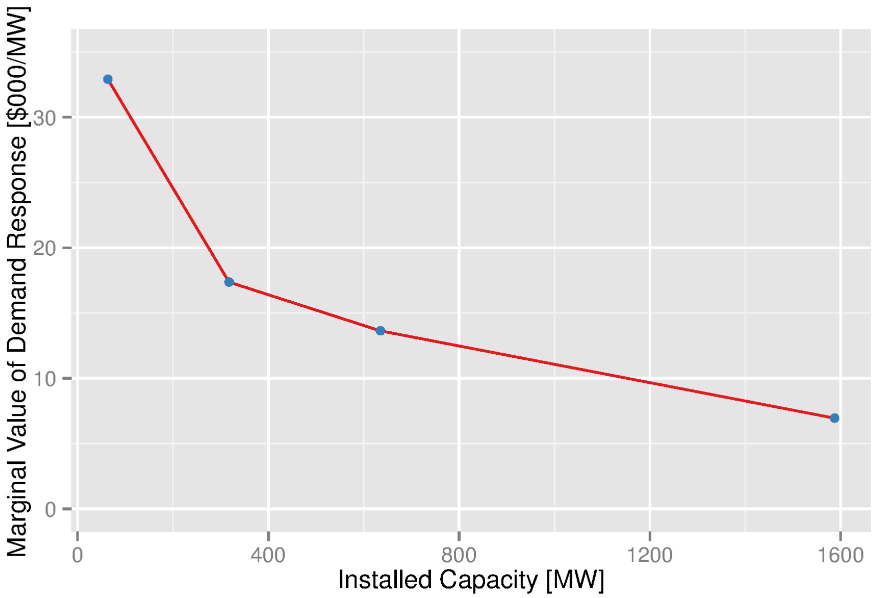


Figure 4.4: Marginal value of DR as the DR resource capacity increases [Paper D].

capacity is $4,890, reducing to $1,030 at the highest studied resource capacity. Even in the lowest capacity case, the per supermarket value appears to be very low, possibly insufficient to justify the infrastructure investment and staff training required to operate the DR resource.

The impact of DR on existing system generation resources can be seen in Fig. 4.5. It can be observed that DR displaces generation from less efficient and more expensive generators that typically provide flexibility; gas combustion turbines (CT). Generation from inflexible but efficient combined cycle (CC) units is supported. Furthermore, DR can be seen to support generation from renewable resources including wind, solar photovoltaic and dispatchable hydropower. Support of non-dispatchable renewable resources is achieved through avoided curtailment. It is clear that DR has a significant impact on thermal generation units, which are typically operated by large utilities with substantial market shares and political influence. If DR is perceived to negatively impact their resource, through for example reduced capacity factors as indicated in Fig. 4.5, they may engage their substantial influence to discourage the development of DR, as predicted in [6]. A similar result indicating a reduction in capacity factors is found in [31], however it is noted that thermal generators are capable of providing inertial and voltage support, which DR cannot.

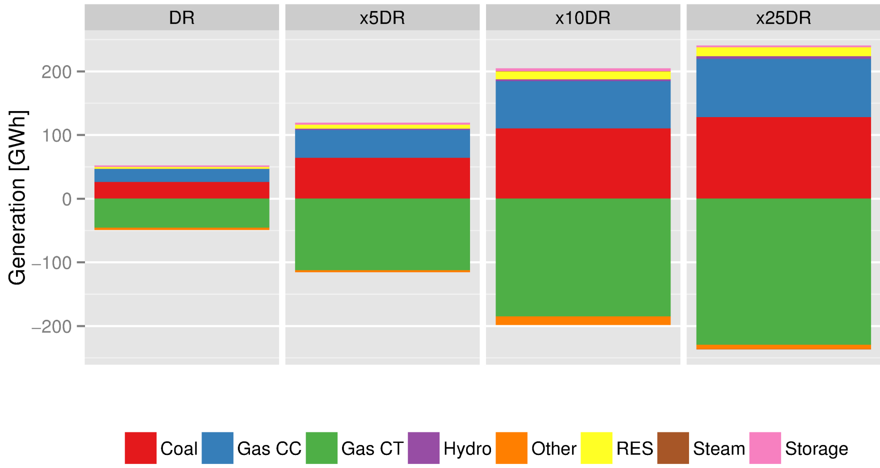


Figure 4.5: Impact of DR on generation portfolio at different levels of DR capacity [Paper D].

4.1.2.3 Discussion on the Sensitivity of Demand Response Value to System Parameters

Case studies of DR provide a valuable analysis of this novel resource in the context of existing power system frameworks, however it is important to note that the value of DR is highly system dependent. The numerical results that we provide in Paper D should therefore not be treated as definitive results, but instead as indications of orders of magnitude. The value offered by DR depends on the existing generation portfolio, the level of interconnection with adjacent power systems, the availability of energy storage, and transmission constraints, as well as policy and regulatory decisions that may support certain technologies, such as renewables, over others.

Our revenue calculations reveal a low per-supermarket net revenue, particularly as the available DR capacity increases, but this value is driven primarily by the system price differentials. Demand response will supply power to the system through load curtailment during high price intervals, and recover the energy at lower price intervals. As prices on the test system are determined mainly by fuel costs, revenue is sensitive to the portfolios of generators on the system. Systems with higher fuel cost differentials may offer a more attractive environment for DR, from a revenue maximisation perspective. Additionally, regulatory measures such as the introduction of carbon taxes or financial support mechanisms for DR may have a profound impact on the revenue that can be generated.

Transmission constraints are also expected to have a significant impact on the value offered by DR. In large-scale power system studies, transmission constraints are typically considered at an aggregate level, where only interconnections between adjacent zones are considered. This reduces the computational burden of a very large optimisation problem, but eliminates a possibly significant source of value, as DR could potentially be employed to avoid transmission system congestion.

In summary, it appears from our analyses in Paper D that the outlook for DR is quite negative; per unit value is low, and the revenue that is generated is unlikely to support the technical and educational measures necessary to establish and operate DR. However, given the correct set of system conditions, the outlook is likely to improve. On constrained systems, DR can provide the necessary flexibility to avoid the use of high cost peaking generation units or delay the reinforcement or upgrade of transmission networks, resulting in more significant cost savings than those seen in Paper D where the system is relatively unconstrained. It is furthermore possible that while DR does not offer an appreciable value in the context of an entire power system, it may find value in an area of the network that is constrained or in the provision of a niche power system service such as extreme peak load reduction.

4.2 Assessing the Commercial Value of Demand Response

It is imperative that the revenue generation potential of DR be assessed in addition to its social welfare benefits. In the absence of a profitable business case, no commercial entity will be willing to invest the capital necessary to establish and operate this novel resource. The difficulties of establishing a business case for DR are highlighted in [12], where it is noted that although DR is capable of generating social welfare benefits, these benefits are distributed across a number of power system stakeholders and it may be difficult to gather sufficient social welfare to justify a commercial venture into a single business case.

We investigate the revenue generating potential of a DR resource offering load curtailment products on the day-ahead, intra-day, and regulating power markets in Paper E. We develop optimal trading strategies for DR on both the pool-based day-ahead market and the continuous trade intra-day market, while any remaining power imbalance at real-time is rectified through the regulating power market. Our trading strategies employ stochastic mixed integer programming to determine the optimal dispatch of an uncertain DR resource. We provide a brief introduction to stochastic programming in Appendix A. Consideration of uncertainty is an important contribution of this work, as DR is an inherently uncertainty resource and the revenue that it can generate through market participation will naturally be affected by this uncertainty. We investigate two key research questions in this study; on which market is the participation of DR most profitable, and what is the impact of resource uncertainty on the revenue that can be generated? These are addressed in detail below.

4.2.1 Suitable Markets for Trading Demand Response

Intuition would suggest that the trade of an uncertain power system resource should occur as close as possible to the delivery hour, when much of the uncertainty has been eliminated and the risk of incurring financial imbalance penalties is reduced. In the case of DR, this would encourage trading on the intra-day market, where trading occurs up to one hour before delivery, over trading on the day-ahead market, which has lead times of up to 36 hours.

Our analysis in Paper E reveals that while trading on the intra-day market is profitable, it is more advantageous to initially trade on the day-ahead market and then trade any remaining capacity on the intra-day market. The intra-day market also offers the opportunity to correct any uncertain imbalances that have been revealed closer to real-time.

Fig. 4.6 illustrates the revenue that can be generated by trading in both the day-ahead and intraday markets, and trading solely on the intraday market. As it can be expected that the forecast of achievable DR is poor at long horizons, the day-ahead DR forecast is distinct from the forecast used when trading in the intraday market. Three day-ahead forecast qualities are employed; *poor* underestimates the resource, *moderate* overestimates it, and the *perfect* forecast is the same forecast employed when trading intraday. In this figure we consider two intra-day forecasts; time varying and time invariant. The time varying forecast considers that the achievable curtailment varies across the day, while the time invariant assumes that the expected curtailment is constant. The time invariant forecast corresponds to the expected response from the time varying forecast over a day.

It can be seen that in most cases it is more profitable to trade on the day-ahead market prior to trading on the intraday market, regardless of the quality of the day-ahead DR forecast. This can be attributed to more advantageous pricing on the day-ahead market, and notoriously low liquidity on the intraday market, which may lead to cases where there are no suitable trades available to the DR resource.

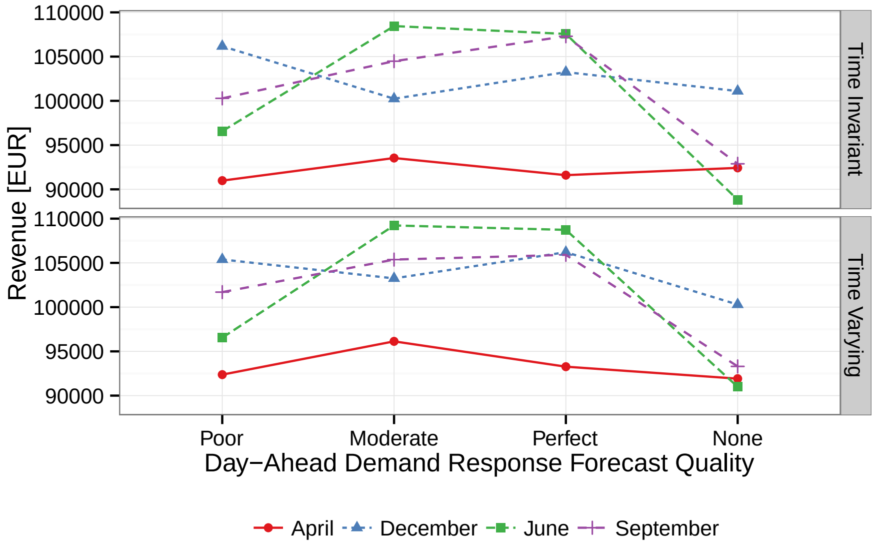


Figure 4.6: Revenue generated on the day-ahead and intra-day markets with a range of day-ahead DR forecast qualities, and without day-ahead trading, for two real-time DR uncertainty distributions; time varying and time invariant. Trading is considered in four representative weeks across a calendar year [Paper E].

It is also evident from Fig. 4.6 that there are some cases in which the *moderate* day-ahead DR forecast out-performs the *perfect* forecast. The moderate forecast overestimates the available curtailment, and consequently offers more energy on the day-ahead market than it can deliver. In this manner, the higher prices on the day-ahead market are exploited while the resulting shortfall in energy delivery at real-time can be corrected either through the intraday market or the regulating power market. However, if advantageously priced trades are not available on the intraday market the imbalance must be settled at the regulating power price, which is at least as high as the day-ahead price, resulting in a poorer revenue outcome.

It should be noted that the revenue values in Fig. 4.6 are generated over a week of trading, and the DR resource employed consists of 3000 supermarkets each offering a maximum load curtailment of 10kW. Thus, the revenue per supermarket amounts to approximately €30-37/week, a very small amount. Individual supermarkets are capable of providing significantly more curtailment than 10kW, however as a load curtailment product does not allow for any form of rebound it is necessary to limit the curtailment. It seems unlikely that this small weekly return would support a complete business case for DR, however further research is necessary to determine the costs of establishing and operating this resource.

4.2.2 Assessing the Impact of Demand Response Uncertainty on Revenue

The load curtailment that can be achieved is affected by sources of structural and environmental uncertainty. Structural uncertainty refers to errors in modelling the resource, while environmental uncertainty results from interactions with external factors such as ambient temperature and end-users. The impact of this uncertainty is investigated by applying a number of uncertainty distributions to the DR resource and comparing the revenue that can be generated in each case. Time varying distributions reflect the assumption that there are certain times during the day at which the response will be more reliable that at other times. The time invariant counterparts are also considered, where the probability distributions are the time averaged values of the time varying distributions.

Fig. 4.7 illustrates the revenue that can be generated in three difference cases, where the probability distributions are differentiated by the degree of distribution variation over the course of a day. It can be seen that the larger the time variations in the expected DR resource, the lower the revenue that can be accrued. There is a significant variation in the expected revenue with uncertainty distribution. This indicates that consideration of uncertainty is crucial in any

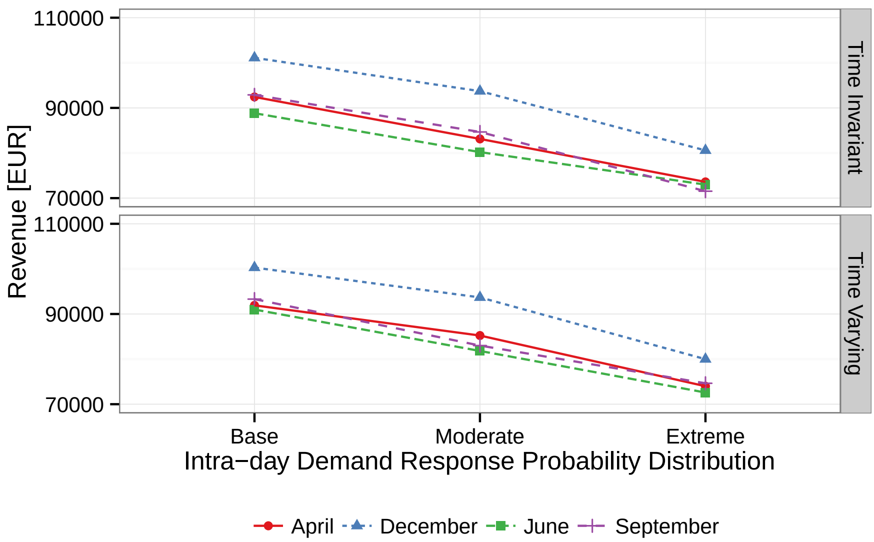


Figure 4.7: Revenue generated on the intra-day market with a range of day-ahead DR uncertainty distributions, both time varying and time invariant. The x-axis indicates the degree of daily variation in the expected DR resource [Paper E].

evaluation of this resource. Assuming a perfectly known resource is not sufficient, and may result in misleading conclusions on the benefits of DR, or the feasibility of a business case to develop this resource.

Chapter 5

Conclusions

5.1 Contributions

In the course of the research described in this thesis, we have provided a number of novel contributions to the state of the art. We have developed a set of methodologies for the modelling, operation, and trading of DR that bring it from an abstract resource to one that can be realistically implemented within current power system operation and market frameworks.

Our saturation curve concept underpins all of the DR offering structures that we have developed here, but also offers value as a stand-alone representation of DR. Resulting from detailed mathematical modelling and simulation of the flexibility of a refrigeration system, the saturation curve that we present here offers an easily understood graphical representation of the extent of the flexibility offered, as defined by the physical characteristics and constraints of the underlying load. Applicability to a broad class of flexible loads is ensured, as the base attributes of saturation and rebound are exhibited by all thermal-electric loads that are capable of offering load shifting DR. Consequently, the saturation curve is an important tool for the comparison of the flexibility offered by candidate flexible loads. It facilitates an assessment of the suitability of a given load for the provision of particular flexibility services, as may be differentiated by power, energy storage volume, or duration requirements. The saturation curve offers value to a number of power system stakeholders, including for example utilities considering establishing specialised DR programmes for distinct load groups. Employing the saturation curve in the design of such programmes will help to ensure that the programme requirements are suited to the abilities of the participating loads and that the maximum possible value can be attained.

The offering structures that we have developed for the optimal dispatch and trading of DR offer tangible methods for the exercise of consumption-side flexibility. Power system stakeholders are restricted to participating through established dispatch and market frameworks, and despite the disruptive nature of the DR resource and its potential to significantly alter the structure of the power system and how it is operated, any implementation of DR in the near future will have to respect these frameworks.

We have developed the asymmetric block offer as a methodology for the integration of load shifting DR within these conventional frameworks, expanding on the already employed concept of a block offer. Extending the existing block offer structure to include both power supply and consumption is a relatively minor alteration, and it can be expected that an asymmetric block offer would be readily accepted and implemented on electricity markets that currently accept conventional block offers. The ability of a population of flexible loads to achieve a flexibility profile that has been scheduled using the asymmetric block offer structure is assured, as the profiles have been selected from the saturation curve.

We have also proposed a relaxed structure by which to offer load shifting DR, which exhibits reduced computational burden in simulation studies but which has the drawback of potentially scheduling flexibility profiles that the DR resource may not be able to fulfil. In this relaxed structure, DR can be scheduled in the same manner as conventional energy storage technologies, though it has the added benefit of offering multiple storage configurations from a single DR population. Our relaxed formulation has facilitated the large-scale power system study that we have conducted as part of this thesis, which has revealed the value that DR can offer over large geographic and temporal scales, and the impact that it has on existing power system participants. In addition, this scheduling framework can be employed by market participants wishing to trade DR in the same manner as existing storage technologies on forward electricity markets.

Much of our research has focussed on load shifting DR, however load curtailment is another candidate DR resource that may play a significant role in the power system of the future. We have developed a novel trading strategy for load curtailing DR on the day-ahead and continuous trade intraday markets and, significantly, we have also considered the uncertainty in load curtailment that might be realised. Consideration of DR uncertainty is not common in the current literature in this field, but through our research we highlight that uncertainty can have a considerable impact on the revenue that can be generated through trading DR. This is an important contribution, as it indicates the need for a full characterisation of the uncertainty of DR and for its consideration in all future DR evaluation studies.

5.2 Perspectives and Opportunities for Further Research

Activating the demand side through massive distributed DR has the potential to vastly alter the power system and to support its development towards a more sustainable and economically efficient paradigm. In a future power system in which resources are constrained, substantial reductions in carbon emissions are sought, and flexibility is at a premium, it can be foreseen that DR will be highly valued and will play a significant role. In the current paradigm though, the development of DR faces significant challenges.

These challenges are not technology-related. No further technological advancements are necessary to facilitate the intelligent control of large numbers of individual electrical loads. It is simply a case of deploying existing technology, but establishing the necessary communications and control frameworks requires significant capital investment. Such an investment will only be made if it can be demonstrated that DR is capable of producing a return on that investment.

We have shown through the proof-of-concept study that we conducted in Paper B that the optimal control of the DR resource is not necessary to access the value offered by flexible consumption. Rather, a coarse representation consisting of a finite set of offered DR behaviours is sufficient. Consequently, the investment in communications and control infrastructure can be reduced while still accessing a significant portion of the available flexibility. However, from the subsequent studies presented here we can see that under current system conditions, and operating within existing dispatch and market frameworks, the ability of DR to generate a return on *any* investment is minimal.

Demand response generates value by displacing marginal power system resources. On a constrained system this value can be significant; displacing high cost peaking plants or alleviating network congestion can result in substantial reductions in operational costs. Yet, it doesn't appear that power systems have reached the point of sufficient scarcity to allow DR to prosper financially. Resource scarcity is reflected in high and volatile prices, which would allow DR to generate value by curtailing load or by conducting energy arbitrage through load shifting. The research that we have conducted here reveals that despite the physical ability of DR to react to variations in system costs and prices, the value accrued through this response is very low. We show through our analysis in Paper D that the social welfare benefits offered by DR when deployed on a large-scale power system are modest. This result is corroborated by our finding in Paper E that the commercial value of DR when participating on the day-ahead and intraday markets is similarly very low.

If large-scale distributed DR were deployed today, it would be required to offer its flexibility through established market frameworks. These market frameworks were originally designed for large inflexible thermal generators, and are simply not suitable for the optimal use of DR. We have demonstrated through our research in Paper E that the greatest potential for revenue generation lies in participation on the day-ahead market, which is primarily characterised by long lead times to energy delivery. This prevents the use of one of the greatest assets of DR, its ability to deploy flexibility rapidly. As power systems evolve in the direction of higher shares of stochastic renewable generation, an increase in liquidity is observed on markets with gate closures closer to real-time. However, even in regions with notably high shares of wind generation, such as Denmark, the greatest value remains in the day-ahead market. This is clearly a sub-optimal framework for DR, and if flexibility truly becomes a priority these market structures will require an overhaul, such that the value of flexible resources is reflected in the price that they are offered.

The analyses conducted in this thesis are by no means exhaustive, and the argument can be made that there are many niche cases in which DR can offer significant value today. However, they are just that, niche cases. Demand response does not appear to be the all-encompassing solution that many have proclaimed it to be. Power systems have not yet reached the point at which they need such a solution. This presents researchers with the opportunity to further explore the capabilities of DR, identify cases in which it offers real value, and to determine what changes are necessary to allow us to fully benefit from its capabilities.

One aspect of DR that we have not explored in detail here is its use for the provision of power system reliability services very close to real-time. On many power systems the provision of such services can be lucrative, as DR can benefit from capacity payments regardless of whether or not the offered energy service is exercised. The challenge for DR here is the need to demonstrate its ability to adhere to strict reliability requirements. While it appears that one of the most valuable aspects of DR is its ability to adjust power consumption rapidly and with limited forewarning, this has not yet been demonstrated on a large scale. The importance of demonstration studies for DR cannot be overstated, as only through realistic trials can we as researchers identify the true capabilities and limitations of DR and consequently design frameworks in which it can be optimally employed.

In this thesis we have approached the task of evaluating DR from the perspective of fitting this novel and diverse resource into conventional operating frameworks that were designed at a time when DR was not considered to be a serious contender for contribution to power system operations. A continuation of this research agenda should consider the complementary problem; how can we design novel frameworks for the operation of a future power system in which DR plays a central role, and what benefit does DR offer in such tailored frameworks? By addressing this problem we can establish an upper bound on the possible value offered by DR, and determine if the steps necessary to establish such idealised frameworks are worth pursuing.

Appendix A

Mathematical Modelling Frameworks for Demand Response in Power System Operations

The central focus of this work is the characterisation and evaluation of DR. The research questions addressed translate naturally to a set of optimisation problems, to investigate the optimal behaviour or dispatch of DR in a variety of settings. This chapter provides an introduction to the central optimisation techniques employed in this thesis; model predictive control, mixed integer programming, and stochastic optimisation.

This chapter is intended to give the reader a basic understanding of the concepts employed in the publications that are included in this thesis. For further details on these subjects, the reader is directed to [48, 49] on model predictive control, [50] on mixed integer programming, and [51] on stochastic programming.

A.1 Model Predictive Control

A.1.1 Theory

Model predictive control (MPC) is a form of control in which a model of the system under control is employed to determine the optimal control actions to achieve the desired outcome. Fig. A.1 provides a conceptual overview of the structure of a typical MPC framework. In such a framework, the controller receives feedback of the measured output of the system, and identifies the controls actions necessary to cause the output to follow the reference trajectory as closely as possible. The controller consists of an optimiser, with associated objective function and constraints, and a model of the system under control. The external disturbance noted in Fig. A.1 can come from unmodelled system behaviours, or from external stimuli that are not considered in the system model inputs.

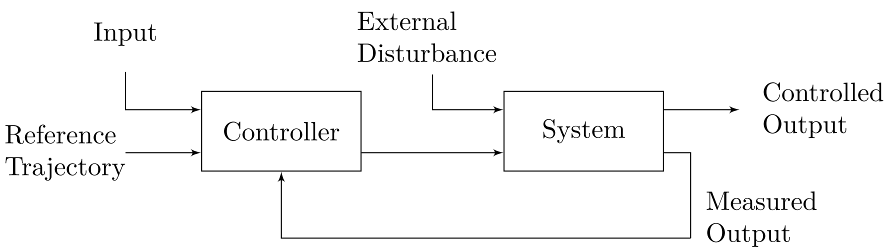


Figure A.1: Model Predictive Control Framework

The key element of MPC that distinguishes it from other control frameworks, is the use of models to estimate the response of the system to control actions. The model employed in MPC can take many forms, the most common being state space models, transfer function models, impulse response models, and step response models.

MPC is exercised as a sequence of optimisation problems. At each control step, the optimal control actions over a fixed, finite horizon from the current time, say $[k, k + N]$, are determined. The optimisation considers the current state of the system, historical inputs, and the reference trajectory or control objective when determining the control actions over the horizon. Only the control action for the first interval, k, is applied and the optimisation procedure is repeated for the subsequent horizon, $[k + 1, k + N + 1]$.

A sample MPC optimisation framework is given in (A.1) below, considering the case where a flexible refrigeration system is required to follow a reference trajectory for power consumption.

$$\min_{\mathbf{P}} \quad \sum_{t \in T_{opt}} (P_t - P_t^{ref})^2 + \nabla P_t \gamma \tag{A.1a}$$

subject to:

$$\phi(B) T_t = \omega(B) P_t \tag{A.1b}$$

$$\nabla P_t = P_t - P_{t-1} \tag{A.1c}$$

$$T^{min} \leq T_t \leq T^{max} \tag{A.1d}$$

$$P_t \leq P_{max} \tag{A.1e}$$

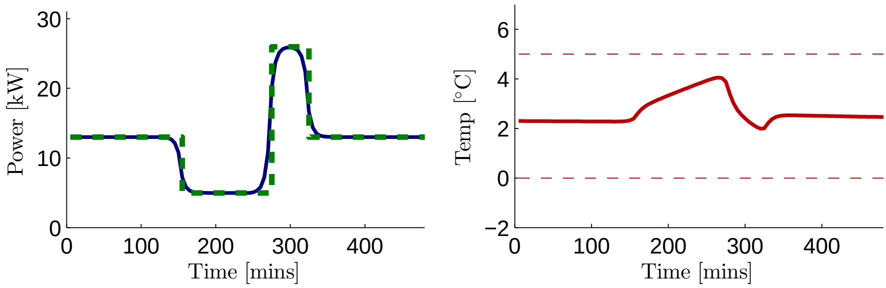
$$P_t \geq 0 \tag{A.1f}$$

The optimisation problem in MPC consists of an objective, or cost, function, and a set of constraints. The cost function is often termed so as to minimise the difference between a modelled system state and a given reference. In problem A.1, the control variable is the power consumption at each simulation time step, P_t, and the objective is to minimise the squared error between P_t and the power consumption reference signal P_t^{ref} over the optimisation horizon T_{opt}. In addition to this basic objective, a penalty term may be included to discourage undesired system behaviours. In the example shown, a penalty of γ is placed on the rate of change of power consumption, ∇P_t as defined in (A.1c). Such a penalty function is intended to prevent rapid variations in power consumption that might be damaging for some appliances.

The thermal dynamics of the system are described in (A.1b), which relates the temperature on the refrigeration system, T_t, to the power consumption in its compressors, P_t. The relationship is described as an Auto-Regressive Moving Average with eXogeneous inputs (ARMAX) process [52], where $\phi(B)$ and $\omega(B)$ are polynomials in the backshift operator B. The backshift operator is defined as $B : Bx_t = x_{t-1}$, and is used here to relate current values of temperature and power consumption to historic observations. The noise component of the ARMAX process is not included in this MPC problem formulation for simplicity.

The temperature on the refrigeration system is restricted to lie within acceptable limits, often termed comfort limits in DR applications. These limits are defined in (A.1d). Additionally, the power consumption is limited to the capacity of the refrigeration system compressors, (A.1e).

Fig. A.2 illustrates the behaviour of a flexible refrigeration system participating in a load shifting DR event through MPC. The system is provided with a power



(a) Power Consumption

(b) Temperature

Figure A.2: Load shifting behaviour in a flexible refrigeration system as controlled using MPC. Temperature bounds are indicated by dashed red lines.

consumption reference, indicated by the dashed green line in Fig. A.2a, which includes the load shifting trajectory. The system successfully follows this trajectory, which consists of a load curtailment followed by an energy recovery, driving the temperature on the system (shown in Fig. A.2b) towards its upper limit, and then returning it to a normal operating point following the DR event. The effect of the penalty term can be seen where the modelled power consumption trajectory appears to exhibit a slower rate of change than the power consumption reference. This effect has been exaggerated for illustrative purposes.

A.1.2 Applications in the Literature

MPC has emerged in recent decades as a successful control methodology for industrial processes, and its application to DR is explored in a number of works in the literature. MPC is a very flexible tool, facilitating both indirect and direct control frameworks. Indirect control makes use of economic MPC (EMPC), where the objective is to minimise the cost of energy consumption, subject to a price signal issued by an aggregator. Direct control is simulated using a more traditional form of MPC, where an aggregator issues a reference trajectory for an operating state of the flexible appliance. The use of EMPC for the control of commercial refrigeration is detailed in [53] and its use in the control of electric vehicle charging is described in [54]. Traditional MPC is employed in [55] for building climate control and in [56] for the control of flexible electric water heaters and air conditioning units.

A.2 Mixed Integer Programming

A.2.1 Theory

Optimisation problems in which some or all of the decision variables are restricted to integer values are known as mixed integer problems. Such problems are frequently found in the energy sector, a classic example being the unit commitment problem in which generating units are assigned a commitment status (online or offline) and dispatched to serve the load [57, 58]. The use of binary variables to indicate commitment status necessitates the formulation of the unit commitment problem as a mixed integer programming problem, while the binary variables also facilitate the definition of constraints on minimum up-times and down-times, as well as a description of fixed and variable cost components for the operation of power plants.

Mixed integer programming is also well suited to the scheduling of DR products in optimal trading strategies and system dispatch frameworks. The following is a simplified formulation for the dispatch of load curtailment, with specific applications of integer programming techniques highlighted.

$$\max_{\mathbf{P}} \quad \sum_t \left(P_t \lambda_t - (\alpha_n u_{t,n} + \beta P_t)\right) \tag{A.2a}$$

subject to:

$$P_t \leq \sum_n u_{t,n} P_n^{max} \qquad \forall\ t \tag{A.2b}$$

$$\sum_n u_{t,n} \leq 1 \qquad \forall\ t \tag{A.2c}$$

$$\sum_{\tau=t}^{t+\mathrm{Up}_n} u_{\tau,n} \leq \mathrm{Up}_n + (1 - u_{t,n})M \quad \forall\ t, n \tag{A.2d}$$

Fixed Charges

The objective of this optimisation, given in (A.2a), is to maximise the revenue that is generated through the trade of load curtailment, P_t, on the day-ahead market, subject to a point forecast of the day-ahead price λ_t and assuming that the market agent representing the DR resource on the market is a price taker.

The revenue at a given hour t consists of the income generated through trade, $P_t\lambda_t$, minus the cost of procuring DR from the flexible consumers. The cost structure of DR procurement consists of a fixed cost component and a variable cost component. Here, we assume that the market agent can offer n different load curtailment products on the market, and each product has a distinct fixed cost component, α_n. Fixed costs are incurred at any time that curtailment is provided regardless of the level of curtailment. The status of a given load curtailment product (online or offline) is indicated by the binary variable $u_{t,n}$. Variable costs are dependent on the level of curtailment. This non-linear cost structure cannot be implemented in a linear programming problem, but is easily implementable in an integer formulation as shown.

Logical Contraints

Logical constraints are easily formulated using integer programming, and are demonstrated in (A.2b) - (A.2d). In this problem, the DR resource is capable of providing n mutually exclusive load curtailment products which are differentiated by the magnitude of load curtailment allowable, P_n^{max} , and the maximum duration for which the curtailment can be maintained, Up_n.

The requirement that only one load curtailment product is offered at a given time is enforced in the logical **or** constraint (A.2c), for example where product n_1 **or** n_2 can be offered, but n_1 **and** n_2 cannot be offered simultaneously.

The maximum duration of each curtailment product is imposed in (A.2d), which restricts the sum of online indicators for a given product, $u_{t,n}$, over a horizon ranging from the current time, t, to the maximum duration for the product, $t+\mathrm{Up}_n$, to be less than that maximum duration. This maximum up-time constraint is only active while a given product is being provided, that is, $u_{t,n}$ is non-zero. If $u_{t,n}$ is zero, the summation on the left hand side is constrained to less than the maximum duration plus a large value, M, resulting in a non-binding constraint. This constraint formulation is known as the *Big M* formulation, which facilitates constraints that are only binding under certain circumstances. The ability to formulate conditional constraints in this manner is another advantage of integer programming. Note that the conditional formulation is not necessary here as the constraint is not binding in any case that $u_{t,n}$ is zero, however as this formulation is used extensively in Part II of this thesis, it is included here as an introduction to notation.

A.2.2 Complexity in Mixed Integer Programming

Integer problems are computationally intensive, and long computation times often preclude the use of mixed integer programming for real-time applications. In the power sector, unit commitment is typically employed to plan the operation of power plants at long horizons. Closer to real-time, the commitment status is fixed and the operating point of online power plants is optimised through economic dispatch, a linear programming problem [59]. As it can be expected that the dispatch of DR will be determined or adjusted close to real time, consideration of problem complexity is necessary and appropriate steps to reduce complexity should be adopted where possible.

Integer problems are solved using the branch-and-bound technique. In brief, this technique divides the master integer problem into sub-problems. The linear relaxation of each sub-problem is found by removing the restriction to integer valued variables, and the sub-problems are evaluated. Sub-problems are continuously divided (branched) until the resulting sub-sub-problem is either infeasible, linearly optimal and has a worse outcome than its master problem, or integer optimal. This branch-and-bound technique can lead to a very large number of sub-problems, resulting in long computation times. A problem with n binary variables can lead to 2^n sub-problem, thus the size of the problem grows exponentially with the number of binary variables.

Many of the optimisation problems that we have developed in this thesis involve extensive use of binary variables, and it has been necessary to implement code simplification techniques to reduce their computational burden. The following is a brief description of such techniques, which is presented as an introduction to the topic rather than an exhaustive discussion.

Binary Encoding

As the number of binary variables is the key determining factor on the computational burden of the problem, a natural first step is to reduce the number of binary variables. This can be achieved by applying binary encoding, where $2^n - 1$ binary variables can be represented by n encoded binary variables. Table A.1 illustrates the case where the online indicators, u_n, for 3 DR products are represented by the combination of two encoded variables, α and β. This requires a more complex formulation of the problem constraints, as any reference to u_n must be replaced with the relevant binary encoding of α and β. Thus, for smaller problems this may not be beneficial, but as the problem size grows the reduction in computation time can be significant.

The multiplication of α and β is a non-linear formulation that must be linearised to allow the problem to be solved using mixed integer solvers. This is achieved by defining a third binary variable γ, and imposing the following constraints:

$$\gamma \leq \alpha \tag{A.3a}$$

$$\gamma \leq \beta \tag{A.3b}$$

$$\gamma \geq \alpha + \beta - 1 \tag{A.3c}$$

The combination of equations in (A.3) performs the logical operation that γ is equal to α **and** β, thus transforming the non-linear $\gamma = \alpha\beta$ into a set of linear constraints that are readily solvable. The addition of this third binary variable does not increase the computational burden as it is simply a function of the other two binary variables. An example of binary encoding as applied to the problem of strategic bidding under uncertainty in short-term markets is provided in [60].

Efficient Problem Formulation

The manner in which the problem constraints are formulated can have a substantial impact on the computational effort required to solve the problem. There is no single guaranteed method to build constraints that result in an easily solvable problem, but there are a number of general guidelines that can be followed.

Symmetry in the problem formulation often leads to difficulty in the branch-and-bound process, resulting in longer computation times, and should therefore be avoided. Symmetry occurs when there are multiple options with the same cost outcomes. In the previous example of the population of flexible loads offering different DR products (A.2), the problem of scheduling these products would exhibit symmetry if all the products had the same parameters, resulting in the same objective function value regardless of which product was scheduled.

Table A.1: Binary Encoding

	α	β	Encoding
u_{n1}	0	1	(1-α)β
u_{n2}	1	0	α(1-β)
u_{n3}	1	1	$\alpha\beta$

Another approach to reduce computational burden is to increase the number of constraints on the integer variables. This often reduces the complexity of the problem, as the additional constraints can be used to reduce the number of non-integer solutions to the linear relaxation of the integer problem (or its sub-problems). This reduces the number of branches required in the branch-and-bound process.

For the same reason, it is important to use the smallest possible value for M when formulating *Big M* constraints. For example, consider the constraint that $u_{n1} + u_{n2} \leq M u_{n3}$, where all u_n are binary variables. The intention of such a constraint would be that u_{n1} and u_{n2} can only be non-zero if u_{n3} is non-zero. If M is 10, under a linear relaxation u_{n3} only needs to be 0.2 to allow both u_{n1} and u_{n2} to be 1. Thus, there are many non-integer solutions to the linear relaxation. Setting M to 2 results in a more efficient problem.

A.3 Stochastic Programming

A.3.1 Theory

In the energy sector, many decision making problems are subject to uncertainty. Stochastic programming provides a framework in which the uncertainty of parameter values and outcomes can be considered within an optimisation.

In stochastic programming, each uncertain parameter is modelled as a random variable. Where the uncertainty distribution of the random variable is unknown, it can be represented by a finite set of realisations, or scenarios. Each scenario represents a possible outcome of the uncertain parameter.

Stochastic optimisations contain multiple stages, where decisions are made at each stage based on the most recent forecast for the outcome of the uncertain parameters. The most basic stochastic optimisation contains two stages; at the first stage so-called *here-and-now* decisions are made; at the second stage *wait-and-see*, or *recourse* decisions are made. A classic example of a two-stage decision making process in the energy sector is that of offering energy on the day-ahead market subject to uncertainty in the available real-time power generation, and using the ability to purchase and sell energy on the regulating power market for recourse. Two-stage decision making problems are described for trading uncertain wind energy in [61], scheduling uncertain electric vehicle charging loads in [62], and for optimal trading strategies for hydropower producers under price uncertainty in [63].

A simple formulation of a two-stage decision making process for scheduling uncertain load curtailing DR is given as

$$\max_{P^{\text{offer}},\Delta_\omega^+,\Delta_\omega^-} \quad Z = \sum_{\omega\in\Omega} \pi_\omega \left(P^{\text{offer}} \lambda_\omega^{\text{DA}} - \left(\Delta_\omega^- \lambda_\omega^- - \Delta_\omega^+ \lambda_\omega^+ \right) \right) \tag{A.4a}$$

subject to:

$$P^{\text{offer}} \leq P^{\max} \tag{A.4b}$$

$$P_\omega^{\text{realised}} = P^{\text{offer}} + \Delta_\omega \quad \forall\, \omega \tag{A.4c}$$

$$\Delta_\omega = \Delta_\omega^+ - \Delta_\omega^- \quad \forall\, \omega \tag{A.4d}$$

$$P^{\text{offer}}, \Delta_\omega^+, \Delta_\omega^- \geq 0, \quad \Delta_\omega \text{ free} \tag{A.4e}$$

In this problem, the objective is to maximise the expected revenue subject to uncertain realisations of the day-ahead price, λ^{DA}, the positive and negative imbalance volumes, Δ_ω^+ and Δ_ω^- respectively, and the corresponding imbalance prices λ_ω^+ and λ_ω^-. The scenarios for the considered realisations of the random variables are indexed by ω, and there are Ω scenarios in total. The probability of each outcome is given by π_ω.

