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Risk implications of investments in demand response from an aggregator perspective

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Abstract

Aggregators are expected to play an important role in making households provide flexibility to the electricity system. We investigate the business case of aggregators offering a demand response product in a competitive retail market, then directly accessing their customers' flexibility through remotely controlled demand response devices and marketing it on the electricity markets. As the value of flexibility largely relies on price variations, we use a stochastic electricity price model, which we combine with a linear optimisation program and a cash-flow model to determine expected operating gross margins and their probability distributions. We find that, for a case of Danish residential customers with optimistic assumptions on the available flexibility in terms of flexible volumes and load-shift time horizons, the benefits may be in the range of current investment cost for automation equipment. Furthermore, a Value-at-Risk analysis shows that income expectations are rather stable with more upside than downside potential. With foreseeable cost reductions for smart devices the aggregator business case might soon become attractive, particularly in markets with high shares of renewable production.

Keywords: demand response, aggregator, cash-flow model, stochastic electricity price

1. Introduction

In electricity systems with large shares of intermittent renewable production, a growing challenge arises to provide sufficient flexibility. This has reinforced interest in utilising the flexibility potential of the demand side. From a technical perspective, this is certainly a feasible option. Some practical issues, however, prevail in actually exploiting demand-side flexibility. These issues include how to organise market access for the demand side

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and how to activate consumers who are used to receiving electricity as an unconditional service and often do not attach much significance to contract structure and pricing of electricity. To cope with such organisational and motivational issues it has often been proposed that end user flexibility should be marketed by an entity aggregating many consumers' flexible units (see Katz, 2014). Moreover, it has been found that automatic control will be far more effective than relying on an active manual response by customers (e.g. Lund et al., 2015).

We investigate in this paper the business model of such aggregators with remotely controlled demand response devices added to appliances of end customers. The aggregators' operative conditions will be highly dependent on variable market prices and their capability to profit from these variations. It is therefore crucial to understand the inherent risks of their business model. In our analysis we also explore risk implications of aggregated demand-side response regarding the exposure to uncertain future market prices and how it influences the decision of aggregators to invest in demand response equipment.

In the business model that we propose, aggregators market end user flexibility in the electricity wholesale market, while remunerating their customers in the form of a reduction in their contracted electricity price. In order to be able to access certain customer devices for flexibility purposes, the aggregators equip their customers with remotely controllable switches that should be installed with the relevant flexible appliances. Such switches require additional upfront investment by the aggregators.

In this paper we investigate whether such a business model is feasible for an aggregator, i.e. whether the additional revenue from marketing demand-side flexibility is sufficient to justify the required investment. For this, we develop an investment appraisal model consisting of a price module, a demand response module and a cash-flow module. For the stochastic electricity price model we choose to apply a framework proposed by Lucia and Schwartz (2002). We see this model fit as it provides the possibility to incorporate seasonality into the price process and therefore is helpful in the context of electricity. We calibrate the stochastic process to the Danish electricity market. The realistic results from the specific case application shall help to strengthen our point. The demand response model is an optimisation model based on load shifting, calibrated to historical profiles of Danish residential customers. We explore three different scenarios of the share of consumption available for flexibility and four different scenarios for the load-shift horizon. The cash-flow model is based on a single-period operational gross margin indicator.

Using Monte Carlo simulations we calculate the aggregator's income as well as the threshold levels that indicate the maximum allowable investments to ensure a certain expected gross margin for the aggregator. Doing this, we can identify not only the expected average benefits for the aggregator (and the customers), but can also explore the related risks by analysing the probability distribution of the outcomes. Applying a Value-at-Risk approach we quantify the risk of adverse outcome, i.e. when prices develop in a direction where demand-side flexibility is not valuable enough so that the installation of equipment leads to a loss for the aggregator. Having determined the maximum allowable investment levels under different flexibility assumptions, we compare this to currently available technology and assess whether the business model of an aggregator is viable in the current market environment.

