

Offering Strategy of a Flexibility Aggregator in a Balancing Market Using Asymmetric Block Offers

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Abstract—In order to enable large-scale penetration of renewables with variable generation, new sources of flexibility have to be exploited in the power systems. Allowing asymmetric block offers (including response and rebound blocks) in balancing markets can facilitate the participation of flexibility aggregators and unlock load-shifting flexibility from, e.g., thermostatic loads. In this paper, we formulate an optimal offering strategy for a risk-averse flexibility aggregator participating in such a market. Using a price-taker approach, load flexibility characteristics and balancing market price forecast scenarios are used to find optimal load-shifting offers under uncertainty. The problem is formulated as a stochastic mixed-integer linear program and can be solved with reasonable computational time. This work is taking place in the framework of the real-life demonstration project EcoGrid 2.0, which includes the operation of a balancing market on the island of Bornholm, Denmark. In this context, aggregators will participate in the market by applying the offering strategy optimization tool presented in this paper.

Index Terms—Flexibility aggregator, asymmetric block offers, balancing market, load shifting, offering strategy, risk.

NOTATION

Sets and indices

- \mathcal{T} Set of time steps t and t' in the optimization horizon.
- Ω Set of balancing market price scenarios ω .
- \mathcal{S} Set of possible shapes s for an offer's response/rebound part.
- \mathcal{S}^+ Subset of \mathcal{S} : set of up-regulation shapes.
- \mathcal{S}^- Subset of \mathcal{S} : set of down-regulation shapes.
- Ξ Set of all variables of the optimization problem.

Continuous Parameters

- $\lambda_{t\omega}$ Balancing market price forecast for time t and scenario ω [€/MWh].
- π_ω Probability associated with scenario ω .
- μ A relatively small value, defined as $(T + 1)^{-1}$.
- P_s Regulation power of shape s [MW].
- \bar{P} Maximum regulation power that the aggregator can provide [MW].
- α Confidence level for CVaR calculation.
- β Weighting parameter for CVaR in objective function.

Integer Parameters

- T Number of time steps in the optimization horizon.
- T_s Duration of shape s [time steps].
- T_{rec} Minimum recovery time between two blocks [time steps] (should only take values 0 or 1 with this problem formulation).

Continuous Variables

- p_t^{resp} Power offered during the response period of a block starting at time t [MW].
- p_t^{reb} Power offered during the rebound period of a block starting at time t [MW].
- $q_{tt'}^{resp}$ Contribution of the response part of a block starting at time t' to the power offered at time t [MW].
- $q_{tt'}^{reb}$ Contribution of the rebound part of a block starting at time t' to the power offered at time t [MW].
- ζ, η_ω Auxiliary variables used in the calculation of CVaR.

Integer Variables

- τ_t^{resp} Duration of the response period of a block starting at time t [time steps].
- τ_t^{reb} Duration of the rebound period of a block starting at time t [time steps].
- s_t^{resp} Shape of the response part of a block starting at time t .
- s_t^{reb} Shape of the rebound part of a block starting at time t .

Binary Variables

- v_{ts}^{resp} Indication that a block starting at time t has a response part following the shape s .
- v_{ts}^{reb} Indication that a block starting at time t has a rebound part following the shape s .
- $u_{tt'}^0$ Indication that time step t is not before time step t' .
- $u_{tt'}^1$ Indication that time step t is after the response period of a block starting at time t' .
- $u_{tt'}^2$ Indication that time step t is after the rebound period of a block starting at time t' .
- $u_{tt'}^3$ Indication that time step t is beyond the recovery period of a block starting at time t' .

I. INTRODUCTION

In the context of increasing penetration of intermittent energy sources, there is a growing demand for flexibility in power systems around the world. Demand response (DR) is considered as a promising flexibility resource [1]. In particular, there is substantial potential for flexibility provision using

This work was supported by the Energy Technology Development and Demonstration Programme (EUDP) through the project of EcoGrid 2.0 (64015-0082/EUDP).

demand-side assets that are already installed and connected to the grid [2]. Activation of DR however poses challenges, especially due to the lack of appropriate business models [3]. To unlock this potential, novel market structures and control methods are necessary and it is envisioned that aggregators will have a key role to play in this new process [4].