The first stage decision is to determine how much load curtailment to offer on the day-ahead market, P^{offer}, subject only to an upper limit, $P^{\max}$. The second stage recourse decision is the amount of power to purchase, Δ_ω^-, or sell, Δ_ω^+, on the regulating power market. This is determined by the positive or negative deviation between the volume sold on the day-ahead market and the realised curtailment, $P_\omega^{\text{realised}}$.

In the above formulation the objective is to maximise the expected revenue, as such it is assumed that the decision maker is risk neutral. Alternative formulations can include consideration of risk aversion. In robust optimisation, decisions are made with respect to the worst possible outcome of the uncertain parameters. A robust unit commitment problem considering uncertainty in wind generation and DR is developed in [64]. A more moderate consideration of risk aversion can be considered by employing the conditional value at risk (CVaR) approach, where the expected revenue over a given proportion of the worst outcomes is considered. Alternatively, the CVaR can be considered alongside the expected revenue over all scenarios, by introducing a parameter β that balances consideration between the expected revenue and the CVaR, for example as $\beta Z + (1-\beta)\text{CVaR}$. Risk averse trading for wind generation under uncertainty in price and output is described in [65]. A further method of considering risk is to employ chance constrained optimisation, where constraints are placed to ensure that the probability of a given outcome is less than a specified value. Chance constrained optimisation is employed in [66] for the management of consumption through price responsive DR.

A.3.2 Evaluation Metrics

Instead of solving the stochastic optimisation, it is possible to reduce the problem to a deterministic one by considering only the expected value of the random variables. A number of metrics can be employed to justify the use of stochastic programming in place of the simpler deterministic approach. The two most common metrics are the Value of the Stochastic Solution (VSS) and the Expected Value of Perfect Information (EVPI).

The VSS quantifies the benefit of employing scenarios to represent the realisation of the random variables over simply using their expected value. Thus, it evaluates the benefit of using stochastic programming in place of a deterministic optimisation. Consider that the optimal objective function value in the stochastic programming optimisation is denoted z^{S*}. In the comparative optimisation, the problem is first solved by setting all random variables to their expected values. The first stage decision variables from that problem are then passed to the stochastic optimisation problem, which is solved with fixed first stage decision values, resulting in the objective function value z^{D*}. For a maximisation problem the VSS is calculated as

$$\text{VSS} = z^{S*} - z^{D*} \tag{A.5}$$

For a minimisation problem the VSS is calculated as

$$\text{VSS} = z^{D*} - z^{S*} \tag{A.6}$$

The EVPI evaluates the benefit of acquiring perfect forecasts for the random variables considered in the optimisation. This metric places an upper limit on the amount that the decision maker is willing to pay for perfect forecasts. To calculate the EVPI, the solution to the stochastic optimisation is compared to that of a modified stochastic problem. In this modified problem, all decisions are made at the *wait-and-see* stage, when the uncertainty has been removed. Taking the example of trading DR in the day-ahead market, this modified problem assumes that the day-ahead offer decisions can be made at real-time when the realised load curtailment is known. The objective function in the modified optimisation corresponding to (A.4) is given as

$$\max_{P^{\text{offer}}{}_{\omega},\Delta_{\omega}^{+},\Delta_{\omega}^{-}} \quad Z^{WS} = \sum_{\omega\in\Omega} \pi_{\omega} \left(P_{\omega}^{\text{offer}}\lambda_{\omega}^{DA} - \Delta_{\omega}^{-}\lambda_{\omega}^{-} + \Delta_{\omega}^{+}\lambda_{\omega}^{+}\right) \tag{A.7}$$

For a maximisation problem EVPI is calculated as

$$\text{EVPI} = z^{WS*} - z^{S*} \tag{A.8}$$

For a minimisation problem the EVPI is calculated as

$$\text{EVPI} = z^{S*} - z^{WS*} \tag{A.9}$$

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Part II

Publications

Paper A

Benefits and Challenges of Electrical Demand Response: A Critical Review

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Benefits and Challenges of Electrical Demand Response: A Critical Review

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Abstract

Advances in IT, control and forecasting capabilities have made demand response a viable, and potentially attractive option to increase power system flexibility. This paper presents a critical review of the literature in the field of demand response, providing an overview of the benefits and challenges of demand response. These benefits include the ability to balance fluctuations in renewable generation and consequently facilitate higher penetrations of renewable resources on the power system, an increase in economic efficiency through the implementation of real-time pricing, and a reduction in generation capacity requirements. Nevertheless, demand response is not without its challenges. The key challenges for demand response centre around establishing reliable control strategies and market frameworks so that the demand response resource can be used optimally. One of the greatest challenges for demand response is the lack of experience, and the consequent need to employ extensive assumptions when modelling and evaluating this resource. This paper concludes with an examination of these assumptions, which range from assuming a fixed linear price-demand relationship for price responsive demand, to modelling the highly diverse, distributed and uncertain demand response resource as a single, centralised negative generator, adopting fixed characteristics and constraints.

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A.1 Introduction

Power systems are experiencing a period of rapid evolution. The previous status quo of large centralised generators operating within a monopoly is being replaced by a paradigm within which sustainability and competition are key priorities [A1, A2]. Vertically integrated power utilities have been dismantled and competitive market places [A3, A4] have been established to encourage the most effective use of generation and network resources. The push towards sustainability has resulted in the introduction of emission limits [A5], carbon taxes, and most importantly going forward, ambitious renewable energy targets [A6, A7]. Under current operating practices, large amounts of expensive and carbon intensive system operating reserves are often required to ensure the security of power supply. This is a particular issue on power systems with high penetrations of uncertain renewable generation.

A number of solutions have been proposed to remedy this situation. Flexible generation resources are typically employed to maintain the system balance, while interconnection between power systems and regions can increase geographical diversity and smooth fluctuations in renewable power output. Electricity storage can also be used to balance periods of over- and under-supply of power. Demand response is a further option that is widely explored in the literature, but to date has had limited widespread usage. Demand response is regarded as an elegant solution to the issues of uncertain and fluctuating power supply, as the potentially significant latent flexibility of electrical demand can be harnessed to provide the required power system services to support renewable power generation. It is important to note that the benefits of demand response for renewable resources are neither the only, nor the primary, driver for demand response. Rather, the abilities of demand response are a fortunate coincidence with the recent focus on renewable generation.

A key advantage of demand response is the lack of major technological impediments, as much of the required communications and monitoring technology has been developed, with the roll out of advanced metering infrastructure already under-way in a number of regions [A8, A9]. The central remaining technological obstacle is the development of standards and protocols so that all components of this complex system are harmonised, and efficient communication can be achieved across the system. The greatest remaining challenge for demand response as a whole is to develop accurate control and market frameworks to ensure that this diverse and geographically distributed resource can be optimally employed, considering the needs of both the power system and the individual consumer. This is not an insignificant challenge, requiring the development of complex models of electrical demand at both the component and system levels. Simulation and forecasting models of demand are required to establish a realistic view of this resource for planning and evaluation purposes. These will facilitate the determination of its suitability for the provision of various system services and the value it can provide to the system. Going forward, operational models of demand will be required so that appropriate and accurate control signals can be issued. Such models are highly complex, as they must represent the highly diverse, dynamic and uncertain nature of demand, as well as the complexities of end-user interaction with the system.

A.1.1 Existing Uses of Demand Response

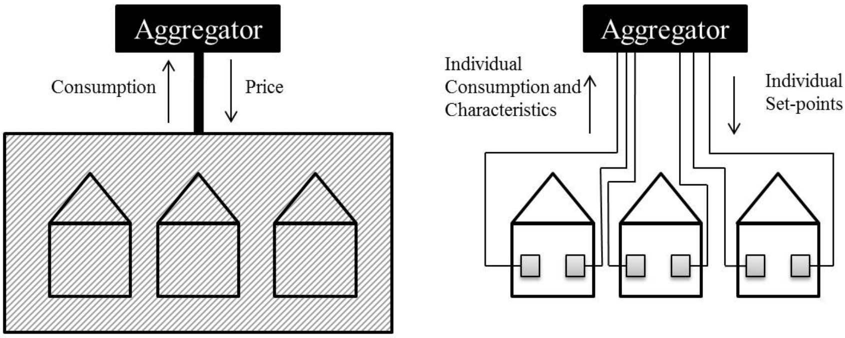
Demand response is not a new phenomenon and has been employed in various forms across the globe for decades. The most obvious form of demand response is systematic load shedding, a last resort to avoid system blackout, however more sophisticated approaches have been implemented in a number of power systems.

Time of use (TOU) rates where consumers are subject to expensive tariffs during fixed peak hours, or cheaper rates during night hours, have traditionally been used to incentivise reduced peak consumption, and so-called "night-valley filling" behaviour respectively [A10]. The objective of TOU rates is to reduce the difference between the peaks and troughs of the demand profile, thereby reducing the need for generator cycling or part-load operation. This allows a more efficient usage of generation, transmission and distribution resources.

Critical peak pricing (CPP) is an event-based tariff scheme employed for larger commercial and industrial consumers with the objective of decreasing peak loads. Under this scheme, higher electricity rates are applied during peak demand events. This approach has been adopted by the Californian independent system operator (ISO), and is most commonly employed to reduce loads during hot summer days from noon to 6 p.m. when the load from air conditioning units is excessive [A11].

A.1.2 Future Developments in Demand Response

Traditional approaches for demand response were adopted due to the predictable and cyclic nature of electricity demand and the dispatchable nature of generating resources. While this is appropriate in power systems dominated by conventional generation, systems with large penetrations of renewable resources require demand, and the system as a whole, to behave in a flexible manner on a continuous basis. This will allow the optimal usage of the renewable resource



(a) Indirect control **(b)** Direct control

Figure A.1: Demand response control mechanisms

and ensure that the system balance is maintained. As such, continuous demand response is the focus of this paper. The concept of continuous demand response, and in particular the use of price signals to elicit this response, was proposed as far back as 1988 in the seminal work of Schweppe et al. [A12] on spot pricing of electricity. In this work it was proposed that price signals at a resolution of five minutes could be used to maximise the economic efficiency of the power system, revealing the true cost of electricity provision to consumers and thereby providing an economic signal to maintain the system balance. The use of price signals to this effect is termed indirect load control. At a time resolution exceeding five minutes, it was deemed that direct load control was required to ensure the stability of the system. This view is shared by Callaway and Hiskins [A9], however they prefer the use of direct control for all ancillary services as the system operator has greater certainty when demand is controlled directly rather than indirectly through a price signal where the price response must be predicted.

Fig. A.1 shows a conceptual illustration of indirect and direct control. Under indirect control, the aggregator has limited information about the demand that is being controlled, and must estimate the price response of its demand portfolio. Prices are then issued to induce an expected response. Prices can be geographically varying, up to the resolution of information available to the aggregator, which may be at the level of several hundreds or thousands households. Direct control involves direct communication with individual appliances, and detailed information on their interactions with the surrounding environment. This is more computationally and communicationally intensive, but allows a more precise response and individual control set-points can be sent to each appliance, facilitating control of demand response at the highest possible geographic resolution. The interested reader can consult the works of Koch and Piette [A13] and Jónsson et al. [A14] for more information on the relative benefits of direct and indirect control.

A.1.3 Contribution of this Work

Demand response has been established as a promising method to increase power system flexibility and consequently facilitate the integration of renewable energy. However, significant investment is required to establish a communications, control and monitoring infrastructure if demand response is to be provided on a continuous basis from all sectors of electrical demand. While the control and computational requirements for direct control will be more intensive than for indirect control, both paradigms will require investment in communications, measurement and control. It is therefore imperative that the benefits of such an investment are clear. A substantial body of work has accumulated analysing the benefits and challenges posed by demand response and this paper aims to compile those works and present a clear overview of the issues pertaining to widespread demand response. A key concern is the lack of experience with demand response, particularly at high temporal resolutions and at the level of residential loads. This has resulted in the need for significant modelling assumptions in the evaluation of demand response, which may unduly influence the outcome of such evaluations and present misleading conclusions. The central assumptions in this field are critically discussed within this paper.

An overview of existing demand response programs is provided in [A15, A16, A17]. A high level overview of the benefits and costs of demand response is also provided in [A15] and [A16], where analysis is limited to the immediate impact of demand response, such as reduced consumer costs and the cost incurred to establish metering and communication infrastructures. These topics will be discussed and debated in greater detail in this work, with new insight gained from recent developments in this field and experiences from demand response demonstration projects. In particular, the more long term and less intuitive impacts of demand response are considered within this paper. These include the potential impact of demand response on market prices and the consequences for consumers, which may not include a reduction in costs.

The experience with demand response in the European Union is discussed in [A17], and the lack of policy measures supporting demand response is highlighted. The greatest barriers for establishing policy to support the development of demand response are seen as: the uncertainty surrounding the true benefits and costs of demand response, how best to integrate it within competitive electricity markets, and how it should optimally interact with other solutions for energy efficiency and climate change mitigation. These uncertainties are afforded detailed discussion in this paper, and the need for intensive research effort in the areas of realistic modelling, simulation and demonstration is highlighted.

This work outlines the benefits and challenges posed by demand response in Sections 2 and 3 respectively, while Section 4 details a critical analysis of some of the key modelling assumptions employed in works analysing demand response. Closing remarks and conclusions are given in Section 5.

A.2 Benefits of Demand Response

The benefits of demand response are widely lauded in the literature in this field. Advances in modelling and IT capabilities have made demand response an attractive option to increase power system flexibility. This will consequently allow a more efficient use of system assets and resources.

This coincides with the recent focus on increased penetrations of renewable generation in power systems. The flexibility provided by demand response can be used to meet the fluctuations of renewable generation and facilitate a higher penetration than could be achieved by relying on conventional generation alone. Although the energy cost of renewable resources, for example wind generation, is typically quite low, the associated system costs can be substantial [A18]. Operating costs are increased as both online (spinning) and quick start (standing) reserve generation is required to manage the frequent and often extreme fluctuations in the wind power output. Demand flexibility has been highlighted as a mechanism to facilitate higher penetrations of wind generation, while also reducing the system cost of its integration [A18, A19, A20]. Traditionally variability and uncertainty from wind generation has been managed through a combination of ramping and part-load operation of conventional generating plant, interconnection to neighbouring regions, and storage. Going forward, the many benefits brought about by demand response may make this a more attractive option than the traditional solutions. These benefits are not limited to the reduction in system operating costs, but also include more profitable use of interconnection, reductions in generation capacity requirements, transmission and distribution network congestion management, and increased economic efficiency.

A.2.1 Operating Benefits of Demand Response

Operating a system with large amounts of wind generation under current operating practices requires a significant amount of reserve generation to safeguard against fluctuations in the wind output. In this manner, wind displaces energy from conventional generators, but the capacity of these generators is required to maintain system security. Demand response can provide these security services through load curtailment and shifting. Some authors predict that the reliability of demand for the provision of system services may be greater than that from conventional generators; Kirby [A21] and Callaway and Hiskins [A9] hypothesise that the variability of a small number of large generators is likely greater than that of a large amount of small loads.

Furthermore, a central benefit of many load types is that their power consumption can be adjusted instantaneously, allowing a much larger effective ramping rate from the aggregate demand resource than can be achieved by larger generating plants [A22]. This is particularly true of appliances that provide an energy service rather than a power service, such as heating or cooling loads, where power consumption can be adjusted and shifted significantly in time with limited or no immediate impact on the energy service, such as heating or cooling to maintain a given indoor temperature range, provided to the consumer. The physical characteristics and operating constraints of large generating plants limit the rates at which they can change their power output. While the diverse nature of demand means that a certain proportion of demand may be limited in their ability to alter consumption rapidly, the aggregate demand portfolio may have a highly competitive ramping capability. The use of demand response to provide system security reduces the need to operate generating plant at part load, which is inefficient and results in higher fuel costs [A23]. Part load operation is required if generators are providing spinning reserves as this allows them to either increase or decrease power output as required. Additionally, ramping of generators is reduced, and the associated cycling costs can be avoided [A24] .

In addition to reducing the use of generators to balance wind power fluctuations, the dependence on power import and export through interconnections to neighbouring regions can be reduced through effective use of demand response. This is particularly economically attractive as it allows these inter-regional links to only be used when it is profitable, rather than out of necessity to balance the system. Often when countries have high penetrations of wind power they rely heavily on interconnection to maintain system balance. Unfortunately, due to the nature of weather patterns, when the wind output is high in one region it is likely also high in the neighbouring regions, causing the exported wind power to be sold at a very low price [A25]. Effective co-optimised planning and operation of generation, inter-regional power flow and demand response shows potential for significant welfare gains over the current operating standards, as it allows the best combination of resources to be employed.

A.2.2 Planning Benefits of Demand Response

In the power industry, the cost of acquiring and maintaining generating capacity is a significant component of the total costs [A26]. Using demand response to reduce the capacity requirements of the system could result in substantial cost reduction. The ability of flexible demand to balance wind fluctuations and reduce peak demand through demand shifting reduces the need for investment in expensive and often inefficient peaking and flexible plant such as open cycle gas turbine (OCGT) units. This increases the utility of existing plant as they can maintain a more constant output while allowing demand to meet the fluctuations in wind generation [A23]. This is most effective in systems operating with market based demand response mechanisms as even a relatively minor demand response will tend to displace the most expensive peaking units, reducing the system marginal cost and resulting in substantial welfare gains [A27, A28]. A further consequence of this is the potential for a reduction in emissions from power generation. Generally, a reduction in generation from fossil sources will result in a reduction in green house gas (GHG) emissions, however if those generating units with the highest marginal cost have a greater emissions rate than lower cost units, the potential savings are even greater [A26].

The temporal diversity of demand has clear benefits as outlined here, however the geographic diversity can equally provide benefits. Congestion on transmission and distribution networks is a long standing issue which drives the need for costly network upgrade and reinforcement. Many power markets have resorted to using locationally differentiated pricing mechanisms to divert power flow away from congested regions and avoid the excessive degradation of the network through overloading. A number of studies have highlighted that demand response through real time pricing that is not locationally differentiated may exacerbate this issue [A29]. Traditionally networks were designed considering that the peaks of individual loads do not occur simultaneously and it is therefore sufficient to set the power flow capacity according to the magnitude of the coincident peak (a proportion of the potential maximum peak), rather that the sum of individual peaks [A30]. The use of a global signal to elicit a response, for example to maintain the system balance, has the intention of increasing the coincidence of demand. On a local level, this has the potential to induce congestion as the coincident peak may exceed the power flow capacity on the network. Demand exhibits a natural diversity, with a wide range of flexible appliances operating in different states with distinct operating constraints and control strategies. The degree to which the load coincidence will be increased at the local level is therefore uncertain, and the diversity may be sufficient to prevent power flow on the network exceeding its capacity, however there is a risk that congestion will be caused by responsive demand. Fortunately, whether or not congestion becomes an issue, research has found that the spatial diversity of demand can be harnessed not only to avoid this additional congestion but also to maximise the utility of the network, thereby delaying or eliminating the need for network upgrade and reinforcement [A23, A31, A32].

A.2.3 Economic Benefits of Demand Response

In recent years, efforts to increase the economic efficiency of the power system have seen a broad movement from the vertically integrated model, to one in which competition exists across the system. As yet, however, there is limited participation of demand in the power market, an omission that must be corrected to ensure a fully competitive electricity market [A33]. Unfortunately, in those markets that do permit demand to submit bids, participation is generally limited to loads that can offer bids in units of 1MW, allowing only the largest consumers to participate [A11].

Many markets in the United States include frameworks for demand bids in both day-ahead and ancillary services markets, the most well-known example being the Texan market, ERCOT, where demand provided half of all spinning reserves as of 2008 [A21]. However, the structure of these markets, with minimum bid sizes and advance notification requirements, precludes a large proportion of demand from participating.

The participation of responsive demand in the power market brings about a number of key benefits. Both supplier and locational market power can be reduced by allowing demand to respond to locationally differentiated and time varying price, as this limits the ability of larger producers to manipulate the wholesale price of electricity [A34, A35, A36]. A further benefit is the reduction in average wholesale prices, as well as a reduction in volatility of peak prices [A37]. In addition to short term efficiency gains related to prices, demand response demonstrates significant long-term efficiency gains in the form of efficient capacity planning, as explored by Borenstein [A28].

Exposing consumers to time varying prices, particularly at high resolutions such as the 5-minute price suggested by Schweppe et al. [A12], provides them with an incentive to consume electricity in an economically efficient manner. Under the traditional flat rate pricing structure this efficiency signal is not passed to the consumer, and they have no incentive to alter their consumption behaviour [A38]. Consumption patterns are therefore determined only by the consumers behaviour, often resulting in the use of low value appliances during periods of high wholesale prices [A28]. For example, the use of many common household appliances can simply be delayed with minimal burden on the consumer, but only if the consumer is aware of the need or economic benefit of doing so. Corradi et al. [A39] illustrate the ability of residential demands to respond to electricity prices; automated control of heating appliances was found to reduce peak residential consumption by 5%, and achieve a shift in consumption of 11% over the period of a day. Another inefficiency of flat rate tariffs is the phenomenon of cross-subsidising, where those customers that consume primarily during off-peak periods are subsidising customers who consume during peak periods [A23]. Off-peak consumers clearly have a lot to gain from a switch to time variable prices, while on-peak customers will be incentivised to shift their consumption to off-peak periods.

Flat rate tariffs are widely accepted as highly inefficient, and the introduction of time varying prices presents substantial potential for increases to consumer welfare [A26, A20, A40]. Consumer welfare refers to the benefit that consumers experience from consumption of electricity, given the cost of purchasing that electricity. Studies have shown that the increase in welfare for larger customers far exceeds the cost of responding to this varying price [A28]. However, for smaller consumers the cost benefit analysis is not as attractive, as the expenditure on electricity represents only a small proportion of a typical household budget. A study conducted by Allcott [A26] found that moving from a flat rate tariff to RTP resulted in an average increase in welfare for households of only $10 per year, which is approximately 1-2% of the expenditure on electricity and is insufficient to justify the investment in metering infrastructure. This figure has little relevance as a general result as it is highly system dependent, however the fact that this is such a small value clearly indicates that demand response from residential demand may provide an insignificant financial benefit to the household, even if demand response as a whole provides benefits on a societal level. This view is supported by the findings of Borenstein [A28] who finds that the overall welfare gains that can be achieved through RTP are significant, although the incremental benefits decrease as the share of total consumption responding to real time prices increases. Furthermore, the cost of increasing this share increases as the customer size decreases. This indicates that focussing on the most responsive consumption types with the greatest potential for net welfare gain is the optimal strategy when rolling out real time pricing. Net welfare gain is used as a metric here as it reflects the ability of a particular load type to shift demand in time and take advantage of time differentiated prices. It also considers the scale of the demand, with a larger shift or adjustment in demand generating a correspondingly larger increase in welfare. Finally, welfare gain reflects the value that this flexible demand provides to the system, where this value is reflected in the price of electricity. By considering the *net* welfare gain, the cost of both installing the required infrastructure and responding to the resulting price or control signal is included in the evaluation.

While residential loads have been demonstrated as possessing a great potential for demand peak reduction and shifting over many hours [A39], the greatest potential for net welfare gain may lie with industrial and commercial loads. Loads such as supermarkets and shopping centres with significant heating and cooling requirements, swimming pools or commercial refrigeration warehouses appear possess the necessary flexibility capabilities and scale to benefit significantly from RTP. Ma et al. [A41] discuss how certain commercial buildings are capable of achieving temporary reduction in consumption of 25-33%. Aside from the physical capabilities, the financial incentive to consume flexibly will likely be a determining factor in the success or otherwise of demand response programs. As an example, expenditure on electricity accounts for only 4.4% of the typical household budget in Ireland [A42], and only 2.6% in Australia [A43], so a 10% decrease in electricity costs would have a negligible impact on the household budget. In comparison, expenditure on electricity in a supermarket typically accounts for only 1% of costs, however this is approximately equal to a typical supermarket operating margin [A44], so a 10% decrease in electricity costs would have a significant impact on profits, making flexible consumption an attractive option. Furthermore, the widespread use of automation in industrial processes implies that power consumption can be shifted in time without many of the complexities of end-user interaction that are expected with residential demand response. Detailed modelling is required to determine the exact flexibility achievable from such resources, and the value that such flexibility could provide to the system. Industrial and commercial applications are likely designed with efficiency in mind, and may not have a great scope for adjusting power consumption without breaching their operating constraints. However, if demand response appears to be financially lucrative, this should be included in commissioning assessments and may reveal an interesting option of over-sizing capacities for the express purposes of providing flexibility.

A.3 Challenges for Demand Response

While it is true that much of the monitoring and communications technologies required for widespread demand response are currently available, the challenges for the control and optimisation of the response are not insignificant. Here we detail the central obstacles for the adoption of demand response as a contributor to system services, and some of the challenges that will remain if it is successfully implemented. These challenges are wide ranging and include establishing an efficient market environment for demand response, building a profitable business case, and effectively controlling demand through price signals, considering that the consumer will not behave in an entirely economically rational manner. The term economically rational is employed here in the sense that consumers will seek to minimise their cost of consuming electricity above all other priorities, and consequently that electrical demand exhibits a linear demand curve, where any change in price of electricity will induce a proportional change in demand.

A.3.1 Market and Regulatory Frameworks

One of the greatest barriers for demand response is the lack of appropriate market mechanisms in current market structures [A45]. Currently, demand response is primarily employed for the provision of emergency contingency support and ancillary services, with limited participation in the day-ahead market. This participation occurs in the form of direct market bidding as well as contracts between individual market stakeholders. The restrictive nature of these markets and contracts often requires that demand response is planned many hours ahead, or that substantial advance notice is required before the demand is adjusted in emergency scenarios. Such limitations, as well as stringent telemetry and performance standards, prevent demand from participating effectively in the power market [A41]. Concerns over the burden placed on consumers limit the frequency and duration of demand adjustment events in many cases. System operators recognise that demand is a valuable resource, but that consumers may withdraw from demand response programmes if the inconvenience of participating becomes too great. The requirement of advance planning of demand response causes uncertainty in the response that can be achieved in real time. Furthermore, the requirement for advanced warning of adjustment events reduces the effective flexibility that demand response can provide, regardless of its physical capabilities. A particular load may be capable of adjusting demand instantaneously, but if regulations require an advance warning of 3 hours, the effective switch-on time of this resource becomes 3 hours, which is simply not competitive with existing flexible generation. Cutter et al. [A45] have evaluated that while demand response is capable of providing substantial flexibility to the system, under current market structures the effective flexibility is not comparable to current combustion turbine (CT) generating plants. The central issue is that current markets are designed in a centralised homogeneous manner, which does not suit the diverse and distributed nature of demand.

A further barrier for demand response relates to current regulatory and tariff structures, particularly for residential customers. If customers are to respond to a price signal, a basic requirement is that this price signal is visible to them. Currently, the actual price of electricity in a customer's bill is not obvious, as the final bill includes other charges such as taxes, public service obligation (PSO) payments, and transmission and distribution network charges. Fig. A.2 shows

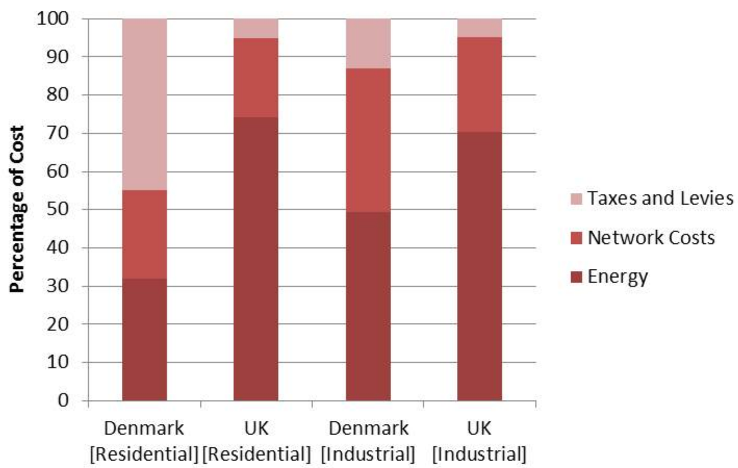


Figure A.2: Electricity Price Components for residential and industrial consumers in the UK and Denmark.

a breakdown of the electricity prices for residential and industrial consumers in the UK and Denmark. The UK clearly has a more favourable pricing structure for demand response as the energy costs account for over 70% of the electricity cost for both industrial and residential consumers, while the Danish pricing structure filters the cost of energy heavily, with the share barely exceeding 30% for residential consumers.

An overhaul of this structure is required; however careful consideration is required to ensure that any redesigned market ensures the economic stability of the system. For example, while a move to RTP would increase social welfare, such tariffs do not adequately reflect capacity costs under the current market structure where generators bid their marginal costs. The use of marginal cost pricing in general is limited in its ability to reflect the overall cost of supplying electricity, considering both capital and operating costs, and to ensure that investment in system resources can be recouped. Introducing demand response into a marginal cost market framework is a complex task, as the marginal cost of demand response is not immediately evident as there is no direct equivalent to the marginal cost components of generators. Further complications are introduced when the capital cost of demand response is considered, and a method of compensation is sought. The question can be posed whether the capital cost should be compensated at all or to what degree, as the primary purpose of demand is not to provide flexibility but to serve the consumer with a particular service. Such complexities warrant a thorough examination of possible market frameworks to ensure that all parties are adequately compensated and the stability of the market is ensured.

Any regulatory or market redesign must consider that the market must remain stable, providing efficient signals for generation capacity and network upgrades, while maintaining reasonable rates for consumers. Historically, the system operator was responsible for maintaining system security by requesting certain actions from generators and compensating or charging them appropriately.

By moving to a framework in which price responsive demand is employed to provide certain system services, the responsibility for maintaining system security is indirectly shifted from the system operator to the end-user. This framework differs from the current regime where consumers have no regard for the real time price of electricity or any concern for maintaining the reliability of the power system. Under a demand response regime, consumers are active participants in the power system and have to acknowledge and understand that their willingness to adjust their consumption in response to a price has a direct impact on the reliability of the service they receive. In such a case, if appropriate limitations are not put in place end-users may be exploited to provide system services. This could be achieved by exposing them to extremely high or fluctuating prices. This places an excessive burden on the end-user to provide a service that was previously the responsibility of the system operator.

A suggestion to this issue is provided by Zugno et al. [A46] where end-user tariffs could be restricted to a given range so that the burden of providing system services is not excessive, and other system stakeholders are still required to contribute to maintaining system security. Jonsson et al. [A14] further suggest that customers could pay a premium to restrict the range over which prices vary. This would have the effect that the least flexible customers could remain at a fixed tariff, but would be required to pay a substantial premium. While this option may be attractive for consumers, a certain level of price variation may be required to ensure the viability of dynamic pricing and demand response. Strbac [A23] notes that the economics of demand response are heavily dependent on the price differentials in dynamic tariffs. If the price varies over only a small range, the savings for consumers may not be sufficient to induce investment in demand response programs [A26]. With smaller price variations, the incentive to shift demand is reduced, and even the most flexible and responsive of consumers may not be able to recoup their costs of installation or justify the burden of responding to prices. Additionally, if the demand response is limited, the system benefits of demand response may not be sufficient to cover the cost of the control and communications infrastructure. On the other hand, if the price differentials are substantial, and consumers have the ability to respond sufficiently rapidly to them, the financial benefit could be significant, particularly in the case where the price of electricity is negative, as has been occurring with increasing frequency on a number of power markets. A striking example occurred on Christmas Day of 2012 where the wholesale price of electricity in Denmark sank to -200DKK/MWh for six consecutive hours, a magnitude far greater than the average price in 2012 of approximately 37DKK/MWh [A47].

The impact of demand response on the power market is difficult to predict. Previous discussion in this paper has highlighted how a reduction in price volatility is commonly seen as a key advantage of demand response, as demand will respond to extreme prices, thereby reducing their incidence over time. If extreme price events are caused by a scarcity of certain resources, such as regulating power, and demand response can provide this service at a lower cost, then such extreme price events will certainly be reduced in frequency or magnitude. This result seems quite intuitive, but it overlooks the complexity of the market to the extent that the true outcome may be quite different.

There is a clear conflict of priorities here, as the market seeks to find the most efficient solution, which may coincidentally reduce the variability in price, while the consumer sees the most benefit when prices are highly variable. This uncertainty over the impact of demand response on price variability brings into further question the results of studies such as that by Allcott [A26], which provides numerical values for the benefit of demand response. This is further compounded by the scope of the study, which only considered a limited population of responsive demand acting as a price taker and did not consider that demand response may have an impact on the determination of the price.

Without more accurate market and demand response models, it is difficult to predict the true impact of demand response on the market, so the financial benefit for consumers could be significantly different from that calculated using existing market models. A similar argument can be applied to electrical storage technologies; demand response and storage share a number of key characteristics, most importantly the possibility of consuming power during low price periods to reduce consumption (or to discharge stored energy) during high price periods. Thus, the need for detailed market studies is not limited to systems with high levels of demand response, but is required on all systems that expect a high penetration of technologies capable of energy arbitrage.

A.3.2 Establishing a Business Case for Demand Response

Strac [A23] highlights a central issue that is not generally considered, that of the difficulty in establishing a business case for demand response. While it is acknowledged that extending the electricity market to incorporate demand results in a more efficient market with increased social welfare, this welfare is distributed among a number of different parties. It may be quite difficult to develop a business model that can collect a sufficient amount of this increased welfare with sufficient certainty to make the business viable and to justify the required investment in infrastructure [A41]. For example, if a wind plant owner operates a demand response resource it will benefit from the balancing services that demand can provide. At the same time, this behaviour may result in more efficient use of transmission or distribution capacity, resulting in a benefit for the otherwise separate transmission system operator. Another example of unintended redistribution of welfare occurs in the case where only a portion of the customer base is subject to time varying prices. In this case, the overall cost of electricity is reduced through the behaviour of flexible customers, resulting in a transfer of wealth from generators to inflexible customers [A36]. This occurs as flexible consumers respond to peak prices by reducing consumption, thereby reducing the need for peak generation plants and reducing the average price of electricity. Consequently, generators lose out through reduced operating hours and revenue while consumers on a flat rate tariff see the reduction in the average wholesale price reflected in their bill.

A number of suggestions for business and market models are presented in the literature. A common proposal is the use of an aggregator to represent the flexible behaviour of a large number of demands in existing market models [A48, A49, A50, A51]. Under this proposal, the aggregator bids into the market and must then meet its obligations through its demand portfolio. This can be achieved either through direct or price-based control. In the case of price-based control, the price that customers see may vary significantly from the price that cleared on the market, as its intention is simply to induce a demand behaviour that meets the aggregator's obligation. The aggregator will submit a bid to the market, however this doesn't mean that the aggregator's bid price is the market clearing price, so the aggregator must issue a separate price to its demand portfolio. This price has no relation to the marginal costs of electricity, so while the aggregator is capable of meeting its contractual obligation with the market, the end-user is not paying the true marginal cost of providing electricity, as is commonly presented as a benefit of real time pricing.

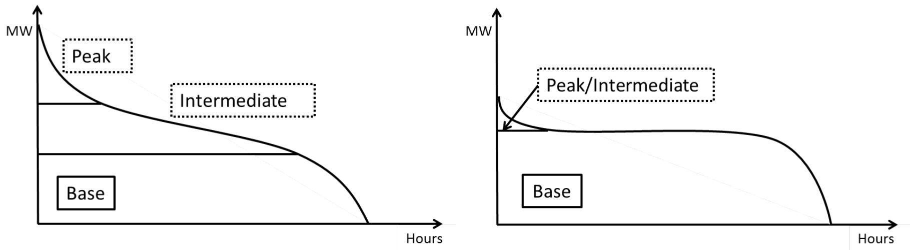
An alternative approach that is discussed in a number of works is to allow demand to respond directly to the market price in real time. The response of demand in this case can be expressed in the form of a price elasticity value, which relates a change in price and the consequent change in demand. If this price elasticity value can be observed, an aggregate demand curve can be constructed which allows the responsiveness of demand to be considered when clearing the wholesale market [A50, A52]. Difficulties with this approach can be experienced when the demand curve is not sufficiently well approximated. Roozbehani et al. [A53] discusses the issue of demand and price volatility under real time markets, where this volatility is due to control issues and is separate from the variability in price discussed previously. In particular, asymmetry of information is found to contribute to oscillatory behaviour in demand. Asymmetry of information occurs when there is a delay between price setting and consumption, so a prediction of the response is required, that is, the market operator must predict information which the end-user already knows. In the case that consumers are very flexible they have no incentive to reduce the price volatility as their flexibility allows them to minimise their costs. If, however, customers have a constraint on the rate at which they can alter their consumption, it is in their interest to reduce price volatility. Price volatility could be reduced by consuming power in a more predictable manner or by providing the system operator with information on the intended consumption profile. A similar discussion is presented by Callaway and Hiskins [A9] where plug in electric vehicles (PEV) are subject to time varying prices while charging. The demand from vehicles displayed oscillations when the population of vehicles became very large, this oscillation was driven by the interaction between demand and price. This work suggests that RTP may not introduce such oscillations where the population of responsive demand is small, as the impact of the demand response on the price is reduced. However, the nature of the PEV fleet as a homogeneous load, where each PEV has similar operational characteristics, may have improved the prediction of price response in this case, resulting in a more stable system. Roozbehani et al. [A53] note that appropriate control laws could be used to regulate the interaction between demand and the market to reduce demand and price volatility caused by information asymmetry, although this would cause a loss in economic efficiency.

This issue raises the question of the value of information on the responsiveness of demand. Indirect control is generally favoured as this price-based control allows for the most economically efficient outcome, however if the uncertainty and instability associated with this control paradigm are excessive it may be necessary to consider direct control. Direct control requires detailed information on the demands subject to control and their surroundings, as well as substantial computational power to process this information. In comparison, indirect control simply estimates the responsiveness of demand from aggregated demand and price data. If the benefit of the certainty of response provided through direct control exceeds the associated computational costs and the loss of economic efficiency due to the elimination of price signals, direct control is an attractive option.