2. Methods

2.1. Model concept

We build a model that determines the operational gross margin for the aggregator based on several different input factors. First of all, it depends on the contractual relation that the aggregator has with the electricity customers: The aggregator may be their supplier, i.e. delivering the full volumes consumed, or may only be a third party optimising the load profile of a customer portfolio on behalf of the actual supplier. In the latter case, the added value must be shared amongst all parties subject to the contractual arrangements. For simplicity, we assume that the aggregator is also the supplier. We further assume that the aggregator offers an annual fixed price contract to their customers, with the price being determined by the expectation on the annual cost of procuring electricity for the customer portfolio from the spot market plus a margin. We assume that the aggregator then undertakes the required investment in demand response equipment and generates additional revenue by being able to optimise procurement of electricity on the spot market using the obtained flexibility from load-shifting. The aggregator may pass through some of this additional revenue to the customers in form of a reduced price.

As we focus on the aggregator role and the marketing of demand flexibility we do not directly analyse the risks involved in the supply business case. That is, depending on the price development, the supply business may be subject to higher than expected cost of procuring electricity on the spot market and thus the risk to achieve lower margins than expected. This part of the business risk is not in scope of the analysis here, so in the risk analysis we focus on the margin added by utilising the flexibility potential only.

The margin contribution from demand flexibility depends on the demand profile, the flexibility potential and characteristics of the underlying appliances as well as the market price for electricity. We take into account all of these elements in different modules. Figure 1 provides an overview of the model set-up.

The demand profile depends on the customer portfolio. In planning the business case an aggregator will face uncertainty about the characteristics of potential customers. Using average and standard profiles may be a good first approximation. It might be the case, though, that aggregators will attract and maybe even target a type of customer different from the average. Our focus will be on a small portfolio of residential customers. As

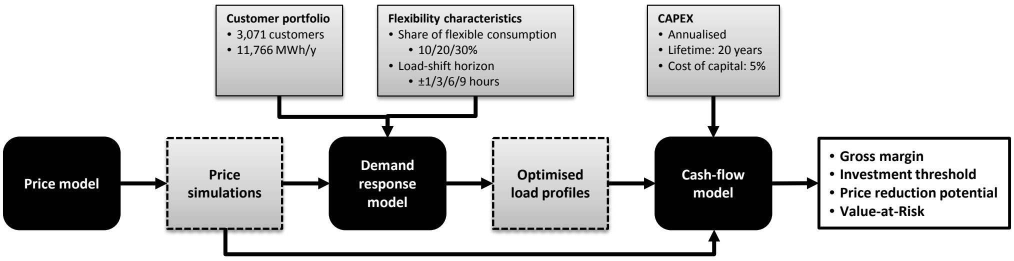

Figure 1: Overall model concept

limited data is available on the portfolio level it might for some application cases be necessary to scale down consumption data of a larger data set, e.g. of a country or region. We are able to avoid that by having access to a consistent set of historical individual profiles of Danish residential customers aggregated to a joint portfolio (Dansk Energi, 2013). The portfolio consists of 3,071 residential customers with a total annual consumption of 10,766 MWh.

We generate electricity price developments using a stochastic price model. The price paths are then fed into a demand response model together with the aforementioned load profile. The model optimises available flexibility using a linear programming approach utilising the solver *LPSolve*. Finally, the results of the optimal demand response in form of savings achieved in the procurement price of electricity are used together with the assumed investment costs for the demand response equipment to determine the profitability of the aggregator business in an annualised cash-flow model. Each part of the model is described in more detail in the following sections.

2.2. *Stochastic price model*

To simulate electricity prices for our analysis we define a stochastic price model including a deterministic seasonal component. We use a one-factor model based on the log spot price as defined by Lucia and Schwartz (2002):

$$\ln(P_t) = f(t) + X_t \tag{1}$$

where P_t denotes the spot price, $f(t)$ is a function defining the seasonality and X_t is a variable that follows a mean-reverting stochastic process reverting to a mean of zero such that the increments are determined as:

$$dX_t = -\kappa X_t dt + \sigma dZ \tag{2}$$

Here κ defines the speed of mean reversion and σ represents the volatility. The term dZ

stands for the random increments of a Brownian motion.