There is extensive literature on bidding strategies for aggregators seeking to purchase power in the day-ahead market for a pool of flexible loads. These works differ in how they model flexibility from the aggregators' perspective. Some papers model flexible demand-side resources as price-responsive loads [5], [6], while others directly model the loads' flexible power consumption using a set of constraints in an optimization problem. Such models may use time-varying power and energy constraints, and apply well to time-shiftable loads such as electric vehicles, water heaters or dishwashers [7], [8].

Other works have focused on the provision of balancing services by aggregators, either through direct contracts with intermittent power producers such as wind power producers [9], [10], or through participation in balancing markets [11]. These works are valuable because they unlock substantial potential for the provision of balancing services from aggregate flexible loads. However, when details are provided on the relation between market prices and regulation power provision, common approaches adopted in these works are either to assume a simple price response curve with no coupling of successive time steps, or to assume that the aggregator has full knowledge of the characteristics of each responsive element.

In [12], an alternative approach for representing the flexibility of supermarket refrigerators is proposed, based on the concept of *saturation curves*. Such curves are meant to model the potential rebound effect after DR activation, and thereby to ease the planning of load-shifting operations. In [13], it is proposed to solve an economic dispatch for regulation power provision which integrates load-shifting options in the form of *asymmetric block offers*. A method for the definition of such blocks is proposed in [13], and its positive effect on system costs is demonstrated. In the real-life demonstration project EcoGrid 2.0 [14], a balancing market which accepts asymmetric block offers from aggregators is being implemented on the island of Bornholm, Denmark. Based on this project, we develop in this paper an optimal offering strategy tool for a flexibility aggregator participating in such a balancing market with asymmetric block offers.

The main contribution of this paper is the formulation of a stochastic mixed-integer linear optimization problem to derive the optimal offer of a risk-averse aggregator in the form of asymmetric block offers. This allows exploiting flexibility from demand-side assets represented by saturation curves, using probabilistic forecast of balancing market prices. Applying this formulation, a case study is presented, where results are demonstrated and compared with different risk preferences. Computational issues are then discussed. To the best of our knowledge, there is no offering strategy tool for an aggregator in the literature that allows to derive asymmetric block offers.

The rest of this paper is organized as follows. The balancing market and the format of asymmetric block offers are defined in Section II. The proposed optimization problem for offering strategy is described in Section III. In Section IV, a case study is presented, along with a discussion on computational complexity. The paper is concluded in Section V. Finally, an Appendix provides the mixed-integer linear equivalent of the proposed model.

II. MARKET DEFINITION

In this paper, we study the offering problem for a flexibility aggregator participating in a balancing market which accepts *asymmetric block offers*. This offer format is proposed in [13] and is being implemented on the island of Bornholm, Denmark, in the framework of the demonstration project EcoGrid 2.0. An asymmetric block offer represents the possibility of shifting load, in the form of load advancing or load delaying, and is characterized by five attributes, as shown in Fig. 1:

- duration τ_t^{resp} and power effect p_t^{resp} of the *response part* of the offer,
- duration τ_t^{reb} and power effect p_t^{reb} of the *rebound part* of the offer,
- recovery time T_{rec} following the load-shifting operation.

In the case of a *load-advancing* offer (as in Fig. 1), the response part of the offer corresponds to down-regulation and the rebound part to up-regulation. In the case of a *load-delaying* offer, the response part of the offer corresponds to up-regulation and the rebound part to down-regulation¹. The “asymmetric” term implies that the power quantities p_t^{resp} and p_t^{reb} , as well as the time durations τ_t^{resp} and τ_t^{reb} are not necessarily identical. The duration of each part of the offer is counted in number of market time steps, the length of which is defined by the market operator (eight 15-minute time steps in the case of the EcoGrid 2.0 project). Along with these five attributes, an asymmetric block offer comes with an offering price for each time step.