A.3.3 Difficulties Establishing Demand Response as a Valuable Resource

Widespread adoption of demand response may not be viewed favourably by all participants in the power market. In particular, if the capacity value, or the availability in times of need, of demand response is significant, owners of peaking plants will likely see their capacity factors decrease as demand response takes over some or all of the responsibility for regulation, load following and ramping [A48, A45]. Fig. A.3 shows a possible outcome of widespread demand response adoption; under an extreme scenario, demand response will be sufficient to meet almost all fluctuations in power output from non-dispatchable renewable resources, and the net load will consequently be almost constant, allowing conventional generators to operate at a constant power output. Subfigure A.3a shows a typical load duration curve (LDC) on a conventional power system, where fluctuations in both (non-flexible) demand and renewable resources mean that the net demand profile is variable, and flexibility is required from generators to maintain the system balance. The LDC orders the demand on a power system in descending order for each hour of a year, where the highest demand levels (furthest left on the LDC) are met by peaking plant, which have a very high marginal cost, while intermediate demand levels are met by intermediate generators. These peaking and intermediate generators are required to be quite flexible as they are typically brought online to meet ramps in demand. Base demand is approximately the minimum level of demand on the system for the year, and is met by inflexible, low cost generators such as nuclear plants, which operate most efficiently at a constant output. Subfigure A.3b shows the extreme demand response scenario. The LDC shows that inflexible base generation is sufficient for almost all hours of the year, while flexible generation is required to meet any fluctuations that demand response cannot eliminate. Under such a scenario, the operating hours (and consequently the capacity factor) of the flexible (intermediate and peak) plant will be significantly reduced. This will have a significant impact on the potential for generator owners to recover their investment, possibly leading to the decommissioning of otherwise operational plant. Such a scenario would clearly be greatly opposed by operators of flexible generators, even though it may present an efficient solution for the system as a whole. The decommissioning of such generators may additionally cause difficulties for the system operator as conventional generation will still be required to provide such services as inertial and voltage support, which demand response is incapable of providing [A48].

Even if opposition from existing stakeholders is overcome, demand response may not be a valuable addition to the system if the existing power system has a high proportion of flexible plants in its generation portfolio. The most significant factor affecting the value that demand response provides to the system is the



(a) Typical load duration curve without demand response **(b)** Possible load duration curve with high levels of demand response

Figure A.3: Comparison of Load Duration Curves

flexibility of the existing generation on the system [A23, A54]. Systems with large amounts of inflexible base load generation and a high penetration of wind generation show the greatest potential for demand response to provide additional system value. In fact, Strbac [A23] shows that it is only in such systems that demand response becomes competitive over traditional flexible generation plants. Their analysis is based on a comparison between demand response and conventional generation for the provision of spinning reserves[4], and the reduction in fuel costs brought about by using demand response over conventional plant. However, the note is made that demand response doesn't provide spinning reserves, but standing reserves, so the true competing resource would be plants capable of a rapid start such as open cycle gas turbines (OCGT). The additional capitalised value of demand response over OCGT is calculated as less than £50/kW which is most likely insufficient to fund the implementation of demand side management, and furthermore unlikely to be considered sufficiently attractive to drive investment in an as yet unproven technology over a tried and tested approach.

A.3.4 End-User Behaviour

Human nature is a further issue which compounds the problem of market design for demand response. While large generators typically exhibit economically rational behaviour through their profit maximising objective, smaller customers do not show the same rationality in their consumption decisions. End-users, particularly in the residential sector, have many different priorities, and min-

[4]Spinning reserves are provided by generation units which are already online, or spinning, and have the ability to increase or decrease their production. Standing reserves are provided by generators which are not online and must start up, which typically takes some time. Generally only quick start units are employed for standing reserves.

imising their electricity bill may not be at the forefront of their concerns. In contrast, the profit driven objectives of generators means that their behaviour fits established economic models. Consequently, enough information can be drawn from their bidding behaviour for their supply curve to be revealed [A55]. The corresponding demand curve is much more difficult to extract from demand behaviour due to its dependence on many different and time varying external factors, ranging from the weather to whether the consumer cooks dinner using an electric oven or a gas cooker. Empirical studies have demonstrated some of the ways in which consumer demand doesn't fit the conventional economic model.

Thorsnes et al. [A27] consider 400 households in Auckland, New Zealand which were subject to TOU rates. Their price elasticity of demand was found to vary with time and according to the external temperature. During winter peaks the demand was less elastic as home heating became critical, even though this is when demand response would be most beneficial to the system. This indicates that although demand may be present, it may not be capable of providing flexibility. Furthermore, the households were divided into two groups with different price differentials between on and off peak periods, however no significant difference was found between the consumption patterns of the two groups. This indicates that the consumption change is not linearly related to the price change as is conventionally assumed, but that the consumption change to any price change will be similar regardless of the magnitude of that price change. If the conventional linear price-demand relationship were applicable in this case we would expect the housing group subject to a larger price differential to exhibit a correspondingly greater change in demand. This conclusion may only hold in the particular case of TOU tariffs, where the price differential is fixed and known to the consumer. Under RTP, this effect may be reduced, however other effects may be experienced, such as consumer fatigue. Requiring consumers to interact with the power market and adapt their consumption pattern to a continually changing price is very intensive, and may lead to the case where only the most extreme prices induce a response from demand.

An additional aspect of demand response behaviour that doesn't fit the conventional economic model was found by Thorsnes et al. [A27] when comparing the consumption patterns of TOU consumers to their previous fixed-tariff consumption patterns. Consumers exhibited asymmetric response to prices, with limited reduction in demand during peak periods, but with a significant increase in consumption during off-peak periods. This effect was particularly evident in higher income households. A similar study is discussed by Allcott [A26] where households in Chicago were subject to hourly varying prices. Asymmetry of response was also evident here, but interestingly it was in the opposite direction, with a substantial decrease of consumption during peak periods, but no increase during cheaper periods.

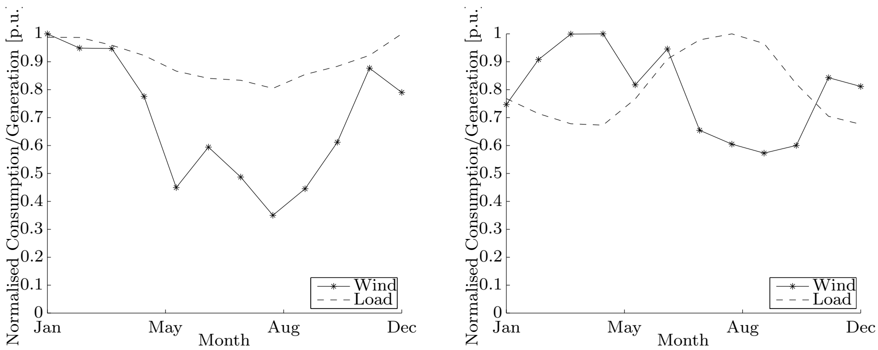
These seemingly irrational features of demand behaviour are said to stem from two central issues. Firstly, there is a lack of understanding of the need for demand response and about electricity consumption in general. Kim and Shcherbakova [A56] highlight the fact that the vast majority of consumers have little to no understanding of electricity markets, or even of their own consumption. Studies have shown that simply informing the consumer of their consumption in real time through a display mounted in the home can have a dramatic impact on their consumption. Faruqui et al. [A57] show that even with a fixed tariff total consumption can be reduced by between 7% and 14% by installing an in house display of current consumption. Allcott [A26] discusses a similar phenomenon where information on the price is provided to the consumer in real time. This study showed that by placing coloured lights on flexible appliances which change colour according to the current price of electricity, the elasticity of consumers can be significantly increased.

Secondly, the manner in which consumers view their purchase of electricity makes them less likely to exhibit rational economic thinking. For most consumers, electricity is viewed as a service rather than a commodity, making it difficult to understand variations in price and the need to consume flexibly. A comparison between buying a new car and paying for electricity is made by Kim and Shcherbakova [A56]. Both of these actions account for approximately the same proportion of annual household expenditure (when considering annualised car payments), but significantly more thought is put into the car purchase. This is because payment for electricity is a passive action which occurs at regular intervals, so does not require substantial consideration from the consumer. This lack of interest results in a low response to price changes; Kim and Shcherbakova [A56] suggest that moving customers to a pre-payment plan could make purchasing electricity into a discrete purchase. The payment for electricity would then no longer be at regular intervals, and would require more consideration from the consumer. Increasing consumer awareness in this manner can increase their flexibility to price signals.

It is evident that requiring consumers to respond directly to prices is suboptimal and results in behaviour that cannot be explained by conventional economic models. This is a clear argument for the use of extensive automation for demand response, both to reduce the burden of price response on consumers and to ensure a more predictable and efficient response from demand. Consumer interaction could be simply limited to the selection of temperature limits and the on/off state of the appliance, while allowing a controller to determine the optimal consumption profile in response to the price signals. Nevertheless, there will still be a degree of human interaction that should not be overlooked and should be incorporated into demand models for price setting. This is because the impact of human interaction with demand is not limited to economic decisions, but also influences the physical availability of the flexible demand resource. Even if appliances are controlled automatically with limited input from the consumer, if an appliance is not switched on, it cannot be used for providing flexibility. Similarly, if the appliance must operate at its maximum output level just to meet the end-use demand, it cannot provide flexibility. An example of this was provided previously from the work of Thorsnes et al. [A27] where heaters cannot provide flexibility when the demand for heat is critical. As such, the consumer's need for a particular appliance dictates the demand flexibility available to the system.

Kirby [A21] considers the diurnal profile of consumption and explains that on a diurnal scale, demand is well suited to providing flexibility as demand is typically highest when spinning reserves are scarce. This conclusion was reached following an analysis of the diurnal profile of air conditioning loads in the United States and the corresponding profile of prices for contingency reserves. The peaks in reserve price and demand were well correlated, indicating that demand is available when reserves are most expensive, or equivalently most scarce, however it doesn't consider whether demand is capable of providing flexibility at these times.

This argument raises the question of the capacity value of demand response. The capacity value of demand response as employed here refers to the availability of demand for the provision of flexibility, and its correlation with the need for system services. If demand is frequently available to provide flexibility, but not at those times when critical balancing services are required, then it provides limited value to the system, that is, it cannot replace many MW of capacity from an ideal generator which has 100% availability. The presence of demand can be considered as a necessary (but not sufficient) condition for the availability of demand flexibility (as employed by Kirby [A21]). If we consider the example of demand response balancing fluctuations in wind power output, the most ideal scenario would be a high correlation between wind and demand. Fig. A.4 shows the average normalised seasonal profiles of demand and wind generation on the Irish and ERCOT power systems. The Irish system shows a reasonable correlation between wind and demand, giving a high level indication that demand response could be a valuable resource in terms of balancing wind fluctuations. In comparison, the ERCOT system shows a distinct lack of correlation, where a high wind output in the winter months coincides with lower electricity consumption. This indicates a reduced availability of demand to manage wind fluctuations when wind output is greatest, which may suggest that another resource such as flexible generation or storage may be better suited to provide this service. The simple illustration in Fig. A.4 shows that the value of demand response is highly system specific; depending on consumption behaviour, prevailing wind and weather conditions, and the availability of, or need for, support services. However, it is important to consider this capacity value on a number of different time scales. Averaged seasonal profiles provide easily



(a) Irish power system **(b)** ERCOT sower system

Figure A.4: Correlation between wind and demand on the Irish and ERCOT power systems [A58], [A59]

digestible results, however they don't reflect the operational challenges faced on an hour-to-hour and minute-to-minute basis. A favourable seasonal correlation may give a false indication of the value of demand response if the demand is either unavailable, or incapable of providing flexibility when it is required.

This discussion highlights two key points; firstly, that the capacity value of demand response should be considered on many different time scales, and secondly, that this capacity value should be incorporated into resource capacity planning. The long-term benefits of demand response primarily concern a more efficient use of system resources. Previous discussion in this paper has shown that this is mostly considered in terms of a reduction in generation capacity requirements. It is imperative that the capacity value of demand response is considered when evaluating the impact on generation capacity requirements, as the intuitive concept that demand response will reduce the operating hours, or capacity factor, of the most expensive generators may not apply in all cases, particularly when the seasonal variations in availability of demand flexibility are considered. Furthermore, the long-term impacts of demand response are not limited to generation capacity requirements, but will influence the composition of the entire system resource portfolio, including generation, storage, interconnection and transmission, while also encompassing adjacent systems such as natural gas distribution, district heating and water treatment and distribution. An integrated approach to portfolio planning is required to ensure the development of the most efficient portfolio of resources, considering the interaction and complementarity between different components, in particular considering a range of different time scales.

A.4 Demand Response Modelling Assumptions

The works in this field have outlined the many benefits that can be brought about by increasing the responsiveness of electrical demand. Unfortunately, a lack of experience with demand response has necessitated the employment of numerous assumptions in the modelling approaches adopted. As a consequence, it can be argued that the estimations of the benefit of demand response are dependent on these assumptions and an accurate evaluation has yet to be achieved [A37]. The widespread implementation of demand response requires significant investment, and at such a critical stage in the development of policy and technological strategies for demand response, it is essential that all of the involved parties are correctly and fully informed. Here we detail some of the most significant assumptions used, and highlight their shortcomings.

A.4.1 Economically Rational Demand Behaviour

One of the most common assumptions is that all demand behaves in a completely economically rational manner and can be described by a linear demand function, most commonly based upon an elasticity value. The value selected for the elasticity of demand is often selected at random, with limited consideration for the physical characteristics and constraints of demand [A20, A19, A52]. While this is a tempting approach as the concept of an aggregate demand bid curve fits well with the current wholesale market model, the representation of demand in this manner is unrealistic. Firstly, previous discussion in this paper has highlighted that the responsiveness of demand is dependent on a number of external variables such as temperature, that it may be non-linear [A27], and asymmetric, where the magnitude of the response to a high price may be different to the response to a low price [A26]. Secondly, modelling demand response based on a single elasticity value assumes that demand can only increase or decrease its consumption instantaneously, and cannot shift in time. In order to represent this behaviour, an elasticity matrix would be more appropriate as it incorporates both self- and cross-elasticity, where cross elasticity considers the shift of demand to another time period due to a change in price at the current period. An elasticity matrix therefore considers that energy which is not consumed now, through a reduction in demand, must be recovered later; a simple elasticity value doesn't consider this at all. The need for consideration of cross elasticity has been acknowledged in a number of works, however it is employed in very few cases. Sioshansi [A52] argues that consideration of cross elasticity can only serve to support the case for demand response. The example is given where wind generation in a given period is lower than was expected and the price is consequently higher. In this case the demand would respond to a greater extent if cross elasticity is considered, as it responds to the higher price in the current period (self-elasticity) and the relatively cheaper price in adjacent time periods (cross-elasticity) where the wind output was as forecast. A contradictory position is adopted by De Jonghe et al. [A20], as their numerical calculations conclude that consideration of the cross-elasticity value reduces the demand response attainable. The authors considered the case where several consecutive hours have similarly high prices; in this case the demand reduced in one period is shifted to another period, or over multiple periods, and this occurs for each of the periods during which the price is high. This results in the combined effect that some demand from a given period is reduced, but demand from many other periods may be shifted to this period. Thus, the total demand response attainable when both self- and cross-elasticity are considered is reduced from the case where only self-elastic behaviour is exhibited. These two contradictory viewpoints clearly demonstrate the lack of understanding pertaining to this area.

Fig. A.5 is a very simple example of the impact of considering self- and cross-elasticity of demand. In this case, the basic demand level is constant, and the objective is to induce as much flexibility as possible through a varying price signal. The benefit function of demand is derived as by De Jonghe et al. [A20], using two separate elasticity matrices; one with only self-elasticity and the other with the same self-elasticity but also incorporating cross-elasticity. The resulting demand levels are found by maximising the benefit of demand with respect to the price signal shown in the figure. It is clear here that the flexibility achieved in the self-elastic case exceeds that in the case where both self- and cross-elasticity are considered, however this simple example only stands as an illustration of the impact of considering different forms of elasticity, as demand response is very poorly represented in the form of an elasticity matrix and more detailed modelling is required to achieve a realistic representation of its capabilities.

A further phenomenon that is not represented through an elasticity value is that of response saturation, that is, the energy limited nature of demand. Taking the example of a household space heating appliance, consider that the power system conditions dictate that a decrease in consumption is required over a prolonged period, and the necessary price signal is issued. The appliance will comply initially by reducing its consumption, but its local constraints dictate that the temperature cannot fall below a given threshold so the response can only be maintained until the minimum temperature is reached, at which point the local control will require that the appliance commence power consumption again. This phenomenon is acknowledged in certain works, but is not considered in any of the modelling approaches adopted. Saturation is a clear illustration that even when demand response is controlled automatically and operates in a least cost manner, the resulting demand behaviour may not fit the conventional economically rational model. The phenomenon of saturation is discussed by

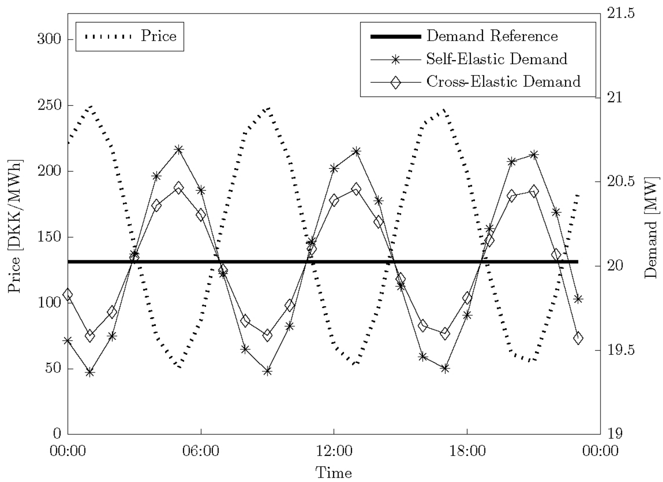


Figure A.5: Comparison of the effects of self- and cross-elasticity on the achievable demand response

Roozbehani et al. [A53] who described price responsive demand as having a dependence on both price and the current state of the demand, that is, the amount of demand that was scheduled for consumption previously but has been delayed until now due to price conditions. This behaviour mimics that of a storage facility, where balancing support can only be provided until its storage capacity is reached, or the stored volume has been expended.

A.4.2 Demand Modelled as Negative Generation

Another commonly adopted modelling approach is to incorporate demand response into a unit commitment model[5]. This is predominantly employed in studies considering the impact of demand response on the system capacity requirements and the need for generation reserves [A48, A50, A60]. In such studies, demand response is modelled as a few large units, with the assumption that individual loads are grouped together through an aggregator which participates in

[5]Unit Commitment is a combinatorial optimisation problem that is employed in power systems on the day before operation to determine which generation or demand resources should be online, or committed. It allocates sufficient generation to meet predicted demand, as well as providing reserve generation to insure against contingencies and uncertainty in renewable generation

the market on their behalf. There is no consideration given to how this aggregator will achieve the required demand response, with generic constraints imposed on demand within the unit commitment formulation. Demand is modelled similarly to negative generation in these cases, with minimum and maximum consumption constraints as well as ramp rate limitations. A slightly more detailed approach is considered in [A48] where demand is categorised into load clipping and load shifting units, which reflect the general categories of demand response commonly considered; demand shedding and deferral of demand. Consideration of demand deferral is also given in [A61] which examines the capacity value of demand response from air conditioning units; in this work demand response is considered for peak load events and load is clipped for a given period and then repaid over five hours following the clipping event.

While these approaches are useful to find high level conclusions about the contribution of demand response, a lack of investigation at a more detailed level means that many of these models may be flawed and the conclusions reached may be misleading. A key oversight in such studies is the lack of consideration for uncertainty in demand response. As unit commitment is a day ahead optimisation, the uncertainty of the demand response that can be attained in real time is significant. This uncertainty would undoubtedly impact on the amount of reserve generation that is required to ensure the stability of the system. An initial step towards considering the uncertainty of demand response in unit commitment is presented in [A62]. In this work demand response is represented in a relatively simplistic manner, employing the concept of bid curves to represent the participation of demand response in the market. Uncertainty is included in the formulation by considering that both the demand response in a given hour and the consequent shifting of demand to adjacent hours is uncertain. This work is an important step towards establishing stochastic unit commitment models with more realistic representations of demand response resources.

Furthermore, the diverse nature of demand makes it ill-suited to be represented as a single generation unit with fixed constraints. The aggregated demand is composed of many different load types with many diverse operating characteristics and constraints; it therefore likely that both the magnitude of the resource and its ability to respond to a price or control signal vary in time. This could equivalently be viewed as time varying capacity and ramping ability respectively. Incorporating these effects into the unit commitment model would have significant impact on the optimal generation schedule and may substantially alter the conclusions regarding both the total required generation capacity and the amount of flexible spinning reserves required. Extending this analysis to an annual scale, the seasonal availability of demand response will have a considerable impact on longer term generation capacity planning.

A.4.3 Perfect Knowledge of the System and Demand

A third modelling method applied in a number of works assumes perfect knowledge of the system. Zugno et al. [A51] and Zhang et al. [A63] employ this approach for market design and aggregate demand model building respectively, where a thermal model of the load and its temperature constraints are directly included in the system model. Model predictive control is also commonly used in studies considering building climate control for demand response [A64, A65, A66], and again in these studies the thermal parameters and constraints of the system are taken as known. Such studies provide great insight into the capabilities of the system for the specific scenarios considered, but the behaviour of the larger system may not be well represented by these isolated cases, particularly as the characteristics of individual households and appliances would not be known by the system operator. Furthermore, the population of responsive demands can be expected to be highly diverse, with many different appliance types operating subject to different constraints and environments. The aggregate demand response is therefore not well represented by these in depth studies that consider a single appliance type operating in a given environment. Even if all the necessary characteristics of the system and appliances are know, such that the demand behaviour resembles that of these studies, the calculation time and power required to process this information in real time would be prohibitive. In the case that prices are issued every 5 minutes, it may not be possible to determine the optimal control or price strategy before the deadline for price issuance has passed.

These studies consider specific cases however, on a real system, the load response is likely to be highly heterogeneous, as already experienced with commercial loads [A22]. Therefore, consideration of this heterogeneity is essential when modelling demand response in order to attain results that are applicable in a wider setting. Halvorsen and Larsen [A67] explain that it is not possible to infer conclusions about demand behaviour from aggregated data when the load base is heterogeneous, and while their study considers long term policy decisions, the same conclusion can be applied to short term demand response. Zhang et al. [A63] have conducted some initial work on managing heterogeneity of load, and have employed clusters to use a single representation of price response for a group of demands with similar characteristics. Their findings showed that heterogeneity introduces a natural damping of demand oscillations into the system and results in a more stable response, however the study was limited to thermal appliances with similar control architectures, so this conclusion may not hold in a wider setting. The concept of employing clusters to characterise demand response is an interesting one and was also proposed by Zugno et al. [A51].

A.5 Conclusions

The discussion in this paper has shown that while demand response has the potential to bring about a great number of benefits, there are a number of challenges that must be overcome before it can be considered as a valuable contribution to the power system. The overriding issue is the lack of experience and understanding of the nature of demand response. Too much of the work in this field is based upon simplistic models with superficial results. At this crucial stage in the development of demand response it is imperative that a clear and concrete understanding of demand response is established, so that a realistic evaluation of its suitability for the provision of system services can be determined.

Demand is clearly a highly diverse and complex resource, varying according to a multitude of external factors. Despite the limited understanding of the nature of demand response, particularly at the system level where the response of demand from many different sectors and applications is aggregated, it is clear that the resource is highly diverse, so using a single model type to represent all demand is unrealistic. Similarly, it is evident that demand does not fit the conventional model of economic rationality. The interaction of end-users with demand and the constraints of appliances themselves mean that the resulting demand profile exhibits a non-linear, time varying, dynamic and stochastic relationship with price, even in the best-case scenario where the price response is determined through automated control rather than a response from the end-user. It is therefore necessary that novel modelling approaches are adopted. In particular, it is necessary to extend the models to incorporate demand of many different types, and to consider the aggregate behaviour at the system level, and how it interacts with other system resources.

A further aspect of demand response that warrants attention is the uncertainty of the response. Demand is affected by a number of stochastic variables, including the weather and the sheer randomness of end-user behaviour, and consequently the response of demand to price or other control signals is uncertain. If the intention is to use demand response for the provision of system services, it is imperative to determine the reliability at which the service can be provided. If the reliability of demand response cannot be guaranteed to be sufficiently high for a particular system service, it will simply be disregarded in favour of more reliable resources. The primary concern of the system operator is to maintain system security, and if demand response cannot contribute to this, it should be limited to those activities that do not impact on the stability of the system, such as the conventional night-valley filling behaviour that is commonly incentivised today through TOU rates. Furthermore, if it is determined that the required reliability can be achieved through direct control, where price plays no role in determining the demand response, a thorough system wide economic analysis is required to determine if this option presents an improvement over the current set-up, particularly as many of the economic efficiency benefits brought about by price based demand response are not present in the case of direct control.

Demand response, where it is currently employed, participates to a limited extent in the power market. Current market structures are poorly suited to demand response, and consequently its most beneficial aspects cannot be accessed. Novel market structures should be investigated, and this should be conducted in conjunction with the development of detailed demand response models. The financial benefit of demand response will be accessed through these market structures, and a poorly structured market could prevent demand response from achieving economic viability. Appropriate market structures that consider not only demand response, but all other system resources, will ensure system wide economic efficiency, and may further strengthen the economic case for demand response. A number of fundamental questions remain with regards to the interaction of demand response and the power market. The most prominent of these is perhaps how exactly demand response should be priced, considering both the capacity and operational costs of providing a response. Again, demand simply doesn't fit into the conventional models for calculating marginal cost as there is no direct equivalent to generator fuel cost in this case. Furthermore, the cost structure of demand response in terms of capital and operating costs is unclear as the primary purpose of a responsive appliance is not to provide demand response but an end-user service.

When evaluating demand response, it is imperative that it is considered in the context of the entire energy system. Demand response alone may offer certain benefits, however when the interaction with other system components is considered demand response may become a very attractive option. Integrated resource planning should be employed to consider how the relative benefits of demand response, interconnection, storage, conventional and renewable generation can be optimally combined to result in the most efficient use of the system as a whole. Broadening the scope of consideration to encompass previously distinct systems such as natural gas distribution, district heating and biomass may facilitate a truly optimal global solution, revealing opportunities that would not be seen with a narrower focus on the traditional power system. In an operational context this would ensure that the most effective resources are used to maintain total system security on a day-to-day basis, while in a planning context this would ensure that the optimal capacities of each resource are installed on the system. Planning should be considered on a portfolio basis, rather than examining resources in isolation, and on a range of different time scales. As more focus is placed upon renewable resources and demand response, the climate will play a greater role in determining the availability of system resources on a seasonal scale. This will have a great impact on portfolio planning, as complementary resources will be important to ensure that system balance can be maintained at all times without requiring excessive redundancy of resources. Capacity planning is an important area here, and applies not only to generation and transmission resources, but also to demand. In fact, the capacity of demand response can have a significant impact on the economic benefits of participating in demand response programmes. Demand response is provided by appliances and devices that have an alternative primary use, that of providing the end-user with a service. Such appliances are typically sized according to the maximum end-use demand, however when we consider their use for demand response this may limit the flexibility achievable. Depending on the appliance type, the inability to provide flexibility may correlate with periods of power system stress, particularly if they are affected by weather conditions, such as heating or cooling loads. There may be an economic or operational case in certain circumstances to over-size certain flexible demands so that they can provide a highly valued flexibility service at those times where other demand types are incapable of responding. Clearly, an integrated energy system approach is required to evaluate the merits of such an action.

By considering demand response in isolation, using simplistic models, and in the context of existing market frameworks, a full and accurate impression of the benefits of demand response cannot be established. Novel, integrated approaches are require to reveal its full potential.

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Paper B

Regulating Power from Supermarket Refrigeration

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Regulating Power from Supermarket Refrigeration

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Abstract

This paper presents an analysis of the demand response capabilities of a supermarket refrigeration system, with a particular focus on the suitability for participation in the regulating power market. An ARMAX model of a supermarket refrigeration system is identified using experimental data from the Danfoss refrigeration test centre. The complexities of modelling demand response are demonstrated through simulation. Simulations are conducted by placing the identified model in a direct-control demand response architecture, with power reference tracking using model predictive control. The energy-limited nature of demand response from refrigeration is identified as the key consideration when considering participation in the regulating power market. It is demonstrated that by restricting the operating regions of the supermarket refrigeration system, a simple relationship can be found between the available up- or down-regulation power, and the duration for which the service can be sustained. The available demand response resource within these operational restrictions is reduced from the optimised physical capabilities. The benefit of these restrictions is that the available demand response can be represented in a manner that is sufficiently simple to communicate to a market operator in the form of a bid for the provision of regulating power.

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B.1 Introduction

The advent of renewable power generation as a central participant in global power systems has brought about a paradigm shift in the power sector. Power system flexibility is now a key concern, to facilitate fluctuating renewable generation and to ensure the most cost effective operation of the power system. The activation of the inherent flexibility of certain electrical loads, demand response, is a potential source of power system flexibility that could be more economically favourable than traditional sources of flexibility such as interconnection, storage and flexible generation. Current research on demand response focusses on how to model, control, evaluate, and operate demand response in a competitive electricity market (see [B1, B2] and references therein).

Scale, technical ability and financial incentive are the three key components for a profitable demand response program. Supermarket refrigeration systems fulfil all of these requirements. The electrical consumption of supermarkets in Denmark is approximately 550GWh per year, which corresponds to 2% of the annual Danish electricity consumption [B3]. The electrical consumption of the average supermarket is comprised of a number of electrical sinks, including lighting and indoor heating, however refrigeration accounts for the largest share, at up to 47% [B4]. As a comparison, the balancing energy required to compensate for forecast errors in wind power generation in Denmark in 2011 was 1.3TWh [B5]. The electrical consumption of Danish supermarket refrigeration systems corresponds to approximately 20% of this imbalance.

Regarding the financial incentive, the cost of electricity only accounts for 1% of the operating costs of a supermarket. However, as the typical profit margin is only 3%, any improvement in the cost efficiency of energy consumption corresponds to a sizeable increase in profit to the supermarket operator [B6].

Finally, considering the technical feasibility of achieving demand response, the refrigeration system and the foodstuff within it are a substantial thermal mass which acts as an energy storage medium and can be harnessed to shift electrical consumption in time. This allows the electrical demand of the system to be adjusted or optimised towards energy or cost efficiency, as well as for the provision of conventional power system services such as regulating power. This can be achieved while maintaining the temperature of the food within acceptable limits to prevent spoiling, and the consequent loss of revenue to the supermarket operator. Demand response can be considered as a secondary revenue stream or business model for a supermarket chain. Its existing structure and the established potential for demand response provide the basis of a virtual power plant, or aggregator, that can both interface directly with the electricity market and control the response from its population of refrigeration systems.

A high level discussion on the provision of ancillary services from demand response is presented in [B7], where a number of demand response applications are considered at the aggregate scale. There is a limited body of work focussing on the particular case of demand response from supermarket refrigeration systems. Non-convex economic model predictive control (MPC) is employed in [B3] to optimally schedule the operation of a supermarket refrigeration system with respect to the price of electricity. Direct-control based demand response from supermarkets is demonstrated briefly in [B8], where an ordinary differential equation (ODE) based model of a supermarket system is simulated and successfully follows a power consumption reference. The use of refrigeration systems for the provision of frequency control from small drink chillers in local markets is proposed in [B9].

The central contribution of this work is a demonstration of how the complexities of operating demand response can be overcome to result in a simplified resource, but one that can be easily implemented within existing market structures. We simulate a data-driven model of a supermarket refrigeration system using a model predictive control architecture to demonstrate the complex behaviour of demand response. We then determine the operating restrictions required to achieve a sufficiently simple resource, such that the available demand response can be communicated with a power system or market operator in a timely and understandable manner.

Section B.2 of this paper describes the refrigeration system analysed in this work, its key characteristics and the model employed in subsequent simulations. Section B.3 then illustrates the key characteristics and complexities of demand response from supermarket refrigeration systems. Section B.4 explores how these complexities can be reduced or eliminated. Section B.5 presents a discussion on the necessity and benefits of establishing a simple representation of the practical capabilities of a demand response resource. The conclusions to this work are presented in Section B.6.

B.2 System Description and Model

B.2.1 System Data

The model and simulations presented in this work are based on experimental data from a Danfoss refrigeration test centre. The dataset spans eight days, during which three step changes are imposed on the reference temperatures in the refrigeration system. This facilitates the identification of the dynamics of the system that are pertinent for demand response applications. The power consumption of the refrigeration system compressors and temperature data are recorded at a resolution of one minute. This dataset includes high frequency components in power consumption due to compressor switching. These components are not relevant for demand response studies and are consequently smoothed from the dataset, and the resolution of the data is reduced to five minutes. Temperature data are recorded at a number of locations within each food display unit in the refrigeration system. Two representative temperatures are extracted, one for each group of low-temperature and medium-temperature display units.

B.2.2 System Model

The data provided is employed to identify an ARMAX (Auto-Regressive Moving Average with eXogeneous Input), single-input, two-output model of the system [B10]. The two outputs of the system are the representative temperatures for the medium- and low-temperature units - these are denoted RMT and RLT respectively. The power consumption is the considered input.

The ARMAX model has the form:

$$\phi(B)Y_t = \omega(B)X_t + \theta(B)\epsilon_t \tag{B.1}$$

where B represents a time lag and each of $\phi(B)$, $\omega(B)$ and $\theta(B)$ is a polynomial, whose order is specified in the model fitting process. The MATLAB system identification toolbox [B11] is used to determine the parameter values for each polynomial, using the least squares method with respect to the one-step prediction errors.

The model selected here is of the form ARMAX(2,1,2), that is, it contains a second order AR component and a first order MA component, and considers the current and directly previous input values. The performance of this model for simulation is demonstrated in Fig. B.1. In this case, the model is not provided with any updated information on the actual realisation of temperatures within the system, but estimates them based on the provided power consumption data. The model is found to replicate the general behaviour of the system satisfactorily, particularly considering that the model identified here is intended for high level simulations to estimate the demand response capabilities, rather than an in-depth study of the dynamics of the refrigeration system. Note that the peaks in the recorded temperatures are not present in the simulation. These

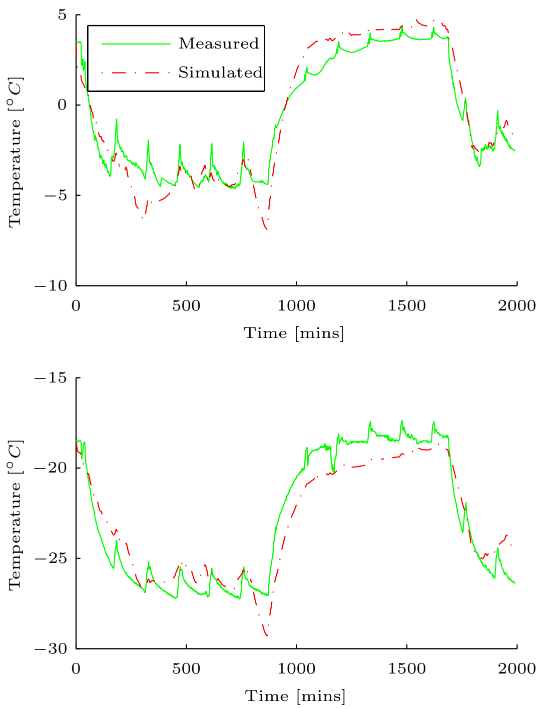

Figure B.1: Measured (green) and simulated (red) RMT (upper plot) and RLT (lower plot) using the identified ARMAX model of the refrigeration system.

temperature peaks are the result of defrosting within the display units of the refrigeration system. Defrosting occurs periodically and is achieved by placing air heaters below the evaporators in each display unit. The power consumption of these heaters is not recorded in the dataset. Therefore, these temperature peaks cannot be explained by the model. Defrosting is not relevant for the demand response simulations considered in this work as they must occur regardless of demand response operations.

The time constants of this model are 10 and 0.12 hours. This is a promising indicator of the potential of the system to shift electrical demand over many hours, as well as providing instantaneous-type demand response products. This result is supported by the work in [B3] on refrigeration system modelling, where it is found that the system temperature with the slowest dynamics (comparable to RLT here) increases from the minimum to maximum allowed temperatures in 11.5 hours if no cooling is applied.

The model identified here is limited by the available data. Other relevant model inputs include the external temperature as well as the opening hours of the supermarket. These inputs would facilitate the identification of diurnal and seasonal trends in the baseline power consumption, and the consequent impact on the available demand response resource. The model identified here does not include these factors and is therefore not suitable for extended power or energy system integration studies but rather provides a general impression of the abilities of the system for demand response.

B.3 Simulations

The demand response capabilities of the refrigeration system are simulated by placing the identified model within a model predictive control environment. Direct control based demand response is assumed, and the modelled power consumption is required to track a reference power consumption, as could be supplied by an aggregator, for example. The controller is described as:

$$\min_{\mathbf{P}} \sum_{t=1}^{T} \left(P_t - P_t^{ref}\right)^2 \tag{B.2a}$$

s.t.

$$\begin{bmatrix}\phi_{11}(B) & \phi_{12}(B)\\ \phi_{21}(B) & \phi_{22}(B)\end{bmatrix}\begin{bmatrix}T_t^{RMT}\\ T_t^{RLT}\end{bmatrix} = \begin{bmatrix}\omega_1(B)\\ \omega_2(B)\end{bmatrix} P_t + \begin{bmatrix}\theta_1(B)\\ \theta_2(B)\end{bmatrix}\epsilon_t \ , \tag{B.2b}$$

$$T_{min}^{RMT} \leq T_t^{RMT} \leq T_{max}^{RMT} \ , \tag{B.2c}$$

$$T_{min}^{RLT} \leq T_t^{RLT} \leq T_{max}^{RLT} \ , \tag{B.2d}$$

$$P_t \leq P_{max} \ , \tag{B.2e}$$

$$P_t \geq 0 \ . \tag{B.2f}$$

The identified ARMAX model defines the dynamics of the system, (B.2b). The constraints on temperature, (B.2c) and (B.2d), and power consumption, (B.2e) and (B.2f), restrict the operation of the model. The capacity of the system is selected as 30kW, and the temperature constraints are set to -6°C and 6°C for RMT, and -35°C and -10°C for RLT. These values are selected from inspection of the dataset. It is acknowledged that the temperature constraints may not be realistic for a commercial supermarket where food spoilage is a concern. Other relevant control architectures for this system include temperature tracking, a

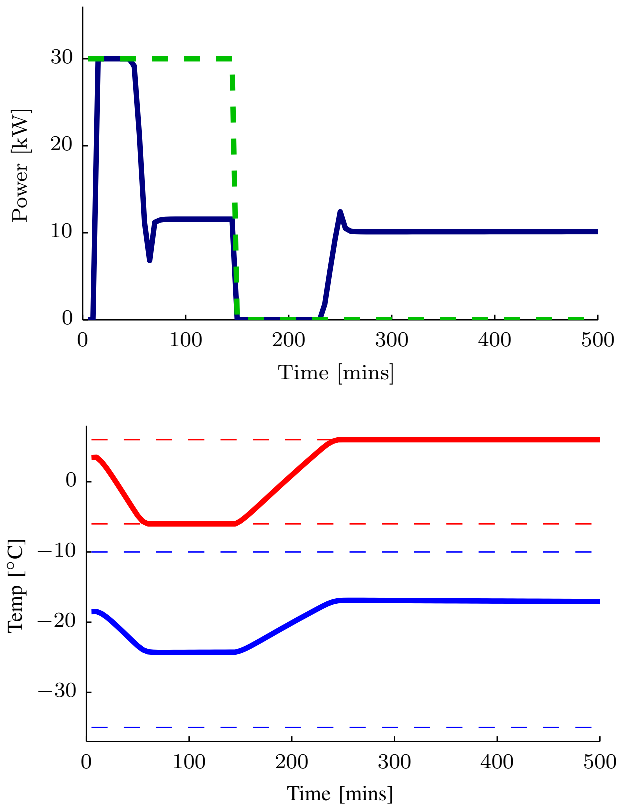

Figure B.2: Simulation of the refrigeration system using model predictive control to track a power reference. Power consumption is shown in the upper plot, with the reference power (green) and achieved power (blue). Modelled RLT (blue) and RMT (red) are given in the lower plot, with their respective limits (dashed)

direct-control architecture, and economic MPC, an indirect-control architecture. Both possibilities are presented in detail in [B12].