Adding the stochastic and deterministic components of the model, we get a mean-reverting price process around a fixed seasonal pattern.

The seasonal pattern should capture observable patterns within a year. In order to do so we use a harmonic model (as described in Sørensen, 2002, Hannan et al., 1970). As electricity prices are very different on working days as compared to holidays and weekends, we include a factor for the type of day as well. Moreover, we include a linear trend. The resulting seasonal model is defined as:

$$f(t) = \alpha + \beta t + \gamma D_t + \sum_{k=1}^{K} (a \cos(2\pi kt) + b \cos(2\pi kt)) \tag{3}$$

with D_t representing a dummy variable for whether a day is a working day or non-working day (i.e. holidays and weekends), and the integer value K defining the number of annual cycles. α, β and γ as well as a and b are parameters that need to be estimated.

2.3. Price model calibration

To calibrate the model we follow a stepwise approach similar to the one applied by Lucia and Schwartz (2002). We use hourly Nordpool spot price data for the Western Danish price zone for ten historic years (2006–2015). As a first step we calibrate the deterministic seasonal component using ordinary least squares. This provides us with a fitted model and we can derive the observed residuals. The stochastic component is then fitted to the series of residuals (according to Iacus, 2008, p. 113ff.).

The first two steps are based on daily average spot prices. For the demand response optimisation, however, we require more detailed price simulations. We therefore extend the approach by applying normalised hourly profiles to the daily averages in order to achieve hourly prices.

The simplest approach to normalising an hourly price series would be to divide by the daily average. This approach, however, cannot be applied with a series including negative prices. There is the option of neglecting negative values and set those prices to zero. As far as possible we would like to reflect the full price variation in our model, because it determines the value of demand response, in particular for small residential customers with limited load-shift horizons. Moreover, we want to keep extreme cases like spikes or negative prices, because they hold a significant share of the value potential. We therefore choose to calculate the hourly deviations from the daily average and normalise by the annual average like this:

$$P_{t,nrm} = \frac{P_t - \overline{P}_{t,d}}{\overline{P}_{t,y}} \tag{4}$$

with $\overline{P}_{t,d}$ and $\overline{P}_{t,y}$ representing the average price over a time period of the day and year that the hour t is a part of. This approach would thus result in the same absolute hourly deviations from the daily average as long as the yearly average is the same. With increasing annual average, we would assume the hourly profile to become more pronounced as well. A negative hourly price would be represented by a large negative absolute deviation from the daily average, which would likely produce a new negative price based on a different daily average in the stochastic model as well.

We apply the normalised hourly profiles to the simulation results by random sampling of daily 24-hour-sets depending on the type of day. We thus randomly apply observed hourly profiles of working days and non-working days to the daily averages in our simulation:

$$P_{t,sim} = \overline{P}_{t,y} P_{t,nrm} + \overline{P}_{t,d} \tag{5}$$

This way we are able to preserve the extreme prices that can be observed in electricity price series with a probability reflecting the frequency of occurrence in the sample series.

2.4. Demand response model

We use a generic demand response model that implements only load shifting. Demand is based on historical profiles of residential consumers, and a certain percentage of the profile is assumed to be flexible, while the remaining load cannot be shifted.

Assuming the aggregator uses demand response to minimise spot market procurement costs, we need to solve a minimisation problem for all sets of modelled prices, such that:

$$\min_{d \geq 0} \sum_{t \in T} d_t P_t \tag{6}$$

where d_t denotes consumption in hour t at a price of P_t.

