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Abstract

This paper explores the economic benefits that wind and photovoltaic power plant operators can extract from the activation of flexible loads during their market operations. We compare two alternatives: (1) use of flexible loads to maximize relative day-ahead market value by shifting the portfolio balance in view of day-ahead price developments; (2) use of flexible loads in intraday operations to minimize the costs incurred when balancing forecast errors. We find that the latter option yields greater value than the former, both from an analytical and a market data perspective. On these grounds, we propose a model to shift loads before trading production forecast errors in continuous-trade intraday markets under uncertainty. In an illustrative example, the model is applied to simulate the trade operations of a small-scale wind power operator in the German power market with access to a limited pool of flexible loads in the household segment. The simulation demonstrates that demand-side flexibility can yield significant cost reductions; the extent is influenced by the volatility of prices and the time spans across which loads can be shifted.

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1 Introduction and background

Two effects decrease the economic viability of non-dispatchable renewable power production in energy markets: a *low relative market value* and *balancing costs*. The former is a direct result of non-dispatchability. Since the output level of wind or photovoltaic (PV) power systems is dictated by weather conditions, operators cannot choose when to offer what output level. Instead, in the absence of (massive) energy storage capacity, they are forced to offer their product as it becomes available. With weather conditions being similar across fairly large geographical regions, wind or PV operators within specific market areas face strongly correlated output levels. In a market, prices are determined by the intersection of demand and supply, which implies relatively low (high) price levels in times of strong (weak) production. Consequently, the relative market value that can be realized with non-dispatchable power production can be expected to range below the market value of constant production[1]. The issue is amplified by the rising market shares of (non-controllable) PV and wind power capacities observed in energy markets around the world. Hirth (2013), for instance, using a European electricity market model, shows that the market values of both wind and PV power drop drastically with increasing market shares.

Balancing costs result from production forecast errors. With respect to wind and PV power, actual production almost always deviates from (day-ahead) projections and sales. As a result, shortages and surpluses have to be balanced, either within portfolios or in the intraday market. All remaining deviations are then compensated in the imbalance market, often at substantial cost premiums. Overall, the expenses incurred in order to match day-ahead sales present a significant burden on the market value of PV and wind power production. Von Roon (2011) identifies costs amounting to more than 10% of the day-ahead revenues incurred by the German TSOs, due to deviations from day-ahead forecasts of wind and PV power in Germany between March 2010 and October 2010. About half of the costs can be attributed to actual balancing efforts; the other half are opportunity costs arising from the sale of volumes intraday that would have yielded higher value day-ahead. Henriot (2014) underlines that intraday balancing costs and losses of value are amplified by the (still) limited liquidity observed across European continuous-trade intraday markets. Several studies have investigated this liquidity deficit, for instance for the German intraday market (Hagemann and Weber, 2013; Weber, 2010).

Due to subsidies and exemptions from balancing obligations, PV and wind power operators in many markets have been insensitive to the two aforementioned threats to market value. But with regulatory shifts towards market exposure and reduced subsidies[2], operators must miti-

[1] For PV, this negative effect is partly offset by the fact that times of high output tend to coincide with times of high demand.

[2] In Germany, for example, the recent amendment of the Renewable Energy Sources Act (EEG 2014) will oblige operators of many PV and wind power assets to self-market their production outputs.

gate these threats in order to achieve profitability and ultimately competitiveness. There are three means for mitigation: (1) increased forecast accuracy; (2) optimal handling of uncertainty through bidding strategies; (3) and the acquisition of time-wise flexibility. While the first two measures are primarily related to mitigating balancing costs, time-wise flexibility could help to both increase relative market value and minimize balancing costs. Relative market value can be improved by shifting *expected* supply surpluses and resulting (day-ahead) sales into delivery slots with high prices. Balancing costs can be minimized by using flexibility to compensate or shift *unexpected* short or long positions arising from forecast errors.

The scientific and economic debate around flexibility usually involves two alternative kinds of resources: demand-side flexibility and storage. In this paper, we address time-wise flexibility by assessing the value created by demand response (DR) – accruing from flexible, responsive loads – when applied to either day-ahead marketing or intraday balancing of forecast errors for PV or wind power assets. Our interest in DR is motivated by its vast potential and the research gap we suspect regarding the comparison between day-ahead and intraday DR leverage.

The remainder of the paper is structured as follows. Section 2 summarizes relevant recent research on DR resources. Section 3 suggests a valuation logic for day-ahead and intraday DR activation and compares both scenarios from a theoretical and from an empirical perspective for Germany. Section 4, extending from Garnier and Madlener (2014), presents a practical intraday DR deployment model in combination with a PV and wind power bidding strategy. The performance of the deployment model is tested by simulating German intraday market conditions in section 5. Section 6 concludes.

2 Recent research on demand response

Recent research on DR has primarily focused on three dimensions. First, exploration of technically and economically available DR resources (Elberg et al., 2012; Kohler et al., 2010; Klobasa, 2007); second, valuation of the application of DR resources in different contexts (Feuerriegel and Neumann, 2014; Madaeni and Sioshansi, 2013; Sioshansi, 2010); and, third, pricing and incentives for DR providers (Zugno et al., 2013; Faria and Vale, 2011; Na et al., 2011; Schmautzer et al., 2011).

Regarding the exploration of technically and economically available DR resources, research is typically regionally embedded. Different regions or, more generally, market areas, have different demand structures and, consequently, different load patterns and flexibility potentials. For our focus region Germany, a number of valuable insights have become available. Klobasa (2007) conducts a very detailed analysis of DR resources within industry, services, and the residential sector. He investigates subsectors, using power demand data and information on processes and energy-consuming devices to arrive at DR estimates. These estimates include the absolute technical potential as well as the maximum number and time spans of demand shifts. Generally, he finds that the greatest DR potential lies in the private sector (11.3 TWh or 3.7 GW, excluding heat pumps and night storage) as opposed to industry (1.35 TWh or 2.8 GW), and commercial services (3.1 TWh or 2.9 GW, without heating, ventilating, and air conditioning, HVAC). The ratio between estimated capacity and production indicate that DR resources in the residential sector are suspected to be available for activation more often. The time span within which loads can be shifted is found to be very process-specific and duration-specific, ranging from one to 24 hours.

In Kohler et al. (2010), the technical demand-side flexibility potential is assessed for the residential and the energy-intensive industrial sectors. Private households are estimated to have an average positive potential (increase in load) of around 6.7 GW and a negative potential (decrease in load) of about 35 GW. The most relevant energy-consuming devices are found to be white goods and heating appliances. For the energy-intensive industries, around 2.1 GW of positive and 0.5 GW of average negative potential could be identified in sectors such as steel, aluminum, cement, paper, and chemical processes. The study also takes a look at costs related to leveraging DR resources, focusing on investment costs as well as fixed and variable operating costs. Similarly, in Elberg et al. (2012), estimates of total demand-side flexibility are derived, in part based on input data used in Kohler et al. (2010), but with some additions and updates. The study distinguishes between load-clipping and load-shifting, attributing significantly higher potentials to load-shifting. For the evening time on a high-demand day, the study indicates a sizable demand-side flexibility potential of 12.5–14 GW, with about half attributed to residential loads.

Next, we turn towards research on the value that can actually be realized with DR resources in different contexts. For instance, Feuerriegel and Neumann (2014) take on a German retailer's perspective and quantify the procurement cost savings that DR can potentially yield. They formulate a straightforward model, leveraging peak-clipping and load-shifting to optimize procurement efforts in futures and day-ahead markets. Their estimates for DR potentials are taken from Klobasa (2007), a study that focused on the technical potentials. Applying their model to 2011 and 2012 EPEX price data, they find that using DR can yield both cost savings of around 3.5% and cost variance reductions of almost 8%. Feuerriegel and Neumann (2014) skip the intraday market, arguing that it lacks the liquidity to matter in a retailer's procurement strategy. Further, they assume that the retailer does not have any own production assets.