Fig. B.2 illustrates the behaviour of the system when it is required to track a power consumption reference, shown in green. The system is only capable of maintaining the reference for a limited period of time, both prior to and following the step change in the reference power consumption. This is due to the temperature constraints of the system. In this case RMT, shown in red, is the limiting factor. The upper and lower limits on the temperature are hard constraints and prevent the system from maintaining the requested power consumption. This phenomenon is known as the saturation of response, where a requested alteration in power consumption can only maintained for a given period of time. This is an important factor to be considered when modelling demand response in more general terms. It must be reflected that demand response from thermal loads is an energy and power limited resource, similar to storage, rather than simply a power limited resource, such as generation.

The behaviour of flexible refrigeration loads is quite complex, influenced by both the physical characteristics and constraints of the system and the control architecture. Saturation of response is illustrated using a very simple case in Fig. B.2, where it is clear that the time to saturation is different when the increase in power consumption is required to when the decrease is requested. In fact, the time to saturation is dependent on the system temperature at start of a power adjustment event (for up- or down-regulation), the extent of the power reference forecast available to the system controller, the adjustment in power consumption requested and the temperature constraints on the system [B12]. Furthermore, the flexibility of the system is asymmetric. The power consumption required to maintain a steady-state temperature on this system ranges between approximately 10kw and 11.5kW, for the maximum and minimum allowed temperatures respectively. As the system has a power capacity of 30kW, this results in a potential increase in consumption of 20kW from steady-state, but only an 11.5kW decrease in power consumption. This asymmetry is not unique to the system considered here, as refrigeration systems are dimensioned to accommodate the highest thermal load in, for example, 10 years. These complexities must be considered when evaluating demand response for participation in the power system, and when devising bidding strategies on an electricity market.

B.4 Demand Response on the Regulating Market

B.4.1 Nordic Regulating Power Market

The Nordic regulating power market is a market for manual reserves which can be activated within 15 minutes to provide up- or down-regulation. Bids for regulating power can be submitted up to 45 minutes before the operating hour, but can be activated at any time during the operating hour. The current minimum bid size on the regulating power market is 10MW, precluding individual refrigeration systems from participating [B13]. Participation could be accommodated through an aggregator, which would act as a balance responsible party for a population of supermarkets.

B.4.2 Saturation of Response

In order to participate in the regulating market, the supermarket operator or aggregator must be able to quantify the available power adjustment and the duration for which this can be maintained.

Power adjustment simulations were conducted on the model presented in the preceding sections, with a range of initial conditions in both power and temperature. This determines the relationship between the power adjustment and the time to saturation. Here, time to saturation is defined as the time from the initial change in power reference until the power adjustment can no longer be maintained and deviates by more than 5% from the reference. Fig. B.3 shows the time to saturation for both upwards and downwards adjustments in power consumption (down- and up-regulation respectively). Each colour on the figure corresponds to a different set of initial conditions in the simulation, as described in Table B.1. The purple and orange lines exhibit the expected behaviour, that is, as the magnitude of power adjustment decreases, the time to saturation increases. There is a non-linear relationship in both of these cases. In comparison, the green and red lines shown unexpected behaviour. Focussing on the green line, we can see a peak in the time to saturation with a power adjustment of approximately -5kW, and a decrease on either side of this adjustment. This can be explained by considering the starting conditions of this simulation, and by noting that the system is not at steady-state when temperatures are between the upper and lower bounds. At an initial power consumption level of 15kW and temperature of 5°C, any increase in power consumption will result in the system temperature decreasing to the minimum allowed, -6°C. The behaviour with a decrease in power consumption is more complicated. A decrease in power in excess of 5kW, to 10kW or lower, will result in the system temperature increasing to the maximum allowed, 6°C. On the other hand, a decrease less than 3.5kW will result in a consumption level greater than 11.5kW which drive the system temperature down towards the minimum. Thus, the saturation can occur in two different directions, depending on the level of negative power adjustment. This is illustrated in Fig. B.4, where the power consumption required to maintain a steady-state temperature is highlighted, and the impact of altering power consumption from these levels is indicated. To accurately predict the time to saturation in this case, the supermarket operator or aggregator must therefore know the initial conditions of the system, as well as the steady-state conditions. This requires intensive monitoring of the system, and analysis of the time to saturation of the system at a large number of initial condition sets. This complicates the task of devising regulating power bids, as the precise initial conditions must be forecast ahead of the delivery hour.

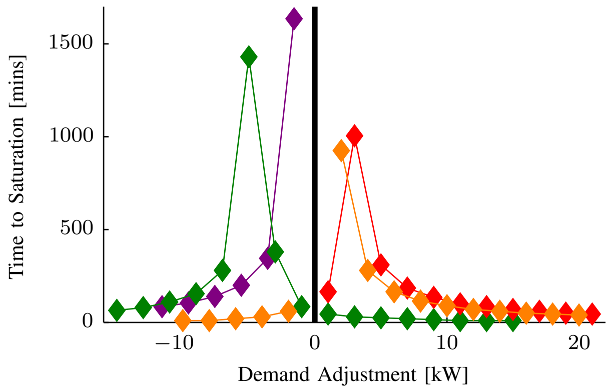

Figure B.3: Time to saturation of response, with a range of initial conditions

B.4.3 Saturation of Response with Restricted Operating Conditions

By restricting the operating conditions of the system, we can simplify the relationship between power adjustment and time to saturation. If the system is limited to operating at steady-state conditions when not providing regulating power, we can ensure that the system commences each up-regulation event (consumption decreases) at the initial condition of {11.5kW, -6°C}, and each down-regulation event (consumption increases) at {10kW, 6°C}. The relationship between power adjustment and time to saturation in this case is illustrated in Fig. B.5. This is a much simpler relationship than that shown in Fig. B.3, and one that can be easily communicated to the electricity market operator in the form of a bid. It is important to note that restricting the refrigeration system to operate at steady-state conditions implies that the system must return to steady-state following a regulation event. Thus, an up-regulation event may be followed by a rebound period where power consumption is increased temporarily (similar to down-regulation) to regain the previous steady-state condition. The

Table B.1: Initial conditions for simulations shown in Fig. B.3

Line Colour	T_0 [°C]	P_0 [kW]
Purple	-6	11.5
Green	-3.1	15
Orange	5	11
Red	4	10

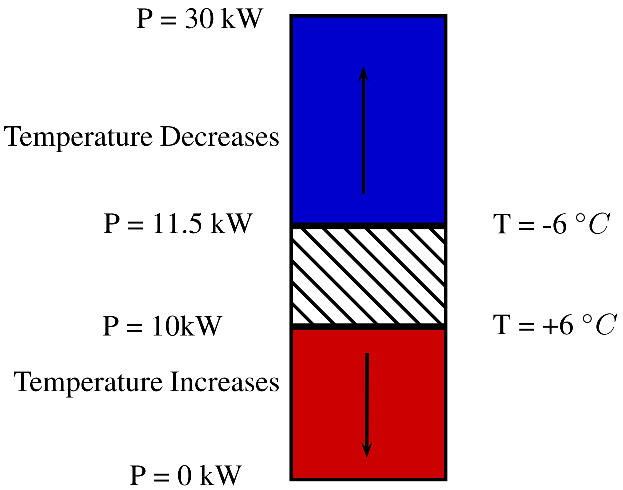

Figure B.4: A graphical explanation of the direction of temperature changes at different power consumption levels. Blue indicates a temperature decrease, red indicates a temperature increase. The hashed area corresponds to the steady-state condition where a constant temperature can be maintained.

rebound time can also be found in Fig. B.5. If an up-regulation event brings the system from the initial steady-state of {11.5kW, -6°C} to the final steady-state of {10kW, 6°C}, the rebound time corresponds to the time to saturation for a down-regulation event (in green on the figure). Rebound is not always necessary. If the need for down-regulation is anticipated following the provision of up-regulation, the supermarket operator or aggregator can chose to remain at the new steady-state of {10kW, 6°C} and provide down-regulation when it is needed.

The information provided by Fig. B.5 can be used by the aggregator to formulate bids on the regulating market. Joint or conditional bids can be used to inform the market operator of the possibility of rebound. This could be formulated as an up-regulation event of -10kW at hour 1 combined with a rebound period, or down-regulation event, of 5kW for hours 2 and 3. Alternatively, the the aggregator could submits bids in the conventional manner, where they offer regulation for a series of hours, and alter the offers in later hours as bids are accepted or otherwise. This takes advantage of the possibility to alter bids on the regulating market up to 45 minutes prior to the delivery hour [B13].

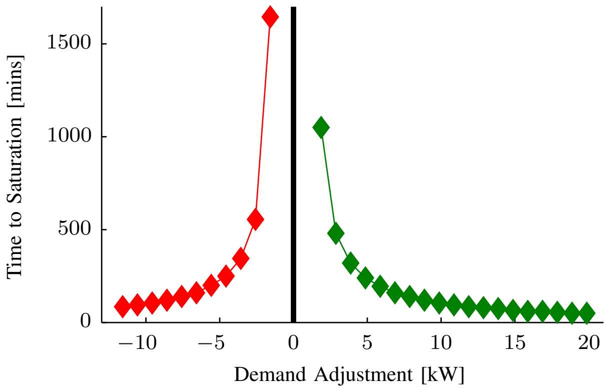

Figure B.5: Time to saturation, for up-regulation (red) and down-regulation (green)

B.4.4 The Impact of Forecast Horizon on the Time to Saturation

The time to saturation can be tailored by adjusting the extent of the power reference forecast available to the refrigeration system controllers. All of the simulations presented previously considered a 30 minute forecast of the power reference. By extending the forecast we can adjust the time to saturation. The general impact of extending the forecast is a shorter period of power adjustment, as the controller anticipates the change in power reference earlier, and consequently begins adjusting the power consumption earlier. Note that the impact of changing the forecast horizon is asymmetric on up- and down-regulation, where the impact on down-regulation is negligible for power adjustments less than 10kW. This information should be taken into account by the supermarket operator or aggregator when providing the refrigeration system with a power reference, as the forecast they they provide will influence the demand response capabilities, and the resulting bids that should be communicated to the market operator.

B.5 Discussion

There is a wealth of literature examining methods to extract an optimal demand response behaviour from a large variety of applications, however the common trend is that the power system or market operator either has full knowledge

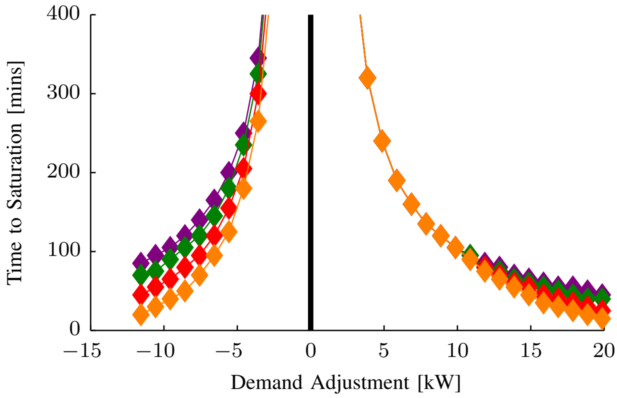

Figure B.6: Time to saturation for up- and down-regulation, at forecast horizons of 6 hours (orange), 4 hours (red), 2 hours (green) and 30 minutes (purple).

of the characteristics and constraints of each responsive element, e.g. [B14], or they assume a simple linear price response curve, e.g. [B15]. Neither approach facilitates a realistic analysis of the participation of demand response in an electricity market, or the consequent development of a business case for demand response. The saturation phenomenon demonstrated in this work is common to all thermal-electric loads and clearly precludes the use of a linear relationship between price and demand response. This relationship is better suited to to representing power limited resources rather than energy limited resources such as thermal-electric demand response. Furthermore, it is unrealistic to assume that the market operator has full knowledge of each of the responsive components on the system. Current electricity markets are operated at a very granular scale, where participating resources provide the market operator with a simple representation of their willingness to participate in the market, in the form of a bid comprising of a power level and the corresponding price.

The role of the market operator is simply to clear the market. Its role is not to determine the capabilities of individual demand response resources, or to issue control signals to realise the required response. That is the role of an intermediary, or an aggregator, that will facilitate the participation of demand response resources in the market. An aggregator must have sufficient knowledge of its portfolio of demand response resources to understand their dynamic capabilities, constraints, uncertainties and the relevant control mechanisms necessary to realise their capabilities. Additionally, and crucially, the aggregator must be able to communicate this information to a market or power system operator, in such a manner that their resulting market clearing or system dispatch operation is numerically tractable and computationally feasible within the time allowed for such operations. The simplifications required to achieve such a representation will naturally lead to a loss in optimality, as some of the capabilities of the demand response resource may not be representable in such a way. This is seen with the refrigeration system considered in this work, where the operating regions must be restricted to allow a reasonably simple market offer structure.

B.6 Conclusions

This paper presents the initial work towards establishing a realistic model of the practical capabilities of demand response in a market environment, considering the particular case of supermarket refrigeration. An ARMAX model of a supermarket system is identified using experimental data from a Danfoss refrigeration test centre. The characteristics of demand response are demonstrated through simulations employing a direct-control based control architecture with MPC. The complexities of demand response due to the energy-limited nature of thermal-electrical loads are highlighted, with a particular focus on the saturation of response and the consequences for participation in the regulation market. It is shown that by restricting the operating regions of the refrigeration system, a simple relationship is revealed between the available up- and down-regulating power and the duration for which this can be maintained. Restricting the system in this manner results in a solution with reduced optimality, but one that is sufficiently simple to communicate to a market operator in the conventional manner of a bid.

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Paper C

Economic Dispatch of Demand Response Balancing through Asymmetric Block Offers

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Economic Dispatch of Demand Response Balancing through Asymmetric Block Offers

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Abstract

This paper proposes a method of describing the load shifting ability of flexible electrical loads in a manner suitable for existing power system dispatch frameworks. The concept of an asymmetric block offer for flexible loads is introduced. This offer structure describes the ability of a flexible load to provide a response to the power system and the subsequent need to recover. The conventional system dispatch algorithm is altered to facilitate the dispatch of demand response units alongside generating units using the proposed offer structure. The value of demand response is assessed through case studies that dispatch flexible supermarket refrigeration loads for the provision of regulating power. The demand resource is described by a set of asymmetric blocks, and a set of four blocks offers is shown to offer cost savings for the procurement of regulating power in excess of 20%. For comparative purposes, the cost savings achievable with a fully observable and controllable demand response resource are evaluated, using a time series model of the refrigeration loads. The fully modelled resource offers greater savings, however the difference is small and potentially insufficient to justify the investment required to fully model and control individual flexible loads.

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C.1 Introduction

Demand response is frequently presented as a solution to a multitude of challenges in the power system. It is said to bring about such benefits as supporting higher penetrations of renewable generation [C1], increasing economic efficiency [C2], and alleviating distribution network congestion [C3], among others [C4, C5]. Demand response is not without its challenges however. Chief amongst these is the uncertainty over the value that demand response provides to the power system

A number of academic works have attempted to quantify this value. The concept of price elasticity of demand is often adopted as a representation of the flexibility of demand in the presence of dynamic or real-time prices [C6, C7, C8]. This approach assumes economic rationality and overlooks the significant complexities of electrical demand. Demand response is fundamentally characterised by the physical limitations and dynamics of electrical end-uses and highly complex interaction with consumers, which are not accurately described in the form of a linear price curve or single elasticity value.

On the other end of the scale, detailed models are used to assess the abilities and value of demand response resources, where it is assumed that the internal states of individual resources are known and can be controlled [C9, C10, C11, C12]. This approach is a valid method of establishing the theoretical value of demand response, however, the financial and computational costs of establishing a framework to dispatch many thousands of individually modelled flexible loads are prohibitive. Furthermore, current market clearing and power system dispatch algorithms interface with large conventional generating resources through bids consisting of a volume and a price [C13], or limited set of constraints [C14]. These frameworks are unsuitable for the management of a large number of individually modelled and controlled flexible loads.

This paper demonstrates the value that demand response can provide to the power system when its representation in the system dispatch algorithm is limited to one that is comparable in complexity to that of conventional generating units. The representation described here is suitable for the interface between an aggregator, managing a population of responsive loads, and the market or system operator. The interface between the aggregator and the individual loads can be handled using such control frameworks as detailed in [C11, C12].

This work contains two novel contributions to the field of demand response research. Firstly, building on material presented in [C15], we develop a methodology of defining block bids that populations of flexible demand units can offer to the power system or market operator. The block offers reflect the load shifting abilities of individual demand units, considering their flexibility to provide a response to the power system and the subsequent necessity of energy recovery. The dispatch of these block offers is considered in the context of the regulating power market,where energy is sourced on an hour-ahead basis to serve forecasted imbalances close to real-time. Offers on the regulating power market must be fully activated within 15 minutes of being called by the system operator, and the rapid ramping capabilities expected from flexible loads makes them well suited to the provision of this service [C16].

Secondly, we present an optimisation framework to dispatch these block offers for demand response alongside conventional generating units for the provision of regulating power. This optimisation differs from conventional economic dispatch algorithms as it is a combinatorial problem, where demand response blocks can be accepted in their entirety, or not at all.

Case studies are conducted to assess the value of demand response when represented by a limited set of block offers in the system dispatch algorithm. A comparative study evaluates the demand response resource when described as a fully observable and controllable system, using a time-series model. The flexible load considered in these case studies is supermarket refrigeration, which has with significant potential for load shifting demand response [C17, C18, C19].

The remainder of this paper is structured as follows. Sections II and III present the demand response model, both the full and limited representations. The optimisation framework employed to dispatch the system considering demand response is detailed in Section IV. The case study framework is outlined in Section V and results are given in Section VI. Concluding remarks can be found in Section VII.

C.2 Demand Response Resource Model

In this work we consider load shifting demand response on a short-term horizon, specifically for the provision of regulating power. A number of load types are considered as candidates for load shifting. In particular, thermal-electric loads such as building heating and cooling [C10, C20], water heating [C21], and refrigeration [C17, C18, C19], are considered ideal candidates due to their ability to alter their power consumption while maintaining an acceptable temperature range. These thermal loads share two key characteristics, namely, saturation and rebound. Saturation refers to the limited time extent of the response from a thermal load. This is due to the temperature constraints that limit the duration for which power can be adjusted either upwards or downwards from a given baseline. Rebound refers to the phenomenon that is observed after control is returned to the device from the aggregator. Upon return of control, the device will attempt to return to the state it occupied directly preceding the request from the aggregator, resulting in a sudden reverse in the direction of the power consumption deviation.

The representations of flexibility developed in this work are applicable to all flexible loads capable of providing load-shifting demand response. Different load types will exhibit differing dynamics, and consequently the block offers and saturation curves for each will have different parameter values, but the concepts underlying these representations hold. Supermarket refrigeration is employed in this work as an example case study, owing both to its suitability for the provision of load shifting demand response and the availability of data and models describing its flexibility. Supermarket refrigeration systems are well suited to demand response as they have the ability to respond, the volume to provide a tangible service to the power system, and the financial incentive to participate in the power market [C15].

The demand response capabilities and characteristics of supermarket refrigeration systems are explored through the combined use of time-series modelling and simulation. A second order auto-regressive moving average with exogenous inputs (ARMAX) model of a supermarket refrigeration system is identified from data procured from a Danfoss refrigeration test centre in Denmark. Full details of this model are provided in [C15].

The demand response behaviour of a single supermarket refrigeration system is simulated in a model predictive control framework, where the refrigeration system tracks a temperature or power reference. A demand response aggregator can request a response from the refrigeration system for a specified duration. When providing a response, the refrigeration system follows a power reference, at all other times the refrigeration system follows a temperature reference. The control objective for the refrigeration system is given as

$$\min \quad \sum_{t=1}^{T} a_t(P_t^{ref} - P_t)^2 + (1 - a_t)(T_t^{ref} - T_t)^2 \tag{C.1}$$

where the control variables are temperature, T_t, and power, P_t. A binary indicator, a_t, governs the effective control objective at time t. When a_t is 1, the aggregator specifies a power reference, P_t^{ref} for the refrigeration system to track. When a_t is zero, the supermarket tracks a temperature reference, T_t^{ref}. The power consumption and system temperatures are inter-dependent and cannot be independently controlled simultaneously. The control is subject to upper and

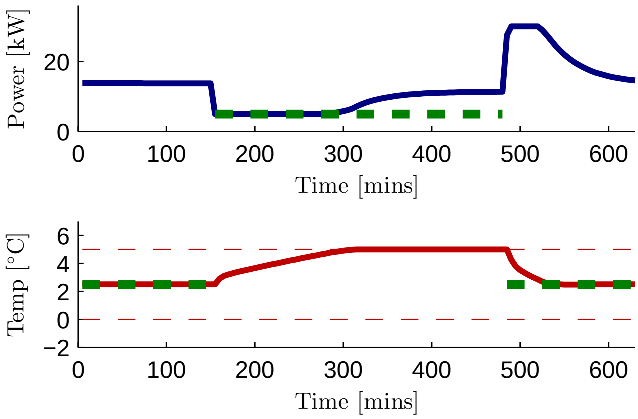

Figure C.1: Power consumption and representative medium temperature of the refrigeration system when a reduction of power consumption to 5kW is requested. The heavy dashed lines indicate the temperature/power references to be tracked.

lower bounds on temperature in both the medium and low temperature display units. Power consumption is limited by the capacity of the compressors on the system. As the flexibility of this system is restricted by the least flexible system temperature, that of the medium temperature display unit, there is no further reference to the low temperature unit in this work.

The behaviour of the refrigeration system over a period of both supermarket and aggregator control is illustrated in Fig. C.1. During this simulation the aggregator requests a reduction in power consumption to 5kW for 325 minutes. Saturation occurs when the upper temperature bound is reached. Rebound occurs upon return of control from the aggregator to the supermarket; power consumption increases to the upper limit, facilitating the fastest return to the supermarket defined reference temperature.

Under the described control framework, the power consumption of the refrigeration system can be considered to consist of a baseline power consumption and a deviation from this baseline.

In the current model, the baseline power consumption is constant. This is because the system used for model identification is not a fully operational supermarket, and therefore does not include the complexities of customer interaction or widely varying external temperatures. On an operational system the baseline power consumption varies according to a number of factors This baseline power

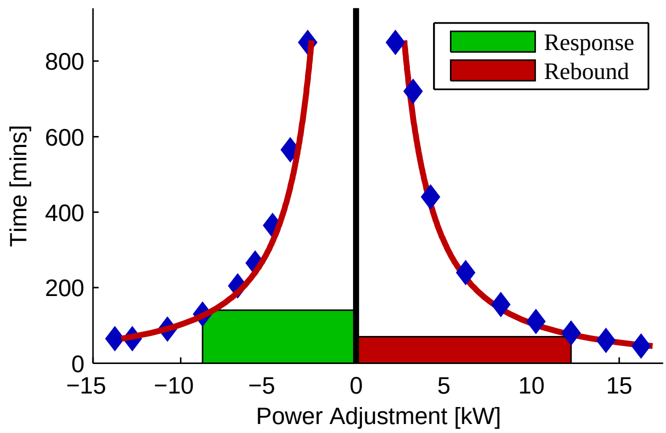

Figure C.2: Saturation curve of a supermarket refrigeration system, with a sample response-rebound block definition.

consumption can be modelled and forecast [C22], and purchase of the necessary energy to meet this demand can take place on the day-ahead market. Any deviation from the baseline can be employed to provide regulating power. In order to achieve this it is imperative that the saturation and rebound characteristics are fully described in a manner that can be easily communicated to a power system operator.

C.3 Characterising Demand Response

C.3.1 Saturation Curve Concept

The time to saturation defines the maximum duration for which any deviation from the baseline can be reliably maintained. This can be found by simulating the response of the system to a range of power adjustments and finding the duration for which the requested power reference can be maintained before a temperature constraint is reached and saturation occurs. The results of these simulations are presented in Fig. C.2, which plots the time to saturation against the power adjustment, and shows the closest fit to these points.

The rebound phenomenon can also be described using this curve. If the system is allowed to rebound in an uncontrolled manner, it will tend to do so at either its maximum or minimum power consumption levels, and the duration of this rebound is found at the outer points of the curves. If the aggregator includes a power reference for the rebound, the necessary duration can be found from the corresponding point on the saturation curve. In order to avoid any unexpected saturation or rebound, any service offer from the aggregator to the power system operator must consist of power levels and durations for both response and rebound as defined by the saturation curve. The offer thus has the form of an asymmetric block.

Fig. C.3 illustrates the behaviour of the refrigeration system under a request for a response-rebound block consisting of a reduction in consumption by 8.75kW for 145 minutes (response) and an increase in consumption by 12.25kW for 75 minutes (rebound), the block definition shown in Fig. C.2. The adjustments occur from a baseline power consumption of 13.75kW. It can be observed from Fig. C.3 that the temperature reaches its upper bound, which indicates saturation, and the subsequent rebound is fully controlled. This is achieved without feedback from the supermarket to the aggregator; the aggregator decides on the composition of the entire block before issuing the power references to the supermarket.

The use of the saturation curve to achieve this response illustrates the ability of an aggregator to obtain effective demand response from a single refrigeration unit without the need for detailed modelling, monitoring or communications infrastructures. A similar representation can be found for a population of supermarkets by summing individual saturation curves to form an aggregate curve. The saturation curve of a homogeneous population of supermarkets will have the same form as the saturation curve of an individual supermarket, with a scaled power axis. For example, the combined flexibility of 1000 identical supermarkets is described by the saturation curve of a single supermarket, scaled in mega-watts rather than kilo-watts.

C.3.2 Saturation Curve Extension

The saturation curve presented in Fig. C.2 represents the limits of the demand response capabilities of the refrigeration system. Naturally, the system is also capable of maintaining a power adjustment for a duration less than the saturation time, however the necessary rebound following such a response must be defined.

Temperature behaviour within refrigeration units exhibits an exponential relationship with time, for a given power consumption level [C17]. However, for small values of t the temperature trajectory can be approximated as linear.

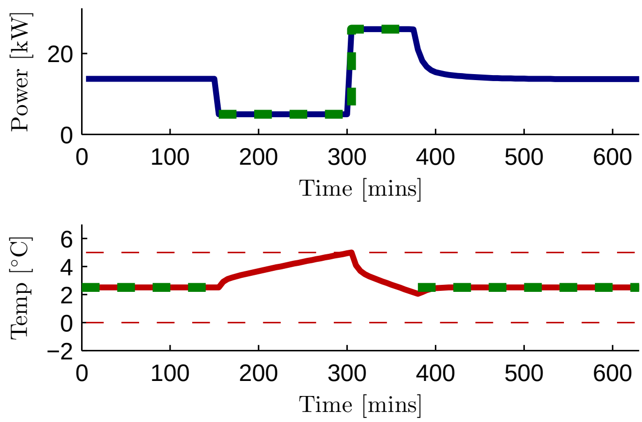

Figure C.3: Power consumption and representative medium temperature of the supermarket refrigeration model during a controlled response and rebound event, with power and temperature references indicated by the heavy dashed lines, they are active when non-zero.

Within the refrigeration systems considered here, the temperature range is relatively small, and the duration for which a given power adjustment can be maintained is limited by saturation. Consequently for values of ΔP above a given threshold, the duration for which ΔP is maintained is short and the temperature behaviour in the refrigeration system can be considered linear. This facilitates the identification of partial saturation curves and the definition of the corresponding rebound, if power deviations are only considered outside of a dead-band region. This has been verified through simulation for the model considered in this work, where the dead-band range is {-4, 4}kW.

Consider the extension of the saturation curve concept to incorporate the case where the response is maintained for $X\%$ of the saturation time. An $X\%$ saturation curve can be found for all power adjustments within the linear region by multiplying the original saturation curve by $X/100$. This facilitates the identification of the appropriate rebound following an $X\%$ response. Fig. C.4 illustrates the case where $X = \{25, 50, 75, 100\}$. The advantage of using $X\%$ saturation curves is that the refrigeration units are not stressed to their temperature limits, but instead occupy a limited region around the baseline temperature.

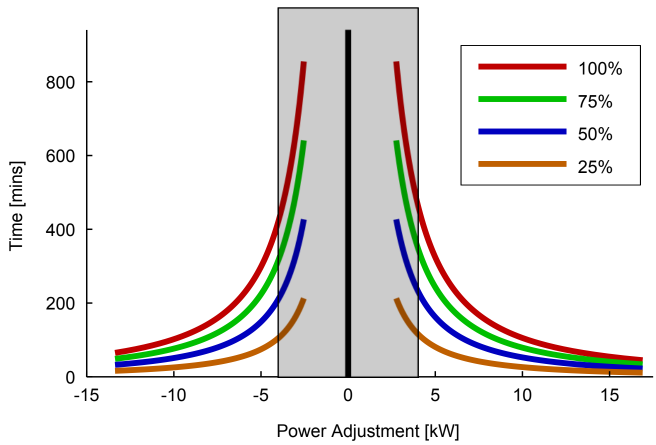

Figure C.4: Partial saturation curves with the dead-band indicated by the shaded grey section. To ensure accuracy, partial saturation curves should not be considered for power adjustments within the shaded region.

C.4 Scheduling Demand Response for Provision of Regulating Power

C.4.1 Problem Context and Assumptions

Demand response units are scheduled alongside conventional generating units for the provision of regulating power. The system dispatch is subject to two key simplifying assumptions. Firstly, that the system operator has perfect foresight of the required regulating power within the considered horizon. Typically regulating power is dispatched on an hourly basis [C23], which is less than the four-hour horizon considered in the simulations that follow. It is acknowledged that there is a degree of uncertainty in the regulating power required over the considered dispatch horizon. The risk of dispatching excess or insufficient regulating power could be mitigated by employing a chance constrained or robust optimisation framework for system dispatch, however determining uncertainty sets for the required regulating power is non-trivial. Furthermore, employing a stochastic optimisation framework is computationally expensive and potentially infeasible at the short horizons considered here. Therefore, the simplification of accepting a perfect forecast of the required regulating power is accepted as necessary and representative of the practical manner in which regulating power is currently dispatched on existing power systems.

The second simplification is that all conventional generating units can provide up- and down-regulation, and the capacity available for each is fixed for the duration of the optimisation. It is assumed that their existing dispatch (e.g. from the day-ahead market) allows for this.

C.4.2 Problem Formulation

The optimal dispatch of conventional and demand response units is found by employing the mixed integer linear programming optimisation given as

$$\min_{\mathbf{x}} \quad \mathbf{c}^{\mathbf{T}}\mathbf{x} \tag{C.2a}$$

subject to:

$$\mathbf{h}(\mathbf{x}) = 0 \tag{C.2b}$$

$$\mathbf{g}(\mathbf{x}) \geq 0 \tag{C.2c}$$

where $x = \{P_{i,t}, P^{DR}_{d,c,t}, v_{d,c,t}, SU^{DR}_{d,c,t}, SD^{DR}_{d,c,t}\}$, the conventional generator power output of each generating unit, i; the demand response power output for each block, d, and unit, c; the online status of the demand response block, d, at unit c; and its start-up and shut-down indicators respectively. The objective function, (C.2a), minimises the cost to the system operator of sourcing regulating power subject to the sets of equality and inequality constraints governing the generating and demand response units on the power system. The generating unit constraints are those typically employed in economic dispatch and can be found in a number of references, including [C24].

The constraints governing the behaviour of the demand response units are provided in equations (C.3) - (C.6). The initialisation and conclusion of a demand response block are indicated by a change in the online status of a given block, $v_{d,c,t}$, as detailed in (C.3).

When a demand response block is requested by the system operator, the demand response unit must follow the profile of the block, as defined in (C.4). This profile is comprised of the response, $P^{DR,resp}_{d,c}$, and rebound, $P^{DR,reb}_{d,c}$, for the corresponding response and rebound durations, $T^{resp}_{d,c}$ and $T^{reb}_{d,c}$. There may also be a recovery period following the completion of a demand response block, $T^{rec}_{d,c}$. Each demand response unit offers a number of demand response blocks, however simultaneous activation of blocks from a single demand response unit is not allowed. This is imposed in (C.5). Finally, any activated block must be fully realized within the dispatch horizon. This constraint is enforced in (C.6) which ensures that demand response blocks cannot commence in the final periods of the dispatch window, where this restricted region is defined by the response and rebound durations of each block. These constraints are summarised as

$$v_{d,c,t} - v_{d,c,t-1} = SU_{d,c,t}^{DR} - SD_{d,c,t}^{DR} \ , \tag{C.3}$$

$$P_{d,c,t'}^{DR} = \begin{cases} P_{d,c}^{DR,resp} \ , & \text{if} \quad t \leq t' < t + T_{d,c}^{resp}, \\ & \quad \forall \ t : SU_{d,c,t}^{DR} = 1 \\ P_{d,c}^{DR,reb} \ , & \text{if} \quad t + T_{d,c}^{resp} \leq t' < t + T_{d,c}^{resp} + T_{d,c}^{reb}, \\ & \quad \forall \ t : SU_{d,c,t}^{DR} = 1 \\ 0 \ , & \text{if} \quad t + T_{d,c}^{resp} + T_{d,c}^{reb} \leq t' < t + T_{d,c}^{resp} + \\ & \quad T_{d,c}^{reb} + T_{d,c}^{rec}, \quad \forall \ t : SU_{d,c,t}^{DR} = 1 \end{cases} \tag{C.4}$$

$$\sum_{d=1}^{D} v_{d,c,t} \leq 1 \ , \tag{C.5}$$

$$SU_{d,c,t} = 0 \quad \forall \ t > T - (T_{d,c}^{resp} + T_{d,c}^{reb}) \ . \tag{C.6}$$

C.4.3 Implementation

The limits on the power supplied by demand response block d from unit c depend on the orientation of the block. A block which commences with up-regulation followed by down-regulation is positively orientated, and the orientation parameter $\alpha_{d,c}$ is assigned the value 1. The opposite orientation has the value zero. Consideration of the orientation of the block is necessary when defining its power limits, as described in equation set (C.7). This set of four equations employs the 'Big M' formulation such that only two constraints are active for any given block, depending on its orientation. For a positively oriented block, the second-half of the right hand side of (C.7a) and (C.7b) becomes zero and these constraints are active. The other two constraints are not relevant as an arbitrarily large value of M (e.g. 10000) ensures that the these constraints are overridden by (C.7a) and (C.7b). The converse applies for a negatively oriented block. These power limits are given as

$$P^{DR}_{d,c,t} \leq P^{resp}_{d,c} v_{d,c,t} + (1-\alpha_{d,c})M \ , \tag{C.7a}$$
$$P^{DR}_{d,c,t} \geq P^{reb}_{d,c} v_{d,c,t} - (1-\alpha_{d,c})M \ , \tag{C.7b}$$
$$P^{DR}_{d,c,t} \geq P^{resp}_{d,c} v_{d,c,t} - \alpha_{d,c}M \ , \tag{C.7c}$$
$$P^{DR}_{d,c,t} \leq P^{reb}_{d,c} v_{d,c,t} + \alpha_{d,c}M \ . \tag{C.7d}$$

During the response and rebound portions of a demand response block, the demand response unit must maintain the dictated power supply level. This is imposed in equation set (C.8). Considering constraint (C.8a), for a positively oriented block, the power consumption must be at least as large as the defined response power, $P^{DR,resp}_{d,c}$, for the response duration $T^{resp}_{d,c}$, given that a block has commenced at time t. As the power supply of the block is simultaneously limited to be less than or equal to the response power, the combination of constraints (C.8a) and (C.7a) ensures the power supply of the block is equal to the defined response power. Equation (C.8b) ensures the corresponding power limit for the rebound portion of the block. Equation (C.8c) imposes a minimum recovery period, $T^{rec}_{d,c}$, between the activation of blocks from unit c. This constraint ensures that no block is active (i.e. $v_{d,c,t} = 0$) for the recovery period following the response and rebound, given that a block has been activated at time t. This implementation is given as

$$\sum_{t'=t}^{t+T^{resp}_{d,c}} \left(P^{DR}_{d,c,t'} - SU^{DR}_{d,c,t} P^{resp}_{d,c}\right) \begin{cases} \geq & -(1-SU^{DR}_{d,c,t})M \ , \\ & \text{if} \quad \alpha_{d,c} = 1 \\ \leq & (1-SU^{DR}_{d,c,t})M \ , \\ & \text{if} \quad \alpha_{d,c} = 0 \end{cases} \tag{C.8a}$$

$$\sum_{t'=t+T^{resp}_{d,c}}^{t+T^{resp}_{d,c}+T^{reb}_{d,c}} \left(P^{DR}_{d,c,t'} - SU^{DR}_{d,c,t} P^{reb}_{d,c}\right) \begin{cases} \leq & (1-SU^{DR}_{d,c,t})M \ , \\ & \text{if} \quad \alpha_{d,c} = 1 \\ \geq & -(1-SU^{DR}_{d,c,t})M \ , \\ & \text{if} \quad \alpha_{d,c} = 0 \end{cases} \tag{C.8b}$$

$$\sum_{t'=t+T^{resp}_{d,c}+T^{reb}_{d,c}}^{t+T^{resp}_{d,c}+T^{reb}_{d,c}+T^{rec}_{d,c}} \sum_{d=1}^{D} \left((1-v_{d,c,t'}) - SU^{DR}_{d,c,t}\right) \geq 0 \tag{C.8c}$$

C.5 Case Study Definition

Case studies are employed in this work to demonstrate the value of demand response to the system operator when its abilities are described using the limited form of a response-rebound block. Demand response is considered for the provision of regulating power on the Belgian regulating power market. Three cases are considered:

1. Dispatch of the system without demand response.
2. Dispatch of the system considering a limited set of demand response block offers.
3. Dispatch of the system considering a fully observable and controllable demand response resource.

Historical regulating power data from the Belgian system operator, Elia, is employed in all case studies. On this power system, regulating power is recorded at a 15 minute resolution. The data is interpolated to 5 minute resolution using cubic splines to match the time resolution of the demand response models. The only further adjustment to this historic data is down-scaling such that the required regulating power can be serviced by the available generating capacity. This ensures that the regulating power dispatch is feasible both with and without demand response. To provide context, Elia is a mid-sized power system, its peak-load in 2012 was 13,362MW [C25]. Each case study considers a dispatch window of 4 hours, using data from 2012.