We ensure that the resulting consumption d_t in any given hour will at least cover the inflexible base demand determined as a share of $1 - k^{flex}$ of the the total demand D_t^0 before demand response with k^{flex} as consumption share assumed to be flexible:

$$d_t \geq D_t^0 \cdot \left(1 - k^{flex}\right) \quad \forall\ t \in T \tag{7}$$

Moreover, we need to take into account restrictions keeping flexibility within a technical bound of the underlying appliances. We use a rolling time horizon of S to contain volumes shifted in the short-term within a predefined time span. In every hour volumes may be shifted back or forward in time resulting in an interdependence of load shifts also beyond the defined horizon. We contain such interdependencies within a second larger time horizon L.

$$\sum_{t-S}^{t+S} d_t \geq \sum_{t-S}^{t+S} D_t^0 \quad \forall \{ t \in T \mid S < (t \bmod L) < L - S \} \tag{8}$$

The long-term horizon is furthermore governed by the following contraint:

$$\sum_{t}^{t+L} d_t = \sum_{t}^{t+L} D_t^0 \quad \forall \{ t \in T \mid (t-1) \bmod L = 0 \} \tag{9}$$

In both equations (8) and (9) the modulo operator produces the remainder of dividing the two values providing a way to refer to individual hours within the longer time horizon. The two constraints may be interpreted as the possibility to shift volumes, but at the same time shifted consumption in total over a certain time needs to equal consumption before load shifting. An example of a resulting profile is shown in Figure 2. It is based on parameters $S = 3$ and $L = 24$ with a flexible share of $k^{flex} = 10\%$. The lower panel shows a corresponding price scenario generated by the stochastic model that is used as the basis for cost minimisation.

2.5. Cash-flow model

We determine the profitability of the aggregator business using a single-period operational gross margin as indicator. The demand response module aggregates the demand response effect into annual values, so that we can keep the cash-flow model on the same basis.

We determine the operational gross margin in a simplified way by approximating net profits based on Earnings before Interests, Depreciation and Amortisation (EBITDA) (thus neglecting taxes and several other elements) and then dividing this by the total revenues. We thus calculate the operational gross margin (OGM) as:

$$OGM = \frac{R_{sales} + R_{DR} - O_{power} - O_{other} - I_{DR}}{R_{sales} + R_{DR}} \tag{10}$$

where R_{sales} is the annual revenue of power sales to customers, R_{DR} is the annual revenue from demand response activity, O_{power} is the annual cost of procuring power from the spot market, O_{other} is additional operating cost of the aggregator, and I_{DR} is the annuity