Madaeni and Sioshansi (2013) compare the value contribution of DR and stochastic programming to the unit commitment of conventional power generators in markets with strong wind power integration. The study shows that DR, simulated by means of a real-time pricing system, significantly helps compensating for wind power uncertainty. In fact, up to 70% of the costs associated with wind power supply uncertainty can be compensated through DR. This clearly exceeds the impact that stochastic programming has in their model, yielding at best cost savings of 7%. With a similar focus but a slightly different angle, Sioshansi (2010) shows that applying real-time pricing can significantly increase the share of wind power that a given system can absorb without losing stability. Focusing on the Texas ERCOT area, this study further suggests that about two thirds of the DR potential become available even when residential electricity customers are omitted. Klobasa (2010) analyzes the general potential of DR to reduce the costs of balancing wind power supply deviations from day-ahead forecasts in Germany. Using a two-stage day-ahead and intraday model with German TSO data, he estimates that exploiting the load flexibility potential in Germany can reduce balancing costs by up to 20% (Klobasa, 2010).

While the third research dimension, pricing and incentives for DR providers, is not central to our analysis, some insights from previous research are worth mentioning. Generally, there is a distinction between the stimulation of self-enacted adjustments to load profiles based on price signals, and remote, pre-agreed manipulation enacted by a DR operator. Regardless of the mode, providers of DR face opportunity and often activation costs requiring compensation. Numerous works highlight the effectiveness of price signals from analytical and empirical viewpoints as a way to stimulate the provision of DR (Zugno et al., 2013; Na et al., 2011; Schmautzer et al., 2011). Meanwhile, it is acknowledged that a higher degree of automated power consumption (through smart appliances) allows for a greater degree of remote control, and ultimately a higher realized DR availability (Hillemacher et al., 2013). The less involved actors need to be in order to flexibilize their loads, the lower the operational barriers and opportunity costs are. For these reasons, it is often argued that commercial and industrial business segments are better suited for DR, since much of the consumption is automated and thus remotely controllable. However, with the expansion of home automation and smart meters, the automation of electricity-consuming home appliances is gradually turning into a reality, and may in the foreseeable future significantly facilitate DR activation in households as well (Hillemacher et al., 2013).

Acknowledging the contributions of the aforementioned studies, our research seeks to contribute some new insights to the DR literature in two ways. First, research on leveraging DR for wind (or PV) power integration has so far not compared day-ahead with intraday activation. Given the fact that wind and PV power plants today face value challenges both at the time of sale and at the time of forecast error balancing intraday, it seems far from obvious where finite flexibility resources can be allocated most valuably. Second, the activation of DR to the balancing of forecast errors under uncertainty has, to our knowledge, not been modeled from a wind or PV power plant operator's perspective yet. However, we consider this to be a highly appealing and realistic scenario. We thus believe that our work provides an applicable model and useful new insights into value creation at the interface of DR and renewable energy supply.

3 Demand response valuation logic

In this study, we consider two alternative DR strategies: (1) a day-ahead activation strategy (denoted by DA) to increase sales revenue, and (2) an intraday activation strategy (denoted by ID) to minimize forecast error balancing costs. DR is modeled as L^t units of flexible load, to be understood as a share of (by assumption perfectly predictable) demand D^t for any time slot that can be shifted by r slots within a predetermined time range $R^t \rightarrow t-r,\ldots,t,\ldots,t+r$. D^t is set below the day-ahead supply forecast Y^t_{DA} at all times, in order to avoid short positions day-ahead[3].

3.1 Model formulation

In strategy (1), the operator has different amounts of excess power available for delivery or sale across all time slots within R^t. Value is derived from flexibility by shifting demand into times of low market prices, such that further supply volumes are freed for sale in the market at times of high prices. Assuming that flexible loads can be shifted from their initial consumption slot at time t into the least-cost available slot M within range R^t, $M \rightarrow \min P^t_{\mathrm{DA}}\{R^t\}$, the value of units shifted day-ahead is defined by

$$V(L^t)_{\mathrm{DA}} = L^t \times \left[P^t_{\mathrm{DA}} - P^M_{\mathrm{DA}} + \frac{c_{s\,\mathrm{DA}}^{\;M} - c_{s\,\mathrm{DA}}^{\;t}}{2} - \left(C^{\mathrm{O}}_{\mathrm{DA}} + C^{\mathrm{A}}_{\mathrm{DA}}\right) \right] . \tag{1}$$

It shows that the value of shifting loads away from t is determined by differences in price P and bid-ask spread (BAS) c_s between the current slot t and slot M. The costs of shifting loads arise from both opportunity costs of customers $C^{\mathrm{O}}_{\mathrm{DA}}$ and variable activation costs $C^{\mathrm{A}}_{\mathrm{DA}}$. Evidently, the value of flexibility at slot t increases with the difference in day-ahead prices between t and M. This illustrates nicely that the key value driver is (price) volatility.

For strategy (2), valuation not only depends on prices, but also on forecast error dynamics. Depending on the forecast error sign, an operator is either short, and has to buy intraday for the current slot t, or he is long and can sell volumes intraday for the current slot at time t. In both settings, there are two options for the operator:

(a) to shift loads from the current short (long) position slot into another slot with a short (long) position within range R^t that offers a lower price, or

(b) to net (enhance) an open position by moving loads from the current short (long) position slot into a slot with a long (short) position within R^t. For obvious reasons, this is only possible if R^t is "mixed", i.e. there are slots with both long and short positions.

[3] Note that these requirements are given in order to focus on the aspect under investigation – relative market value optimization for PV or wind. Relaxing the constraints is easily possible; however, it would introduce other effects, i.e. short day-ahead portfolios and demand volatility.

The valuation of option (a) is similar to the day-ahead valuation. For long intraday positions, the formula is identical to eq. (1), except that intraday variables replace day-ahead variables.

$$V(L^t)_{\mathrm{ID}}^{\mathrm{Long}} = L^t \times \left[P_{\mathrm{ID}}^t - P_{\mathrm{ID}}^M + \frac{c_{s\mathrm{ID}}^{\ M} - c_{s\mathrm{ID}}^{\ t}}{2} - \left(C_{\mathrm{ID}}^{\mathrm{O}} + C_{\mathrm{ID}}^{\mathrm{A}} \right) \right] . \tag{2}$$

At short position slots, the only difference occurs regarding the BAS terms: instead of $(c_{s\mathrm{ID}}^{\ M} - c_{s\mathrm{ID}}^{\ t})$, we now have $(c_{s\mathrm{ID}}^{\ t} - c_{s\mathrm{ID}}^{\ M})$. This is because the short position at time t is reduced, leading to BAS savings. Meanwhile, the short position at slot M is enhanced, implying that more BAS incurred at M, leading to

$$V(L^t)_{\mathrm{ID}}^{\mathrm{Short}} = L^t \times \left[P_{\mathrm{ID}}^t - P_{\mathrm{ID}}^M + \frac{c_{s\mathrm{ID}}^{\ t} - c_{s\mathrm{ID}}^{\ M}}{2} - \left(C_{\mathrm{ID}}^{\mathrm{O}} + C_{\mathrm{ID}}^{\mathrm{A}} \right) \right] . \tag{3}$$

The valuation of option (b) calls for further differentiation. In the case of a short position, the current shortage is netted with a long position available within R^t. To this end, the long position with the lowest corresponding market price is chosen, i.e. $N \to \min P_{\mathrm{ID}}^t \{R^t | Y_{\mathrm{DA}}^t < Y_{\mathrm{ID}}^t\}$. We define the value of flexible load in this setting as

$$V(L^t)_{\mathrm{ID}}^{\mathrm{Net}} = L^t \times \left[\left(P_{\mathrm{ID}}^t + \frac{c_{s\mathrm{ID}}^{\ t}}{2} + TC \right) - \left(P_{\mathrm{ID}}^N - \frac{c_{s\mathrm{ID}}^{\ N}}{2} - TC \right) - \left(C_{\mathrm{ID}}^{\mathrm{O}} + C_{\mathrm{ID}}^{\mathrm{A}} \right) \right] . \tag{4}$$

The first term within the squared brackets refers to the value created by shifting loads away from the current short slot. Here, purchasing volumes at price P_{ID}^t with the corresponding (half) spread and transaction costs is avoided. The second term defines the value created by shifting these loads into the lowest-priced long slot within R^t. While revenues are foregone by reducing the volumes sold at price P_{ID}^N, half a spread and transaction costs for the sale are avoided.