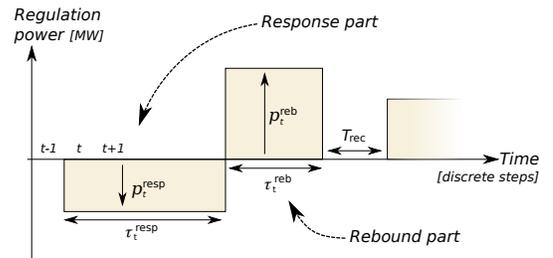


Figure 1. Illustration of an example asymmetric block offer.

The market setting that is considered in this paper is a balancing market in the transmission level, which clears both conventional regulation offers (single-time-step upward- or

¹The convention for the sign of power quantities used in the paper is as follows: a *positive* amount of regulation power corresponds to *up-regulation*, i.e. a *decrease* in load power consumption; a *negative* amount of regulation power corresponds to *down-regulation*, i.e. an *increase* in load power consumption.

downward-regulation offers) and asymmetric block offers. We consider the case of an aggregator which seeks to maximize its expected profit by submitting asymmetric block offers to this market. It is assumed that the aggregator makes only one offer at a time, but optimizes over a time horizon. As a consequence, foresight of future opportunities may influence the offering strategy for the most immediate market clearing.

In line with traditional self-scheduling problems [15], [16], the aggregator forecasts the future market prices, but this may bring uncertainty, which is characterized by a set of foreseen scenarios. The other sources of uncertainty, e.g., availability of flexible resources in the aggregator’s portfolio, are not considered; however, it is straightforward to consider them by additional scenarios.

III. OFFERING MODEL

In this section, we present the optimization problem which gives an optimal offering strategy for a flexibility aggregator participating in a balancing market with asymmetric block offers.

A. Saturation curve modelling

We consider that the aggregator is controlling a population of flexible assets with load-shifting capabilities, described by a single saturation curve for the whole portfolio [12], [13]. This saturation curve describes the possible combinations of attributes for an asymmetric block offer representing a feasible load-shifting operation. By feasible, it is meant that the load-shifting operation does not bring the assets to a point outside the operating region defined by the end-user, and that the assets are at the same operating point before and after the operation. For instance, in the case of a refrigeration system, it means that the system’s temperature should be in the comfort limit both before and after DR activation, and that the system’s temperature does not exceed specific lower and upper bounds during the operation. It is thus expected that a decrease in power consumption is followed or preceded by an increase in power consumption, according to the feasible combinations described by the saturation curve. Fig. 2 depicts a sample saturation curve based on a series of measurement points (blue asterisks), and modelled as two functions of the form $y = \frac{a}{x^b}$, $(a, b) \in \mathbb{R}^2$ (solid red lines). The interpretation of this curve is that any pair of points respectively falling on its negative and positive sides gives a feasible response-rebound combination as defined in Section II.

From these curves, discrete options are extracted based on the length of the market time resolution. Indeed, if the balancing market is cleared for time steps of 15 minutes, only offers whose duration is a multiple of 15 minutes can be cleared. These options (red circles in Fig. 2) are used as parameters within the mixed-integer optimization problem presented in this section, where they are referred to as *shapes*.

Accordingly, an aggregator with a saturation curve as in Fig. 2 has several options for the down-regulation part of its offer. It could for example offer a load increase of 8.7 MW for 60 minutes, or a load increase of 7.4 MW for 75 minutes

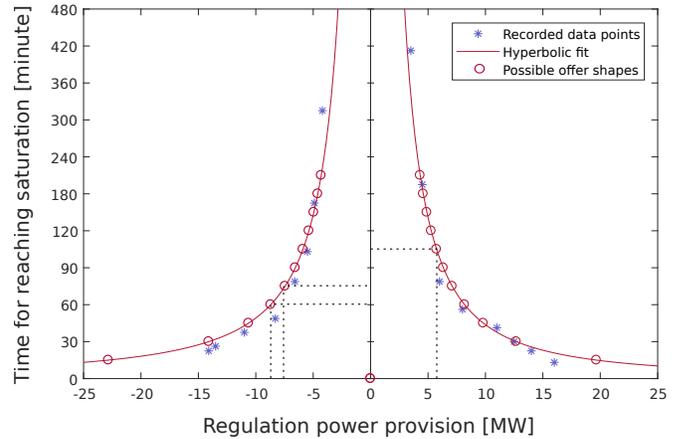


Figure 2. Illustration of a sample saturation curve, including the down-regulation part (left) and the up-regulation part (right).