The demand response resource consists of two demand response units, which each consist of a population of flexible loads. The flexibility of each unit is described using six response-rebound block offers, as detailed in Table C.1. While the physical capabilities of the units are the same, different blocks are offered for dispatch. This reflects the expectation that in a real-world implementation supermarkets would be clustered together to offer different services to the system operator. The blocks are selected from the 50% saturation curve shown in Fig. C.4.

For comparative purposes, the demand response resource is also implemented in its fully observable and controllable form, as a time series model. The time series model is that from which the saturation characteristic and block offers are obtained. Dispatch of the fully modelled units is subject to the restriction that they must reach the mean of their temperature bounds at the end of the dispatch horizon. This ensures an approximate energy balance and a fair comparison between the full and limited representations of the demand response resource.

Each demand unit has a maximum up-regulating capacity of 13 MW and down-regulating capacity of 17 MW. The capacity of the demand response units is scaled to be comparable to the capacity of the conventional units considered

Table C.1: DR Response-Rebound Units and Blocks for 50% Saturation

Unit	Block	P^{resp} [MW]	τ^{resp} [min]	P^{reb}[MW]	τ^{reb} [min]
1	1	13	30	-17	20
	2	-17	30	13	30
	3	10	50	-10	50
	4	-17	20	10	50
	5	-9	40	11	45
	6	11	45	-9	40
2	1	-17	20	8	70
	2	8	70	-17	20
	3	13	30	-15	25
	4	-15	25	13	30
	5	-10	50	12	35
	6	12	35	-10	50

Table C.2: Conventional Generation Unit Definitions

Unit	P^{max} [MW]	P^{min} [MW]	R^{max} [MW/min]	C^{up} [€/Mwh]	C^{down} [€/Mwh]
1	30	-30	3	11.51	9.32
2	40	-40	2	15.57	12.18
3	60	-60	1	28.56	23.87
4	70	-70	7	22.64	18.93

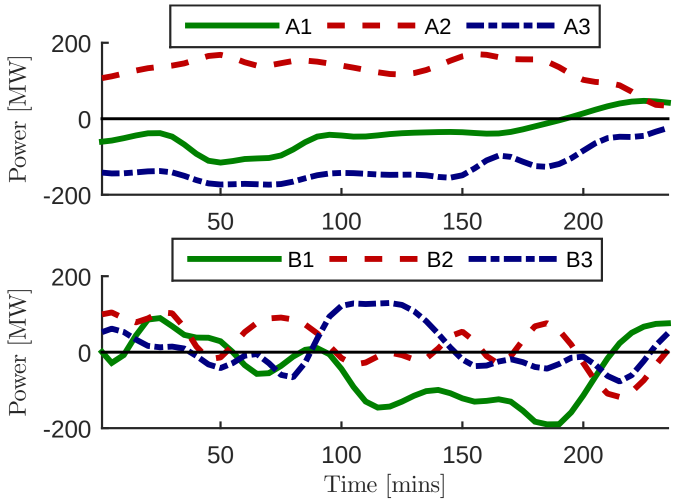

Figure C.5: Regulating power profiles - smooth (Case A - upper) and fluctuating (Case B - lower).

in the case study. This scaling can be interpreted to represent a homogeneous population of 1000 individual supermarkets. The cost of acquiring up- and down-regulation from the demand response units is set at €2/MWh. This is less than the cost of sourcing regulating power from any of the conventional units, ensuring that the demand response resource will be first in the merit order.

Four conventional generating units are considered in the case studies. Table C.2 contains the technical specifications of each unit and the costs of acquiring up- and down-regulation from each. These costs are based on the production cost of each unit, where the up- and down-regulating costs are the production costs multiplied by a factor greater than and less that one respectively. The scaling factors are found through an analysis of the difference between the day-ahead price on the Nordic power market and the up- and down-regulating prices [C13].

Six regulating power profiles are employed in the case studies to evaluate the demand response resource, as shown in Fig. C.5. Case A comprises 3 slowly varying profiles, while Case B comprises 3 fluctuating profiles, each is a historic time series of activated regulating power on the Elia power system, as detailed above. It is expected that the demand response blocks will have greater value in situations where the regulating power requirement fluctuates significantly due to their asymmetric shape and the large effective ramp rate between the response and rebound portions of the block. The two sets of regulating power profiles are considered for comparison. It is the experience of the authors from sourcing these profiles from historic data that Case B is more representative than Case A of typical operating conditions on the Elia power system.

C.6 Results and Discussion

The case study results are presented in Tables C.3 and C.4. The theoretical value of demand response is defined as the amount by which the cost of meeting regulating requirements is reduced when demand response is represented using a fully observable and controllable model. This is compared to the practically accessible value that this resource can provide to the system when represented by a limited set of blocks. It is evident that demand response is capable of providing substantial value to the system, and as expected there is a significant difference between the theoretical and practical resources.

This difference is due to two key factors. Firstly, the block definition imposes the need for a response and rebound that directly follow one another. This differs from the operation using the full model of the refrigeration system, where the only restriction is that an approximate energy balance is maintained (as imposed with a final temperature constraint). This allows the response and rebound to be separated. Consequently, the flexible demand unit has greater flexibility to follow the regulating power profile rather than requiring a rebound which may be in the opposite direction to the required regulating power. Secondly, the block definitions are formulated using the 50% saturation curve, which has an effective temperature range of approximately 50% of the full range using the absolute limits imposed by the supermarket operator. In comparison, the fully modelled demand resource is free to employ the full temperature range, resulting in greater overall flexibility. Imposing tighter temperature limitations on the fully modelled resource allows the comparison of the value of both the block definitions and the full model when they are operating with the same physical flexibility. This comparison is included in the last row of Table C.4, where it is observed that the disparity between the two forms of demand response is significantly reduced. This indicates that a very limited representation of the demand response capabilities of this thermal system has comparable value to a fully described system. The cost of establishing, controlling, monitoring and operating a fully modelled system is very high, and this result indicates that such a cost may not be justified by the additional value it brings to system operation.

Comparison of Tables C.3 and C.4 reveals that there is a greater disparity between the theoretical and practical values when the regulating power profiles vary slowly, as in Case A. Analysis of the behaviour of the fully modelled units in Cases A1-A3 reveals that they tend to provide both response and rebound in the prevailing direction of the regulating power profile. In contrast, when the demand response behaviour is limited to the asymmetric block offer structure, a rebound is necessary immediately following the response. This must be compensated for by conventional units if the rebound is in the opposite direction to the required regulating power. Consequently, scheduling blocks for slowly varying regulating profiles is either very costly, or the blocks are not scheduled at all. This is confirmed in Table C.3, where a larger difference between the theoretical and practical values is observed in case A1 than in any of the B cases, and in case A3 where the value of demand response described using blocks is negligible. In case A2, the demand response is incapable of bringing any significant value to the system, regardless of the resource description used. This is because the regulating power requirement is very high so the percentage contribution from demand response is lower than in the other cases.

Table C.4 presents the cost reductions for regulating power procurement when the demand response resource is represented with a varying number of blocks. For cases with less than 6 blocks, the blocks are taken in order from Table C.1. It can be concluded from Table C.4 that the value of the demand response resource when described using block offers approaches the value of the fully modelled resource as the numbers of block offers increases. In fact, if the flexibility of the demand response resource were described using an infinite number of block offers, it would be equivalent to the flexibility described by the fully modelled system.

It is shown in Table C.4 that in some cases, increasing the number of blocks has no impact on costs. This is because the additional block offer is not selected for dispatch, and can be understood to be unsuitable for the considered regulating power profile. The results of this analysis reveal that cost savings greater than 20% can be achieved with only four block offers. This demonstrates that even a very limited representation of the flexible demand resource facilitates significant cost savings.

Fig. C.6 illustrates the aggregate dispatch of the generating and demand response units for case B1. The most beneficial behaviour in terms of system dispatch cost would be for the demand response blocks to reduce the power pro-

Table C.3: Cost Reduction with Demand Response - Case A

	A1	A2	A3
6 DR Block Offers	10.53%	4.14%	0.1%
Fully Modelled Demand	36.63%	4.88%	11.36%

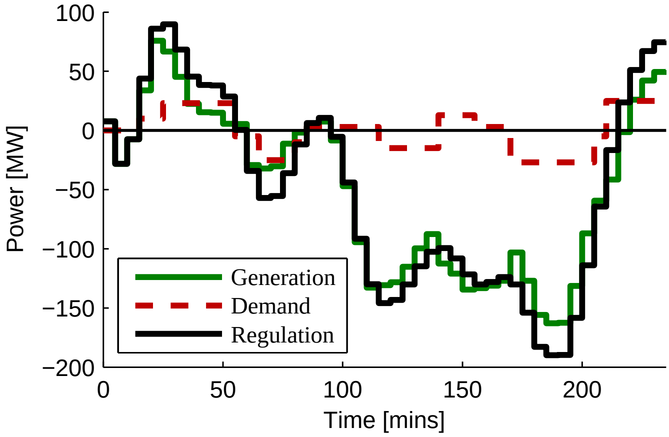

Figure C.6: System dispatch of conventional and demand response units for the provision of regulating power - Case B1.

vided by generating units. This behaviour is observed for the majority of the dispatch horizon, however there are brief periods where the generating units are required to compensate for the rebound of the demand response units. This can be observed during the interval between minutes 145 and 160. During this interval, one of the demand response units is rebounding in the opposite direction to the required regulating power and the generating units must provide additional down-regulation. From minute 165, the second demand response unit begins providing down-regulation which partially compensates for the rebound of the first unit and reduces the over-provision from the generating units. Despite this need for compensation, the demand response blocks offer significant value to the system when optimised for cost minimisation. In the case of a volume-based optimisation, this form of demand response may not be attractive.

Table C.4: Cost Reduction with Demand Response - Case B

	B1	B2	B3
2 DR Block Offers	9.54%	18.10%	19.70%
3 DR Block Offers	17.10%	23.42%	21.25%
4 DR Block Offers	20.81%	23.42%	25.13%
5 DR Block Offers	21.23%	23.43%	25.13%
6 DR Block Offers	21.43%	23.63%	26.00%
Fully Modelled Demand	36.78%	41.8%	43.44%
Limited Temperature Range	24.45%	28.72%	34.22%

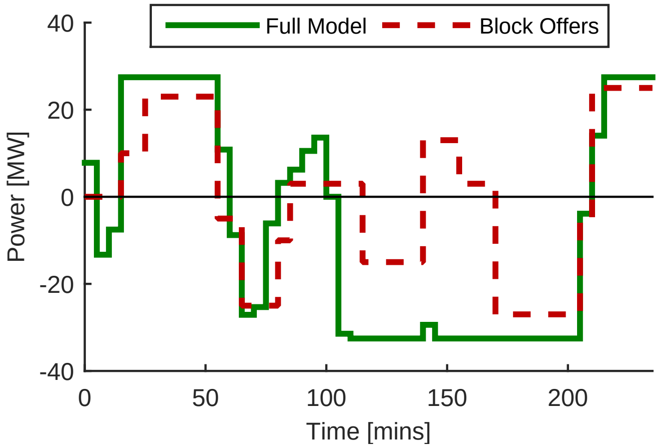

Figure C.7: A comparison of the dispatched aggregate demand response resource in case B1 when considering block bids and the fully modelled resource.

Fig. C.7 illustrates the dispatch of the demand response blocks and the fully model resource for case B1. It is evident that the demand response blocks attempt to replicate the behaviour of the fully modelled resource where they can. The key difference occurs between minutes 110 and 210 where the fully modelled system is capable of providing down regulation continually, whereas the demand response blocks have to alternate between response and rebound. This is due to the wider effective temperature limits in the fully modelled case.

C.7 Conclusion

This paper presents a method of representing the physical capabilities of flexible loads in the system dispatch algorithm at a comparable level of complexity to conventional generating units. A novel system dispatch algorithm is developed that schedules demand response units using asymmetric block offers that encompass both the response and rebound that are exhibited by flexible loads. Such block offers are limited in that they describe a subset of the capabilities of the demand response resource, but have the advantage that they are compatible with current system dispatch and market clearing algorithms.

Case studies have demonstrated that demand response from supermarket refrigeration systems, as described using a limited set of block offers, is capable of achieving substantial cost savings in the procurement of regulating power. The value of the demand response resource, as described using block offers, is compared to the theoretical value that could be achieved if it were possible to include a fully observable and controllable model of each flexible load within the system dispatch algorithm. The disparity between the theoretical and practical values is found to be relatively low, which indicates that significant costs involved in establishing the theoretical framework may not be justified by the additional value it may yield. It is important to note that this work is not intended to prove the value of demand response from supermarket refrigeration, or any other form of demand response. The objective rather, was to develop a methodology of scheduling demand response that is applicable to all forms of flexible loads capable of providing load-shifting. The flexibility of any thermal-electric load can be described in the form of a saturation curve, from which asymmetric block offers can be obtained, and scheduled in the manner described in this work.

In this work the characteristics of the demand response resource have been established through simulations, however going forward it would be advantageous to explore analytical approaches to this characterisation. Further more, it will be beneficial to investigate methods to reduce the computational effort required to optimally dispatch demand response block offers, which require binary variables that are computationally burdensome for large scale implementation. A continuation of this research agenda should also consider uncertainty in both the achievable demand response, and the resource which it is providing, be that regulating power or another power system service.

Acknowledgements

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Paper D

On the Inclusion of Energy-Shifting Demand Response in Production Cost Models: Methodology and a Case Study

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On the Inclusion of Energy-Shifting Demand Response in Production Cost Models: Methodology and a Case Study

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Abstract

In the context of future power system requirements for additional flexibility, demand response (DR) is an attractive potential resource. Its proponents widely laud its prospective benefits, which include enabling higher penetrations of variable renewable generation at lower cost than alternative storage technologies, and improving economic efficiency. In practice, DR from the commercial and residential sectors is largely an emerging, not a mature, resource, and its actual costs and benefits need to be studied to determine promising combinations of physical DR resource, enabling controls and communications, power system characteristics, regulatory environments, market structures, and business models. The work described in this report focuses on the enablement of such analysis from the production cost modeling perspective. In particular, we contribute a bottom-up methodology for modeling load-shifting DR in production cost models. The resulting model is sufficiently detailed to reflect the physical characteristics and constraints of the underlying flexible load, and includes the possibility of capturing diurnal and seasonal variations in the resource. Nonetheless, the model is of low complexity and thus suitable for inclusion in conventional unit commitment and market clearing algorithms. The ability to simulate DR as an operational resource on a power system over a year facilitates an assessment of its time-varying value to the power system.

The modeling methodology is demonstrated through a case study of aggregated supermarket refrigeration systems providing balancing energy reserves in real-time markets at different levels of variable generation (VG). This DR resource is implemented in a test power system that represents a subset of the U.S Western Interconnection

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centered on Colorado. The value of DR from the population of supermarkets in Colorado is found to be \$32.85 per kilowatt-year (kW-yr) presuming no other DR resources. The value decreases significantly (to \$6.95/kW-year in the most extreme case) when we increase the capacity of the DR resource to naïvely represent the incorporation of DR from other flexible loads (in actuality, other DR resources will have different characteristics, such that the decrease in value will not be as steep). Refrigeration DR is found to offer greater value to the power system during the winter months than the summer months due to operational constraints that limit the flexibility of the resource during the summer. The value of DR is found to increase as the penetration of VG increases, reaching \$46.05/kW-year for our baseline DR penetration and a variable generation (VG) penetration of 55%. We do see a plateau in the value of DR going from 45% to 55% VG. This is attributable to the inability of DR to provide energy storage on horizons longer than 24 hours.

Overall, this work is a study in methodology. The case study is included primarily to show that the model is working properly and that this line of research is worthwhile. The reported numbers do not represent a true value of DR, but they do suggest orders of magnitude for a particular DR resource providing a particular grid service in a particular power system; they also confirm expected correlation directions between value and DR penetration (decreasing) and between value and VG penetration (increasing). Future work includes extending this method and developing new methods to be able to model physically realistic DR resources at scale. Some important aspects not studied here include capturing all possible value streams for a single resource (capacity, energy, and ancillary service values), simultaneously evaluating DR from multiple resources, and economically competing DR resources based on their costs of enablement and the trade-offs between end-user disutility and participation payments.

D.1 Introduction

The structures of future power systems are uncertain. Several common objectives have emerged, including the accommodation of high penetrations of renewables, increased economic and resource efficiency, and the maintenance of current reliability standards; yet, there is no consensus on how best to achieve these objectives. Across most future scenarios being explored in large-scale integration studies, the need for operational flexibility emerges as a common theme [D1], [D2]. Flexibility can be realized on both the supply and demand side, and even within transmission networks. The focus of this work is the modeling of energy-shifting demand response in production cost models.

Demand response (DR) is a broad term that encompasses all manners in which end-use electrical load can be altered to support the operation of the power system. It covers a range of time-scales and services, from frequency regulation, to load shifting on an hourly scale, and further on to long-term capacity provision and end-use efficiency improvements. At all of these scales, there is a general lack of accurate models depicting how DR will participate in the bulk power system. Thus, while DR appears to be a promising candidate for providing power system flexibility, its true value is as yet unknown.

Recent work has shown how DR might be incorporated into large-scale integration studies, and thus competed against other energy resources on both a capacity and an operational basis [D3], [D4]. The framework developed by Hummon et al. is based on DR resource data estimated using a top-down approach that applies time-varying fractional estimates of sheddability, controllability, and acceptability, to aggregate power consumption data broken down by end-use [D5]. The work described in this report complements that earlier work by developing a methodological framework for bottom-up analysis of load-shifting DR from thermal-electric loads (e.g., air conditioning, water heating, heat pumps and refrigeration). For these loads in particular, it is difficult to model the physical characteristics and constraints of the underlying end-use accurately from a top-down perspective. We thus seek to more accurately model resource availability and constraints through the use of dynamic models of individual loads while respecting the mixed-integer programming (MIP) complexity of representation allowable in a conventional unit commitment algorithm. The methodology is demonstrated on the motivating example of supermarket refrigeration, which, from the perspective of DR, has the positive characteristics of high thermal mass, and potentially low enablement costs (e.g. based on large-scale rollout across an entire supermarket chain).

A wealth of research addresses DR, yet the body of work concerned with establishing models suitable for its practical implementation in large-scale power system studies is limited. Many authors consider implementing detailed state-space or time-series models of flexible load directly within system dispatch algorithms [D6], [D7]. This approach provides an assessment of the theoretical value that DR would provide if its flexibility were fully accessible, but the complexity of this representation of DR renders it impractical. System operators do not have the ability to manage many thousands of devices, each on the scale of a few kilowatts (kW). The value of this modeling approach for an integration study is also limited as the complexity involved precludes the assessment of the resource over the temporal and geographical scales of interest. Another commonly adopted approach is to represent the price responsivity of load through an elasticity value [D8], [D9]. The simplicity of this approach is appealing; however, it has been demonstrated that the elasticity value of electrical demand is highly variable and exhibits no correlation with the price of electricity [D10]. This holds particularly for thermal-electric loads that exhibit storage properties and non-linear losses, such as those loads used for load shifting. Furthermore, there are concerns that if the price responsivity of loads can be activated, operating large quantities of price-responsive DR could introduce instability into the power system [D11], [D12].

Of the works that directly discuss DR models suitable for an integration study, Zerrahn and Schill [D13] present the most promising approach. In [D13], load shifting is modeled similarly to a battery, with a limitation on the time span over which load shifting can occur. The work presented here expands upon that work by offering a more flexible definition of the services provided to the power system by the DR resource, and by elaborating on how the seasonal characteristics of the resource affect its flexibility. Other works that investigate models of DR suitable for integration studies include [D14], which focuses on the provision of frequency regulation from residential loads. Hao et al. [D14] support the objective of this work by highlighting the importance of developing a compact aggregate representation of the flexibility of loads that characterizes the set of behaviors achievable while respecting the constraints of the constituent loads. Marzooghi et al. [D15] model DR in combination with solar PV and storage at the transmission level. They employ a generic model of DR that has a similar structure to a battery model, but they do not elaborate on how the parameters used can be related to the physical characteristics or constraints of the underlying end use.

The work described here deviates from previous research by developing a modeling methodology for load-shifting DR that incorporates the physical characteristics and constraints of the individual end-uses within the aggregate population flexibility model. The methodology considers the seasonal variations in the resource, which have had limited treatment in previous works, an exception being the work of Hummon et al. [D4] where the seasonal variation in the DR resource is incorporated directly in the top-down resource description. The developed population model is of comparable complexity to that described in [D13], [D15], but it offers a greater scope of flexibility, allowing multiple DR products to be offered from a given flexible load population. The model is demonstrated through a case study in which DR is implemented on a test power system that resembles that of Colorado and Wyoming, using PLEXOS, a commercial production cost modeling tool. The case study simulations span a year and facilitate analysis of the seasonal variations in the DR resource.

This work focuses solely on load-shifting DR. It is acknowledged that flexible loads are capable of providing a range of power system services including reserves and contingency, and the decision to focus on load-shifting DR was due to the complexity of this form of DR and the ability to derive a representation of other services from a load-shifting model. The representation of load shifting in a power system model is more complex than that of, for example, contingency due to the necessity of balancing any response from the flexible load with an energy recovery. The coupling of response and recovery ensures that the local operating conditions return to their normal operating level following the DR event. The load-shifting DR model fully characterizes the flexibility of the resource and consequently also facilitates the characterization of the resource available for the provision of contingency and other ancillary service support. Another reason for the focus on load shifting is that its participation in the power system can be easily understood within the framework of existing day-ahead, balancing, or real-time markets, where the system operator is free to dispatch the DR resource within its declared constraints. In comparison, the requirements for DR providing contingency services are not well defined. This is particularly the case for thermal-electric loads where a recovery is necessary following a response. There are no clear guidelines for how this recovery should be treated if thermal-electric loads participate in contingency support, and it is possible that these flexible loads would be precluded from contingency services due to the necessity of energy recovery.

The DR model developed in this work represents the resource as seen at the interface between the aggregator/retailer and the system/market operator. No consideration is given to how the resulting dispatch will be distributed among the constituent flexible loads in the DR population. A significant body of work discusses the scheduling of individual flexible loads; for examples see [D16], [D17]. Given that the physical constraints of the individual loads are reflected in the population model, it is assumed that any dispatch within those constraints can be achieved by a separate control framework at the interface between the aggregator and the device using established methods.

D.2 Preliminaries

D.2.1 Conventions and Terminology

In this report, any references to the power adjustments that occur during a DR event are taken from the perspective of the power system. When power is supplied to the power system, this is a positive quantity that corresponds to a reduction of load, while power drawn from the power system is a negative quantity representing an increase in load.

The DR resource modeled here is considered to be comprised of two quantities: the base load and the flexible load. The base load is the consumption required to maintain normal operating conditions and is included in the conventional system load. The flexible component of the load is the adjustment away from this baseline. The flexible load is offered to the system operator as a product to be dispatched alongside conventional power system resources.

A DR event consists of a response followed by a recovery. This terminology does not have any implications for the direction of the response or recovery. A DR event can commence with either a supply of power to the system or a draw of power from the power system. At the device level, this translates to a DR event commencing with either a shed of load or pre-cooling/pre-heating.

D.2.2 Running Example: Supermarket Refrigeration

The research described here builds on previous work by the authors wherein a time series model of a supermarket refrigeration system was identified using experimental data from a refrigeration test center [D18, D19]. This time series model facilitated the simulation of the refrigeration system behavior during DR events, and thus informs the DR population model described in this work. The example figures shown in Section 3 are built using the time series model that was developed in our previous work, and refer to the behavior of flexible refrigeration. The characteristics exhibited in these figures can be found across all types of flexible thermal-electric loads, though with different levels of flexibility and coupling with the environment.

D.3 Characterizing Thermal-Electric Load-Shifting Demand Response for Power System Studies

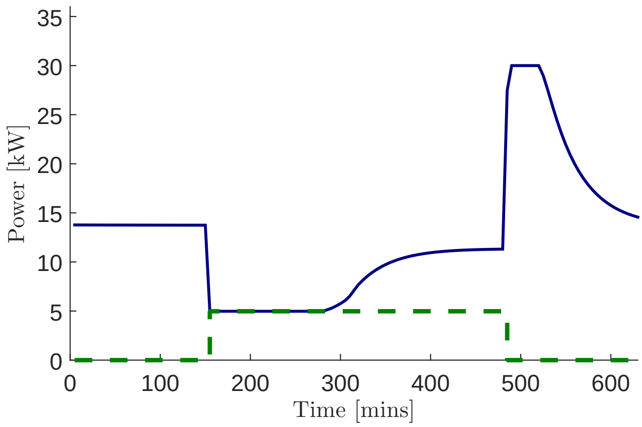
Many thermal-electrical loads share key characteristics that make them ideally suited to providing load-shifting DR. The flexibility to operate within an acceptable temperature range and the dynamic interaction between electrical input and heat output mean that power consumption can be shifted in time while maintaining acceptable operating conditions. Such thermal loads include heating, cooling, and refrigeration, and can be found in residential, commercial, and industrial settings.

The analogy of a battery is often employed to describe load-shifting DR in power systems due to the energy storage that occurs during load shifting [D20, D21]. However, there are several distinctions between batteries and appliances capable of load shifting.

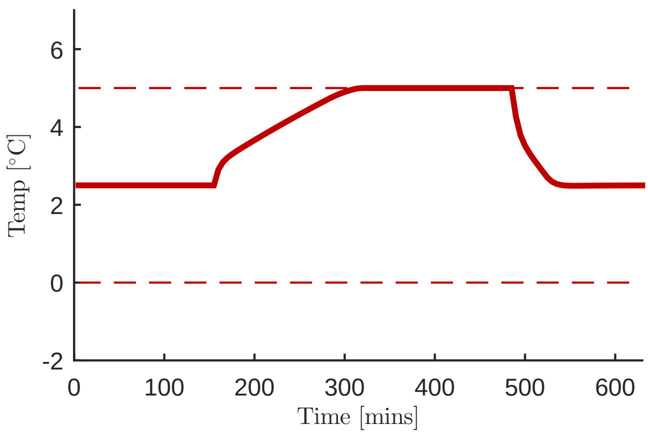
D.3.1 Characterizing Demand Response through the Saturation Curve

The primary distinction between a battery and load shifting is that while a battery contains a fixed energy volume, the amount of energy stored or dissipated through load shifting is non-linearly dependent on the magnitude of the adjustment in power consumption. The ability of flexible loads to adjust their power consumption is limited by constraints at the device level that ensure the controlled temperatures do not deviate from an accepted range; these are often called comfort or operational limits. Thus, the response provided by a flexible load is said to saturate once a temperature constraint becomes binding and the adjustment in power consumption can no longer be maintained.

The phenomenon of response saturation is illustrated in Figure D.1a and Figure D.1b, which illustrate the behavior of a refrigeration unit when it is required to follow a power consumption reference. Figure D.1a shows that the power consumption is steady until it is required to reduce from 14 kW to 8 kW. The reduction of 6 kW can be maintained until the temperature in the refrigeration system reaches its upper bound (as seen in Figure D.1b). Once the upper temperature limit is reached, the prescribed reduction can no longer be maintained, at this point it is said that the response has saturated. When the power reference is no longer active, the system will recover the energy lost during the response event by increasing consumption to the maximum allowable level such



(a) Power consumption in refrigeration system when required to follow a power reference (dashed green line, active when non-zero)



(b) Temperature in the refrigeration system, subject to upper and lower limits (dashed red lines)

Figure D.1

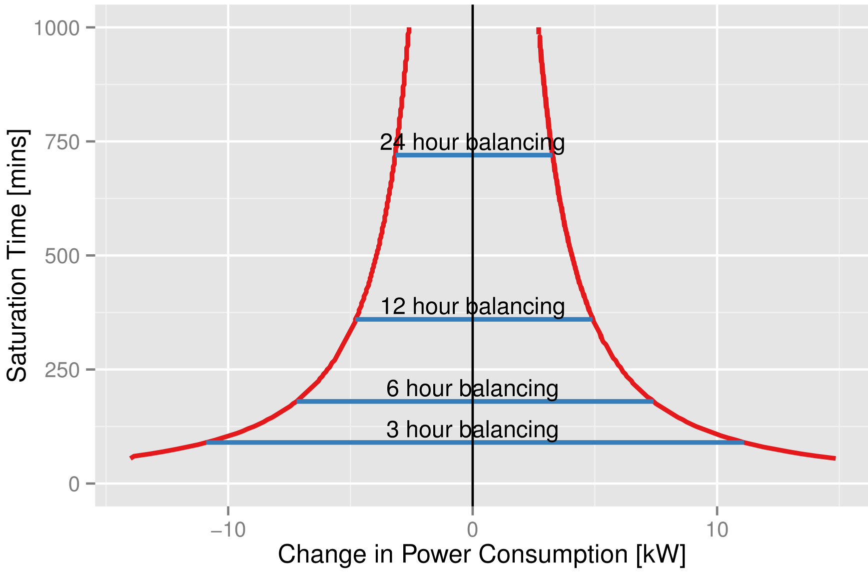


Figure D.2: Saturation curve of a sample refrigeration system as seen from the power system perspective

that all the compressors on the system are operating to bring the case temperature back to the normal operating conditions, that is, following a temperature set-point as shown in Figure D.1b. This recovery is seen in Figure D.1a when the power reference returns to zero. Note that in this case, the consumption at 14 kW is the baseline consumption, and the deviation of 6 kW is the response provided to the power system.

Figure D.2 describes the maximum flexibility of a load-shifting device in the form of a saturation curve, which illustrates the relationship between a power adjustment in a flexible load and the duration for which the adjustment can be maintained. This curve applies to a particular flexible resource or population of resources at a particular time or under a particular set of environmental conditions. Any adjustment in consumption on one side of the saturation curve (a response) must be combined with an adjustment in the opposite direction as found on the other side of x-axis (a recovery) to complete the DR event. This ensures that the energy deviation caused by a response is corrected through a recovery. The combination of a response and recovery, possibly separated by some period of time, form a DR event. The energy stored or dissipated during this response can be calculated as the factor of the magnitude of the power adjustment and the duration for which it is maintained.

The saturation curve provides valuable insight into the capabilities of a single load-shifting appliance, and it can similarly be employed to describe the capabilities of a population of similar appliances. For a homogeneous population of flexible loads, an aggregate saturation curve can be found through simple summation along the power axis. It is intuitive that a group of N identical appliances can maintain an adjustment in power consumption of Nα kW for the same duration as a single appliance can maintain an adjustment of α kW. For a heterogeneous population, one can cluster appliances into approximately homogeneous sub-groups and determine an aggregate saturation curve for each. Clustering has been previously employed to represent heterogeneous populations of DR resources in [D6, D14, D22].

While the saturation curve is an effective representation of the abilities of a flexible load, or population thereof, it is not suitable for direct inclusion in a power system model or market-clearing algorithm. The saturation curve represents a large number of combinations of upwards and downwards power adjustments, each for distinct maximum durations. While there is a relationship between each power adjustment and its saturation time, it is a non-linear relationship that cannot be linearized for inclusion in a linear optimization, such as market clearing or unit commitment.

To simplify the saturation curve sufficiently such that the characterization of the DR resource is suitable for inclusion in a unit commitment model, it is necessary to define a subset of abilities within the saturation curve. Figure D.2 illustrates four possible combinations of capacity and duration that a population of load-shifting DR resources could offer into an energy market. The combinations are defined by the period within which the response and recovery must balance. Once that is specified, the maximum upwards and maximum downwards power adjustments can be read off of the saturation curve. Those, along with the balancing period, that is the sum of the saturation times for the maximum upwards and downwards power adjustments, are used to define the DR thermal storage resource within the unit commitment model. Thus, the saturation time (y-axis value) shown for each selection in Figure D.2 is 50% of the DR storage resource's balancing time. Imposing a balancing period ensures that the underlying flexible load returns to an intermediate temperature following a DR event, so that it is prepared for future events. The DR storage resources are mutually exclusive; only one choice of balancing period can be actively dispatched at a time.

D.3.2 Resource Efficiency

A further distinction between load-shifting DR and a battery is that the round-trip efficiency of a DR event is dependent on the magnitude of the response and recovery. In a conventional battery or energy storage device the efficiency is considered constant and independent of the charging/discharging rate.

The efficiency of a load-shifting DR event can be calculated as the ratio of the energy supplied to the power system and the energy drawn from the power system during a DR event.

$$\eta_{DR} = \frac{\sum_{t=1}^{T} \Delta P^{+}}{\sum_{t=1}^{T} \Delta P^{-}}$$

Determining the round trip efficiency of a DR event is non-trivial, as the efficiency depends on the magnitude of both the response and the recovery. Based on the models developed in [D18], the efficiency profile of DR events from a supermarket refrigeration system has been calculated and is shown in Figure D.3. Figure D.3 illustrates the efficiency of DR events that commence with power drawn from the power system (above) and power supplied to the power system (below).The efficiency has been calculated by combining response and recovery events sampled from the saturation curve. The energy associated with each response and recovery has been calculated from the power magnitude and duration of each.

A higher efficiency (>100%) is most desirable, as this indicates that the amount of energy drawn from the power system is less than the energy supplied to the system. It can be observed from Figure D.3 that the efficiency can range between approximately 60% and 180%, depending on the magnitude of the response and recovery. Events in which the power supplied to the power system are small but sustained for a long time, and the power drawn is large but over a short time, exhibit the highest efficiencies.

This can be understood by considering our running example of a refrigeration system. A power draw from the power system to the refrigeration system reduces the temperatures within the refrigeration system and consequently increases the losses to the system. A prolonged power draw will result in a slow reduction in temperature and large energy losses, requiring more power be drawn from the grid and consequently reducing the efficiency of the DR event. In contrast, a large power draw will reduce the temperature rapidly and can only be maintained for a short period due to saturation. This behavior results in reduced losses to the ambient and improved DR efficiency.

Symmetric events (where response and recovery have the same magnitudes) tend to exhibit an efficiency of just below 100%. The efficiency of symmetric events is indicated in Figure D.3 by the yellow line, while the 100% efficiency contour

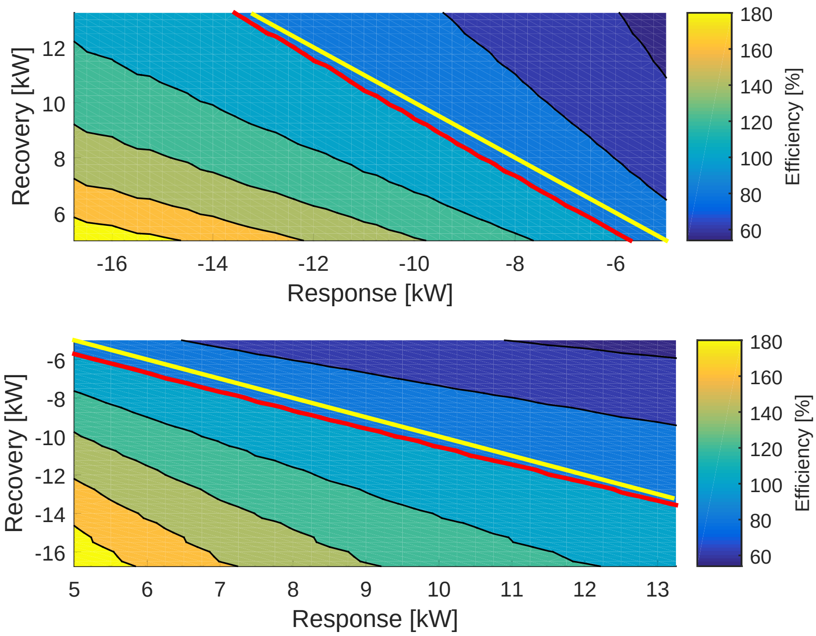


Figure D.3: Round-trip efficiency of a DR event. The red lines show the 100% efficiency contours and the yellow lines show the efficiency of symmetric events (i.e., a response and recovery of the same power magnitude).

is indicated in red. It can be observed that while the efficiency of a symmetric event is close to 100%, it does not exhibit a fixed offset from the 100% efficiency contour and is dependent on the magnitude of the response and recovery.

We did not consider the possible variation in the efficiency with changing environmental conditions because requisite data were not available. This is a possible topic for future research.

D.3.3 Seasonality in the Demand Response Resource

When considering thermal end-end uses for the provision of load-shifting DR, there are three key characteristics to consider; the baseline power consumption, the maximum possible power consumption, and the energy required to achieve a given temperature change. These quantities are influenced by several environ-

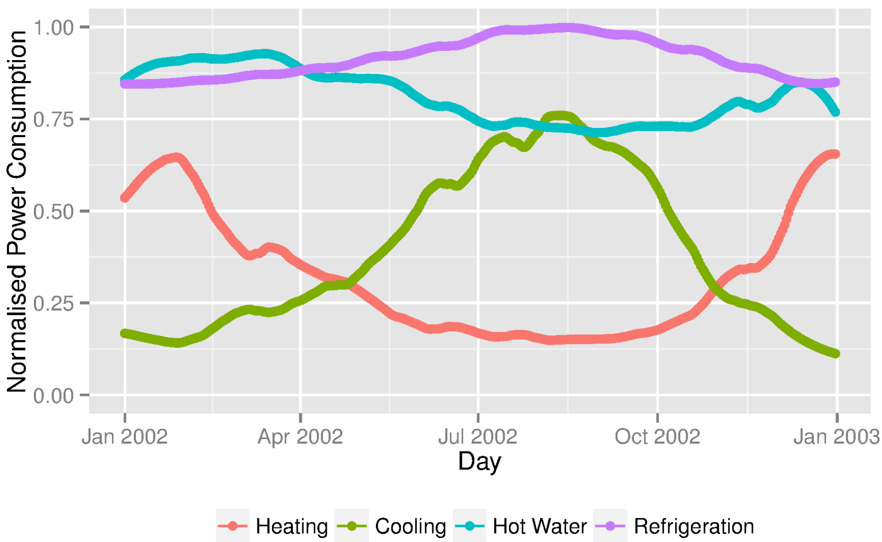


Figure D.4: Normalized consumption of electrical end uses suitable for load shifting[4]

mental factors—primarily the ambient temperature—but also occupancy and typical building operating hours, among other factors.

The baseline power consumption defines the amount of power consumption that can be shed as part of a DR event. Figure D.4 illustrates the normalized power consumption of a number of thermal end uses over a year. The data are sourced from the California Commercial End-use Survey (CEUS) [D23], which recorded hourly power consumption of commercial loads in California throughout 2002. The dependence of the baseline consumption on the ambient temperature can be clearly seen in Figure D.4. For heating and cooling, this variation in consumption is attributable to both the effect of ambient temperature on the performance of the appliance, and the reduced use of cooling devices in the winter and heating devices in the summer. For refrigeration and hot water, the usage is steady year-round, but the impact of the ambient temperature on appliance performance can be seen. It is tempting to conclude that the couplings of refrigeration and hot water heating, and of cooling and heating are well suited to act together to provide a DR resource with stable availability over the year; however, the significant differences in magnitude reduce their complementarity.