A comparison between options (a) and (b) shows that, for short positions, it is beneficial to opt for option (b) whenever $\left[(c_{s\mathrm{ID}}^{\ N} + c_{s\mathrm{ID}}^{\ M})/2 + 2TC + P_{\mathrm{ID}}^M > P_{\mathrm{ID}}^N \right]$. Just from the balance of variables, this seems to hold in the majority of cases. Indeed, market mechanisms make it likely that, on average, $P_{\mathrm{ID}}^M > P_{\mathrm{ID}}^N$, as long as the portfolio of the operator is sufficiently correlated with the portfolio of the other PV or wind power plant operators in the market. This is because the aggregate balance of market actors is reflected in the market prices. Hence, in the presence of strong correlation, prices are likely higher for slots with short positions than for slots with long positions.

In contrast, if the operator decides to shift flexible loads away from a long position towards a short position, he does not net but rather enhance positions. Since demand is reduced at time t, the supply surplus is even larger. Similarly, the shortage at the short slot to which demand is shifted, $E \to \min P_{\mathrm{ID}}^t \{R^t | Y_{\mathrm{DA}}^t > Y_{\mathrm{ID}}^t\}$, is increased. Consequently, higher transaction costs are incurred at both the long and short position slots. We thus have the (already simplified) term

$$V(L^t)_{\mathrm{ID}}^{\mathrm{Enhance}} = L^t \times \left[P_{\mathrm{ID}}^t - P_{\mathrm{ID}}^E - \frac{c_{s\mathrm{ID}}^{\ t} + c_{s\mathrm{ID}}^{\ E}}{2} - 2TC - \left(C_{\mathrm{ID}}^{\mathrm{O}} + C_{\mathrm{ID}}^{\mathrm{A}} \right) \right] . \tag{5}$$

Applying a similar logic as before, we can show that option (b) at long position slots is value-increasing iff $\left[P^E_{\text{ID}} + ({c_s}^E_{\text{ID}} + {c_s}^M_{\text{ID}})/2 + 2TC < P^t_{\text{ID}}\right]$. Again, from the balance of variables, this seems unlikely. Further, the market mechanism implies that, on average, $P^E_{\text{ID}} > P^t_{\text{ID}}$. This is because the price at the least-cost short position E is likely higher than the price at the current long position t, as long as the operator's portfolio is correlated with the market. Thus, option (b), under the correlation assumption made, will not be executed at many long position slots even for slots within mixed ranges.

3.2 Value comparison

Ignoring differences in prices, BAS, and other costs between day-ahead and intraday markets for the moment, we can analytically derive that the activation of flexible demand indeed creates greater value intraday. This can be shown by setting the day-ahead value equation equal to the intraday valuations for the different scenarios.

For long intraday positions, the most likely outcome is that value is equal to day-ahead activation value. This is because eq. (2), which values option (a) at long position intraday slots, is formulated identically to the day-ahead eq. (1). Since we expect option (a) to be more valuable than option (b) even within mixed ranges, as explained at the end of section 3.1, we can infer indifference between day-ahead activation and the activation of DR with respect to long position intraday slots.

In contrast to that, activation of DR to short position intraday slots yields greater value than day-ahead use. At short positions within homogeneous ranges, the value difference is driven by the difference in BAS between the slots t and M. This can be seen when setting DA = ID and eliminating redundant variables (table 1). As long as the BAS at t is higher than at M, intraday activation is more valuable than day-ahead activation. Since the price at t by definition must be higher than at M, the average BAS can be assumed to be higher at t as well. The case becomes even more compelling when looking at short position intraday slots within mixed ranges. Comparing eq. (1) for day-ahead value against eq. (4) for netting value intraday shows that DR activation intraday for netting yields more value whenever

$$\left(-P^N_{\text{ID}} + {c_s}^t + \frac{{c_s}^N_{\text{ID}}}{2} + 2TC\right) > \left(-P^M_{\text{DA}} + \frac{{c_s}^M_{\text{DA}}}{2}\right). \tag{6}$$

Recalling that, under the assumption of correlation between the operator's and the entire market's positions, $P^N < P^M$, and comparing the balance of BAS and transaction cost elements on both sides, we can see that intraday activation can be expected to yield more value with a very high probability. Consequently, the share of short position slots intraday drives the value advantage of intraday DR activation. Analytically, in the absence of a systemic error in production forecasts, short position slots should occur as often as long ones. With respect to real

Table 1: Equality DA $=$ ID reduced to differentiating variables, assuming equal day-ahead and intraday values for corresponding parameters

Slot positions in R^t	Current slot t: long	Current slot t: short
Homogeneous[a]	(a)[b] DA $=$ ID $\rightarrow 0$	(a) DA $=$ ID $\rightarrow {c_s}^M = {c_s}^t$
Mixed[a]	(a), or	(a), or
	(b) $\rightarrow -P_{\mathrm{DA}}^M + {c_s}_{\mathrm{DA}}^M/2 =$	(b) $\rightarrow -P_{\mathrm{DA}}^M + {c_s}_{\mathrm{DA}}^M/2 =$
	$-P_{\mathrm{ID}}^E - {c_s}_{\mathrm{ID}}^E/2 - 2TC$	$-P_{\mathrm{ID}}^N + {c_s}^t + {c_s}_{\mathrm{ID}}^N/2 + 2TC$

[a] Homogeneous ranges only include either short or long positions, mixed ranges include both.
[b] Option (a) is possible within both homogeneous and mixed ranges. Option (b) involves either netting (from short to long slot) or enhancing (from long to short slot). It requires mixed ranges.

data, this share even amounted to 61% for the dominating German operators in 2013[4]. In other words, an operator of PV or wind power assets can be expected to be short intraday very many times, implying that the allocation of DR resources to intraday operations promises to create more value than the allocation to day-ahead operations. Table 1 summarizes the results from setting DA $=$ ID and eliminating variables that occur on both sides of the equations wherever possible.

So far, for simplicity reasons, we have argued from an analytical perspective, treating day-ahead and intraday parameters equal, hence assuming that they always take on equal values. In practice, values can be expected to differ widely, with the effect that intraday activation of flexible demand turns out to be even more advantageous. Recalling eqs. (1)-(5), we find four value determinants that work in different directions: prices, BAS, and other transaction costs increase the DR value, whereas DR costs lower it. Focusing on the value-increasing elements, prices have the largest impact. BAS constitutes a fraction of price, and other transaction costs for trading amount to only a small fraction of the BAS.

When investigating EPEX market data for Germany in 2013, we find numerous indications that intraday price dynamics increase the value of DR more than day-ahead dynamics. First, absolute prices of hourly deliveries average higher intraday (38.5 €/MWh versus 37.9 €/MWh), while the variance of the former is much higher than of the latter (+20%). For an exemplary range of $R^t = 5$ [5], intraday variance exceeds variance day-ahead for the same range regarding the 2013 average value (68.9 €/MWh versus 59.5 €/MWh, i.e. an increase by +16%). Further, the spread between the highest and the lowest price intraday exceeds the day-ahead spread by more than 9% (16.0 €/MWh versus 14.6 €/MWh). All of these measures support the notion that in-

[4] In Germany, much of the PV and wind power production is currently integrated into the market by the transmission system operators (TSOs). The 61% short positions refer to actual production deviations from forecasts for 15-minute delivery slots, aggregated across all TSOs.

[5] This means that demand can be brought forward or postponed by up to two hours, i.e. $r = 2$.

