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 the structure of trades on the intraday market.

Keywords: Demand Response, Trading Strategies, Electricity Markets, Uncertainty, Stochastic Optimisation

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Nomenclature

Indices:

t	Time index
k	Time index relative to start-up of DR event
e	Index of environmental uncertainty state
s	Index of structural uncertainty scenario
n	Index of load curtailment component
o	Index of trade offer on the intraday market

Parameters:

λ_t^{DA}	Day-ahead price
λ_t^{D}	Down regulation price
λ_t^{U}	Up regulation price
π_ω	Probability of scenario ω, combining probabilities of structural uncertainty scenario s and environmental uncertainty state e
$P_{k,s,n}^{DR,scenario}$	Available load curtailment in scenario s for structural uncertainty
A_e	Proportion of scheduled load curtailment that can be achieved in DR response state e
$P_n^{component}$	Component n of the available load curtailment products
D_n	Maximum duration for which load curtailment component n can be active
S	Offer to sell energy on the intraday market (Sell trade)
B	Offer to purchase energy on the intraday market (Buy trade)

$(\cdot)_{t,o}^{P}$	Trade price for intraday buy or sell trade
$(\cdot)_{t,o}^{V}$	Trade volume for intraday buy or sell trade

Variables:

$\Delta_{t,\omega}^{+}$,$\Delta_{t,\omega}^{-}$	Positive and negative deviations between scheduled and realised load curtailment
$P_{t}^{DR,S}$	Load curtailment scheduled on the day-ahead market
$P_{t}^{DA,R}$	Volume of day-ahead trade that is maintained during intraday trading
P_{t}^{DR}	Combined load curtailment scheduled on all markets
γ_t, n	Proportion of DR component n scheduled
$P_{t,\omega}^{DR,R}$	Load curtailment realised in scenario ω

Binary Variables:

$v_{t,o}$	Indicator that a buy trade has been accepted
$w_{t,o}$	Indicator that a sell trade has been accepted
$u_{t,n}$	Indicator that DR component n is active
SU_{t}^{DR}	Indicator of the start-up of a load curtailment event
SD_{t}^{DR}	Indicator of the shut-down of a load curtailment event

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 (De Jonghe et al., 2012), alleviating network congestion (Sundstrom and Binding, 2010), and increasing power system reliability (Kirby, 2008), among others (Strbac, 2008).

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 by Zerrahn and Schill (2015) and O'Connell et al. (2015). Participation of residential demand response in the day-ahead and balancing markets is considered by Ali et al. (2015), while an optimal trading strategy for flexible batch processes is developed by Mohsenian-Rad (2015). Consideration of DR uncertainty in trading and scheduling strategies is less commonly addressed, but is incorporated into the electric vehicle charging strategy developed by Gonzalez Vaya and Andersson (2015) and the scheduling of aggregated thermostatically controlled loads described by Hao et al. (2015). The nature of demand response uncertainty is described in (Mathieu et al., 2011), and its impact is highlighted by Zhao et al. (2013) and Gao et al. (2015). The work presented in this article differs from existing research by collectively considering the inherent uncertainty of the DR that can be delivered at real time, the physical characteristics and constraints of the population of flexible loads offering this service, and the necessity to develop trading strategies that are suitable for existing market structures, rather than focussing solely on a single aspect of the problem.

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 (Dent et al., 2011). Bidding strategies for both the day-ahead market and continuous trade intraday market are provided in (Skajaa et al., 2015), and (Rahimiyan et al., 2011) provides an evaluation of a number of alternative offering strategies for wind power producers. While both DR and wind power are stochastic power system resources, they differ fundamentally in their delivery of power and associated power system services. Wind power generators are primarily limited by the instantaneously available power in the wind, whereas DR aggregators have more flexibility to schedule load curtailment, but are limited in magnitude and duration of DR events by the uncertain operating conditions of the individual participating responsive loads. This fundamental difference offers the opportunity to learn from existing works while providing a novel contribution in the area of trading uncertain demand response.