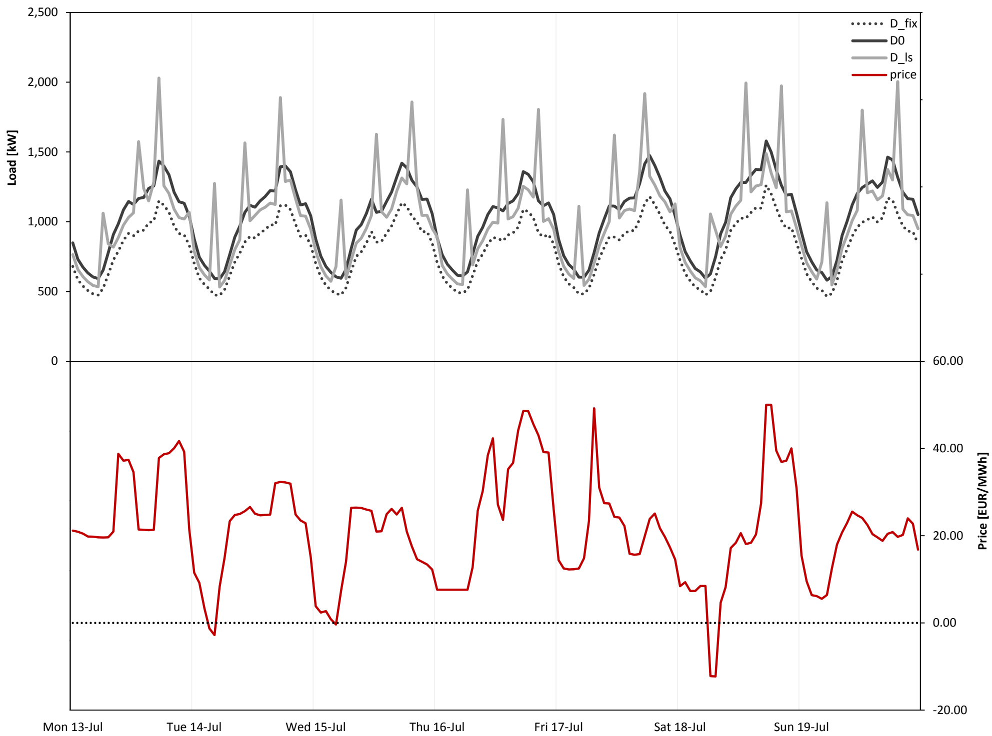

Figure 2: One week example of simulated load and price profiles (10%-flex scenario, ±3 hours load shift)

of the investment cost for demand response equipment. In the base case without demand response, R_{DR} and I_{DR} are zero.

We exogenously set the operational gross margin. The gross margin of Danish suppliers varies between years and products offered. It has been found to lie between 50–100 DKK/MWh in the past years under retail competition (Okholm et al., 2015). Assuming competition to rather increase than decrease in the coming years we use the lower value of 50 DKK/MWh, which transforms to a margin of 18.025% to be used as our baseline. The corresponding electricity sales price to customers in the base case is 37.23 EUR/MWh excl. any levies, taxes and network charges. By then ensuring that the aggregator achieves the same expected profitability in either case, we re-estimate the possible sales price to customers after demand response. If the demand response activity as a whole is good business, the aggregator will be able to offer a discount to their customers.

By choosing the approach of keeping the expected profitability of the aggregator constant, we calculate the maximum potential reduction in sales price to customers that can be achieved by the aggregator through demand response activities. In reality, one could expect that the aggregator will not pass all of the effect through to the customers but that the savings are shared between the two. For our purpose of analysing the business case of an aggregator as such and to enhance transparency between the scenarios we find it appropriate not to split the effect further.

In the same way, we can also find the threshold of maximum allowable investment cost at which the aggregator would start to be interested in entering into the business. Here again, we assume that the aggregator should at least be able to achieve the same expected profitability and to offer at least the same sales price to customers.

2.6. Value-at-risk estimation

Exploiting the information on probability distributions of the demand response effect that the stochastic price modelling generates, we can further analyse the risk that the aggregator assumes when investing into demand response equipment. For this, we use the Value-at-risk measure.

In the Value-at-risk measure, a quantile $\alpha \in (0, 1)$ is specified that represents the risk tolerance of an investor. From the specified α and the mean profit, a value η is calculated, so that the probability of obtaining a profit less than η is lower than $(1 - \alpha)$:

$$\mathrm{VaR}(\alpha, x) = \max\left\{\eta : P(\omega \mid f(x, \omega) < \eta) \leq 1 - \alpha\right\}, \quad \forall\, \alpha \in (0, 1). \tag{11}$$

Commonly used values for α are derived from the standard deviation σ. When using one standard deviation, the profit will lie above the calculated value η with a probability of 68.27%. Using 2σ corresponds to 95.45% probability. In financial analysis, a rounded value of α = 5% is commonly used, and we apply this here as well. Thus, using the VaR to our operational gross margin as the measure for profitability, we determine the level of the margin that the aggregator can expect to at least obtain with a probability of 95%.

2.7. Scenarios

We calculate results for a set of scenarios to account for the uncertainty about the volume of flexible consumption as well as the technical load-shift capabilities of specific appliances. These scenario parameters only affect the demand response optimisation.

The literature on flexibility potentials of Danish households is rather sparse. Ea Energianalyse (2011) provides one of the few estimates: A share of 35% of residential consumption is considered to become flexible if fully equipped with automation units. A similar figure has been used by Kwon and Østergaard (2014) in their analysis of flexible demand in Denmark. Such estimations are in line with international findings as well (e.g. Klobasa and Obersteiner, 2009, Faruqui et al., 2007). Most of the flexibility comes from shifting loads. Only a few categories of lighting as well as some electrical heating could be considered for curtailment or additional load during extreme periods.