Table 2: Difference between day-ahead and intraday market parameter values (€/MWh)

Parameters	Day-ahead	Intraday	Comparison
Price level	37.9	38.5	+0.6 (1.6%)
Price variance	268.7	322.8	+54.1 (20.1%)
Price variance within $R^t = 5^a$	59.5	68.9	+9.4 (15.8%)
Price spread within $R^t = 5^b$	14.6	16	+1.4 (9%)
Price variance within $R^t = 17^c$	43.9	292.2	+248.3 (566%)
Price spread within $R^t = 17$	14.6	51.1	+36.5 (248.7%)
Bid-ask spread levels[d]	0.25	3	+2.75 (1100%)

[a]Referring to hourly delivery slots both day-ahead and intraday, including the current slot t. [b]Spread describes the absolute difference between the highest and lowest price. [c]Referring to hourly delivery slots day-ahead and 15-minute delivery slots intraday, both including the current slot t. [d]Referring to 2010 / 2011 bid-ask spreads, as calculated in Hagemann and Weber (2013).

traday price volatility is higher, and that absolute price movements are larger as well. Referring back to our previous valuations, this implies greater DR value intraday than day-ahead.

Another very important aspect should be mentioned here: while day-ahead trading is possible for hourly delivery and longer slots, intraday balancing of forecast errors is also commonly conducted at 15-minute granularity. When we leave the time distance by which demand can be shifted unchanged, but assume 15-minute granularity, we have a range of $R^t = 17$ [6].Volatility then significantly exceeds the values for hourly slots and $R^t = 5$, with variance amounting to 292.2 €/MWh (versus 43.9 €/MWh for day-ahead hours). The difference between the highest and lowest price averages 51.1 €/MWh (versus 14.6 €/MWh day-ahead). All in all, using DR when balancing forecast errors at 15-minute granularity appears more valuable than any other option.

While BAS dynamics are hard to quantify and less relevant for DR valuation than prices, we can expect them to also boost the value of intraday DR activation. The BAS is much larger intraday than day-ahead. Hagemann and Weber (2013) find an intraday BAS of 3 €/MWh versus 0.25 €/MWh day-ahead. Given the higher absolute BAS values, and the higher volatility of prices intraday, it seems plausible to assume BAS volatility to be higher intraday as well. Another factor is that, derived from our analytical comparison, the DR value is enhanced more through BAS effects intraday than day-ahead (i.e., avoidance of BAS through netting). Table 2 summarizes the market data differences we have described.

Having so far focused on the market-side, value-creating aspects of DR, a note should be

[6] One hour covers four 15-minute intervals. Considering the two hours prior and after the current delivery hour, we get a total of 17 slots, including the current slot. Thus, $r = 8$.

devoted to costs. While both opportunity costs and activation costs will reduce the value created by DR activation, it is nearly impossible to provide a robust quantification that allows comparing day-ahead and intraday activation in general terms. The impact of costs is highly individual; they differ not only by segment, but in fact by agent. If, for instance, a household is to provide load flexibility, opportunity costs will highly depend on the consumption habits and the appliance stock. Activation costs may depend on whether and to what extent the appliances in the household are *smart* and consequentially can be remotely or even automatically controlled. In this case, activation costs would probably approximate zero for shifts in the absence of residents.

With respect to the distinction between day-ahead and intraday activation, some influencing factors are worth mentioning. On the one hand, day-ahead activation implies greater predictability for providers. This may lower both activation and opportunity costs, especially in the household segment. However, the extent of this advantage depends on the timing of intraday activation used for comparison. On the other hand, intraday activation is also possible for 15-minute slots. This allows a more fine-grained shifting and thereby may reduce opportunity costs. Thus, no general distinction is possible between day-ahead and intraday costs of DR resource activation; rather, a case-specific assessment will be necessary.

4 Demand response activation model

Given the attractiveness of intraday DR activation identified in the previous section, we now want to develop a model for practical use. In a first step, we define a procedure to determine the volume and price properties of delivery slots within R^t under certain conditions (i.e. market price and production forecast error volumes are assumed to be perfectly known) and use this information to enact load shifts for value maximization. In a second step, we translate this logic into a setting of trade optimization under price and trade volume uncertainty. This procedure provides us with some guidance on how to integrate DR resources into trading strategies that cope with the realities of continuous-trade intraday markets.

4.1 Demand response under certainty

Let us assume a situation in which both the production forecast error and the intraday price for a specific delivery slot exhibit some perfectly predictable behavior throughout the trading period. Under these circumstances, DR activation is fairly straightforward and can be treated as an independent input factor for trade decisions. First, both depth and breadth of DR resource flexibility should be defined. Depth refers to the volume L of demand for any slot t that can be shifted. Breadth refers to the time span across which loads can be shifted, expressed in the size of range R^t. Second, for any t within any R^t considered, the relevant parameters for valuation need to be identified (i.e., price, BAS, transaction costs, and DR costs), which should be straightforward in a setting with full predictability and transparency. With these data, value maximization can be conducted by running through all the ranges R^t, and optimizing each slot t sequentially. For this purpose, the operator needs to choose the value-maximizing DR strategy for each slot. Thus, for long positions, we have

$$V(L^t)^*_{\text{ID}} = \max\left(V(L^t)^{\text{Long}}_{\text{ID}}, V(L^t)^{\text{Enhance}}_{\text{ID}}, 0\right) \ , \tag{7}$$

while for short positions we have

$$V(L^t)^*_{\text{ID}} = \max\left(V(L^t)^{\text{Short}}_{\text{ID}}, V(L^t)^{\text{Net}}_{\text{ID}}, 0\right) \ . \tag{8}$$

Under the assumption of steadiness and perfect predictability for the relevant parameters, the shifting process as described could be conducted prior to any trade operations in the market. Thus, the adjusted open positions at all the slots t after DR resource activation would simply serve as the new volume base for any bidding strategy,

$$D^t_{\text{New}} = D^t - L^t \ , \tag{9}$$

thereby replacing the initial demand estimate. At the moment of trading in the market, the value created by shifting the loads as suggested by the model would be realized.

4.2 Uncertainty and bidding behavior

In reality, both *intraday markets* as well as *PV and wind power production* are subject to uncertainty. Regarding the *intraday markets*, uncertainty is particularly high in regimes with continuous trading. For each individual slot, trading is possible continuously for a longer time period. For instance, in Germany and Austria, intraday trading begins at 3 PM on the day prior to delivery and ends 45 minutes prior to the actual delivery slot[7]. In our model, we split the entire trading period for one slot t into discrete trade windows $w = (1, \ldots, W)$, following a principle that was applied in Garnier and Madlener (2014) to formulate an intraday bidding strategy.

During the entire trading period for one delivery slot t, prices and corresponding BAS fluctuate, with an inclination to worsen from the viewpoint of PV and wind operators throughout the intraday trading period. The reason is that resources available for balancing either short or long positions become scarcer during the intraday period, due to either long ramp-up times or previously agreed commitments (cf. Garnier and Madlener, 2014; Henriot, 2014). In Garnier and Madlener (2014), volatility and drifting behavior of intraday prices throughout the trading period are represented by means of a discrete stochastic process. It takes the form of a Geometric Brownian Motion (GBM). Thus, the change in price follows

$$\frac{dP(w)}{P(w)} = \alpha_P dw + \sigma_P dZ_P \ , \tag{10}$$

[7] In addition, beginning in 2015, there will be an intraday auction prior to continuous trading.

where α_P describes the expected price drift, σ_P is the volatility of prices, and dZ_P is the increment of a Wiener process. The BAS typically constitutes a certain share of prices and can be assumed to behave analogously.

The uncertainty related to *production forecast errors* is similarly critical. PV and wind power output remains uncertain until the moment of delivery. As a result, forecast error projections imply a (diminishing) uncertainty throughout the trading period for one particular delivery slot t. In Garnier and Madlener (2014), production forecast error uncertainty for an intraday bidding strategy is modeled as a discrete stochastic process, following an Arithmetic Brownian Motion (ABM) of the form

$$dF(w) = \alpha_F dw + \sigma_F dZ_F \ , \tag{11}$$

where α_F refers to the drift, σ_F describes the volatility of the forecast error in absolute terms, and dZ_F is the increment of a Wiener Process.

A further complexity of this constellation is that the production forecast error can be expected to correlate with intraday prices, as already explained in section 3.1. As operators' forecast errors correlate, the aggregate of their short or long positions will impact market prices. In order to understand the possible trajectories of intraday price and production forecast error under uncertainty and correlation, we use a multi-dimensional binomial lattice as in Garnier and Madlener (2014), thus extending from a method developed in Rohlfs and Madlener (2013). This lattice approximates the potential paths of both stochastic processes in discrete time steps.