[4]Data have been smoothed and normalized to facilitate the analysis of the seasonal tendencies of each end use without considering their individual magnitudes. Intra-day variations

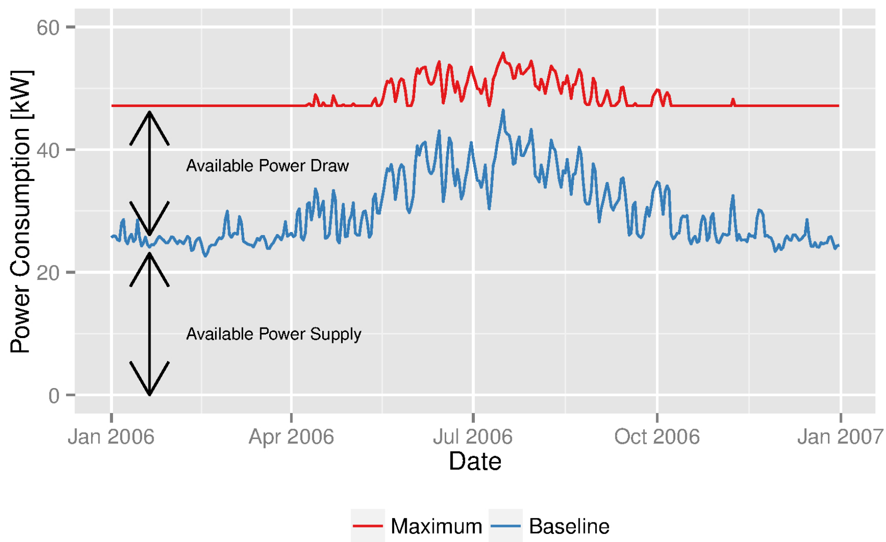


Figure D.5: Variations in available flexibility at the device level, using the example of supermarket refrigeration

The difference between the baseline power consumption and the maximum possible power consumption defines an upper limit on the power that can be drawn from the power system during a DR event. Figure D.5 illustrates the baseline and maximum power consumption for the refrigeration system used in the running example in this work. Due to the characteristics of the compressors on the refrigeration system, this maximum power consumption increases during the summer. Details on the derivation of the maximum and baseline consumption are provided in Section D.5.1. It can be seen that the baseline consumption peaks during the summer, indicating an increase in capacity available to supply power to the power system. However, the difference between the baseline and maximum consumption is minimized during the summer. This means there is a reduced ability to recover energy during a DR event, which possibly limits the value this DR resource offers the system during the summer months.

The energy required to achieve a given change in temperature also varies over the year for a number of thermal end-uses. The coefficient of performance

in the power consumption profiles cannot be seen in the illustrated data, as they have been averaged out in the smoothing process. Normalization is relative to the maximum daily power consumption, the proximity of the illustrated profiles to 1 indicates the level of intra-day variations in the data.

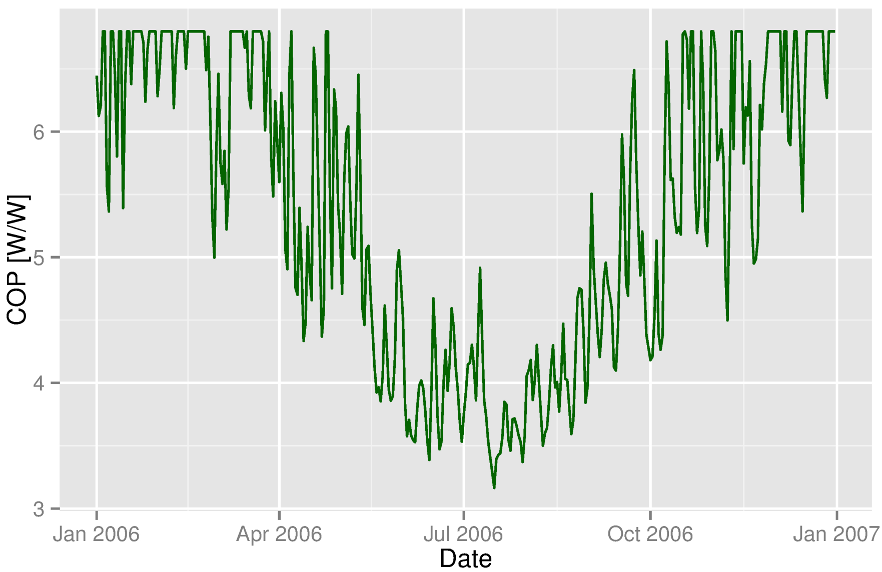


Figure D.6: Variations in compressor COP over a year

(COP) is a temperature-dependent quantity that defines the relationship between power consumption in a thermal appliance and the resulting thermal energy. At high COP values, a smaller amount of power consumption will be necessary to achieve a given temperature change. This affects the definition of a DR product by varying the maximum response and recovery power for a product with a fixed balancing time. Figure D.6 illustrates the COP of the refrigeration system employed as the running example in this work. The COP of this system is maximized during the winter months, indicating less response and recovery power will be offered in the DR products during the winter.

D.4 Mathematical Representation of Demand Response Resource

Though Section D.3 described the differences between load-shifting DR and a battery, their similarities are sufficient to use a battery or conventional electrical storage formulation to represent the load shifting resource in a power system model. This section details the theoretically optimal mathematical formulation for this resource, as well as a simplified representation suitable for inclusion in commercial production cost modeling software. The mathematical formulation describes the constraints on a DR resource offered by a population of flexible loads. Each resource offered consists of a maximum amount of power supplied to or drawn from the power system, and a period over which the power supply and draw must balance. Examples of products are illustrated in Section D.3.1.

D.4.1 Theoretically Optimal Formulation

The load-shifting DR event consists of a combination of power supplied to and drawn from the power system. At the device level, this is seen as a deviation in power consumption from a time-varying baseline. Equation (D.1a) describes the power supplied to the power system, ΔP_t^+, and the power drawn from the power system, ΔP_t^-, as the difference between the baseline power consumption of the population of flexible loads, P_t^{BASE}, and its actual consumption, P_t^{DR}. Both ΔP_t^+ and ΔP_t^- are positive variables; thus, when the actual consumption of the population of flexible loads is less than its baseline, power is supplied to the power system and ΔP_t^+ is non-zero. Similarly, when the actual consumption exceeds the baseline, power is drawn from the power system and ΔP_t^- is non-zero. The baseline power consumption is not considered part of the load shifting resource; it is assumed to be served as part of the conventional load.

$$\Delta P_t^+ - \Delta P_t^- = P_t^{\mathrm{BASE}} - P_t^{\mathrm{DR}} \tag{D.1a}$$

$$0 \leq \Delta P_t^- \leq \Delta P_t^{-,max} u_t \tag{D.1b}$$

$$0 \leq \Delta P_t^+ \leq \Delta P_t^{+,max} u_t \tag{D.1c}$$

Equations (D.1b) and (D.1c) include the binary variable u_t, which is employed to indicate whether a DR product is active. The necessity of this variable is clarified below.

The storage characteristics of the load shifting resource are described below.

$$S_t = S_{t-1} + \left(\Delta P_t^- - \frac{\Delta P_t^+}{\eta^{\text{DR}}} \right) \Delta t \tag{D.2a}$$
$$S_t \leq S^{\text{Balance}} + \Delta S^{+,max} \tag{D.2b}$$
$$S_t \geq S^{\text{Balance}} - \Delta S^{-,max} \tag{D.2c}$$
$$\Delta S^{+,max} = \sum_{t \in \text{Balance}} \Delta P^{-,max} \Delta t \tag{D.2d}$$
$$\Delta S^{-,max} = \sum_{t \in \text{Balance}} \Delta P^{+,max} \Delta t \tag{D.2e}$$
$$S_t - S^{\text{Balance}} \leq M.u_t \tag{D.2f}$$
$$S_t - S^{\text{Balance}} \geq -M.u_t \tag{D.2g}$$

Equation (D.2a) describes the stored energy, S_t, as a function of the inflow to and outflow from the storage device, where Δt is the interval. The stored energy has no direct physical relationship with the underlying flexible load. The storage analogy is simply employed to indicate that the energy level returns to the balance point, S^{Balance}, when the energy supplied and drawn from the power system balance. The value of S^{Balance} is arbitrary, but must be sufficiently large that maximum energy outflow over the balance window does not exceed S^{Balance}. If this is not considered, the lower bound on the storage volume (i.e. zero) may become binding. The lower and upper bounds on the storage device are given in equations (D.2b) - (D.2e), which describe the maximum possible energy deviations from the balance level over the balance window for a given DR resource configuration.

The parameters constraining the behavior of the DR resource, $\Delta P^{+,max}$, $\Delta P^{-,max}$ and P_t^{Base} are time-varying to reflect the change in available DR resource and the variations in the underlying flexible load over the year.

Equations (D.2f) and (D.2g) are coupled constraints used to indicate when the storage level is not at the prescribed balance point. When the stored energy deviates from the balance point, the binary variable, u_t, becomes non-zero. M is an arbitrarily large number that ensures the constraints are non-binding when u_t is non-zero.

The load-shifting product is considered to be online when either power is supplied or drawn from the power system, or when the stored energy is different from the prescribed balance level. When a product is online $u_t = 1$.

$$\sum_{t'=t}^{t+T^{\text{Balance}}} u_{t'} \leq T^{\text{Balance}}, \quad \forall \quad t \tag{D.3}$$

The constraint that the DR product must balance within the prescribed balance window is imposed in equation (D.3), which states that a given product may be online for at most the balance period, T^{Balance}. This ensures the product goes offline once the balance period is exceeded. Requiring that the product be offline consequently imposes that the power supplied to and drawn from the grid during the active period of the product are balanced. This constraint is comparable to a maximum uptime constraint for a conventional generator.

The binary variable employed to indicate the online status of a DR configuration, u_t, can also be used to ensure a given DR resource is not simultaneously offering two configurations to the power system. Each DR configuration allows the maximum use of the resource flexibility, so simultaneous dispatch of multiple configurations would result in the dispatch of services that are not achievable without violating the temperature constraints of the underlying thermal load. If each DR configuration is denoted using the subscript i, each variable in the above equations should be extended to incorporate this additional subscript. The set of DR products is denoted I.

The constraint preventing simultaneous dispatch of DR configuration is given as:

$$\sum_{i \in I} u_{t,i} \leq 1, \quad \forall \quad t \tag{D.4}$$

The use of the binary variable also lends itself to the definition of additional constraints that could be imposed if desired by the aggregator, retailer, or other party responsible for control of the flexible load. One such constraint is an upper limit on the number of DR product activations within a given window:

$$SU_t - SD_t = u_t - u_{t-1} \tag{D.5a}$$

$$\sum_{t \in T} SU_t \leq X \tag{D.5b}$$

Equation (D.5a) defines the startup and shutdown indicators for a given DR product. Equation (D.5b) then limits the number of startup instances over a given period, T, to less than a limit X.

Constraining the number of DR events dispatched within a given period is a useful construct to ensure flexible loads are not inadvertently driven toward unacceptable operating conditions. The concept of linking the response and recovery is intended to ensure the operating conditions (e.g., temperature) return to their initial states following a DR event. This assumption holds if the constant efficiency of the demand response event assumed in the optimization problem formulation is accurate. However, as described previously, the efficiency is dependent on the magnitude of the response and recovery. Including this dependency in a linear programming optimization is not possible, thus a constant value must be selected. By selecting demand response products in which the response and recovery are of equal magnitude, it can be assumed that 100% efficiency is a reasonable approximation (see Figure D.3). However, the DR dispatch algorithm has the freedom to select response and recovery magnitudes below the prescribed maximum levels, which may not be 100% efficient. In such a case, the operating temperatures would not return to their initial levels at the end of the DR event. Initiating a second DR event from this initial point would possibly lead to unforeseen saturation. Limiting the number of events dispatched would allow more time for the flexible load to return to its normal operating conditions outside of the DR event.

The constraints described above have been formulated in an efficient manner for mixed-integer programming using insight acquired from [D24].

D.4.2 Practically Implementable Formulation Suitable for PLEXOS

The constraints described in the Section D.4.1 represent the ideal control of the DR products; however, they are not directly implementable in the selected production cost modeling software, PLEXOS. In particular, equation (D.3) requires the summation of variables over time, which cannot be implemented in PLEXOS.

Equation (D.3) ensures the DR resource will balance within the prescribed balance period following its initialization at an arbitrary time. This can be simplified by instead requiring the DR resources to balance at or prior to a set time. For example, a resource with a three-hour balancing period can be required to balance at 3 a.m., 6 a.m., 9 a.m., and so on.

The variable $u_{t,i}$ is a custom binary variable that is defined in PLEXOS. Each DR product i within each population of flexible loads has an associated binary variable $u_{t,i}$ for each time period t. The constraints detailed in the previous section ensure $u_{t,i}$ is non-zero any time a DR product is online, that is, when it is supplying power to the system, drawing power from the system, or has a stored energy value not equal to the balanced energy value.

D.4.3 Validation of Approach

Implementing the DR resource within PLEXOS requires the constraint simplification described above; however, prior to doing so, it is important to establish the impact of this simplification on the problem solution.

Validation of the constraint simplification has been achieved by comparing the results of a PLEXOS model with simplified DR constraints, and an equivalent model implemented in GAMS with the ideal DR constraints. The General Algebraic Modeling System (GAMS) is a high-level modeling system for mathematical programming problems [D25]. A simple five-bus system model in PLEXOS was replicated in GAMS. The models were validated with and without DR as described by the simplified constraints. Finally, the ideal DR constraints were implemented in GAMS.

The production cost model dispatches the sample five-bus power system on a day-ahead basis over a year. The system contains five thermal generators and no variable renewable generation. Both models use a duality gap of 0.01%. PLEXOS uses the XpressMP solver to determine the model solution, while GAMS uses the CPLEX solver. Table D.1 details the total production cost from the GAMS and PLEXOS implementations with and without DR, and the GAMS implementation with the ideal DR constraints. Differences between the GAMS and PLEXOS solutions are expected due to the different solvers used. A difference of 0.02% in the total production cost is seen between the GAMS and PLEXOS solutions, both with simplified DR constraints and with thermal

Table D.1: Validation of GAMS Model

Model	Total Production Cost ($M)
PLEXOS	158.282
GAMS	158.318
PLEXOS with Simplified DR	157.834
GAMS with Simplified DR	157.799
GAMS with Ideal DR	157.775

generation only. This difference is considered to be within the tolerance for validation. The addition of the ideal DR constraints in the GAMS formulation reduces the cost of production by a further 0.014% compared to the simplified constraints as implemented in GAMS.

The value of DR in this test case is the reduction in total production cost achieved by its implementation in the system. The PLEXOS model reports a cost reduction of 0.282%, while the GAMS model reports savings of 0.33% with the simplified DR representation. Again, the differences can be attributed to differences in the solvers used to generate the solution. The implementation of the ideal DR constraints in GAMS results in total cost savings of 0.34%. Implementation of the ideal DR constraints results in additional savings of 4.52% compared to the simplified DR constraints. While these additional savings are not insignificant, they are sufficiently small that the use of the simplified constraints in PLEXOS can be justified.

In addition to being implementable in PLEXOS, the simplified constraints significantly reduce computation time. A yearlong simulation in GAMS with simplified constraints on a five-bus system has a run-time of 0:07:59, while a simulation with the ideal constraints has a run-time of 0:32:06. Given that these simulations are conducted using a very simple power system model, one would expect the significant difference in computation time to be greatly increased in a larger, more complex system.

D.4.4 Example Operation in a Five-Bus System

Figure D.7 illustrates the results of a small test case run on the five-bus system using PLEXOS. Three DR populations of varying sizes were modeled with four possible balancing periods each, 3-hour, 6-hour, 12-hour, and 24-hour (defined as illustrated in Figure D.2). The system was simulated over a one-week period at hourly resolution to illustrate the operation of the load shifting DR resource. Because the choice of balancing on six-hour intervals was not dispatched in the simulated period it is not shown in Figure D.7.

The upper plot in Figure D.7 shows the electricity price over the simulation period. The higher prices approximately correspond to the periods of peak load during each day. The second plot shows the net load reduction of each DR resource, as defined by the balancing period. By comparing the first and second plots, it can be seen that the DR resource provides net power to the system during periods of higher prices and recovers energy during periods of lower prices.

The differences between the various balancing periods offered to the system are also evident in the second plot of Figure D.7, where the 24-hour balancing period is associated with the lowest power magnitude but is active for a much longer duration than any other resource configuration. The dashed lines represent the power limits on each of the demand response resource configurations. The variations of these limits with ambient temperature can be seen; for example on January 3, the limits are greater than on the other days due to higher ambient temperatures.

When the DR event commences with a supply to the grid (e.g., the first DR event in Figure D.7), at the appliance level the event starts with a shed of load and is followed by a rebound or recovery. When the event commences with a draw of power from the grid, the appliance first undertakes a pre-heating or pre-cooling cycle that pre-charges the thermal storage resource, and only later sheds load to provide energy to the power system. In most cases, the DR event consists of a continuous response followed by a continuous recovery; however, in the first instance of use of the 12-hour balancing period configuration, the DR event consists of a repeated oscillation between supply and draw of power. This is a valid DR behavior that is permitted within the defined characteristics of the DR resource as presented to the grid model.

The impact of the simplified constraints imposed in PLEXOS can also be seen in Figure D.7. For example, the 24-hour balancing period configuration must balance prior to midnight, but it is also possible for the 12-hour balancing period configuration to be active between the time when the 24-hour resource balances and its own balancing deadline occurs, which is also midnight in this case. This can be seen in the repeated pattern from January 4 to January 7.

The third plot in Figure D.7 illustrates the energy volumes involved in each DR event. Here the difference between the DR configurations is again evident, with the longer balancing period exhibiting larger volumes of energy storage. The final plot indicates the online status of each of the configurations offered, illustrating that while the DR resource is presented to the grid model in a multifaceted manner, no two conflicting configurations are ever dispatched simultaneously.

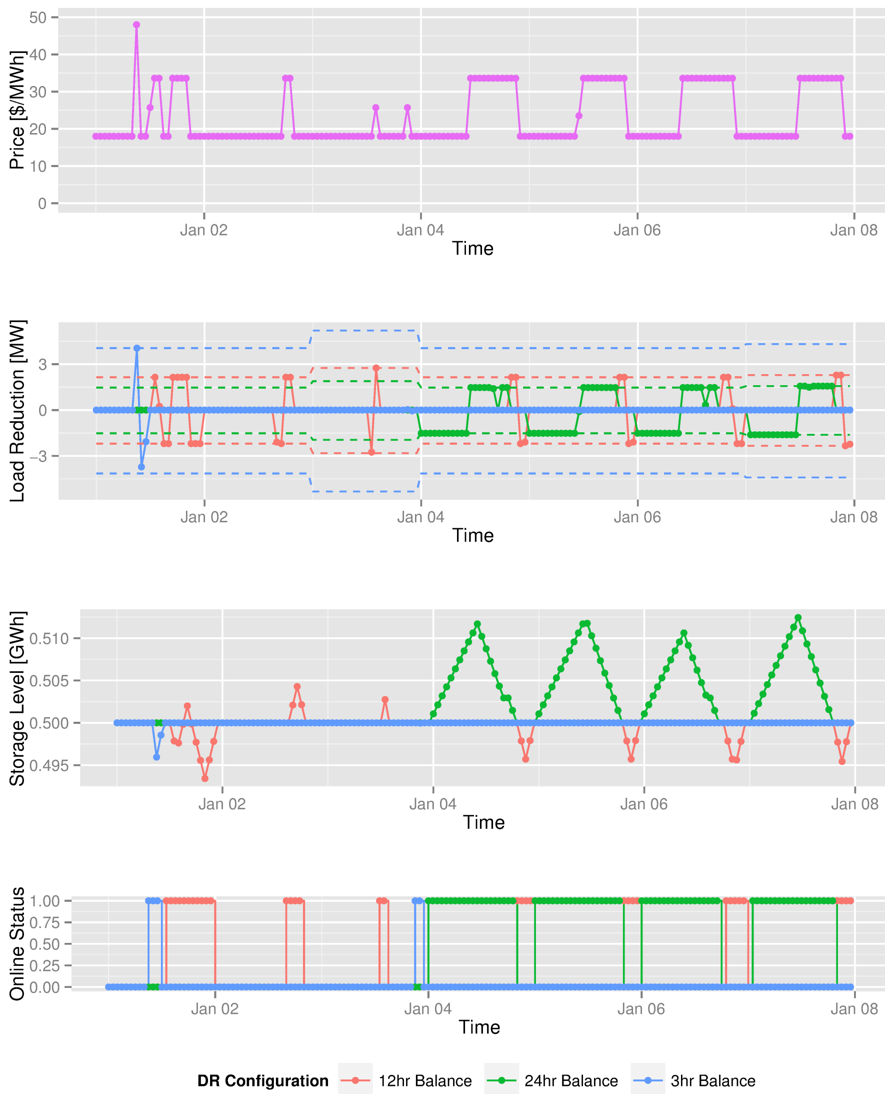


Figure D.7: DR resource behaviour over a one-week period as simulated on a five-bus power system model

D.5 Case Study

We conducted case studies to demonstrate the DR modeling methodology described above and to investigate the impact of DR on the power system. This section details the development of a sample population of DR resources, the power system within which the DR resource is implemented, and the tests that are performed.

D.5.1 Demand Response Resource

The sample DR resource implemented in these case studies is supermarket refrigeration. DR is achieved by altering the compressor operation, which is precipitated by adjusting temperature set-points within refrigerated cases. This resource did not include defrost, display case lighting or anti-sweat, other potential sources of DR that can be leveraged.

Supermarket refrigeration exhibits several characteristics that make it ideally suited to being an early adopter of load-shifting DR:

- The thermal mass present in refrigeration display cases facilitates the adjustment of power consumption while maintaining acceptable temperatures for foodstuff storage.
- Supermarkets operate at a low profit margin, incentivizing them to pursue opportunities for cost savings. If DR can offer easily accessible cost savings, it can be expected that this profit-driven enterprise would adopt an operating paradigm that facilitates load-shifting DR. This differs from residential DR, where consumers are not rational actors and may be driven by many other factors than welfare maximization.
- The structure of a supermarket chain lends itself to the formation of an aggregator. While individual supermarkets are considered large commercial loads, the flexibility they offer is likely below the threshold for participation on many electricity markets. By aggregating a number of supermarkets and offering their combined flexibility as a single product, this threshold can be overcome.

To represent the load shifting flexibility of supermarket refrigeration accurately, it is necessary to establish the saturation characteristics and power consumption limitations of the individual supermarkets. A saturation curve for a sample supermarket has been established in previous work [D18], [D19]. A portfolio of tests was conducted at an experimental refrigeration facility, mimicking the behavior of a supermarket during a DR event. The data resulting from these tests were used to identify a statistical model of the system that was in turn employed to establish the saturation curve. In practice, the same saturation curve can be determined directly through observing the ability of a supermarket to follow a power reference signal.

The model employed to establish the saturation curve does not consider the dependence of the system on the outdoor ambient temperature due to the limited time extent of the available experimental data. This necessitates the consideration of the temperature dependence through an external model.

Three key temperature-dependent quantities have been determined: the baseline power consumption, the maximum power consumption, and the COP. These quantities have been identified using an operational supermarket located in Denver, Colorado as a base case. The precise location of this supermarket cannot be revealed due to commercial sensitivity.

The baseline consumption has been obtained from historical data recorded at the supermarket. A regression model relating the power consumption to ambient temperature was identified and used to simulate the baseline consumption for the case study year, 2006.

The maximum power consumption is not a measured quantity. The maximum power consumption to achieve the required refrigeration cooling is detailed in the data sheets for the compressors on the refrigeration system. The specifications of the compressors were employed to simulate the maximum power consumption over the study year.

The COP of the refrigeration system is a well-defined quantity. Its relationship to the ambient temperature is detailed in the compressor specifications, and can be described by a non-linear regression model. This model facilitated the simulation of the COP over the study year. The variations in the COP impact the DR product definition, as the maximum power offered for response and recovery vary according to the COP.

The COP can be incorporated into the saturation curve by considering that a fixed amount of thermal energy is required to achieve a given change in temperature, and that the electrical energy required to achieve this temperature change will change according to the variation in the COP. The saturation curve identified for the test refrigeration system was found from data recorded at an ambient temperature of 0°C, a temperature at which the COP is at its maximum value. The saturation curve at any other temperature can then be found by scaling the base saturation curve along the power axis according to the change in COP.

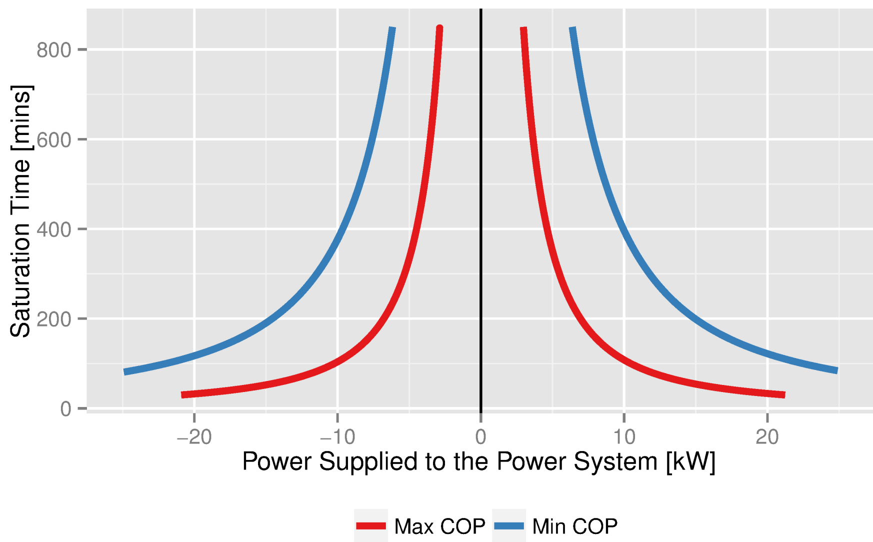


Figure D.8: Impact of COP variations on the saturation curve

Figure D.8 illustrates the difference between the saturation curve at maximum and minimum COP values for the study year.

Variations in ambient temperature are considered at a daily resolution, as considering hourly changes in temperature would require a significant modeling effort to isolate the effect of ambient temperature on the baseline power consumption from other factors, including store opening hours. Ambient temperature is the only external factor considered for the model, as there is a lack of available data on other factors that influence the power consumption. Further work could be conducted to acquire data and model the impact of other factors, including opening and closing hours, and stocking schedules.

D.5.2 Population Building

The models described above provide a representation of the flexibility of a single, sample supermarket. This base model has been used to construct a population of supermarkets representing the population of all supermarkets in Colorado.

The population of supermarkets is divided into three sub-populations: small, medium, and large stores. The supermarkets are assumed to be homogeneous within each sub-population. This facilitates the calculation of an aggregate saturation curve representing the dynamics of the each sub-population. For each sub-population, the saturation curve and power flexibility limits of the base model have been scaled appropriately. The average baseline consumption of small, mid-sized, and large supermarkets is assumed to be 30 kW, 50 kW, and 80 kW, respectively[5]. The baseline and maximum consumption of the small supermarket has been illustrated in Figure D.5 (above).

The saturation curve is adjusted for each population by shifting the curves along the power axis. This adjustment assumes that larger or smaller supermarkets will contain the same type of display cases (which contain the thermal mass providing the storage/flexibility) but will have more or fewer of them. Thus, for a given balancing period (e.g., three hours), the power offered by the large supermarket sub-population will be greater than that of the mid-size or small supermarket sub-population as there are more compressors on the system that will adjust their power consumption and achieve the same temperature change in each of the associated display cases.

The structure of each of the sub-populations was informed by a combination of data from the Commercial Building Energy Consumption Survey (CBECS) [D26] and the County Business Patterns (CBP) data set [D27]. CBECS provides detailed energy micro-data on a small population of commercial businesses across the United States. The CBECS data set only considers a small set of supermarkets, with locations indicated at the resolution of census regions. A census region is typically a group of states. Using the CBECS data, it was possible to determine a link between the floor size of a supermarket and the number of employees. The CBP data set contains less information on each supermarket, but includes all supermarkets and information on the number of employees in each, with their location indicated at the county level. Taking the number of employees as a proxy for store size, it was possible to determine the number of small, medium, and large supermarkets in each county in Colorado.

As the overall flexibility resource in each population is quite small, it was decided to consider a single population encompassing all supermarkets in Colorado, divided into the aforementioned sub-populations. The population is comprised of 482 small supermarkets, 178 mid-size supermarkets and 140 large supermarkets.

[5]The size of the sample supermarket within each sub-category has been informed by discussions with industry experts and analysis of power consumption data from a number of supermarkets located around the United States. The data employed to determine the power consumption characteristics of each sub-population cannot be shared directly as they are commercially sensitive.

D.5.3 Test System Description

To analyze the impact of DR on power systems, it is necessary to employ a model that is large enough to be realistic, but small enough to facilitate repeated simulations and sensitivity studies with reasonable run times. The test system employed in this work was developed for previous integration studies conducted at the National Renewable Energy Laboratory (NREL) [D4], [D28], [D29]. It is based on a subset of the U.S. Western Interconnection consisting of two balancing areas located in and around Colorado: the Public Service Company of Colorado (PSC) and the Western Area Colorado Missouri (WACM). This test system was derived from a database constructed by the Western Electricity Coordinating Council (WECC) Transmission Expansion Policy Planning Committee (TEPPC) and from other publicly available data sets. The system is modeled zonally; PSC and WACM are individually modeled as copper plates, with transmission linking the two regions. The system is simulated using projected values for load and renewable resources in the year 2020. The system is a summer-peaking system with a peak load of 13.7 GW, and annual demand of 79 TWh. The region modeled is primarily comprised of vertically integrated utilities, whose interactions and behaviors are complex and difficult to model. For simplicity, it is assumed that the system as a whole is dispatched for a least-cost solution. Further information on the test system employed in these studies can be found in [D29]. The DR resource represents a very small proportion of the test system, though determining its precise capacity is complicated. The amount of power supply available to the power system can be easily calculated; however, the need to balance the energy supplied to the system within a given time often limits the amount of power that can feasibly be supplied to the system. Figure D.9 plots the penetration of the available load reduction from the DR resource as a percentage of the rest of the generation capacity on the system. It is clear that the population of DR resources representing all supermarkets across Colorado makes a very small contribution to the overall power system, never exceeding a capacity share of 0.25%. Determining an accurate capacity value for DR is complicated, and other works have attempted to establish this metric [D3].

Figure D.10 illustrates the available DR flexibility. It can be observed that when the power supply is at its peak, the available power draw is at its minimum point. This supports the theory that the requirement to balance power supply and draw within the balance window may limit the power supplied to the power system. The power supply corresponds to the baseline consumption of the flexible population; this quantity can be shed, effectively supplying power to the power system. The power draw corresponds to the difference between the baseline consumption and the maximum possible consumption. This quantity is the additional power that can be consumed by the flexible load (i.e., drawn

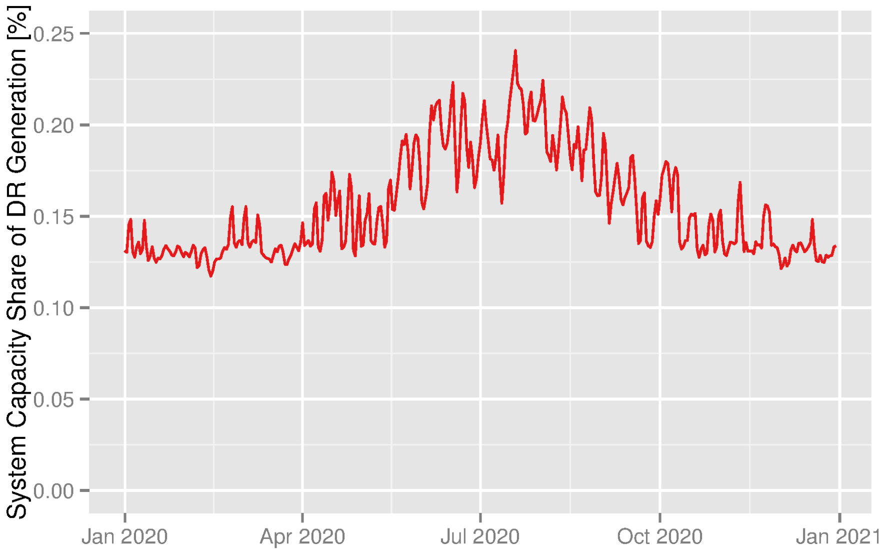


Figure D.9: DR generation share of system capacity

from the power system) to recover energy during a DR event.

D.5.4 System Dispatch Framework

In the case studies, we assess the value of DR for providing flexibility through real-time load shifting. Flexibility is the ability of the power system as a whole to react to forecast errors for base load and variable generation from renewable resources. The ability to react to contingency events (e.g. the failure of a generator or transmission line) is managed through the reserves. The ability of DR to provide reserves is not considered in this work.

To assess the value of DR for providing flexibility, the system is initially committed on a day-ahead basis, using day-ahead forecasts of load and renewables. The day-ahead commitment determines the level of generation from each generator at an hourly resolution for the coming 24 hours, and uses a look ahead for a further 24 hours at three-hour resolution to facilitate the scheduling of storage units and inflexible generators.

Load-shifting DR can be dispatched either day-ahead or close to real-time. In

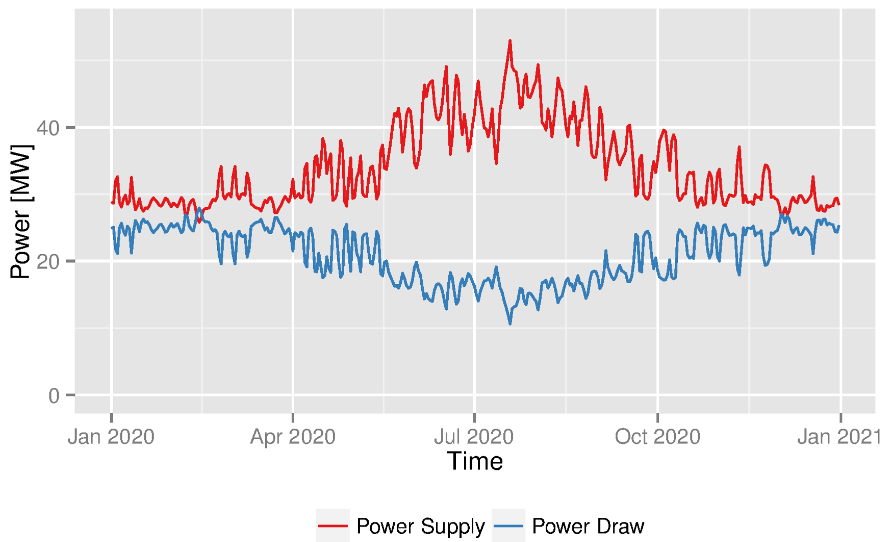


Figure D.10: Available DR flexibility in the study year (2020)

this work, the decision was made to focus on DR as a real-time flexibility resource. Thus, in the models considered here, DR is only dispatched at real-time, when forecast errors for load and variable generation are revealed. Demand response is not included in the day-ahead commitment process.

The system is re-dispatched close to real-time using updated forecasts for load and variable renewable generation, and including the DR resource. The real-time dispatch occurs every hour with 15-minute resolution, with a 24-hour look ahead at 3-hour resolution. The look ahead is necessary to ensure the DR products can balance by the prescribed time. The commit status of inflexible generators, including coal and combined cycle plants is held from the day-ahead commitment. The inflexible generators are permitted to deviate from their day-ahead power dispatch, though any deviation in excess of 10% on either side of the day-ahead dispatch is penalized. This structure is intended to approximately replicate real-time competitive electricity markets, where inflexible generators can only offer a limited amount of their capacity for real-time dispatch. The inflexible generators account for approximately 50% of the generating capacity on the system.

As the objective of these case studies is to establish the value that DR offers to the power system, DR is priced as a zero-marginal cost resource. Thus, the generation it provides to the power system generates revenue at the system price, and power that is drawn from the power system is priced at the system price and must be purchased. This is not intended to reflect the true cost of DR but to facilitate the assessment of its value to the system, which can then be used as a benchmark to justify, or otherwise evaluate, the investment required to establish and operate DR as a power system resource.

D.5.5 Base and Sensitivity Studies

The case study is conducted primarily to determine the impact of DR on the operation of the power system and the value it offers. In the base case, the peak generation available from DR is 63.5MW, and the penetration of variable renewable generation is 16% on an annual energy basis. As the DR resource represents a very small proportion of the power system, it is unlikely that any significant impact on system dispatch will be visible. As such, sensitivity studies are conducted to assess the impact of this resource as its system share grows.

The DR resource included in the base studies represents the flexibility of all supermarkets across Colorado, but it does not include other similar resources, such as refrigerated warehouses. Additionally, the representation of the DR resources in the form of storage configurations with different balancing periods is sufficiently generic that it could reasonably be used to represent the flexibility of a much wider range of loads offering load shifting, for example air conditioning and water heating. Thus, it is reasonable to conduct sensitivities on the size of the DR resource, though an upper bound on potential resource has not been evaluated. Sensitivities are conducted considering that the DR resource is scaled by multiples of 5, 10, and 25.

Sensitivity studies on the penetration of variable renewable generation (wind and solar PV) are also conducted. Previous studies have highlighted the increasing value of storage with increasing penetrations of variable renewables [D28]. As DR exhibits several characteristics in common with conventional energy storage, increases in the penetration of renewables are expected to similarly increase the value of DR to the power system. Following the convention used in previous studies conducted with this test system, the penetration (by energy) of wind and solar PV is increased from approximately 16% (base case penetration) to 35%, 45%, and 55%. A ratio of 5:1 wind to solar PV is maintained in all cases.

D.6 Results

D.6.1 Base Case

The value of DR is defined by the amount by which it reduces the cost of serving the system load. In the case studies considered here, DR is only dispatched at real-time and therefore contributes toward the balancing of forecast errors in load and renewable power generation. The metric employed here to define the value of DR is the difference between the cost of system dispatch adjustment at real time, with and without DR. In general, the cost of real-time system dispatch adjustment can be interpreted as the cost of having uncertainty in the system forecasts. By adding free DR resources, we can determine the maximum possible amount by which DR might be able to reduce these (partially unavoidable) costs.

In the base case, DR reduces this cost of uncertainty by 4.8%. The cost of uncertainty accounts for 3.1% of total system costs without DR, and 2.9% with DR. In absolute terms, the base case DR resource is found to reduce operational costs by $2.089 million in the test year. This corresponds to $32.85/kW-year, the value per unit of DR load reduction capacity available, or 0.014% of total system operation costs without DR. Thus, this base DR resource offers a very limited benefit to the power system, but this is expected given that the resource is very small. Section D.6.2 details the change in DR value at varying resource sizes.

Figure D.11 illustrates the profile of the value of DR over the study year, 2020. As expected, the seasonal availability of the DR resource is reflected in this profile. Refrigeration DR offers greater potential capacity to the power system during the summer months, but its ability to draw additional power to recharge its thermal storage resource is limited. Therefore, it is expected that the overall ability of the DR resource to support system operation will be reduced during the summer months. This can be observed in Figure D.11 where the value of DR is at its minimum point during the summer months of July and August.