The estimated potential of 35% flexible load share on the national level defines an upper bound that is subject to how many customers actually adopt demand response technology and behave flexibly. In our analysis, however, the aggregator creates a dedicated portfolio with flexible customers, so the adoption uncertainty is not relevant here (other than for a potential limit of the possible number of customers in the portfolio itself). At the same time we may assume that those customers that are part of the portfolio utilise a large share of their individual flexibility potential. Still, a full utilisation of the estimated 35% load share potential might be too optimistic, as it e.g. might not be feasible to attach devices to all potentially flexible appliances so that not all of the flexible load can be included in the business case of an aggregator. Furthermore, one should account for some variation in the customer base. We therefore use the following scenarios for the flexibility share k^{flex}: 10%, 20%, 30%.

Regarding the load-shift horizon, Gils (2014) points out that most demand response options are limited to a relatively short time horizon. Other assessments of the flexible potential in residential appliances with regard to timing are available from, e.g., Klobasa (2007) or Paatero and Lund (2006). They find that some load-shifting options provided by fridges and freezers are restricted to one hour, while appliances like washing machines and dishwashers are assumed to be flexible within a whole day. As we use aggregated profiles we do not explicitly account for individual appliances. Instead we use a set of values for the load-shift horizon S that should cover the possible range of shifting potentials from the overall load of residential customers. We choose to set these at: ±1 hour, ±3 hours, ±6 hours, ±9 hours. At the same time we fix the longer load-shift horizon L to 24 hours.

3. Results

3.1. Results for the expected value of load-shifting

In this section we present results based on the expectation of savings generated by load-shifts across all simulated scenarios. All numbers in this section are thus based on the mean value over 1,000 simulations.

As described in Section 2.1, we have calculated for each set of scenarios the operational gross margin and then analysed it from different perspectives. Here the investment cost threshold is one of the crucial elements in the analysis. Note that the investment thresholds of the different scenarios are calculated so that both the margin for the aggregator and the sales price for the customers are kept constant in comparison to the base case without demand response. The investment thresholds presented here are thus the maximum allowable cost which have in reality to be undercut for the aggregator business model to become attractive.

Table 1 provides an overview of the investment thresholds subject to the load shift and flexibility scenarios. With longer time horizons and larger flexible volumes we observe a substantial increase in the investment cost that may be covered by load-shifting returns.

Table 1: Investment threshold [EUR/customer]

	Load-shift horizon			
Flexible share	±1 hour	±3 hours	±6 hours	±9 hours
10%	2.65	8.88	15.97	32.88
20%	5.31	17.76	31.94	65.76
30%	7.96	26.64	47.91	98.64

In addition to determining the feasibility of investment it is relevant to establish by how much customer prices could potentially be reduced. As customers in competitive retail markets like the Danish one will have to be convinced of participating in demand response activities, a benefit to the customer will be essential. Table 2 provides an overview on the leeway that would exist regarding the sales prices based on the full load-shift effect. The values are therefore equivalent to zero investment costs and, in practice, any benefit would have to be shared between the customer and the aggregator: The aggregator needs to cover the investment cost and may want to achieve some additional margin, while the customer must be provided with an incentive to switch to the demand-response product.

Although the absolute price reduction may seem low in comparison to the average sales price of around 37 EUR/MWh, one can conclude that some of the scenarios hold a rather attractive relative reduction potential. It has to be noted, though, that we disregard taxes and network tariffs in our price. Considering these elements, which make up around 80% of the total residential electricity bill in Denmark (cp. Kitzing et al., 2016), one could

Table 2: Maximum price reduction potential [EUR/MWh]

	Load shift horizon			
Flexible share	±1 hour	±3 hours	±6 hours	±9 hours
10%	0.07	0.25	0.45	0.92
20%	0.15	0.50	0.89	1.84
30%	0.22	0.74	1.34	2.75

suspect that the potential reductions resulting from our scenarios may not be sufficient to attract much participation of residential customers.