Before we can use this market understanding to derive guidelines for the use of DR resources intraday, we briefly define the trading strategy of a PV or wind power plant operator when balancing forecast errors, analogously to Garnier and Madlener (2014). Based on the trading strategy, it is possible to formulate a DR strategy afterwards that is in line with the overall intraday operations. In general terms, the strategy needs to help identifying the optimal timing and volume of a trade to balance the production forecast error for any slot t. To this end, it has to weigh the advantages of trading early in the intraday period against the associated risks. The advantages likely include more favorable prices (and corresponding BAS) as explained and a lower risk of not finding a trade partner at all, as balancing resources become scarcer over time. The main risk of trading early is that available forecasts are inaccurate, implying that one may trade too much, and later may be forced to resell (re-purchase). In Garnier and Madlener (2014), this trade-off is translated into a valuation logic. Namely, the value $V(I_w)$ for the immediate trade of any particular volume I_w is defined as

$$V(I_w) = \begin{cases} F_W \times C_{\mathrm{b}} - (I_w - F_W) \times C_{\mathrm{d}}, & \text{for } (I_w > F_W \geq 0) \vee (I_w < F_W \leq 0), \\ I_w \times C_{\mathrm{b}}, & \text{for } (F_W \geq I_w \geq 0) \vee (F_W \leq I_w \leq 0), \\ -I_w \times C_{\mathrm{d}}, & \text{for } I_w > 0 > F_W \vee I_w < 0 < F_W. \end{cases} \tag{12}$$

where C_{b} refers to postponement costs avoided by trading immediately, and C_{d} refers to costs incurred due to excessive trading in case the trade volume I_w exceeds the ultimate forecast error F_W just before delivery.

Based on the previously introduced multi-dimensional binomial lattice, which represents (uncertain) price and production forecast error behavior, the bidding model presented employs options valuation methodology and dynamic programming to identify the optimal timing and volume of trades under uncertainty. At any node within the binomial lattice, the immediate trade valuation logic is applied to the range B of possible trajectories b of forecast error and intraday price, with their respective probabilities of occurrence p_b, to identify the value-maximizing trade volume I_w^* for an immediate trade. Hence we can further specify the value of the optimal trade volume I_w^* as

$$I_w^* \in \text{argmax}_{F_W^{min} \leq I_w \leq F_W^{max}} V(I_w) = \text{argmax}_{F_W^{min} \leq I_w \leq F_W^{max}} \sum_{b=1}^{B} \left(V(I_w)_b \times p_b\right) \ . \tag{13}$$

While the optimal volume of an immediate trade is known from value maximization, it is still unclear whether an immediate trade presents an optimal strategy at all. To determine this, the option of trading the optimal volume immediately is compared to the alternative of not trading and thereby remaining flexible for one more period. This is formulated as

$$O(w) = \max\left[V(I_w^*), \frac{1}{\tau_w} \times \frac{O(w+1)_{uu} + O(w+1)_{ud} + O(w+1)_{du} + O(w+1)_{dd}}{4}\right] \ . \tag{14}$$

Here, the term on the right within the brackets refers to the probability-weighted discounted value of remaining flexible by not trading immediately. In this context, the discount factor τ_w denotes the increased risk of not finding a trade partner when postponing a trade decision beyond the current trade window.

In the model, at any trade window and for any given intraday price and production forecast error, the entire optimization procedure is implemented by conducting a backward-running analysis through the nodes of the multi-dimensional binomial lattice, to ultimately determine the optimal strategy at the current stage and node. Further explanations and clarifications regarding this approach can be found in Garnier and Madlener (2014).

For DR operations, it is important to acknowledge that the timing of trades varies across trade windows and delivery slots, as it depends heavily on the current parameters as well as the behavior of the underlying stochastic processes. While some forecast errors for some delivery slots may be traded right away, other forecast errors may be balanced no earlier than right before market closure for that slot. The DR operational model needs to be able to accommodate this flexibility as well as the underlying uncertainties.

4.3 Demand response under uncertainty

In view of the described uncertainties and the underlying bidding strategy developed in Garnier and Madlener (2014), we define two goals for our operational DR model. First, loads should be shifted such that the *actually realized value* is maximized (when trades are executed). Second loads should be shifted as late as possible, in order *to maximize flexibility.*

A direct consequence is that the DR strategy needs to account for the timing of trades and the expected corresponding prices and forecast errors when guiding load shifts. Further, the effects of price and production forecast error volatilities on DR intraday operations are twofold. First, it is much less obvious and certain which DR strategy is optimal for individual slots. Because prices and the size of open positions are unclear, the optimal strategy[8] and the corresponding shifting target slot (M,N,E) need to be identified with the remaining uncertainty. Second, it may remain unclear whether the value created by choosing the presumably value-maximizing strategy will eventually exceed the costs of using the DR resources. In fact, the DR strategy pursued for any slot t cannot realize any value by itself. Value is realized when the remaining open positions, after shifting loads between the involved slots t and M, N, or E, are actually traded in the market. When this happens is determined by the bidding strategy. Clearly, the DR strategy and the bidding strategy are strongly interdependent and therefore need to be synchronized.

In accordance with the guidelines described above, our DR operational model only considers acting with respect to (the ranges of) those slots for which a balancing trade is immediately executed by the bidding model. All other slots can be treated later and flexibility can be sustained. Let us for now assume that the bidding model triggers an immediate balancing trade for an (expected) forecast error at slot $t = x$. For x, we are now urged to investigate whether either one of following two scenarios holds true:

- value can be increased by shifting flexible loads away from x into other slots within R^x;
- value can be increased by shifting flexible loads towards x from any other slot $z \neq x$ which has x within its range R^z. The quantity of all $z = (1,\dots,Z)$ for which this could be the case needs to be investigated.

The first scenario requires that there is another lower-priced short (long) position slot M for shifting or a long (short) position slot N (E) for netting (enhancing). Then, flexible loads will be shifted accordingly from the short (long) position slot x to the other slot[9]. To figure out whether an M, N, or E exists, prices and the forecast error type (short or long) need to be known for every slot $q \neq x$ within R^x. For all slots that are immediately traded like x, the actually realized price and the traded forecast error volume are known. For the other slots, the forecast error can be expected to remain at its current level, given that it follows an ABM without drift. Prices, however, need to be estimated. To this end, one first has to estimate the trade window w^* at which a trade for this specific price-forecast error trajectory will be triggered. This can be done based on the trade behavior observed for previously traded slots with similar parameters. In

[8] $V(L^t)^{\text{Short}}_{\text{ID}}$ versus $V(L^t)^{\text{Net}}_{\text{ID}}$, or $V(L^t)^{\text{Long}}_{\text{ID}}$ versus $V(L^t)^{\text{Enhance}}_{\text{ID}}$.

[9] Netting will occur to the extent that a long position slot N can absorb volumes without turning into a short position slot.

particular, the possible price increments j, as applied in the multi-dimensional binomial tree, need to be considered and weighed based on their probability of occurrence[10]. The probability-weighted averages of price increases resulting from this analysis provide the expected values that are required to identify whether a particular slot t serves as M, N, or E. Thus, we have

$$\mathrm{E}[P^q_{w^*}] = P^q_w \times \left(\frac{j_{uu} + j_{ud} + j_{du} + j_{dd}}{4} \right)^{w^*-w} , \tag{15}$$

$$\mathrm{E}[F^q_{w^*}] = F^q_w \; . \tag{16}$$

With the known prices and forecast errors for immediately traded slots within R^x and the expected prices and forecast errors for the other slots, it is now possible to determine M, N, or E, as explained in section 3.1, and choose the value-maximizing strategy for the flexible loads for slot x.

The second scenario requires a similar analysis, but applied to more slots. Namely, it needs to be understood whether shifting loads from any z towards x is value-increasing. To this end, the same steps that were necessary to analyze a possible shift away from x need to be conducted for all z. Thus, expected prices and forecast errors need to be calculated for all $y \neq z \wedge y \neq x$ within R^z. Ultimately, with these expected values and the available actual values for x, it can be derived whether shifting loads from z to x is indeed value-maximizing. If so, the newly increased load at x needs to be factored into the trade operation initiated by the bidding model. Likewise, the remaining open positions at all z to be balanced in the future need to be changed accordingly by the volume of load shifted.