(cf. dashed lines on the left side). Similarly, the up-regulation part of the offer can take different shapes, for example a load reduction of 5.7 MW for 105 minutes (cf. dashed lines on the right side). A strategic choice would be based on what seems to be the most beneficial offer in foresight of future balancing market prices.

B. Mathematical formulation

The optimization is made in a probabilistic framework, where balancing price uncertainty is modelled using scenarios. The method for forecasting balancing prices is beyond the focus of this paper, and probabilistic balancing price forecasts are here considered as a given input. Furthermore, the aggregator is considered risk-averse, and a conditional value-at-risk (CVaR) metric [17], [18] is accounted for in the optimization problem. The offering strategy is derived based on the solution of the proposed stochastic optimization problem.

We further make the assumption that the aggregator is price-taker, and we evaluate its expected profit based on a self-scheduling approach, i.e., the offers are considered to be scheduled in all scenarios, and the corresponding market prices are used for calculating the profit associated with each scenario. In line with this approach, we do not focus on the definition of offering prices. In practice, ensuring self-scheduling of asymmetric blocks for a price-taker aggregator could be done by systematically defining extremely low up-regulation offering prices and extremely high down-regulation offering prices.

The proposed stochastic optimization problem for the aggregator’s offering strategy is composed of the objective function (1) and the set of constraints (2)-(8).

The objective function (1), to be maximized, corresponds to a weighted sum of the aggregator’s expected profit given a set of price scenarios and its expected profit in the worst-case scenarios, calculated by the CVaR risk metric. In this expression, the first row corresponds to the expected profit, and is calculated, for each time step, as the product of the expected balancing price and the regulation power offered in

the market. The second row in (1) corresponds to the CVaR risk metric weighted by a non-negative parameter β :

$$\begin{aligned} \text{Max.} \quad & \sum_{t=1}^T \left(\sum_{\omega \in \Omega} (\pi_\omega \lambda_{t\omega}) \sum_{t'=1}^T (q_{tt'}^{\text{resp}} + q_{tt'}^{\text{reb}}) \right) \\ & + \beta \left(\zeta - \frac{\sum_{\omega \in \Omega} (\pi_\omega \eta_\omega)}{1 - \alpha} \right), \quad (1) \end{aligned}$$

where $\Xi = \{p_t^{\text{resp}}, p_t^{\text{reb}}, q_{tt'}^{\text{resp}}, q_{tt'}^{\text{reb}}, \zeta, \eta_\omega, \tau_t^{\text{resp}}, \tau_t^{\text{reb}}, s_t^{\text{resp}}, s_t^{\text{reb}}, v_{ts}^{\text{resp}}, v_{ts}^{\text{reb}}, u_{tt'}^0, u_{tt'}^1, u_{tt'}^2, u_{tt'}^3\}$ is the set of optimization variables.

The variables $q_{tt'}^{\text{resp}}$ and $q_{tt'}^{\text{reb}}$ calculate the contribution of all planned offers to the regulation power provision at all time steps. They follow:

$$q_{tt'}^{\text{resp}} = \begin{cases} p_{t'}^{\text{resp}} & \text{if } t \geq t' \\ \text{and } t < t' + \tau_{t'}^{\text{resp}} & \\ 0 & \text{otherwise,} \end{cases} \quad \forall (t, t') \in \mathcal{T}^2, \quad (2a)$$

$$q_{tt'}^{\text{reb}} = \begin{cases} p_{t'}^{\text{reb}} & \text{if } t \geq t' + \tau_{t'}^{\text{resp}} \\ \text{and } t < t' + \tau_{t'}^{\text{resp}} + \tau_{t'}^{\text{reb}} & \\ 0 & \text{otherwise,} \end{cases} \quad \forall (t, t') \in \mathcal{T}^2. \quad (2b)$$

Note that the current form of (2) is non-linear due to the conditional statements, and its mixed-integer linear equivalent is given in Appendix.