3.2. Results for a distribution of load-shift effects

In addition to analysing the investment thresholds and potential sales price reductions based on scenario mean values, we assess the probability of achieving a certain benefit. For this, we determine the probability distributions of the demand response effects in each scenario. In Figure 3 we show the distributions for all simulated load-shift horizons under the scenario with a 20% share of flexible consumption. As the load-shift horizon is extended, the results become more favourable and move along the x-axis. At the same time it becomes clear how the distributions get wider and thus the return becomes more uncertain. Another observation is that all the distributions have a pronounced upside represented by a thicker tail.

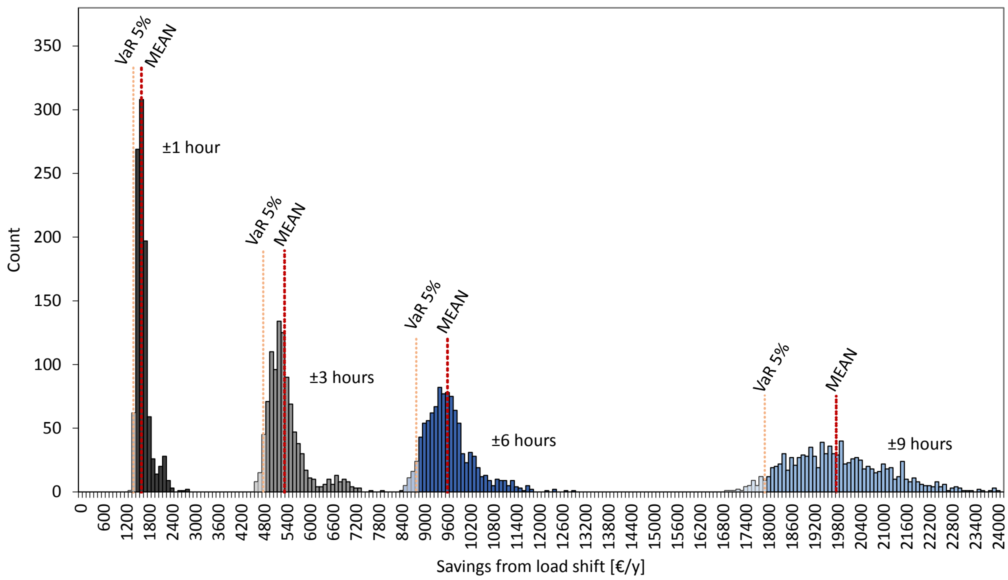

Figure 3: Distribution and Value-at-Risk (5%) for different load-shift horizons in the 20%-flex scenario

The shapes for other simulated shares of flexibility (10% and 30%) are similar to those presented in the graph. The 10%-scenario results are slightly narrower and shifted further towards the left of the x-axis, while the 30%-scenarios are wider and further towards the right end.

Assuming that the aggregator decides to invest as soon as the investment cost undercuts the threshold in the mean outcome, we estimate the Value-at-Risk (VaR) in case of lower than expected demand response potential. The VaR for the different scenarios are summarised in Table 3. For the scenario with a load-shift horizon of 6 hours and a flexibility potential of 20%, for instance, the profitability for the aggregator would decrease from 18.025% to 17.861% for a 5% VaR, corresponding to a 0.9% decrease in gross margin. Overall, the margin reductions lie in a range of 0.1–3%. These relatively small deviations are due to the small share of the load shift benefits in the gross margin as defined in equation (10).