5 Model simulation

The aim of the following model simulation is to quantify the financial impact on total trade value achieved by the introduction of DR resources to intraday trade operations of a PV or wind power operator in the German market. To this end, we compare trade operations in the absence of DR resource activation with trade operations including DR activation.

5.1 Data and parameters

The simulation requires input data with respect to four distinct dimensions: the time frame, market prices, the operator's generation portfolio, and the available DR resources.

Regarding the time frame, the simulation covers intraday operations for different sets of several consecutive hourly delivery slots $t = 1, \ldots, T$ in the first half of 2013. The considered sets of slots are randomly selected from different months of the period to diversify (weather)

[10] The multi-dimensional binomial lattice is constructed such that, from any node and at any stage, four alternative changes in value (j) are possible with equal probability each (i.e. $p_j = 0.25$).

conditions. A limitation in the selection procedure is that the required data need to be available for at least ten consecutive delivery slots, in order to allow for sufficiently long optimization periods. Preceding day-ahead sales and prices are included as given input, ensuing reserve market operations are excluded from the analysis[11]. The trade for an individual slot can be executed hourly, up to five hours ahead of delivery[12], but no later than one hour before delivery. The five trade windows for any time slot t from $t-5$ to $t-1$ are defined as $w = 1,\dots,5$.

Concerning market prices, all intraday prices for the considered sets of delivery slots are derived for all the corresponding trade windows. This is accomplished by calculating the weighted-average prices of all intraday transactions cleared at the EPEX for any particular t, clustered based on their (rounded) time distance to delivery. These price data are used for two purposes. First, they are the prices that are used as actual prices occurring in the simulation. Second, they are used for a simple empirical investigation into the stochastic process of the price, providing input required for the model's *ex-ante* bidding strategy. Both price drift α_P and price volatility σ_P are analyzed across those slots in the first half of 2013 for which trade volumes exceeded zero in all the relevant trade windows[13].

Interestingly, we find evidence that price development is significantly impacted by how short or long the aggregate market is. The current price level as well as the collective forecast error (short or long) of wind power operators have a significant impact on the price drift. If most wind power operators in the market are short (long), intraday prices are likely to increase (decrease) between $w = 1$ and $W = 5$[14]. Further, if the price for a particular slot t at $w = 1$ is low (high), intraday prices are likely to increase (decrease) stronger throughout the remaining four hours of trading. The explanations are straightforward.

Collective forecast errors among wind operators point to a significant need for balancing capacities, e.g. dispatchable production or flexible demand. These capacities become scarcer over time, while the need for balancing becomes increasingly clear. Thus, price increases or decreases occur, depending on the forecast error sign. The degree to which this price behavior can be observed depends on the current situation. If prices are very high in day-ahead and early intraday trading, it points to a tight market with little wind and PV power offered in the first place. Hence, wind power supply shortages due to forecast errors are likely to have only a moderate impact on the supply-demand balance, and thus on prices. However, if wind power forecasts indicate that output levels will exceed previous commitments, significant price

[11] The deliberate use of the imbalance market as a trade resource is prohibited by regulation in Germany. Enforcement of this regulation is expected to be tightened in the future (Schultz, 2013).

[12] This reflects the reality of the German intraday market, where about 85% of trades in the first half of 2013 were enacted within the final five hours.

[13] This applied to roughly 70% of the slots. Outliers regarding price growth, both positive and negative, were removed from the sample.

[14] Wind power operators are represented by the portfolio of all four German TSOs, which forecast wind power production offered in the day-ahead market and derive actual production.

Table 3: Price drifts by category

Price at $t-5$	Wind operators not short $(\alpha_P)^a$	Wind operators short $(\alpha_P)^a$
Low[b]	-3.5%	9%
High[b]	-4.9%	3.2%

[a] Low price refers to values below 38 €/MWh. [b] The collective operators are considered not short whenever their collective shortage is smaller than 281.5 MWh or when they are even long.

decreases can be expected. Contrarily, if prices are low day-ahead and in the early intraday market, much wind and PV power was committed. Hence, on the one hand, any additional offerings due to operators being long will only have a moderate impact on the already low prices. On the other hand, shortages by wind operators will likely cause significant price increases.

In order to incorporate these insights, we introduce a categorization of delivery slots into our simulation, depending on the $t-5$ price level for the slot and the imbalance of wind power operators for that hour. The model retrieves the relevant parameters for each slot, assigns the slot to a category, and, based on that, assumes the current intraday price to develop according to the category's average price drift. This distinction allows us to apply more nuanced drift rates to different slots. The drift rates derived can be found in table 3. Regarding the volatility of price changes between two slots, there were no significant differences between categories. The standard deviations across categories averaged about 3.4. Thus, the same volatility is applied to all price processes for all slots, regardless of the category ($\sigma_P = 3.4$).

Turning towards the operator, a wide range of scenarios would be plausible, regarding both the scale and type(s) of production assets. According to a report published in 2011 by TrendResearch, about 50% of renewable energy power generation assets in Germany were owned by private households and farmers in 2010. On the PV side, many owners either opt for self-consumption or hand market-side operations over to TSOs in exchange for fixed subsidies (roughly 90% of production, with the majority in the subsidy scheme). Regarding wind power, however, the politically desired transition towards *direct marketing*, i.e., a direct placement of volumes in the wholesale power market even by small-scale operators, has progressed far more. According to charts provided by the German *Federal Association of the Energy and Water Industry (BDEW)*, about 80% of onshore wind power production was directly marketed in 2013. Accounting for these facts, we focus on wind power and define a small-scale wind power operator running ten wind power turbines at a capacity of 1.4 MW. These run at 1400 full-load hours per year, reflecting average values derived from Berkhout et al. (2013). The forecast error at $w = 1$ for each delivery slot is derived from the *ex-post* forecast error data provided by the German TSOs for the entire market area. The remaining volatility in the forecast error projection is set to amount to 4% of the initial forecast error at $w = 1$ between two trade windows. This is in

Table 4: Wind power production properties

Parameter	Value	Explanation
Assets under operation	10 wind turbines	
Asset capacity	1.4 MW / turbine	
Asset productivity	$\sim$ 1400 full-load hours	
Forecast error estimate, $w = 1$	F_1 = % TSO error[a]	% of day-ahead sale
Forecast error drift	$\alpha_F = 0$	No systemic bias assumed
Forecast error volatility	$\sigma_F = 4\% \times F_1$[b]	Between two trade windows

[a] As no private forecast error data is available, publicly available *ex-post* TSO forecast error data are used to derive the first forecast error estimates at $w = 1$ for each slot. [b] Represents the remaining uncertainty in the most recent forecast error projection, expressed as the volatility in the forecast between two trade windows.

line with the assumptions made and applied in Garnier and Madlener (2014).

Finally, the properties of the available DR resources need to be specified. This is done by addressing three dimensions: the customer segment(s) and their load profiles; the share of of flexible loads as a function of both segment and time; and the time across which loads can be shifted as a function of segment and potentially time.

For two reasons, the simulation focuses on private customers. First, the DR potential in the household segment is significant, as was highlighted in section 2. In the larger commercial and industrial segments, many DR resources are already marketed, increasing the competitive pressure. Second, we take it that the activation costs for DR in the smaller customer segments are low, once the necessary infrastructure (smart appliances, smart meters) is already in place. Unlike larger commercial and industrial customers, household customers primarily face comfort losses as the sole opportunity costs. This particularly applies to consumption caused by white goods. Opposed to that, industrial customers need to be compensated for serious losses in productivity in order to compel them to participate in load-shifting. While it may be argued that the necessary (smart communication) infrastructure investments to gain access to load flexibility in smaller customer segments need to be factored in, one can oppose that the roll-out of the necessary technology will take place anyhow. Several recently published reports point to the increasing market penetration of connected home technology and smart devices[15]. Based on the anticipation of this development, and due to our focus on operational aspects, we do not consider investment costs as a prerequisite for household DR participation in this simulation.