The auxiliary variables $\eta_\omega \in \mathbb{R}^+$, $\forall \omega \in \Omega$ and $\zeta \in \mathbb{R}$ are used to compute the CVaR risk metric [17], [18]. Equation (3) below defines the relation between these variables and the profit yielded for each price scenario:

$$\zeta - \sum_{t=1}^T \left(\lambda_{t\omega} \sum_{t'=1}^T (q_{tt'}^{\text{resp}} + q_{tt'}^{\text{reb}}) \right) \leq \eta_\omega, \quad \forall \omega \in \Omega. \quad (3)$$

Equations (4) compute the state variables that describe the power effect and duration of each part of a block, based on the different shapes' characteristics. The binary variables v_{ts}^{resp} and v_{ts}^{reb} indicate whether the response or the rebound part of a block starting at time t follows shape s . The integer variables s_t^{resp} and s_t^{reb} determine the shapes of the response part and the rebound part, respectively, of a block starting at time t :

$$v_{ts}^{\text{resp}} = \begin{cases} 1 & \text{if } s = s_t^{\text{resp}} \\ 0 & \text{otherwise,} \end{cases} \quad \forall t \in \mathcal{T}, \quad (4a)$$

$$v_{ts}^{\text{reb}} = \begin{cases} 1 & \text{if } s = s_t^{\text{reb}} \\ 0 & \text{otherwise,} \end{cases} \quad \forall t \in \mathcal{T}, \quad (4b)$$

$$p_t^{\text{resp}} = P_{s_t^{\text{resp}}}, \quad \forall t \in \mathcal{T}, \quad (4c)$$

$$p_t^{\text{reb}} = P_{s_t^{\text{reb}}}, \quad \forall t \in \mathcal{T}, \quad (4d)$$

$$\tau_t^{\text{resp}} = T_{s_t^{\text{resp}}}, \quad \forall t \in \mathcal{T}, \quad (4e)$$

$$\tau_t^{\text{reb}} = T_{s_t^{\text{reb}}}, \quad \forall t \in \mathcal{T}. \quad (4f)$$

Similar to (2), the mixed-integer linear equivalent of (4) is given in Appendix. Additional constraints are required to ensure that, if the response part of a block follows a

down-regulation shape, its rebound part should follow an up-regulation shape, and vice versa. For this purpose, we use the subsets \mathcal{S}^+ and \mathcal{S}^- to designate the up-regulation and down-regulation shapes. Below, constraint (5a) ensures that, for each block, only one part among response and rebound follows an up-regulation shape. Similarly, constraint (5b) ensures that, for each block, only one part follows a down-regulation shape:

$$\sum_{s \in \mathcal{S}^+} (v_{ts}^{\text{resp}} + v_{ts}^{\text{reb}}) = 1, \quad \forall t \in \mathcal{T}, \quad (5a)$$

$$\sum_{s \in \mathcal{S}^-} (v_{ts}^{\text{resp}} + v_{ts}^{\text{reb}}) = 1, \quad \forall t \in \mathcal{T}. \quad (5b)$$

It is further ensured that no blocks overlap. A block is considered to be activated if its corresponding variables p_t^{resp} , p_t^{reb} , τ_t^{resp} and τ_t^{reb} take non-zero values. Equation (6) ensures that no block starts within the period covered by a previously activated block:

$$\tau_t^{\text{resp}} = \tau_t^{\text{reb}} = 0 \text{ if } \exists t' / t \leq t' + \tau_{t'}^{\text{resp}} + \tau_{t'}^{\text{reb}} - 1, \quad \forall t \in \mathcal{T}. \quad (6)$$