Table 3: Gross margin at the 5% VaR level [%]

	Load-shift horizon			
Flexible share	±1 hour	±3 hours	±6 hours	±9 hours
10%	18.004%	17.969%	17.942%	17.838%
20%	17.983%	17.913%	17.861%	17.659%
30%	17.962%	17.858%	17.782%	17.487%

4. Discussion

The maximum allowable investment costs lie between 2.65 and 98.64 EUR/customer in our scenarios, depending on the flexible share and the load-shift horizon. Comparing these results to the current market conditions is rather difficult as no established market exists for neither aggregator businesses nor demand response equipment. Remote controllable smart plugs are offered in the Danish market for around 50 EUR (cp. Develco Products, 2016). Such devices have been applied to control single appliances (see Lakshmanan et al., 2016), but require additional equipment to be installed for automatic remote control not included in the price. Reverting to other studies, Jötten et al. (2011) present the cost of automation equipment for three demand response business cases. One of the cases is similar to the aggregator case in our analysis. In this case, the required device was provided at a cost of 100 EUR/customer. None of our scenarios reach above that level. If actual investment cost for automation equipment will be in this range, we must conclude that in our investigated scenarios for the Danish market and under current market conditions, the business case for an aggregator will be rather difficult. Investment cost in the range of 50 EUR/customer can, however, already provide an interesting business case for aggregators today, depending on the customer portfolio that they are able to attract.

It may be discussed if our assumptions on the flexibility share and the load-shift horizon are realistic. We can see that especially the load-shift horizon becomes interesting as soon as it involves the opportunity to benefit from day-to-night differences, i.e. at ±9 hours and above. But ±6–9 hours load-shifting are already rather optimistic assumptions for many home appliances, and could certainly not be expected from all of them. As mentioned freezers will probably have a much shorter time frame for load shifting. Even heat pump systems might run into problems with such horizons if storages are not large enough. One could thus expect that the longer the load-shift horizon the lower the flexible share of the load and vice versa. On the other hand, for the very short horizon, one could potentially achieve higher flexible shares.

We have made many simplifications in the analysis. One of these is that we operate with constant investment cost in all scenarios. In reality, one should expect higher investment cost for getting access to higher flexible shares, because then probably more appliances have to be equipped with remote control devices at a customer.

Due to the scope of the analysis, it was not possible to consider all kinds of risks in the aggregator business model. One major risk for an aggregator is not being able to access flexibility despite of having invested into the demand response equipment. This risk arises from unforseeable actions by the customers, e.g. if they remove the remote control device from the appliance, or they remove respective appliances on the whole. Customers might also unexpectedly shut down appliances, e.g. when going on holidays and forgetting to inform the aggregator. All such issues pose potential threats to the business case of an aggregator and will in practice have to be factored into the calculation of potential sales prices, thus further diminishing potential benefits for customers.

5. Conclusion

Aggregators are expected to become important providers of flexibility in a system that relies on decentralised demand response. The analysis of a robust business case for such aggregators should not only take into account average values, but also consider risks and their implications for income variability and attractiveness of investments. We have developed a model that is capable of analysing the operational gross margin of an aggregator, related investment thresholds and potential sales price reductions. At the same time, it provides the opportunity to determine probability distributions and thus enables us to do a Value-at-Risk assessment.

Applying the model to the Danish market, we find that aggregators have a difficult business case under current market conditions unless they can find a portfolio of customers with a very high flexibility share of their load and very long load-shifting horizons. In the residential segment such opportunities are limited at present. On the other hand, we do see smart devices emerging in the market with investment cost in a range that could make the business model of an aggregator attractive already today. Furthermore, we find that the income expectations are rather stable and there is more upside than downside related to uncertain electricity market price developments and their exploitation for demand response.

Overall we can conclude that there is still some way to go for aggregators to assume a significant role as providers of flexibility in the future. In terms of analysis, more must be done on the evaluation of the business case; all risks must be assessed. An updated model could, e.g., include implications of volume risk stemming from uncertainty about the exact response from a portfolio of end user devices. In practical terms, the business model of aggregators must still be further elaborated, and investment cost for remote control devices must decrease. Additional sources of income for tapping into the demand-side flexibility potential could be developed by providing reserves or ancillary services to the transmission or distribution grid operators. In combination with foreseeable cost reductions for smart devices the aggregator business case might soon become attractive for highly flexible customer segments.

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