The reduction in system costs brought about through the introduction of DR can be attributed to the reduced dependence on higher cost generation and the reduction in renewable generation curtailment that occurs at real-time dispatch. Curtailment occurs due to an excess of non-dispatchable renewable generation and the inability of the system to adjust the output of inflexible generators in close to real-time. Figure D.12 illustrates the amount of wind curtailment that is avoided by DR per month. The total avoided curtailment over 2020 is 693MWh, representing a reduction in curtailment of 7.2% versus the real-time dispatch without DR.

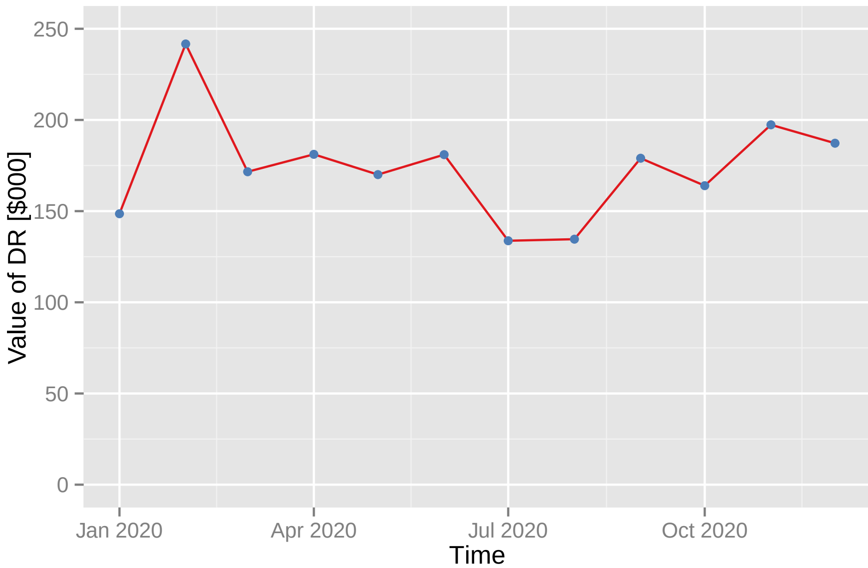


Figure D.11: Monthly value of DR over the study year

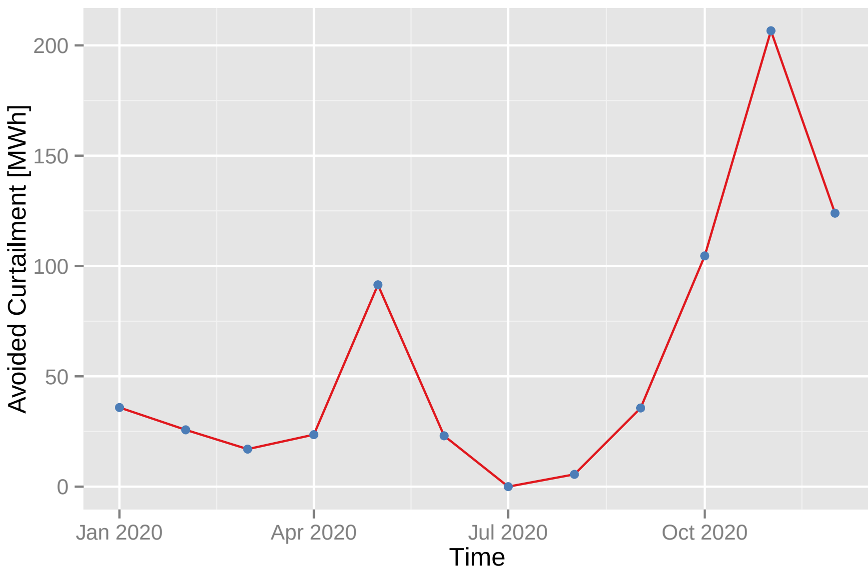


Figure D.12: Monthly avoided curtailment of renewables achieved through the implementation of DR

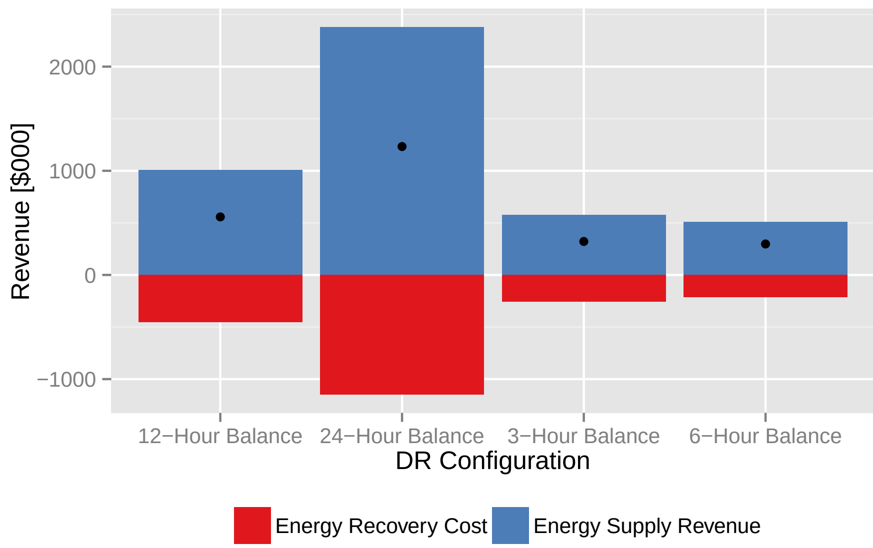


Figure D.13: Revenue breakdown by DR resource definition offered for dispatch. Net revenue is indicated by the black dots.

The DR resource is comprised of three populations corresponding to different supermarket sizes. Each population offers four mutually exclusive storage configurations, demarked by balancing period length, for dispatch. Figure D.13 illustrates the distribution of net revenue of the DR resource across the offered configurations. The net revenue is comprised of the income generated from the sale of power to the power system and the cost of recovering energy; both are priced at the system price. For the purpose of this case study, no operational costs are modeled for the DR resource, neither in the offering of its services into the system nor in the revenue calculation. The 24-hour balancing period configuration generates the greatest net revenue in this case. This is due to its ability to arbitrage over an entire day, taking advantage of the full range of diurnally varying system prices. It is more difficult to generate revenue over shorter balancing periods, as they rely on price differences over a smaller window. This is reflected in Figure D.13 where the three-hour and six-hour balancing period configurations generate the least net revenue. The price on the test system is primarily determined by fuel costs; on other systems where the price includes other factors such as carbon costs, there may be a greater opportunity to arbitrage across greater price differences, resulting in increased revenue for DR.

Figure D.14 illustrates the profile of net revenue for the entire DR resource over

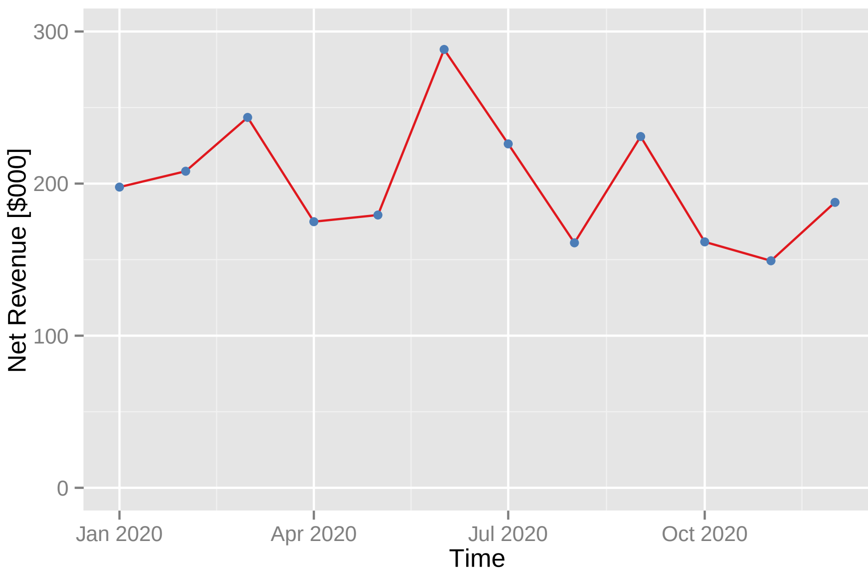


Figure D.14: Monthly net revenue of the entire DR resource over the study year.

the year. Comparing Figure D.14 to Figure D.11, we can see that the profile of net revenue does not exhibit the same clearly understandable seasonal variation as the profile of the value of DR. In fact, although the value of the DR to the system is at its minimum point in July (see Figure D.11), the net revenue generated in July is one of the highest, and is greater than the revenue generated in any of the winter months during which the available DR resource is greatest. Net revenue does not exhibit the same dependence on the availability of the resource as the value of DR to the power system, as it has greater dependence on price variations.

D.6.2 DR Capacity Sensitivities

In the following analyses, the impact of DR is often termed relative to the enabled DR capacity, or on a per-supermarket basis. The base DR resource is considered to have a load reduction capacity of 63.5 MW. This corresponds to the maximum theoretical amount of power by which its load could be reduced. This maximum occurs when the underlying refrigeration systems are operating at their upper power consumption limit and shed their entire load (turn off completely). Note that in this case it would not be possible for the supermarket to recover this lost energy. The sensitivity studies consider increases in the DR resource by factors of 5, 10, and 25, corresponding to enabled DR capacities of 318 MW, 635 MW, and 1,587 MW. The capacities of individual small, medium, and large supermarkets are 56 kW, 93 kW, and 149 kW, respectively.

Figure 16 illustrates the value of DR per enabled megawatt of capacity. The marginal value can be seen to decrease as the capacity increases. This indicates that the early adopters of load-shifting DR represent a significant additional value to the system, but as more supermarkets enter the DR market, the added value of each additional supermarket is less. At the lowest penetrations of DR, a large supermarket has a value of \$4,890 per year; however, this decreases (following the trend shown in Figure D.15) to only \$1,030 per supermarket at the highest investigated penetrations of DR. A small supermarket offers an annual value of approximately \$500 at that penetration level.

The manner in which the DR capacity sensitivities are conducted here is quite naïve, assuming that all of the flexible loads exhibit the same characteristics as the base DR portfolio. In reality, a larger DR resource will incorporate a diverse range of flexible loads. The diversity of a realistic DR portfolio will likely contribute to alleviating the steep decrease in the value of DR that is exhibited in our naïve sensitivity studies.

Figure D.16 illustrates the decrease in the net revenue per enabled megawatt of DR capacity, while Figure D.17 illustrates the same quantity on a per-supermarket basis. The revenue per supermarket is of a similar magnitude to the value it offers to the system. Further research is necessary to determine the capital and operational cost of this DR resource, as this must be subtracted from the net revenue presented here to determine the actual net revenue to the supermarket operator. Additionally, the system operator may offer incentives to support demand response, which can also be considered when assessing expected net revenue. It can be anticipated that any incentives will not exceed the value that DR offers to the system.

Figure D.18 illustrates the change in the generation dispatch at different levels of DR as compared to the real-time system dispatch without DR, where each column represents one of the DR sensitivity studies, e.g. x5DR is the case with five times the base DR capacity. Demand response is seen to displace generation from less efficient gas combustion turbines (CT), while increasing generation from the more efficient but less flexible combined cycle (CC) gas generators and coal (similar to the findings of [D28]). Additionally, DR can be seen to support greater levels of generation from renewable resources, including wind, solar PV, and dispatchable hydropower generation.

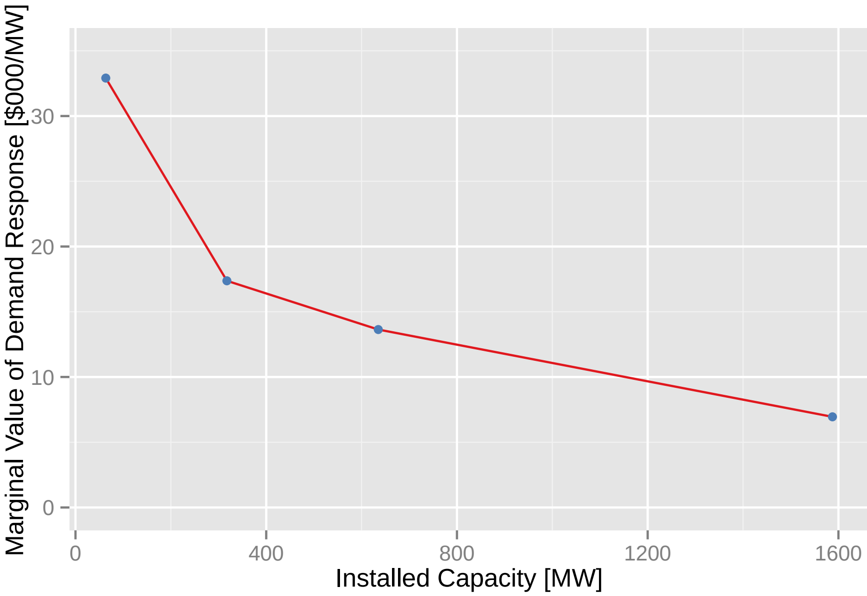


Figure D.15: Annual value of DR per MW of installed DR capacity.

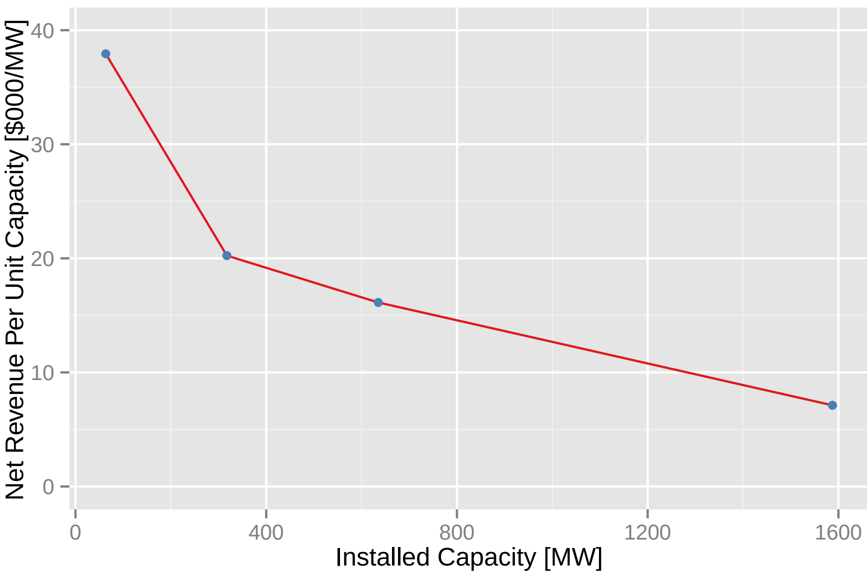


Figure D.16: Annual DR revenue per MW of installed DR capacity.

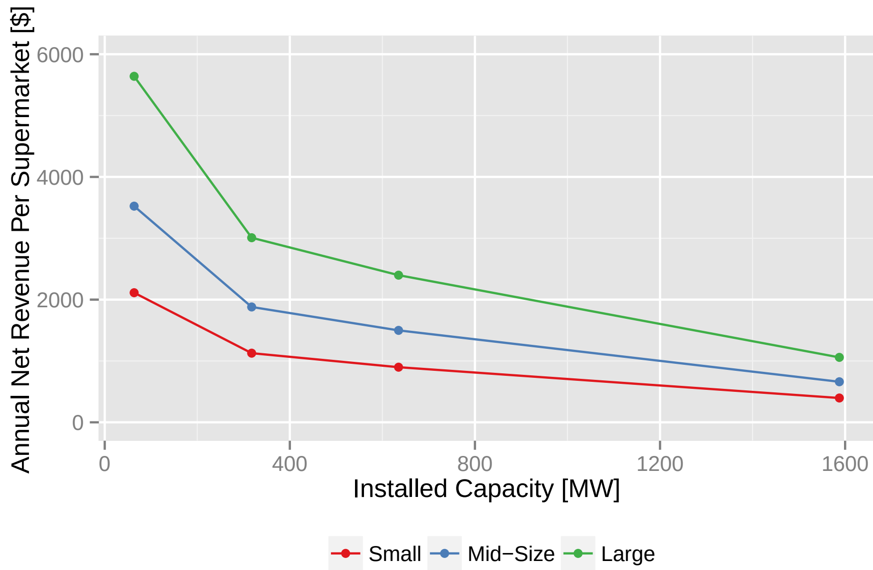


Figure D.17: Annual net revenue per participating supermarket.

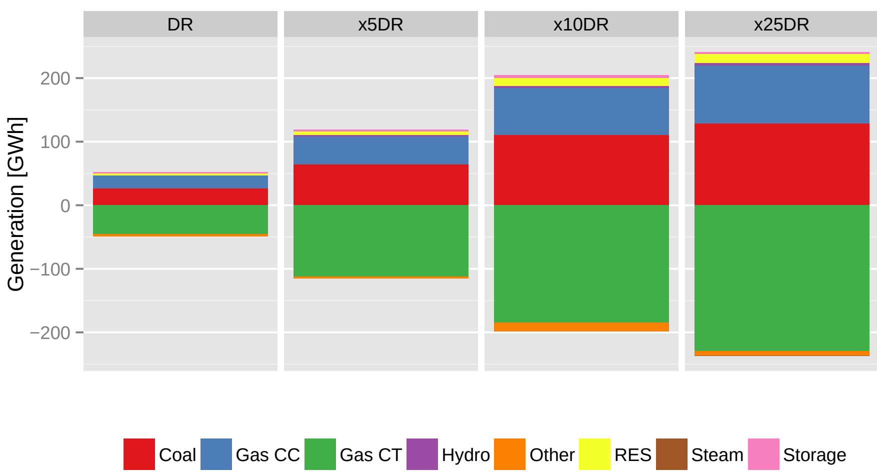


Figure D.18: Impact of DR on the generation portfolio.

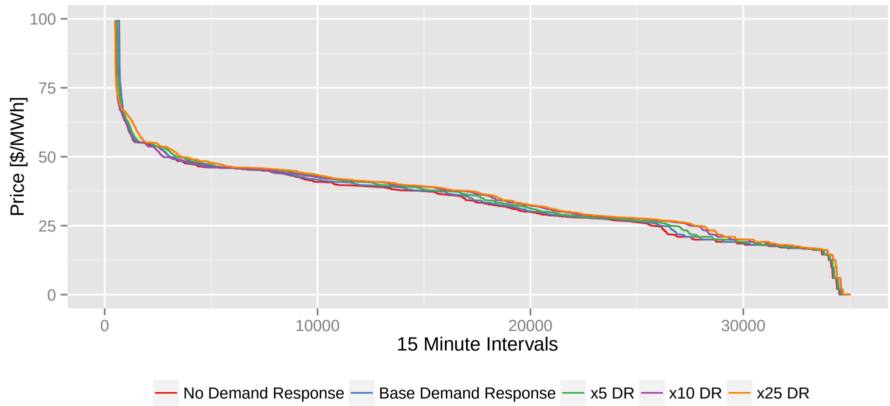


Figure D.19: Price duration curves at different levels of installed DR capacity.

Figure D.19 illustrates the price duration curve for each of the levels of DR capacity considered and the case without DR. It is difficult to identify the base case price curve, as it overlaps with that of many of the DR sensitivities for many hours. Between intervals 10,000 and 20,000, the lowest line (in red) is the price duration curve without DR. The introduction of DR increases the price and extends the number of hours during which the price is high, as can be seen by the shift to the right between intervals 25,000 and 30,000. Despite the visible impact on lower priced hours, there is a very limited impact on peak prices. This is an unexpected result, as conventional storage typically mitigates price fluctuations by reducing peak prices and increasing the price during lower priced hours [D28]. The impact of this change in the price duration curve can be seen in Figure D.16 where the marginal revenue decreases at higher penetrations of DR. This can be attributed to the higher prices during relatively low priced hours, which increases the cost of recovering energy (which usually occurs during low price hours) and consequently reduces the net revenue.

D.6.3 Renewable Energy Sensitivities

Further sensitivity studies investigate the impact of larger penetrations of renewable resources on the power system with the base DR resource (63.5MW). Figure D.20 demonstrates that the value of DR increases with increasing levels of renewable generation, however, the rate of increase slows substantially upon reaching moderate levels of penetration (around 35-45%) and appears to saturate. This result differs somewhat from the findings of [D28], which found

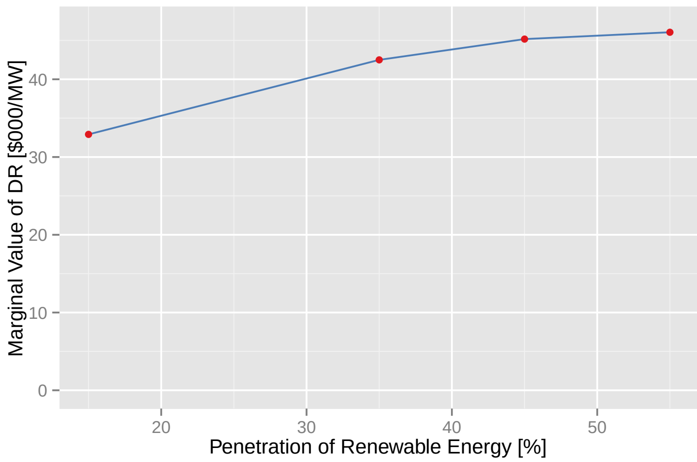


Figure D.20: Annual value of DR per MW of installed capacity with increasing penetrations of renewable energy.

a more constant increase in the value of conventional energy storage with increased renewable generation, but does not seem unreasonable based on a) that earlier study also found a deceleration in value in the high (2x) gas price case and b) the studies offer energy storage into different markets (i.e. day-ahead versus 15-minute markets). At high penetrations of renewables and with the day-ahead unit commitment already in place, it is possible for the system to operate primarily on renewable and already-committed base load generators for long periods of time, a situation in which the short-term energy storage provided by the DR resource becomes less valuable. Longer-term storage solutions could still be of interest in this particular situation, and it could be worthwhile in future work to explore initially scheduling DR alongside the day-ahead unit commitment decisions. This scheduling framework may provide greater system value than scheduling solely in real-time, particularly in high renewable penetration scenarios.

Figure D.21 illustrates the real-time dispatch curve for January 2020, where it can be seen that generation is primarily comprised of renewables and coal. As coal is an inflexible resource, it is expensive to adjust away from its day-ahead dispatch points, so given the choice of displacing coal or renewables, DR will not be dispatched unless the forecast error for renewables is negative and additional generation is required. Figure D.22 shows the curtailed renewable generation during this time (January 2020), and clearly demonstrates that the forecast error of renewables is not generally negative. Overall, there is a long-term excess of generation and consequently no need for DR. Offering the DR in

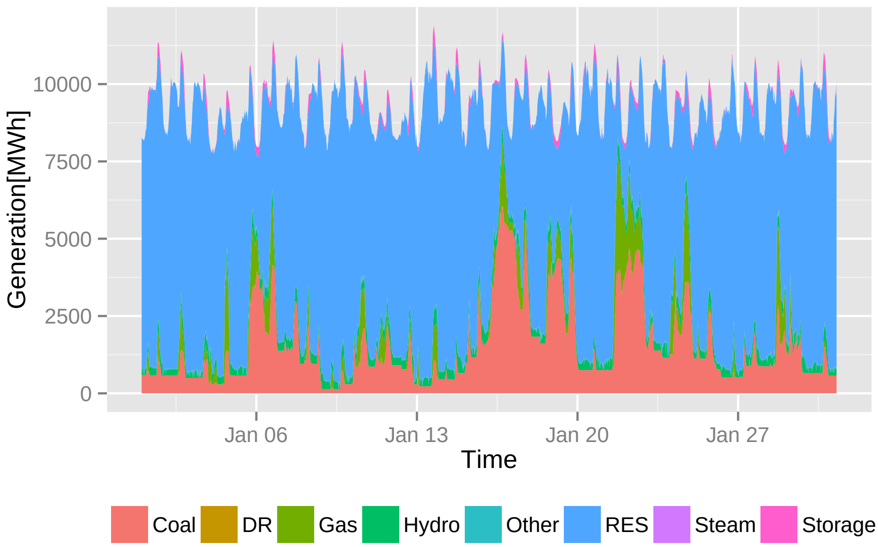


Figure D.21: Real-time system dispatch for January 2020.

the day-ahead market or adjusting the renewables mix toward more solar and less wind could possibly mitigate this situation for this system and this level of renewable generation; however, for most systems we would expect there to be some renewable generation threshold beyond which the main problem is week- or season-long over-supply of (renewable) generation, as depicted in the figures.

Figure D.23 illustrates the amount of load reduction provided by the DR resource for each of the considered scenarios for renewable energy source (RES) penetration. A significant difference can be observed between the highest-penetration scenario and all other scenarios, particularly during the earlier and latter parts of the year. These periods are also the periods with the greatest amount of generation from renewables. This indicates that the short-term DR modeled here is not as valuable to the system during periods of very high generation from variable renewables, at which times a longer-term source of storage would be more beneficial.

Figure D.24 illustrates the impact of DR on the generation portfolio with increasing penetrations of renewable generation. It can be seen that gas CT is consistently displaced across all scenarios, while DR supports increased generation from renewable generation sources as the penetration of renewables increases. At lower penetrations of renewables it appears that DR may induce increased

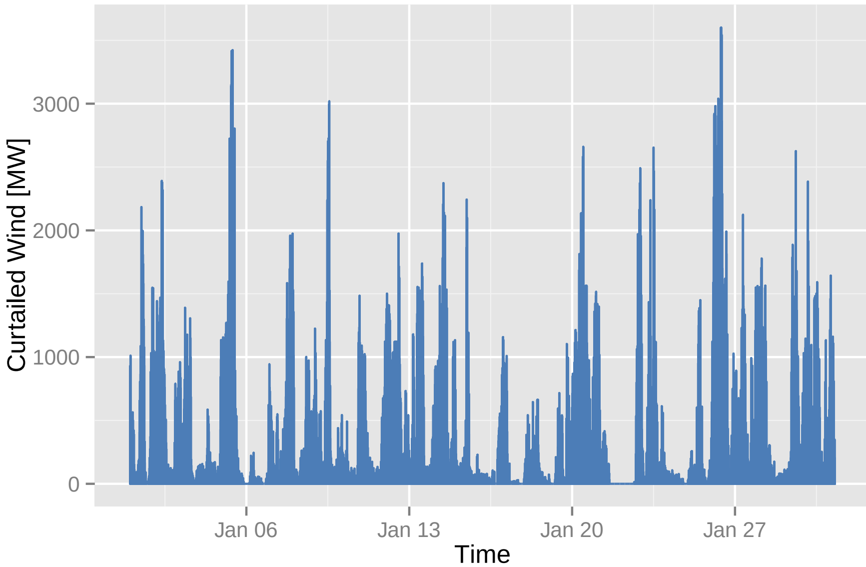


Figure D.22: Curtailed renewable generation during January 2020.

emissions due to its support of additional coal generation. At higher penetrations of renewables, this trend is mitigated as DR begins to reduce renewable curtailments more than it supports generation from coal plants.

Figures D.25, D.26, and D.27 demonstrate the impact of increased penetrations of renewables on avoided renewables curtailment, the value of DR per supermarket, and the net revenue per supermarket respectively. In all cases, the increase in renewables improves the case for DR until the penetration of renewables exceeds 45%, at which point the benefit of DR exhibits no further significant increase.

The trend exhibited by the net revenue of DR with increasing penetrations of renewables is seen to reverse at the highest penetration of renewables considered in these sensitivity studies. This contrasts with the trend of the value of DR, which appears to saturate but not reverse. At increasing penetrations of renewables, peak prices are suppressed, and there is higher incidence of zero-price hours, as shown by the price duration curves in Figure D.28. This would indicate that DR could generate greater revenue due to the opportunity to recover energy from the system at no cost. The impact of a greater number of zero-price hours can be seen in Figure D.29 where the cost of energy recovery decreases continually with increasing penetrations of renewables. However, as the

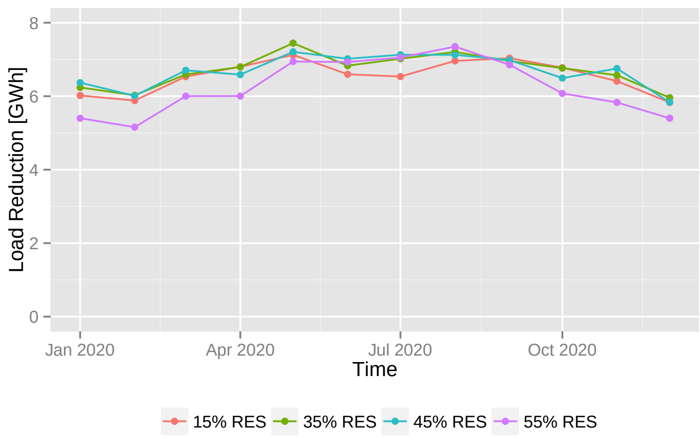


Figure D.23: Monthly DR load reduction for each renewable energy penetration scenario.

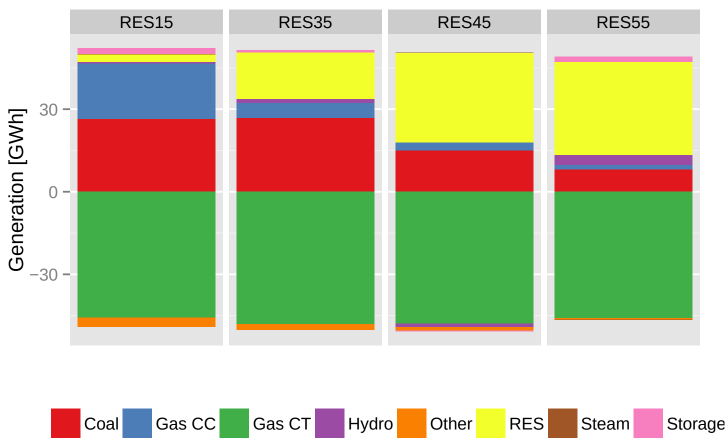


Figure D.24: Impact of DR on Generation with increasing penetrations of renewable generation [15%, 35%, 45% and 55%].

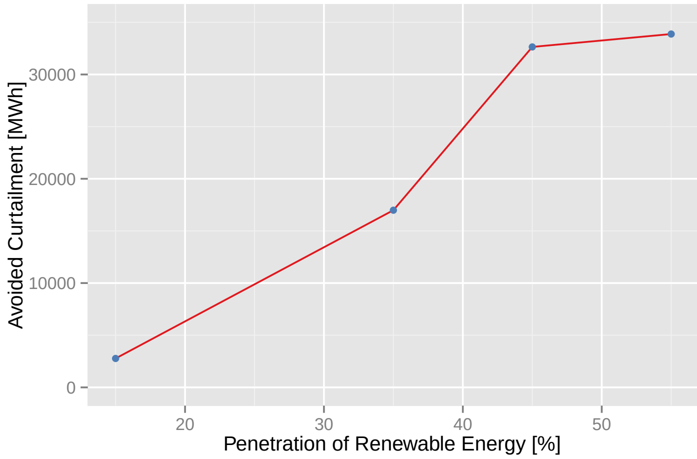


Figure D.25: Annual avoided curtailment of renewable generation per MW of enabled DR capacity with increasing penetration of renewable energy.

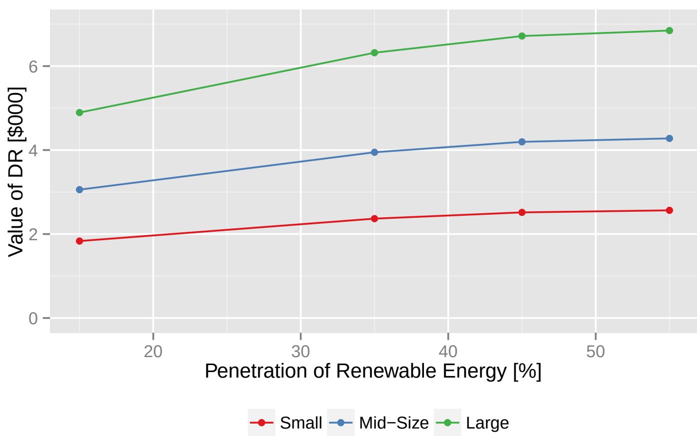


Figure D.26: Annual value of DR per participating supermarket with increasing penetrations of renewable energy.

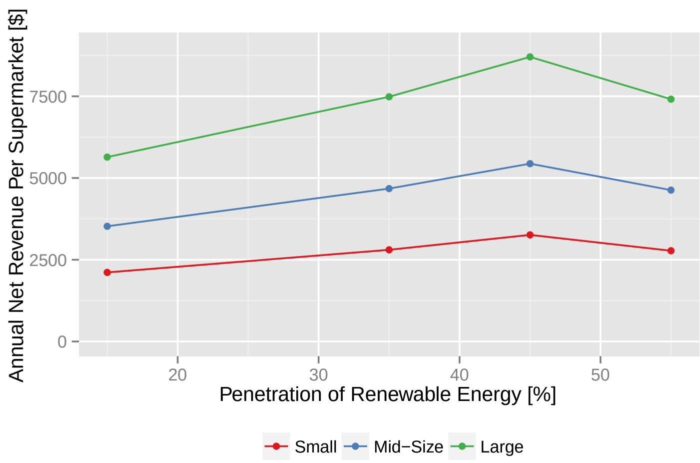


Figure D.27: Annual net revenue per supermarket with increasing penetrations of renewable energy.

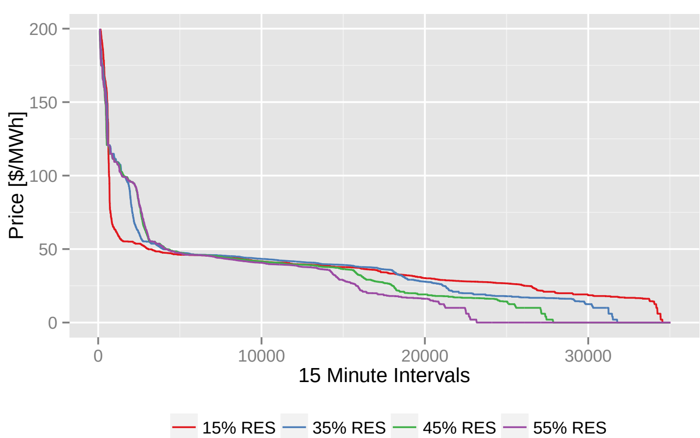


Figure D.28: Price duration curve with increasing penetration of renewable energy and the base case DR resource.

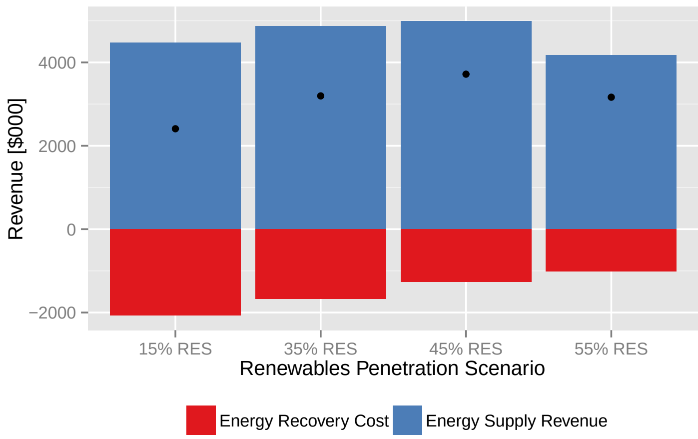


Figure D.29: Breakdown of annual DR revenue for each scenario of renewables penetration considered. Net revenue is indicated by the black dots.

DR resource is dispatched less frequently (as shown in Figure D.23), it has less opportunity to generate revenue through the sale of power. Thus, despite the ability to recover more energy for free, the overall revenue achieved is reduced.

D.7 Conclusions

A methodological framework for the modeling of load-shifting DR using a bottom-up approach has been developed in this work. The modeling methodology is generic and can be applied to a range of thermal-electric loads that are suitable for the provision of load-shifting DR. The model is capable of incorporating the dependency of the resource flexibility on external factors such as ambient temperature and building occupancy, though further work is necessary to fully represent diurnal variations. The methodology developed differs from existing bottom-up DR modeling approaches in that the resulting model is suitable for inclusion in large-scale power system studies of long duration. This facilitates an assessment of the power system operational cost reductions offered by DR over a year.

The modeling methodology is demonstrated using the example of supermarket refrigeration DR resource adjusting compressor power consumption. The flexibility and dynamics of refrigeration are characterized by a saturation curve that relates change in power to the amount of time for which the change can be sustained. Multiple storage configurations, distinguished by different saturation times, are offered for dispatch in the power system as implemented in a commercial production cost modeling tool. The impact of the daily average ambient temperature on the flexibility offered by refrigeration is also characterized and incorporated into the model.

A model representing the load-shifting DR of the population of supermarkets in Colorado is implemented in a production cost model of a test system representing the power system of Colorado. This DR resource is found to have a value of \$32.85/kW-year when it provides an energy service in a 15-minute, real-time market. This value corresponds to the production costs savings achieved by implementing DR and are primarily due to the displacement of gas-fired combustion turbine (CT) plants and through avoided curtailment of renewable generation. The capacity of the population of supermarkets modeled is very small, representing a maximum of 0.24% of the generation capacity on the system. Consequently, the absolute value it offers per year is very low, at \$2.089 million, or \$4,890 for each large supermarket providing DR.

Sensitivity studies revealed the per-unit value of DR decreases as the capacity of the resource increases. The net revenue accrued per supermarket is also found to decrease as the penetration of DR on the system increases. This indicates that the business case for supermarkets or other DR resources to provide DR weakens as the resource grows. It should be noted that prices on the test system are largely driven by fuel costs, and thus the revenue generated by DR is sensitive to the portfolio of generators on the system and their fuel costs. On systems with higher fuel cost differentials and other price components such as carbon costs, it is possible that DR could generate greater revenue.

The framework developed in this work is applicable to a range of flexible loads capable of providing load-shifting DR. An important continuation of this work is an extension of the modelling framework to incorporate DR participation in other power system markets such as capacity and ancillary services. Future work should also consider the application of this methodology to a portfolio of suitable loads, so that a full integration study on load-shifting DR can be conducted. Other key areas of interest for the continuation of this research agenda include the potential synergies between complementary resources such as heating and cooling and the impact of diurnal variations in flexibility on the value of DR.

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Paper E

Trading Flexible Electricity Consumption in Spot Markets under Demand Response Uncertainty

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Trading Flexible Electricity Consumption in Spot Markets under Demand Response Uncertainty

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Abstract

The ability to trade demand response profitably on competitive electricity markets is necessary to ensure its feasibility as a future power system resource. In this work we develop a novel trading strategy for aggregated demand response offering load curtailment on the day-ahead and continuous trade intraday markets, considering uncertainty in the achievable curtailment. Our analysis reveals that despite significant uncertainty at long horizons, it is more profitable to trade on both markets instead of solely the intraday market. The impact of resource uncertainty on revenue is found to be significant, though high forecast accuracy is deemed unnecessary due to structure of trades on the intraday market.