The mixed-integer linear equivalent of (6) is given in Appendix. Moreover, all blocks should be contained within the optimization horizon. Equation (7) ensures that any block that is activated has a duration, including response and rebound, that does not reach beyond the end of the optimization horizon:

$$t + \tau_t^{\text{resp}} + \tau_t^{\text{reb}} - 1 \leq T, \quad \forall t \in \mathcal{T}. \quad (7)$$

Finally, equations (8) ensure that, if the response part of a block follows an empty shape (i.e., $p_t^{\text{resp}} = \tau_t^{\text{resp}} = 0$), then the rebound part also follows the same shape (i.e., $p_t^{\text{reb}} = \tau_t^{\text{reb}} = 0$), and vice versa. This ensures that a block needs both a substantial response and rebound part to be activated:

$$\tau_t^{\text{resp}} \geq \tau_t^{\text{reb}} T^{-1}, \quad \forall t \in \mathcal{T}, \quad (8a)$$

$$\tau_t^{\text{reb}} \geq \tau_t^{\text{resp}} T^{-1}, \quad \forall t \in \mathcal{T}. \quad (8b)$$

IV. CASE STUDY

A. Input data

We evaluate the proposed offering strategy tool with a case study where a flexibility aggregator controls a pool of flexible loads characterized by the saturation curve in Fig. 2, and accordingly submits asymmetric block offers to the balancing market. The offering strategy is based on probabilistic forecasts of the balancing prices over a 12-time-step horizon. Risk-aversion of the aggregator is characterised by a 95% confidence level, i.e., $\alpha = 0.95$.

The uncertain future balancing market prices are characterised by 100 equiprobable scenarios, derived from forecasts of the power system imbalance and from known day-ahead market prices. Fig. 3 shows the 100 price scenarios used in this case study. As can be noted from the figures, the uncertainty on the future power system imbalance, and thus on the prices, is considered to increase with the look-ahead time.

Some of the low-range forecasts in Fig. 3 feature negative balancing market prices. Although rare in the current system conditions, negative balancing market prices are likely to occur

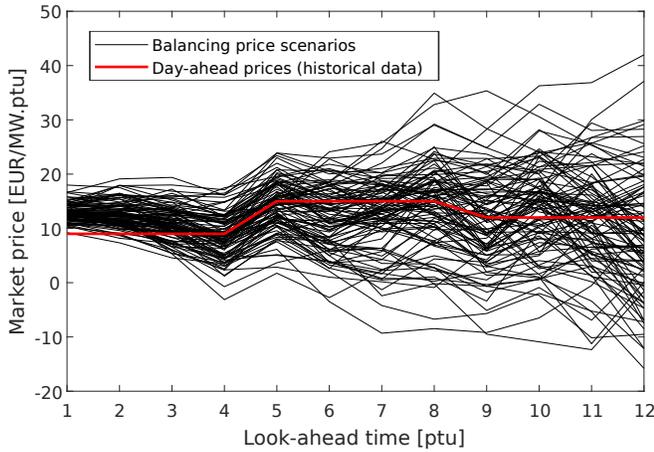


Figure 3. Balancing price forecast scenarios (100 scenarios). Program time unit (ptu) is 15 minutes.

when actors such as wind power producers and demand-side aggregators are participating in the balancing market. In the case of a net demand for up-regulation, it means that some actors are ready to pay to provide up-regulation power; in the case of a net demand for down-regulation, it means that the most expensive scheduled supplier asks for being paid to provide down-regulation power.

B. Results

Offering strategies are derived from the optimization problem for different degrees of risk-aversion, i.e., different values for the CVaR weighting coefficient β . The solutions are analysed for a *risk-neutral* case ($\beta = 0$) and for a *risk-averse* case (e.g., $\beta = 2$). Table I summarizes the outcomes obtained for these two sample cases. The foreseen optimal offering strategy is depicted in Fig. 4 for the risk-neutral case (top) and for the risk-averse case (bottom).