Referring to German Census Bureau data for 2012, we set the average electrical energy consumption per household of 3400 kWh across 40.7 million households. As we are simulating

[15] For instance, a 2013 report by Deloitte predicts that the smart home market in Europe will grow from roughly € 1.7 billion in 2013 to more than € 4 billion in 2017. Further, smart meter roll-out is supported by EU regulation.

Table 5: Demand response parameter values used for the simulation

Parameters	12PM – 6AM	6AM – 12AM	12AM – 6PM	6PM – 12PM
Flexible share (h)	8%	7.5%	10%	7%

the case of a fairly small operator, he is assumed to have access to the flexibility potential of only 0.001% of the German households. Altering the market share would primarily impact the extent, but not the nature of our results. As a result, the portfolio of the operator includes 407 households with a total demand of 1,384 MWh per year. We model the load profiles of customers by making use of the so-called standard load profiles (SLP) provided by the BDEW. With the help of these profiles, consumption patterns in the residential and smaller commercial customer segment can be modeled quite accurately with 15-minute granularity throughout an entire year, including daily and seasonal effects. We aggregate the 15-minute profiles into one-hour profiles.

Researchers in Germany and Austria have increasingly addressed household load-shifting potentials and properties (Hillemacher et al., 2013; Schmautzer et al., 2011; Klobasa, 2007). As is done in many of these works, we focus on white goods, including cooling/freezing, and to a small extent on heat pumps (Schmautzer et al., 2011), when estimating the potential flexibility in demand; this is because the opportunity costs of shifting the consumption patterns of these appliances are relatively low (as opposed to lighting or entertainment devices). Meanwhile, in Germany, they account for about 30% of household demand (Hayn et al., 2014; Hillemacher et al., 2013). In Schmautzer et al. (2011), the load-shift potential for the aforementioned appliances in Austria is provided as a function of the time of day. Interestingly, the difference in flexibility between different times is low, as the derived flexibility potential is dominated by refrigerators with a fairly constant demand. We primarily rely on the estimates in Schmautzer et al. (2011) to derive values for the flexibility share h, by comparing the time-specific flexibility potential to the time-specific average consumption of an Austrian household[16]. For the sake of tractability, we exclude seasonal deviations and cluster the day into four blocks of six hours each.

Regarding the time span across which loads can be shifted, R^t, deriving a clear estimate is difficult. It depends on the perceived opportunity costs for individual households and on the level of automation of appliances. In Schmautzer et al. (2011), time ranges of six to seven hours are suggested for white goods with cleaning functions, and ranges of around 12 hours for refrigerators. We conservatively set R^t to three hours first and then test the impact of augmentation of this parameter in the simulation later.

Note that costs are not considered as exogenous parameters for our simulation. Rather, we

[16] Approximated by using an illustrative (standard) load profile for an average household in a particular region of Austria (the province of Styria).

concentrate on the value created by DR resource activation and afterwards discuss the implications of the identified value for the costs that DR activation may, or may not, imply.

5.2 Simulation results

The results of the simulation are positive across the scenarios. For each of the twelve time sequences tested, the value with DR leverage exceeds the value without DR leverage. While the ratio between the available DR resources and the forecast error volumes to be balanced averages only about 11.5%, the use of DR still achieves cost savings averaging roughly 3%. In theory, scaling up the available DR resources could lead to balancing trade cost savings of about 36%[17]. Table 6 lists the key values for all sequences tested.

A couple of factors appear to determine the value created by DR application. Many of these factors correspond to insights gained from the analytical and data-based investigations in section 3.2. Most notably, the spread in prices between neighboring delivery slots as well as the absolute price level turn out to be important value drivers for DR use in the simulation. This becomes obvious when looking at the behavior of prices and the DR value for individual optimization runs. Those featuring particularly strong price peaks/lows lead to greater DR value creation. The model captures the value obtainable from this price variance by shifting loads accordingly.

In line with our previous analytical argumentation, it shows that the range R^t across which demand can be shifted has a strong impact on value as well. Increasing R^t from 3 to 5 leads to an average increase in savings of roughly 45% across all scenarios. For some scenarios, the value of DR more than doubles when extending R^t from 3 to 5. However, there appears to be no general explanation for the variation in value impact when extending R^t; rather, the individual price differences across slots in each setting seem to be the main determinants.

Furthermore, netting between long and short positions appears to occur in cases where such opposite positions exist for neighbored delivery slots. However, the share of DR resources used for netting never exceeds 5%. Further, there appears to be no direct correlation between the share of DR resources used for netting and the overall DR value contribution in a particular optimization run. A cautionary note here: the applicability of netting strongly depends on the set of delivery slots considered. This implies that no representative conclusions regarding the impact of netting can be drawn from the sample-based simulation.

Next, in order to highlight the more nuanced dynamics, we assess the two sequences with the greatest relative DR value impact as well as the sequence with the lowest relative DR value impact in greater detail: March 28, June 1 and June 27 of 2013. Figure 1 presents an overview of prices (developments) and loads shifted per slot for all three sequences to be discussed in greater detail.

For March 28, it shows that prices fare around 50 €/MWh for most of the delivery slots.

[17] Of course, simply scaling up DR resources does not necessarily imply a proportional increase in savings.

Table 6: DR operations results

Sequence	DR Availability	Savings ($R^t = 3$)	Savings ($R^t = 5$)
Jan 2, 2013, 1PM – 2AM	7.2%	1.5%	1.6%
Jan 3, 2013, 9AM – 2AM	6.8%	1.3%	2.0%
Jan 23, 2013, 11AM – 12PM	51.0%	3.2%	7.4%
Feb 27, 2013, 12AM – 12PM	14.9%	1.8%	3.6%
Mar 3, 2013, 1PM – 1AM	3.1%	0.3%	0.4%
Mar 28, 2013, 12AM – 12PM	17.7%	12.9%	17.1%
Apr 30, 2013, 1PM – 12PM	10.7%	0.9%	2.1%
May 05, 2013, 11AM – 9PM	7.2%	0.8%	1.0%
May 21, 2013, 2PM – 3AM	7.6%	1.0%	1.8%
June 1, 2013, 12AM – 1AM	4.1%	9.8%	11.6%
June 19, 2013, 3AM – 1AM	4.7%	1.5%	1.8%
June 27, 2013, 12AM – 12PM	4.2%	0.2%	0.3%

Furthermore, price changes along trade windows for any particular delivery slot are fairly moderate. A key exception are the prices between 7PM and 9PM, particularly the price for 8PM. This price peaks and exceeds 100 €/MWh in early trade windows, i.e. more than double the prices of most preceding and ensuing slots. By shifting loads away from the 8PM slot, significant value can be created. Thus, this optimization run yields the highest DR cost savings relative to trade costs, despite the fairly calm market behavior prior to 7PM and after 9PM.

Opposed to that, prices on June 1, 2013 move wildly between delivery slots and across trade windows. Volumes are shifted for almost every slot, in the model's attempt to optimize value by shifting loads, and despite great price uncertainty and fluctuation over time. The overall result are cost savings of almost 9% with DR resources amounting to only 4% of the total forecast error volumes that had to be balanced.

For June 27, 2013, a totally different picture emerges. Price spreads between delivery slots are fairly moderate, especially for prices in earlier trade windows. Since most slots in this optimization run are traded prior to W, the earlier prices are the relevant ones for trade and DR value realization. Consequentially, the constantly enacted load shifts only have a mild positive effect on overall trade costs of 0.2%. The ratio between DR resources available and the total forecast error volumes amounts to 4.2%; even a scaling up of DR resources under the assumption of proportional value increase would have yielded no more than a 5% cost reduction.