E.1 Introduction

Flexibility in power system operations is a key priority in the current environment of uncertain energy supply, greater reliance on stochastic power generation, and constrained generation and transmission capacities. At a time when power system flexibility is at a premium, demand response (DR) presents a logical solution. Activating the flexibility of the demand side is said to bring about such advantages as supporting higher penetrations of renewable generation [E1], alleviating network congestion [E2], and increasing power system reliability [E3], among others [E4].

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The ability to profitably trade DR alongside conventional power system resources on competitive electricity markets is a prerequisite for the success of this novel resource. Under current market frameworks, deviations from stated production or consumption profiles are penalised, to encourage trading behaviour that supports the stable operation of the power system. This places stochastic resources, such as DR, at a disadvantage as penalties resulting from their inherent uncertainty can have implications for their business case. In this work we assess the revenue that can be generated through the trade of aggregated DR resources on competitive spot markets, considering the uncertainty of the resource and the consequent impact on expected revenue.

Optimal trading and scheduling of perfectly known DR has been addressed in a number of works. Scheduling of DR alongside conventional power system resources is considered in [E5, E6]. Participation of residential demand response in the day-ahead and balancing markets is considered in [E7], while an optimal trading strategy for flexible batch processes is developed in [E8]. Consideration of DR uncertainty in trading and scheduling strategies is less commonly addressed, but is incorporated into the electric vehicle charging strategy developed in [E9] and the scheduling of aggregated thermostatically controlled loads in [E10]. The nature of demand response uncertainty is described in [E11], and its impact is highlighted in [E12, E13].

Given the limited research attention that has been dedicated to trading strategies for uncertain DR, it is necessary to draw inspiration from the established field of trading strategies for stochastic wind power generators. Analytical results for optimal bidding of wind generators in forward markets considering the penalty of imbalances at real-time are provided in [E14]. Bidding strategies for both the day-ahead market and continuous trade intraday market are provided in [E15], and [E16] provides an evaluation of a number of alternative offering strategies for wind power producers.

This work addresses the lack of research on the trading implications of DR uncertainty by developing a full methodology for the trade of uncertain aggregated DR on spot electricity markets. This work offers two novel contributions to the state of the art. Firstly, an optimal trading strategy for uncertain DR on a continuous trade intraday market is presented, considering that the DR resource offers a load curtailment product. Secondly, a full analysis is provided of the impact of DR uncertainty on the revenue that a market agent can generate on both the day-ahead and intraday markets. This evaluation is informed by a detailed model of the uncertainty sources in demand response, and a comprehensive set of sensitivity studies.

This paper is structured as follows. Section E.2 provides a detailed description of the trading strategies developed for the day-ahead and intraday markets, and models for DR uncertainty and scheduling are presented. Section E.3 describes the case study framework employed in this work. The key research questions considered and results of this work are presented in Section E.4, and closing remarks are provided in Section E.5.

E.2 Methodology

E.2.1 Participation of Demand Response in Wholesale Electricity Markets

E.2.1.1 Market Structure

In this work we consider that the market agent representing the demand response resource operates within the Nordic Electricity Market. Load curtailment can be offered in either the day-ahead market, Nord Pool Spot, or the intraday market, Elbas [E17]. Real-time imbalances must be purchased from or sold to the transmission system operator (TSO) at the regulating power price.

Participants on the *Elspot* day-ahead market submit offers to the market operator Nord Pool before gate closure at 12:00, for delivery of energy from 00:00 of the following day. Each market offer consists of a price and volume, and covers an hour. This market is cleared through an auction process.

Elbas is the continuous trade intraday market. It is a bilateral market where offers to buy and sell energy are matched on a continuous basis by the market exchange. Each offer on this market consists of a price, energy volume and delivery hour. Trading on this market continues until one hour prior to the delivery hour.

The real-time deviation between traded and realised energy volumes must be accounted for through the *regulating power market*. The TSO of each market region within the Nordic market operates the local regulating power market, sourcing generators to supply up- and down-regulation. Regulating power prices are related to the day-ahead price, λ^{DA}, as in (E.1). Production balance responsibles (PBRs) with a positive imbalance will sell their excess energy at the down-regulating price, λ^{D}, while a shortfall in energy is purchased at the up-regulating price, λ^{U}.

$$\lambda^{\mathrm{D}} \leq \lambda^{\mathrm{DA}} \leq \lambda^{\mathrm{U}} \tag{E.1}$$

In this work, the market agent representing demand response is considered a

PBR as the resource it offers is controllable load curtailment, which is analogous to a power plant operator offering power supply.

E.2.1.2 Conventions and Assumptions

Trades on the intraday market are denoted *buy trades* or *sell trades*. Buy trades are those posted by one market participant seeking to purchase energy from another. The DR market agent can accept buy trades and fulfil them through load curtailment. Sell trades are those offered by one market participant seeking to sell energy to another participant. Sell trades can be accepted by the DR market agent to manage energy shortfalls that occur due to uncertainty. In this work, the ability of the DR market agent to issue buy or sell trades on the market is not considered. The market agent is limited to accepting existing trades, as simulation of the acceptance rate of such trades by other market participants is complex and beyond the scope of this work.

In this work the day-ahead and intraday trading strategies are treated as separate problems. The problem of considering the possibility that a more profitable trade will appear on the intraday market when determining the optimal day-ahead trading strategy is substantially more complex than the model developed here. This is an open research question that we leave for future work. Consequently, in the modelling framework employed in this work it can occur that trades that are accepted day-ahead may offer less revenue than a trade that is subsequently offered on the intraday market. In such a case, the intraday trade will be accepted if the cost of not meeting the day-ahead trade obligation is less than the revenue that is available through the intraday trade. Consider for example the case where a day-ahead trade of 10MWh has been accepted at a market clearing price of €30/MWh for 10:00, and at 07:00 on the same day an intraday trade is posted of (€50/MWh, 10MWh) for delivery at 10:00, the up-regulation price for 10:00 is expected to be €40/MWh according to the forecast available to the DR market agent. The day-ahead revenue of €300 is guaranteed as this has been accepted by the market, but if this day-ahead trade is not fulfilled, the DR agent is liable to pay an expected penalty of €400. The intraday trade offers a revenue of €500, resulting in total expected revenue for the DR agent of €400 if the intraday trade is accepted. In such a case, the DR agent will chose to accept this intraday trade and cover the resulting net imbalance with upward regulation in the balancing market.

A similar situation can occur between intraday trades as they can be posted at any time. For example, if at 08:00 a further trade is posted for delivery at 10:00 of (€60/MWh, 10MWh), this trade will be accepted and the net imbalance will be covered through the purchase of regulating power.

In the trading strategies that are developed in this work the DR resource is restricted to offering load curtailment only. Many flexible loads are capable of both load curtailment and load shifting demand response. Load shifting consists of a reduction in power consumption at time t and a corresponding increase in power consumption at time $t \pm k$, whereas load curtailment is only the reduction component. The reduction in power consumption that occurs during load shifting can be greater than that during load curtailment, as the operating state of the flexible appliance can be allowed to deviate further from the typical operating state due to the guaranteed energy recovery. Thus, it is possible that the load reduction component of load shifting could generate greater revenue than load curtailment, however the need to purchase energy for the recovery component could eliminate this additional revenue. Further research is necessary to explore this issue.

E.2.2 Day Ahead Trading

As stated in (E.2), the day-ahead trading strategy maximises the expected revenue with respect to the available point forecasts of day-ahead price and imbalance prices, and scenarios of realisable load curtailment, considering that the DR market agent is a price-taker. The optimisation is subject to the constraints on load scheduling (E.4)-(E.7). The deviation between the scheduled load curtailment, $P_t^{DR,S}$, and that which is realised, $P_t^{DR,R}$, is denoted $\Delta_{t,\omega}$. It is a stochastic variable dependent on scenarios for outcomes in load curtailment, indexed by ω, where the probability of each outcome is denoted π_ω. The deviation can be decomposed into positive, $\Delta_{t,\omega}^{+}$, and negative, $\Delta_{t,\omega}^{-}$ components. The positive deviation (excess curtailment) is sold at the down-regulation price, λ_t^{D} and contributes to the expected revenue. A negative deviation (shortfall in load curtailment) is purchased at the up-regulation price, λ_t^{U} and is a net cost. The problem is formulated as below, where the decision variables $\mathbf{P}$ are the scheduled curtailment at each time point t.

$$\max_{\mathbf{P}} \quad \sum_{t} \left(P_t^{DR,S} \lambda_t^{\mathrm{DA}} - \sum_{\omega} \pi_\omega \left(\Delta_{t,\omega}^{-} \lambda_t^{\mathrm{U}} - \Delta_{t,\omega}^{+} \lambda_t^{\mathrm{D}} \right) \right) \tag{E.2a}$$

subject to:

$$P_{t,\omega}^{DR,R} = P_t^{DR,S} + \Delta_{t,\omega} \quad \forall\, t, \omega \tag{E.2b}$$

$$\Delta_{t,\omega} = \Delta_{t,\omega}^{+} - \Delta_{t,\omega}^{-} \quad \forall\, t, \omega \tag{E.2c}$$

$$\Delta_{t,\omega}^{+}, \Delta_{t,\omega}^{-} \geq 0 \quad \forall t, \omega \tag{E.2d}$$

E.2.3 Intraday Trading

The intraday trading strategy is implemented in a rolling horizon optimisation framework. On each optimisation step, the strategy considers the available sell trades, S, buy trades, B, and trade obligations from the day-ahead market over the current horizon $[t,\ t+h]$. The optimisation will choose to accept trades that result in the maximum expected revenue, subject to the forecast regulating prices. Trades on the first time interval t will be met through realised curtailment and the optimisation process will repeat for the interval $[t+1,$ $t+h+1]$.

On each step, the trade list is updated to include newly issued trades and to remove trades that have been cancelled or accepted by other parties on the market. The optimisation algorithm considers all open trades as well as trades that have been previously accepted by the DR agent. This allows the DR agent to accept newly issued buy trades if they offer greater revenue than previously accepted buy trades, given that the resulting net imbalance must be covered through the purchase of sell trades or regulating power.

All trades on the intraday market are assumed to be all-or-nothing trades, where the trade must be accepted completely or not at all. Trades on Elbas are categorised as *all-or-nothing* or *fill*, where fill trades can be accepted in part. The trade type is not indicated on the data available for this study, thus differentiation between trade types is not considered in the model.

The value of reserving DR resources for possible intraday trades that are not visible in the current horizon, but which may be posted at a later time, is not considered in this model.

To facilitate a fair assessment of the revenue generated through the trade of DR, and the impact of its uncertainty, speculation is not permitted in the trading strategy that is detailed here. To prevent speculation, the restriction is imposed that it must be possible to meet all accepted buy trades through load curtailment, subject to the constraints outlined in Section E.2.5.

The mathematical formulation of the intraday trading strategy is detailed in (E.3), and is subject to the DR scheduling constraints (E.4) - (E.7). The objective function maximises the expected revenue, which is comprised of income from buy trades that are accepted and the expected income from the sale of energy on the regulating power market, minus expenditure from sell trades that are accepted and the purchase of energy on the regulating power market. Trade volumes and prices are denoted $(\cdot)^V_{t,o}$ and $(\cdot)^P_{t,o}$ respectively, where o is the index of the trade, or offer. The binary variables $v_{t,o}$ and $w_{t,o}$ become non-zero to indicate that a buy or sell trade has been accepted, respectively.

Speculation is prevented by (E.3b) and (E.3c). Equation (E.3b) states that the sum of the buy trades accepted at time t and the portion of the day ahead trade that is realised, $P_t^{DA,R}$, must not exceed the curtailment that can be provided by the DR resource, P_t^{DR}. The optimisation can chose to realise a portion or all of the day-ahead trading obligations, $P_t^{DR,S}$ as determined in (E.2), through curtailment, as given in (E.3c). Speculation through the purchase of sell trades is prevented by further constraints, though they are omitted here for brevity.

The net imbalance, defined in (E.3d), is the difference between the trading obligations from the day-ahead market plus the net intraday trade and the realised load curtailment. The net intraday trading position is comprised of trades that were accepted on previous optimisation steps, i, for trading during the current trading horizon plus trades that were newly accepted on this optimisation step. The imbalance is divided into positive and negative components, each of which is charged at the relevant regulating power price, as on the day-ahead market.

$$
\begin{aligned}
\max \quad & \sum_t \Bigg(\sum_o \left(v_{t,o} B^V_{t,o} B^P_{t,o} - w_{t,o} S^V_{t,o} S^P_{t,o} \right) + \\
& \qquad \sum_\omega \pi_\omega \left(\Delta^-_{t,\omega} \lambda^{\mathrm{U}}_t - \Delta^+_{t,\omega} \lambda^{\mathrm{D}}_t \right) \Bigg) && \text{(E.3a)} \\
& \text{subject to:} \\
& \sum_o v_{t,o} B^V_{t,o} + P_t^{DA,R} \leq P_t^{DR} \quad \forall\, t && \text{(E.3b)} \\
& P_t^{DA,R} \leq P_t^{DR,S} \quad \forall\, t && \text{(E.3c)} \\
& \Delta_{t,\omega} = P_t^{DA} + \sum_o B^V_{t,o} (v_{t,o}(1 - v_{i-1,t,o}) + v_{i-1,t,o}) - \\
& \qquad \sum_o S^V_{t,o} (w_{t,o}(1 - w_{i-1,t,o}) + w_{i-1,t,o}) - P^{DR,R}_{t,\omega} \quad \forall\, t, \omega && \text{(E.3d)} \\
& \Delta_{t,\omega} = \Delta^+_{t,\omega} - \Delta^-_{t,\omega} \quad \forall\, t, \omega && \text{(E.3e)} \\
& \Delta^+_{t,\omega}, \Delta^-_{t,\omega} \geq 0 \quad \forall\, t, \omega && \text{(E.3f)}
\end{aligned}
$$

E.2.4 Modelling Uncertainty in Demand Response

Load curtailment is subject to a number of sources of uncertainty, which can be divided into the categories of *structural* and *environmental*. Structural uncertainty arises when the model used to describe the population of flexible loads and their flexibility is inaccurate.

Environmental uncertainty arises when external conditions such as ambient temperature, or interaction with end-users, induce variability into the realised response. Analysis of variability in load curtailment events is provided in [E11].

The sources of uncertainty are dependent on the end-use considered for the provision of demand response. In this work we employ the example resource of supermarket refrigeration. The choice of this flexible end-use is due in part to its suitability for the provision of demand response, and in part due to the availability of data describing its demand response characteristics [E18].

E.2.4.1 Structural uncertainty modelling

The structural uncertainty is estimated by employing the time-series model of a supermarket refrigeration described in [E18]. Monte Carlo simulations of the modelled system were employed to generate scenarios of the possible response for a given curtailment event. The model employed does not consider external stimuli such as ambient temperature, and assumes that the supermarket employs model predictive control, such that deviations from the prescribed power reference can be corrected on each control iteration. Thus, the resulting scenarios only consider the model uncertainty and describe the response that can be expected under ideal external conditions.

E.2.4.2 Environmental uncertainty modelling

Environmental uncertainty in supermarket refrigeration demand response can be considered to come from two main sources: outdoor temperature, and interactions with customers and store employees. In this work we focus on the uncertainty resulting from human interaction. There is no available data that would allow an accurate characterisation of this uncertainty and consequently it is necessary to approximate it with educated estimates.

In a supermarket it can be expected that there is significant disturbance to the refrigeration system during periods in which there are large volumes of customers

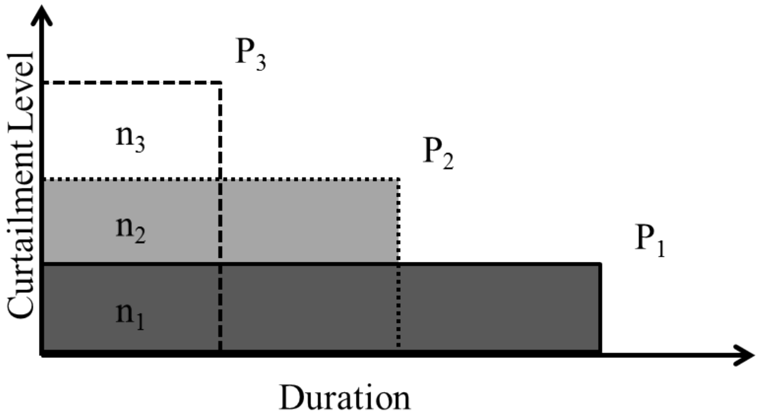


Figure E.1: DR offer structure

in the supermarket, or when restocking of goods occurs. During the low activity night hours it can be expected that the available load curtailment is known with more certainty.

This time varying uncertainty can be represented by assuming that the system can occupy a number of states, and that the probability of occupying each state is time varying. Each state represents the degree to which the scheduled load curtailment can be achieved. This structure resembles that of an inhomogenous Markov process [E19]. In this work, the probability of occupying a given state is defined for each hour of the day, assuming that variations in uncertainty occur on a diurnal cycle. Sensitivity studies are conducted to assess the impact of the uncertainty distribution on the revenue outcome.

E.2.5 Scheduling Demand Response

DR is subject to the same scheduling constraints in both of the energy markets considered. Here we consider that the DR agent can offer a number of different curtailment products. Products are differentiated according to magnitude and duration. Figure E.1 illustrates a sample case where three products, P, can be offered to an energy market. In the mathematical formulation that follows, the offered products are defined in a stacked manner. For example, the magnitude of product P_2 is the summed magnitudes of components n_1 and n_2, while the maximum duration of the product is limited to the duration of component n_2, the highest active product component.

E.2.5.1 Component based products

The magnitude of each product component is denoted $P_n^{component}$. Load curtailment, P_t^{DR} can be scheduled up to the maximum allowable curtailment for a given product, as defined by the sum of its components. This is imposed in (E.4a). The binary variable $u_{t,n}$ indicates whether a given product component is active. Restrictions are placed on the value of $u_{t,n}$ to ensure that the components are activated sequentially, (E.4b). The start and end of a load curtailment event are denoted SU_t^{DR} and SD_t^{DR} respectively. These binary variables are activated by a change in the value of $u_{t,n}$. The behaviour of the start-up and shut-down indicators is governed by (E.4c) - (E.4f).

$$P_t^{DR} \leq \sum_n u_{t,n} P_n^{component} \quad \forall\, t \tag{E.4a}$$

$$u_{t,n} \leq u_{t,n-1} \quad \forall\, t, n \tag{E.4b}$$

$$u_{t,n} - u_{t-1,n} = SU_{t,n} - SD_{t,n} \quad \forall\, t, n \tag{E.4c}$$

$$SU_t^{DR} \geq SU_{t,n} \quad \forall\, t, n \tag{E.4d}$$

$$SD_t^{DR} \geq SD_{t,n} \quad \forall\, t, n \tag{E.4e}$$

$$SU_t^{DR} + SD_t^{DR} \leq 1 \quad \forall\, t \tag{E.4f}$$

E.2.5.2 Limited product duration

The scheduled duration of a curtailment event is limited to the duration of the highest active product component, D_n. This is enforced in (E.5a) which states that the sum of active components over the duration of the DR event must be less than the duration of the highest active product component (multiplied by the number of components in the scheduled product, $\sum_{\nu=1}^{n} 1$). If a component n is not active, the expression $(1 - u_{t,n})$ becomes 1, causing the constraint to be non-binding. Consider for example the product P_2 illustrated in Fig. E.1, the maximum sum of online indicators for components n_1 and n_2 over the duration of the product, two intervals, is four. This constraint assumes that $D_n < D_{n+1}$. Following a curtailment event, (E.5b) prevents the activation of any product component for a rest period, R. The end of a curtailment event is indicated by a change in online status for any product component n from 1 to 0. Consequently, the behaviour illustrated in the last element of Fig. E.2 is prohibited by (E.5b), as n_2 ceases activity, which prevents activity in n_1.

$$\sum_{\tau=t}^{t+D_n} \sum_{\nu=1}^{n} u_{\tau,\nu} \leq (D_n + (1 - u_{t,n})) \sum_{\nu=1}^{n} 1 \quad \forall\ t, n \tag{E.5a}$$

$$\sum_{\tau=t}^{t+R-1} (1 - u_{\tau,n}) \geq SD_t^{DR} R \quad \forall\ t, n \tag{E.5b}$$

E.2.5.3 Permitted Scheduling

To ensure that curtailment products with larger magnitudes are not scheduled for the longer duration of smaller magnitude products, it is necessary to ensure that product components cannot activate at arbitrary points, as imposed by (E.6a). The only time at which product components are permitted to activate is when an event start-up occurs, and only those product components that are activated at the start up time are permitted to be online for the duration of the product. The behaviour that this constraint prohibits is illustrated by the second element in Fig. E.2. If the curtailment event concludes before the stated duration, the constraint becomes non-binding, allowing for the subsequent scheduling of other products. This is illustrated in the last two elements of Fig. E.2, though of course the last element is prohibited. Furthermore, if a start up did not occur at the considered starting time t the constraint is not binding.

$$u_{\tau,n} \leq u_{t,n} + (1 - SU_t^{DR}) + \sum_{\tau'=t}^{\tau} SD_t^{DR}\ \forall \tau \geq t, \tau < t + D_n \tag{E.6a}$$

E.2.5.4 Realised Uncertainty

Uncertainty in the realised curtailment is considered in (E.7a) and (E.7b). Through the combination of these two constraints it is imposed that the realised load curtailment, $P_{t+k,e,s}^{DR,R}$, is equal to the scenarios of realised curtailment $P_{k,s,n}^{DR,scenario}$ (representing structural uncertainty) multiplied by a stochastic parameter of response availability A_e (representing environmental uncertainty). The stochastic indices s and e denote the uncertainty sets for structural and environmental uncertainty respectively, these were previously combined in the uncertainty index ω for simplicity. These constraints are non-binding if an event

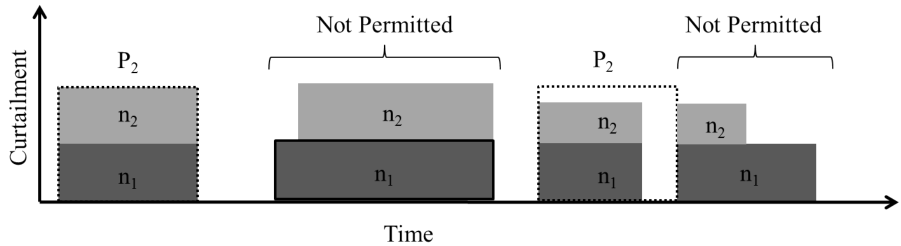


Figure E.2: Illustration of permitted and prohibited scheduling

did not start at time t, or if the component corresponding to the load curtailment scenario is not active, $u_{t+k,n}$, or if a higher product component is active, $u_{t+k,n+1}$. This is achieved through the M value, which is a large number that causes (E.7a) and (E.7b) to be non-binding under any of the above conditions. In this manner, each curtailment event is restricted by constraints concerning the highest active product component only.

As it is possible to schedule load curtailment at a level less than the maximum allowable magnitude of a given product, it is necessary to scale the scenarios accordingly. This is achieved by the scaling parameter $\gamma_{t,n}$ which compares the scheduled load curtailment P_t^{DR} to that defined by the product components. This scaling is essentially linear interpolation between the defined products, as it is not possible to define scenarios for the realised curtailment at every possible level of scheduled curtailment. To minimise the error introduced by this interpolation, curtailment products should be defined at regular intervals of curtailment magnitude. Each additional curtailment product introduces a further binary variable, increasing the computational complexity of the problem. Thus, a compromise must be found between the computational burden and accuracy required by the scheduling algorithm.

$$P_{t+k,e,s}^{DR,R} \geq P_{k,s,n}^{DR,scenario} A_e \gamma_{t+k,n} - \\ ((1 - SU_t^{DR}) + (1 - u_{t+k,n}) + u_{t+k,n+1})M \quad \forall\ t, n \tag{E.7a}$$

$$P_{t+k,e,s}^{DR,R} \leq P_{k,s,n}^{DR,scenario} A_e \gamma_{t+k,n} + \\ ((1 - SU_t^{DR}) + (1 - u_{t+k,n}) + u_{t+k,n+1})M \quad \forall\ t, n \tag{E.7b}$$

$$\gamma_{t,n} = \frac{\sum_{\nu=1}^{n} P_\nu^{component} - P_t^{DR}}{\sum_{\nu=1}^{n} P_\nu^{component}} \quad \forall\ t, n \tag{E.7c}$$

E.3 Case Study

This section describes the parameters of the case studies employed in this work.

E.3.1 Data Description

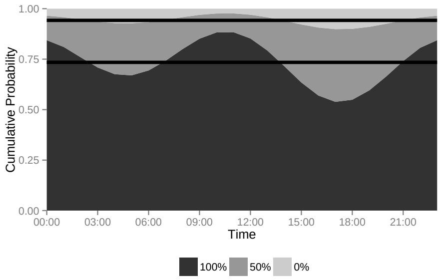
Simulations conducted in this work consider historical price data at hourly resolution from each of the markets considered. The scheduling optimisations consider the most recently available point forecast of the relevant prices, while actual revenue is calculated using the realised prices. In order to achieve an overall representation of the performance of the trading strategy, simulations are conducted using data from four weeks in 2012; 23$^{\text{rd}}$-29$^{\text{th}}$ April, 18$^{\text{th}}$-24$^{\text{th}}$ June, 17$^{\text{th}}$-23$^{\text{rd}}$ September, and 17$^{\text{th}}$-23$^{\text{rd}}$ December.

The historical prices employed are point forecasts of the day-ahead and regulating power prices in the eastern Denmark pricing region, as available at the time of scheduling; realised prices on the day-ahead and regulating power market; and intraday trade offers, including information on when the offer was posted and when it was removed from the list of open trades. Price forecasts for up- and down-regulation prices are issued hourly. A thorough description of the models employed to derive the day-ahead and regulating power prices can be found in Section III of [E15], and [E20].

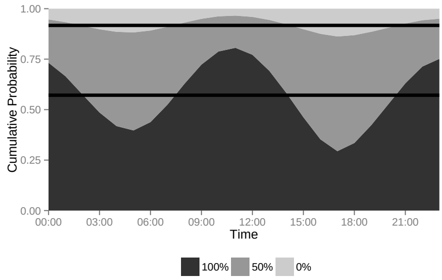
E.3.2 Simulation Framework

The DR resource considered in the simulations that follow consists of 3000 supermarkets offering a maximum load curtailment of 10kW each. The population of supermarkets is considered to offer three DR products: 30 MW curtailment for one hour, 18 MW curtailment for up to two hours, or 15 MW curtailment for up to three hours. These quantities are selected to ensure that the temperature change that occurs on the refrigeration system during curtailment events does not necessitate an energy recovery subsequent to the curtailment. This is informed by studies from [E18].

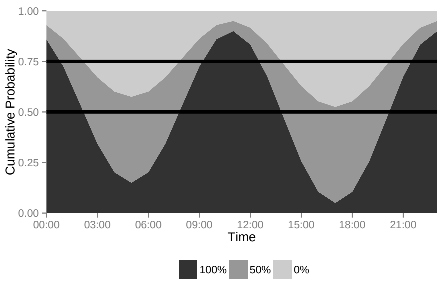
Structural demand response uncertainty is represented through three scenarios for each of the demand response products offered. Environmental demand response uncertainty for participation on the intraday market is represented in the form of six probability distributions for the proportion of the requested demand response that is realised at a given time, as are illustrated in Fig. E.3. It is



(a) Base Distribution



(b) Moderate Distribution



(c) Extreme Distribution

Figure E.3: Environmental uncertainty distributions considered in the case studies. The cumulative probabilities of the response states are indicated by the curved area plots (time varying distributions) and the horizontal lines (time invariant distributions).

considered that the demand response can occupy three possible states; fully responsive, 50% responsive, and not responsive. Three of the probability distributions are time varying, while the second set of three distributions are their time invariant counterparts, where the state probabilities are the time averaged probability values from the first three distributions. The time varying probability distributions are designed such that they represent situations in which there is a mild, moderate and extreme variation in state probabilities over the course of a day. It is assumed that there is no variation in these distributions from one day to the next.

On Elbas, intraday trades are posted and accepted at arbitrary times for energy delivery at set hours, however this level of detail is not warranted for a simulation study. Instead it is assumed that all offers which are posted during a given hour are evaluated together at the start of the following hour, regardless of the order in which they were posted. This simplification increases revenue as multiple trades are assessed in parallel, whereas assessing each trade in turn might result in the acceptance of a trade that would appear sub-optimal compared to other trades that are posted later in the same hour.

The intraday trading strategy is subject to an optimisation horizon of 7 hours. This value represents a compromise between a very short horizon which would induce terminal effects, and a long horizon which is subject to significant price forecast uncertainty. The selected horizon results from analyses of the impact of horizon extent on revenue outcomes.

E.4 Results and Discussion

In this section we present the results of simulations conducted to answer three key research questions.

E.4.1 Is participation on the day-ahead market profitable?

The value of participating on the day-ahead market is illustrated in Fig. E.4. The combined revenue from the day-ahead and intraday markets is shown for a range of day-ahead demand response forecast accuracy levels for environmental uncertainty, as well as the case where no trading occurs on the day-ahead market. The *poor* forecasts case considers that each of the achievable demand response states, 100%, 50% and 0% are equiprobable, while the *moderate* forecast assumes that the response is perfect (100%). The poor forecast therefore under-estimates

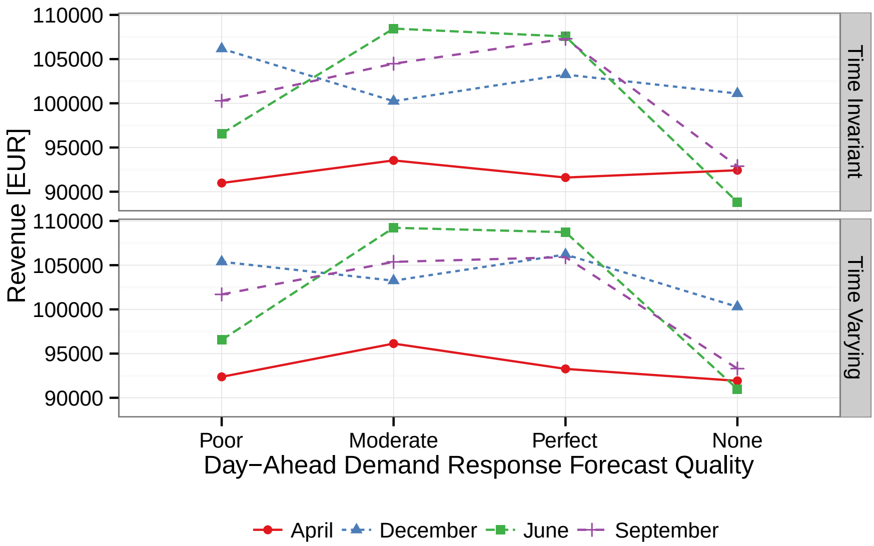


Figure E.4: Expected revenue from trading on the day-ahead and intraday markets with a range of day-ahead DR forecast qualities.

the response while the moderate forecast over-estimates it. The *perfect* forecast considers that the day-ahead optimisation uses the same uncertainty distribution of achievable load curtailment as the intraday trading optimisation. The demand response uncertainty distributions considered in this case are the time varying and time-invariant distributions from Fig. E.3a.

It can be seen that in most cases trading on the day-ahead market is advantageous, even when the DR forecast is poor. In many cases it can be seen that a moderate demand response forecast out-performs the perfect forecast. This is because this forecast overestimates the demand response resource and offers more energy on the day-ahead market than can be delivered. In doing so, the higher prices on the day-ahead market can be harnessed, and the imbalance that occurs at real-time can be corrected through either purchasing trades on the intraday market or on the regulating power market. This strategy of over-estimating the demand response resource on the day-ahead market does not always result in higher revenue than a perfect forecast. If advantageously priced sell trades are not available on the intraday market, the energy shortfall must be purchased at the regulating power price, which is at least as high as the day-ahead price.

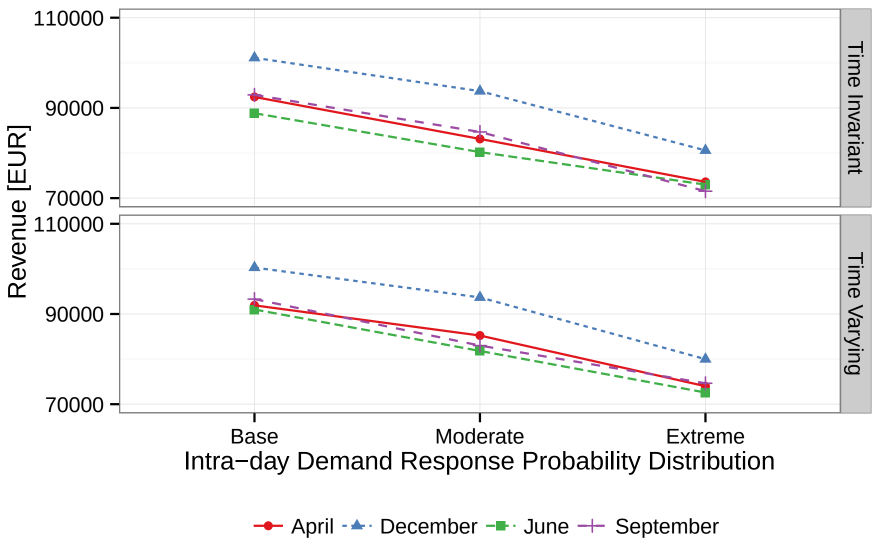


Figure E.5: Expected revenue from trading on the intraday market for each of six DR uncertainty distributions.

It should be noted here that the expected revenue range is approximately €90,000-€110,000. As the DR resource consists of 3000 supermarket providing curtailment, this amounts to a revenue of approximately €30-37/week per participating supermarket. This is a very small sum, which is unlikely to justify the investment necessary to provide DR.

E.4.2 What is the impact of the uncertainty distribution?

The impact of environmental uncertainty can be seen in Fig. E.5, which shows the intraday revenue that is generated in each of the environmental uncertainty distribution cases considered (cf. Fig. E.3). It can be seen that there is a clear difference between the cases considered. This can be accounted for by the difference in the expected curtailment across the cases. The extreme case has the lowest expected demand response resource, and correspondingly the lowest expected revenue. Thus, it can be expected that the larger the variation in time of the demand response resource, the lower the revenue that can be generated. This study leads to the conclusion that the uncertainty distribution of demand response has a noticeable impact on the revenue that can be accrued through

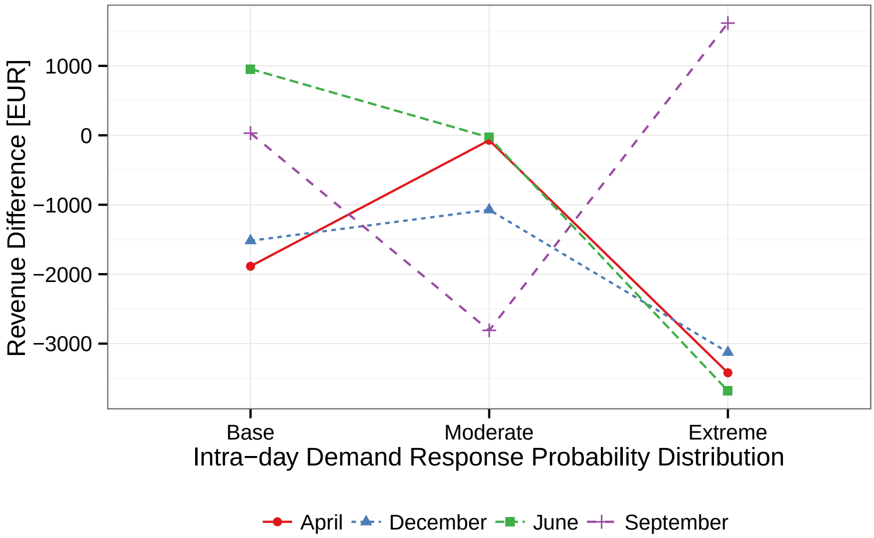


Figure E.6: Revenue difference when a time invariant DR forecast is employed in the trading while the realised curtailment exhibits the time varying uncertainty distribution.

participation on the intraday market.

E.4.3 Is it necessary to consider the temporal structure of the uncertainty distribution?

The impact of intraday demand response forecast accuracy is addressed in Fig. E.6. In the cases illustrated here, the trading was conducted employing time invariant demand response forecasts, and the revenue was validated by applying the time varying distributions to the scheduled load curtailment. The resulting revenue is compared to the outcome if trading was conducted using the time varying forecasts. The revenue difference shown in the figure corresponds to trading with an accurate forecast minus trading with an inaccurate forecast. It can be seen that in many cases, the inaccurate forecast actually improves the revenue outcome, however there is no clear trend and in all cases the change in revenue is under 4%. The inaccurate forecast does not include information on the temporal structure of the load curtailment that is expected as it represents the time averaged probabilities from the time varying uncertainty distribution.

Consequently, approximately 50% of the time, the expected load curtailment under the inaccurate forecast will exceed that with the accurate forecast. This results in cases where some intraday trades will be accepted subject to the inaccurate forecast which would not be accepted were the accurate forecast available. Similarly, some trades are accepted under the accurate forecast that are not accepted with the inaccurate forecast.

Analysis of the revenue breakdown for each of the cases considered reveals that the trade revenues with both accurate and inaccurate demand response forecasts are very similar, with most of the revenue difference resulting from changes to imbalance costs. This can be accredited to the all-or-nothing nature of the intraday trades. Slight changes to the expected achieved curtailment may not affect the decision to accept a particular trade as the revenue associated with accepting the trade far exceeds the imbalance penalty that will be imposed if the achieved curtailment deviates a small amount from that required to fulfil the trade. The use of out-of-sample regulating prices in the revenue calculation contributes to the lack of trend in Fig. E.6.

This result supports the conclusion that the intraday market is a suitable trading platform for demand response. The absence of an accurate forecast of the demand response resource does not preclude profitable trading on this market due to the structure of its trades. Furthermore, the burden of achieving an accurate forecast is reduced as this study has revealed that it is not strictly necessary to capture the temporal structure of the uncertainty distribution.

E.5 Conclusions

This work presents optimal trading strategies for aggregated DR offering load curtailment on the day-ahead and intraday markets under uncertainty. A thorough analysis of the impact of DR uncertainty on revenue outcomes is presented.

Analysis has revealed that despite significant DR uncertainty at long horizons, trading on the day-ahead market prior to trading on the intraday market is preferable to solely trading intraday. The impact of DR uncertainty on intraday trading outcomes is found to be significant, indicating that all future analyses of DR revenue potential should incorporate consideration of its uncertainty. Consideration of the temporal structure of the demand response uncertainty when trading intraday was determined to be unnecessary to ensure a profitable outcome, indicating that advanced forecast products are not necessary for profitable trading on this market.

A continuation of this research agenda should focus on identifying accurate uncertainty distributions for load curtailment.

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