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 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 3 describes the case study framework employed in this work. The key research questions considered and results of this work are presented in Section 4, and closing remarks are provided in Section 5.

2. Methodology

2.1. *Participation of Demand Response in Wholesale Electricity Markets*

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. The Nordic market is selected here as it shares a common structure with many European markets, facilitating the extension of the trading strategies developed in this work to many markets outside the Nordic region.

In the Nordic market, the market agent can offer load curtailment in either the day-ahead market, Elspot, or the intraday market, Elbas (Nord Pool Spot, 2016). 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 (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}.

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

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.

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 (10MWh at €40/MWh). 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 (€300 + €500 - €400). 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.

2.2. Day Ahead Trading

As stated in (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 (4)-(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^{D}_t and contributes to the expected revenue. A negative deviation (shortfall in load curtailment) is purchased at the up-regulation price, λ^{U}_t 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.

$$\max_{\mathbf{P}} \ \sum_t \left(P^{DR,S}_t \lambda^{\mathrm{DA}}_t - \sum_\omega \pi_\omega \left(\Delta^{-}_{t,\omega} \lambda^{\mathrm{U}}_t - \Delta^{+}_{t,\omega} \lambda^{\mathrm{D}}_t \right) \right) \tag{2a}$$

subject to:

$$P^{DR,R}_{t,\omega} = P^{DR,S}_t + \Delta_{t,\omega} \quad \forall\, t, \omega \tag{2b}$$

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

$$\Delta^{+}_{t,\omega}, \Delta^{-}_{t,\omega} \geq 0 \quad \forall t, \omega \tag{2d}$$

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 2.5.

The mathematical formulation of the intraday trading strategy is detailed in (3), and is subject to the DR scheduling constraints (4) - (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 $(\cdot)_{t,o}^{V}$ and $(\cdot)_{t,o}^{P}$ 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 (3b) and (3c). Equation (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 (2), through curtailment, as given in (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 (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.

$$
\begin{aligned}
\max \ \sum_{t} \Bigg(& \sum_{o} \left(v_{t,o} B^{V}_{t,o} B^{P}_{t,o} - w_{t,o} S^{V}_{t,o} S^{P}_{t,o} \right) + \\
& \sum_{\omega} \pi_{\omega} \left(\Delta^{-}_{t,\omega} \lambda^{\mathrm{U}}_{t} - \Delta^{+}_{t,\omega} \lambda^{\mathrm{D}}_{t} \right) \Bigg) \qquad \text{(3a)}
\end{aligned}
$$

subject to:

$$\sum_{o} v_{t,o} B^{V}_{t,o} + P^{DA,R}_{t} \leq P^{DR}_{t} \quad \forall\, t \qquad \text{(3b)}$$

$$P^{DA,R}_{t} \leq P^{DR,S}_{t} \quad \forall\, t \qquad \text{(3c)}$$

$$
\begin{aligned}
\Delta_{t,\omega} = {} & P^{DA}_{t} + \sum_{o} B^{V}_{t,o} (v_{t,o}(1 - v_{i-1,t,o}) + v_{i-1,t,o}) - \\
& \sum_{o} S^{V}_{t,o} (w_{t,o}(1 - w_{i-1,t,o}) + w_{i-1,t,o}) - P^{DR,R}_{t,\omega} \quad \forall\, t, \omega \qquad \text{(3d)}
\end{aligned}
$$

$$\Delta_{t,\omega} = \Delta^{+}_{t,\omega} - \Delta^{-}_{t,\omega} \quad \forall\, t, \omega \qquad \text{(3e)}$$

$$\Delta^{+}_{t,\omega}, \Delta^{-}_{t,\omega} \geq 0 \quad \forall\, t, \omega \qquad \text{(3f)}$$

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 bt Mathieu et al. (2011).

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 (O'Connell et al., 2014).

2.4.1. Structural uncertainty modelling

The structural uncertainty is estimated by employing the time-series model of a supermarket refrigeration described by O'Connell et al. (2014). 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.