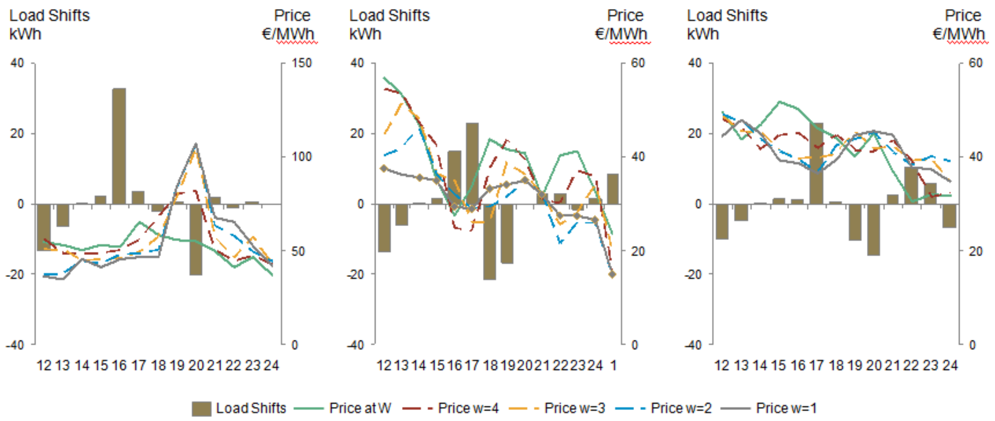

Figure 1: Prices ($w = 1,\dots,5$) and loads shifted for the three selected sequences on March 28 (12AM–12PM), June 1 (12AM–1AM) and June 27 (12AM–12PM).

5.3 Discussion

The outcomes of the simulation confirm the most relevant analytical insights quite accurately. They show that the use of DR resources in the tested sequences reduces balancing trade costs by an average of 3%, with reductions reaching up to 13% in individual scenarios. Accounting for the fact that the available DR resources in the simulation only constitute a fraction of the total balancing need (11.5%), one can infer that a scaling up of DR resources could imply an even much higher potential (about 36% if scaling up to 100% of the forecast errors had a proportional trade value effect).

The relative value created by DR in the simulation is primarily dependent on two aspects: the level and variance of prices within the ranges across which loads can be shifted; and the span of time across which loads can be shifted. Both a greater price variance and a greater R^t allow for a more extensive exploitation of value differences in the market when balancing forecast errors.

We have not tested the impact of splitting the one-hour delivery slots into 15-minute slots. From the previous analytical discussion, we would expect this to have an effect similar to widening R^t. Interestingly, netting of forecast errors occurs to a limited extent. However, this is likely due to the nature of the sets of delivery slots used in the simulation. Fairly few neighbored slots had opposite forecast error signs, which is a prerequisite for netting.

While the results are convincing in relative terms, it shows that only fairly minor amounts of money can be saved in absolute terms. Trading costs go down by an average of €1.1 per simulation run. Regarding this issue of absolute vs. relative cost savings, several explanations and implications are worth a discussion.

First, the amount of DR available was set conservatively. In fact, flexible loads never amount to more than 17.7% of the forecast error volumes which need to be balanced. Obviously, if more flexibility was available, greater value savings could be realized. Second, the overall trade costs in the simulation are low anyhow, averaging at costs of about € 29 per run, and ranging between costs of € 167 and revenues of € 180 per run. Had there been a greater portfolio of supply assets under consideration, higher costs (revenues) would have occurred and consequently greater savings would have been possible. Third, the forecast errors were derived from TSO data, i.e. aggregate forecast data for entire market areas. In fact, small-scale operators such as the one modeled in our simulation are likely confronted with even greater forecast errors, since less netting of deviations across assets is possible.

Despite these explanations, it remains an important insight that the absolute value generated by DR resource activation is low. From the viewpoint of wind (or PV) power plant operators, it likely still presents an attractive resource. Even marginal profitability increases can matter greatly for operators of wind (or PV) power assets. Profits obtainable in liberalized, commoditized power wholesale markets are typically thin, making levers even for moderate profit increases attractive (especially in the absence of feed-in-tariffs and other subsidies).

The challenge then is to incentivize the actors on the demand side to actually provide DR resources. Indeed, the obtainable value per household providing flexibility is low and provides only a minor stimulus for widespread household participation. Thus, it becomes critical to make the provision of flexibility as seamless and comfortable as possible. Opportunity as well as well activation costs need to approach zero from the household's perspective. On the one hand, this can be achieved by means of automated, smart devices, which respond to control or price signals autonomously. Household members cannot be expected to manually alter their consumption patterns for their white goods for savings of a couple of cents per run. On the other hand, DR initiatives should probably focus on larger households with greater flexibility potential. Further, they should target households with higher environmental awareness that are keen to support the transition towards low-emissions renewable power energy systems. Finally, the aggregation of DR resources needs to be handled efficiently.

Generally, the simulation has revealed that the value created by DR resource application depends heavily on market as well as power forecast conditions. More volatile conditions, such as on March 28 and June 1 of 2013, allow for much greater value creation than more stable settings. However, such volatility does not occur every day. As a consequence, DR resource activation could be limited to hours or days with the most volatile conditions. That way, opportunity costs for households could be vastly reduced. They would offer the flexibility on standby, knowing that it will be used only occasionally rather than permanently.

From an operational perspective, the simulation has provided some valuable insights as well. In fact, it shows that leveraging DR appropriately in the intraday market is far from trivial. A view on the price changes along trade windows for the same delivery slot(s) shows that drastic, unforeseeable changes occur frequently. The highest price spreads cannot always be leveraged, given trade strategy imperatives. While the model needs to rely on empirical investigations to forecast prices *ex-ante*, actual prices often behave erratically. This complicates an optimal deployment of DR resources and often reduces the value theoretically obtainable from DR resources. Nevertheless, the model seems to handle this issue quite well, since the value contribution of DR resource activation is always positive.

It should generally be noted that the simulation provides case-based evidence rather than empirical data. While outcomes are positive and robust across all scenarios tested, the focus here is on gaining insights and understanding DR dynamics rather than on statistical significance.

6 Conclusion

In this paper, we have discussed the potential economic benefits of access to flexible demand for operators of PV and wind power plants. Particularly, we have investigated and compared two fundamentally different activation stratgies: (1) the use of flexibility to improve relative market value in day-ahead sales, and (2) the use of flexibility to optimize the economic impact of balancing forecast errors intraday. Both from a theoretical and from a real-world data perspective, we find evidence for the advantages of using flexible demand intraday rather than day-ahead when managing PV or wind power supply. The advantages stem from transaction cost savings and from greater price volatility in intraday markets.

In a simulation for the German market in the first half of 2013, we have tested the analytical arguments regarding the value of using flexibility intraday. The simulation indeed shows that access to flexible loads increases the market value of wind and PV power, by helping to reduce intraday balancing costs. Costs were brought down by about 3%, with the available DR resources only amounting to a 11.5% of the forecast error volumes to be balanced. Thus, the cost reduction potential appears to be even much greater with more DR resources available. In light of these findings, we advocate a more explicit consideration of intraday dynamics and application strategies in future research on DR resource allocation.

However, the simulation also indicated that absolute cost savings may be insufficient to actually stimulate the provision of flexible demand by households. It will therefore be critical to facilitate the provision of load flexibility as much as possible in the future, for instance through appliance automation and smart devices to drive down opportunity and activation costs.

Some limitations of our work should be mentioned. First, we have taken on a purely market-based perspective, excluding physical grid constraints or regional constraints from the analysis. Including these effects may in fact either increase or decrease the realizable value through the use of DR resources. Further, we have treated flexibility as discretionary, one hour blocks. In reality, however, some of the underlying processes last for more than one hour. While we do not believe this to strongly affect the results, the accuracy of the model may be further enhanced by accounting for this. Finally, the underlying bidding model relies on *ex-post* TSO forecast error data. The simulation would reflect the realities of operators even more if including actual forecast data rather than TSO data to estimate the forecast error and its stochastic behavior *ex-ante*. In fact, forecast errors and the resulting costs (cost savings) would likely be even greater. For the time being, we decided to rely on publicly available data.

For further research, deeper investigations into the cost side of DR resources in the household segment would be helpful. Quantifying opportunity costs and the impact on actual flexibility potentials more accurately, both in the presence and in the absence of smart appliances, would help to better understand what share in value providers of flexible loads might expect.

Note

A concise, 6 pages version of this paper is forthcoming in Operations Research Proceedings 2014 (Garnier and Madlener, 2015). It is confined to sections 1 and 3 of this more elaborate and detailed paper.

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