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, as this is expected by the authors to have a greater impact on the certainty of the demand response that can be provided. Furthermore, there is currently insufficient data to support a characterisation of the impact of outdoor temperature on the certainty with which demand response can be achieved in an operational sense. However, work conducted by Rasmussen et al. (2015) has demonstrated how the relationship between power consumption of a supermarket and weather conditions can be modelled using transfer functions coupled with spline functions, which is a promising indication that the work presented in this article can be adapted to incorporate the relationship between demand response and outdoor temperature once supporting data becomes available.

In a supermarket it can be expected that there is significant disturbance to the refrigeration system during periods in which there are many customers 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 (Madsen et al., 1985). 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.

The authors highlight that this characterisation of environmental uncertainty is not founded on operational data of supermarkets participating in DR programs, as there is currently no available data that would support the identification of this uncertainty distribution. In the absence of an appropriate data source, it is necessary to approximate the distribution with an educated estimate. Consequently, the numerical results presented in this work are intended solely to provide an indication of the impact of uncertainty on the revenue that can be generated, not a definitive analysis. Sensitivity studies are conducted to assess the impact of the uncertainty distribution on the revenue outcome, and to emphasize the need to dedicate further research to the identification of representative uncertainty distributions to inform more comprehensive analysis.

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 1 illustrates a sample case where three products,

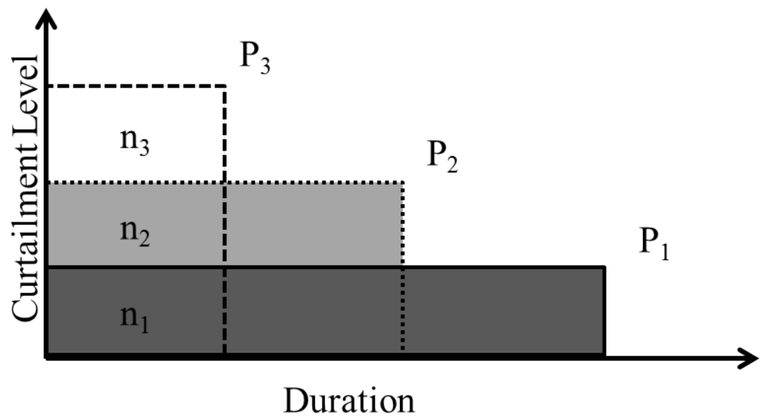


Figure 1: DR offer structure

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. Formulating the problem in this manner alleviates the computational burden associated with the use of binary variables to differentiate between load curtailment products.

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 (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, (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 (4c) - (4f).

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

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

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

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

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

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

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 (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. 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, (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. 2 is prohibited by (5b), as n_2 ceases activity, which prevents activity in n_1.

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

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

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 (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. 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. 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.

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

2.5.4. *Realised Uncertainty*

Uncertainty in the realised curtailment is considered in (7a) and (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 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 (7a) and (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.

$$\begin{aligned}
&P_{t+k,e,s}^{DR,R} \geq P_{k,s,n}^{DR,scenario} A_e \gamma_{t+k,n} - \\
&\qquad ((1 - SU_t^{DR}) + (1 - u_{t+k,n}) + u_{t+k,n+1})M \quad \forall\, t, n && \text{(7a)}\\
&P_{t+k,e,s}^{DR,R} \leq P_{k,s,n}^{DR,scenario} A_e \gamma_{t+k,n} + \\
&\qquad ((1 - SU_t^{DR}) + (1 - u_{t+k,n}) + u_{t+k,n+1})M \quad \forall\, t, n && \text{(7b)}\\
&\gamma_{t,n} = \frac{\sum_{v=1}^{n} P_v^{component} - P_t^{DR}}{\sum_{v=1}^{n} P_v^{component}} \quad \forall\, t, n && \text{(7c)}
\end{aligned}$$

3. Case Study

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

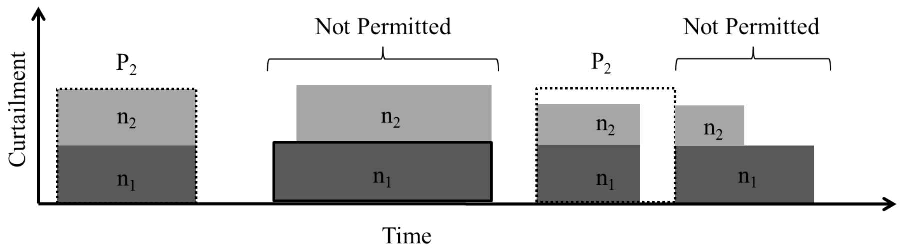


Figure 2: Illustration of permitted and prohibited scheduling

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; 23rd-29th April, 18th-24th June, 17th-23rd September, and 17th-23rd 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; trading on the day-ahead market considers the forecasts issued at 11:00 a.m. on the day before energy delivery, whereas intraday trading considers the most up-to-date version of the forecast at the relevant hour. Forecasts of the up- and down-regulation prices are calculated from conditional probabilities of the deviation between the regulation and day-ahead price, a thorough description of the models employed to derive the conditional probabilities can be found in Section III of (Skajaa et al., 2015), and (ENFOR, 2013).

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 O'Connell et al. (2014).

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. 3. It is considered that the demand response resource 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.

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.

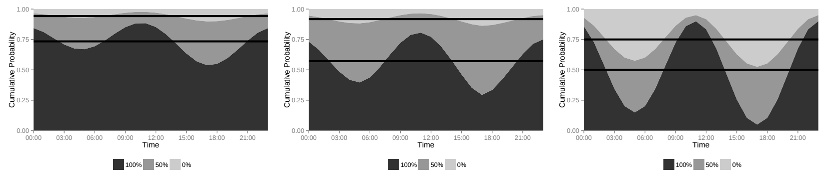
3.3. Assumptions

In the analyses that follow, all possible effort has been made to ensure realistic results. However, in order to extract meaningful results it is necessary to limit the scope of the studies and to make a number of simplifying assumptions.

Firstly, the demand response agent is limited to accepting existing intraday trades, it may not issue trades of its own. This assumption restricts the revenue that the agent can accrue. Limited liquidity on this market means that there may be times at which the agent is capable of providing demand response but there are no suitable open trades. Allowing the agent to post its own trades might result in additional revenue, however it is not possible to realistically simulate whether or not these trades are accepted by other market participants within the scope of this work.

Secondly, all trades on the intraday market are assumed to be all-or-nothing trades, where the trade must be fulfilled 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 dataset of Elbas trades employed in this work does not indicate the trade type, necessitating this assumption. This assumption reduces revenue as certain trades are excluded from consideration as they cannot be fulfilled entirely.

Finally, it is assumed for simulation purposes that trade offers on the intraday market are assessed once an hour. In reality, offers are posted and accepted at arbitrary times for energy delivery at set hours. To reflect this behaviour, it is necessary to run the rolling horizon intraday trading optimisation every time a new offer is posted. This level of detail is not warranted for a simulation study, so 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. It is not clear whether this assumption increases or decreases the market revenue made by the demand response agent, as it produces two conflicting effects: on one hand, the simultaneous assessment of all trades posted in a given hour increases the revenue compared to assessing



(a) Base Distribution (b) Moderate Distribution (c) Extreme Distribution

Figure 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).

each trade in turn as it is posted on the market, because the decision maker has full knowledge of all the available trades; on the other hand, by waiting to consider the acceptance of a given trade until the designated assessment time revenue is reduced, as advantageous trades may be missed because other market participants have accepted them.

4. Results and Discussion

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

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

In this section the value of trading highly uncertain demand response at longer horizons in the day-ahead market is addressed, considering that trade can also occur at shorter horizons on the intraday market at greater certainty. The revenue generated through participation on the day-ahead and intraday markets is illustrated in Fig. 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. This is compared to 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

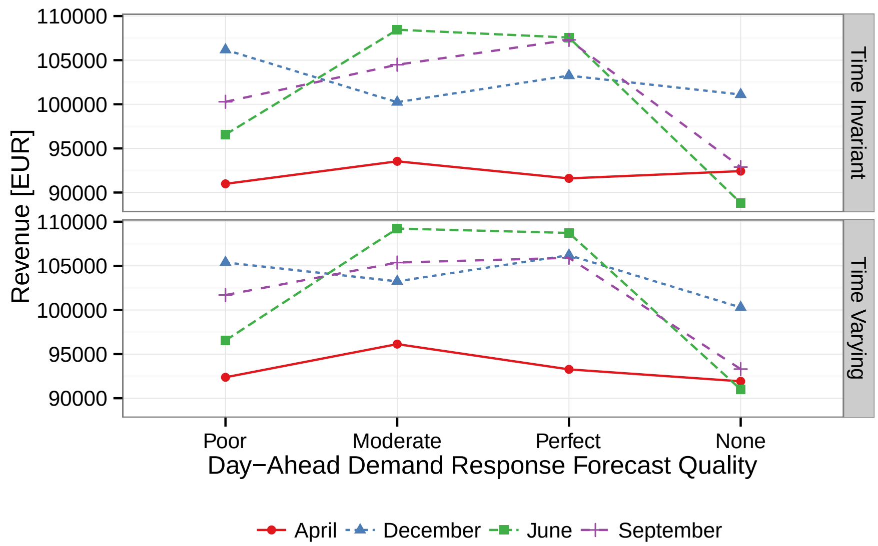


Figure 4: Expected revenue from trading on the day-ahead and intraday markets with a range of day-ahead DR forecast qualities.

DR resource is perfect (100% response at all times). The poor forecast therefore under-estimates the response while the moderate forecast over-estimates it. The *perfect* forecast considers that the day-ahead optimisation employs the same uncertainty distribution of achievable load curtailment as the intraday trading optimisation. The demand response uncertainty distributions considered for the intraday trading optimisation in this case are the time varying and time-invariant distributions from Fig. 3(a).

It can be seen in most of the studied cases that 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 leveraged, 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 overestimating 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. A comprehensive year-long study is required to determine if this trend of higher day-ahead prices prevails over a longer period. As the current study is intended solely to highlight the complexity of trading uncertain demand response, this further analysis will be considered for future work.

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. This does not however rule out the possibility of profitable participation in spot markets for other flexible loads offering DR. The methodology developed in this study is applicable for any market participant offering load curtailment either as an individual or a population of flexible loads. Reduced aggregation, a smaller number of loads offering larger individual curtailment, is likely to significantly improve the benefit case for individual participants.

4.2. What is the impact of the uncertainty distribution?

The impact of environmental uncertainty can be seen in Fig. 5, which shows the intraday revenue that is generated in each of the environmental uncertainty distribution cases considered (cf. Fig. 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

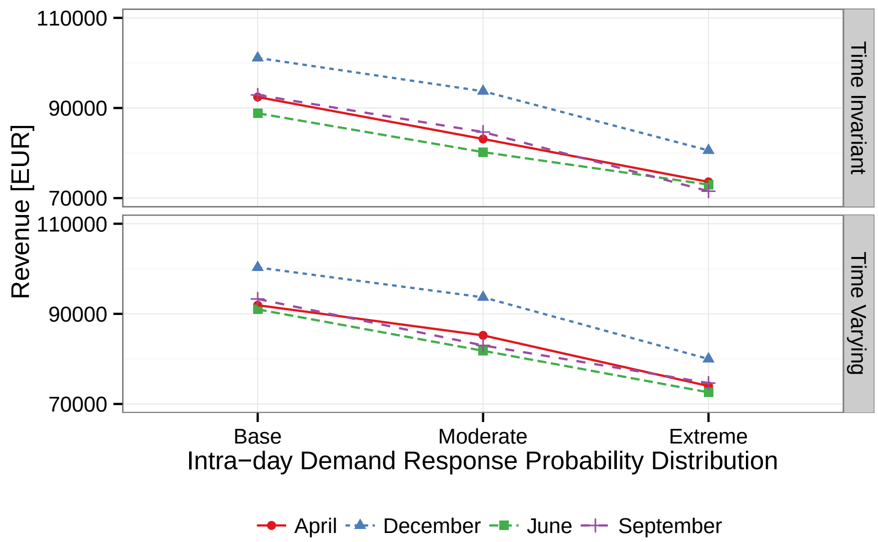


Figure 5: Expected revenue from trading on the intraday market for each of six DR uncertainty distributions.

response has a noticeable impact on the revenue that can be accrued through participation on the intraday market. Consequently it is imperative that uncertainty in achievable response be considered when evaluating the business case of DR and it is not simply assumed that the resource is perfectively responsive at all times.

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. 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 in some cases, that the inaccurate forecast actually im-

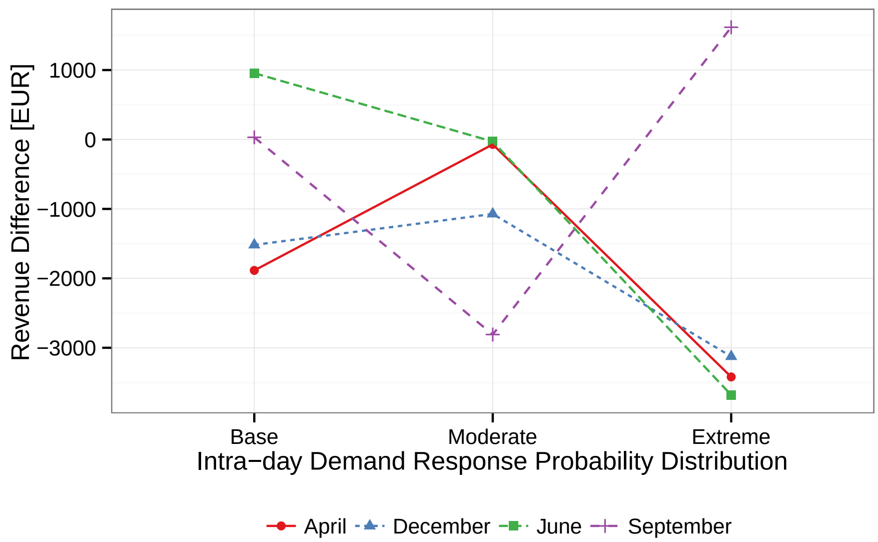


Figure 6: Revenue difference when a time invariant DR forecast is employed in the trading while the realised curtailment exhibits the time varying uncertainty distribution.

proves 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. 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. However, this conclusion is sensitive to the definition of the DR resource. In the cases studied, the magnitude of the load curtailment is comparable to the size of a single or small number of intraday market trades. Should the magnitude of the available curtailment greatly exceed the size of the trades offered on the intraday market, it would be preferable to have an improved forecast of the achievable curtailment so that the optimal combination of concurrent trades can be accepted. This indicates that while the initial deployment of small-scale DR is reasonably insensitive to forecast accuracy, as the resource is further deployed forecasts will play an increasingly important role.

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. Consideration of the temporal structure of the demand response uncertainty when trading intraday was found to be unnecessary to ensure a profitable outcome, indicating that advanced forecast products are not necessary for profitable trading on this market when the resource scale is comparable in magnitude to the intraday trades offered. However, if the resource scale increases significantly it is likely that forecast accuracy will be central to maximising revenue.

The key outcome of this work is that the uncertainty of load curtailment has a significant impact on the revenue that can be generated through trade on competitive electricity markets. Consequently, a continuation of this research agenda should focus on identifying accurate uncertainty distributions for load curtailment to support a comprehensive assessment of the value offered by this novel power system resource.

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