TABLE I
AGGREGATOR'S OUTCOMES FOR TWO DIFFERENT RISK PREFERENCES

	β	Expected profit [€]	CVaR [€]
Risk-neutral	0	432.5	-36.8
Risk-averse	2	282.8	73.0

Note that the risk-neutral strategy (Fig. 4, top) foresees an offer that reaches to the last time step of the optimization horizon. The comparatively high uncertainty at the end of the horizon (see Fig. 3) likely makes it difficult to select risk-hedging offers in the risk-averse case. This encourages the risk-averse aggregator to concentrate offers in earlier time steps, as depicted in Fig. 4 (bottom).

On the other hand, in the risk-neutral case, a comparatively long offer is chosen as, with the saturation characteristics described in Fig. 2, it happens to be a more energy-efficient offer than two successive shorter offers. Indeed, loads may have changing efficiencies at different operation points, e.g., for a cooling system, the ratio between a change in power consumption and the subsequent change in temperature may not be constant for different power or temperature levels. This can make the energy content of the up-regulation and

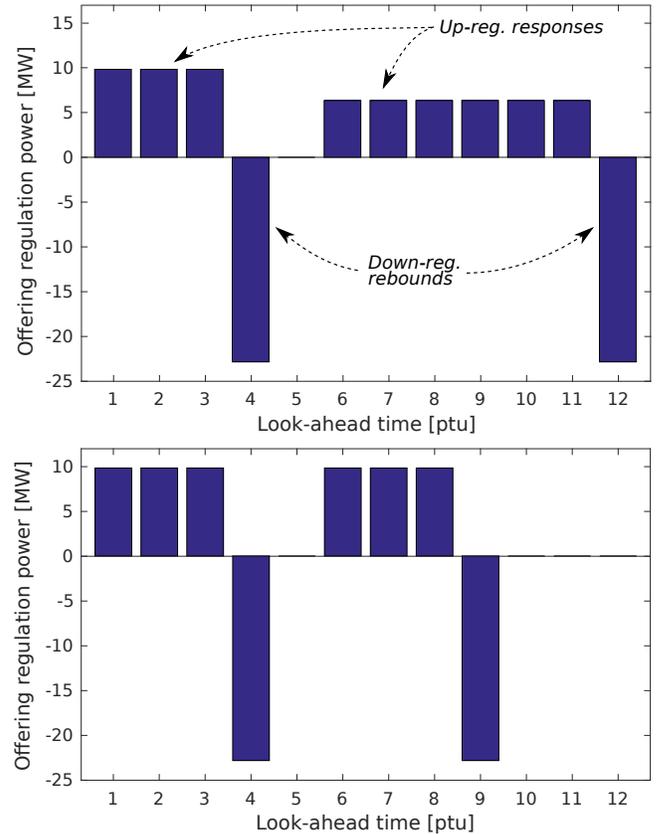


Figure 4. Offering strategy of the aggregator in the risk-neutral case (top, $\beta = 0$) and in the risk-averse case (bottom, $\beta = 2$).

down-regulation parts of an asymmetric block offer unequal, although respecting the flexible loads' saturation curve.

Finally, it appears that the offer chosen for the beginning of the horizon is the same in both cases. This is due to a relatively small uncertainty in price forecasts for the first few time steps. As a consequence, the worst-case scenarios are not very different from the other scenarios yet, and different risk preferences are not affecting the choices made for these steps.

C. Limitations for the expression of risk preferences

All other parameters being equal, changing the risk preference (i.e., using a different value for the coefficient β) will however not yield solutions different from the two alternatives presented above. This is related to the limited number of options for the formulation of asymmetric block offers contained within a 12-time-step horizon. Increasing the number of time steps in the optimization horizon would increase the number of alternative offering strategies, and is thus expected to allow for enhanced expression of risk preferences.

An increased number of time steps corresponds either to an optimization horizon reaching further in the future, or to the use of shorter time steps, i.e., increased time resolution. In the former case, strategic offering can be compromised by increased uncertainty in longer look-ahead times, while in the latter case, market design is a constraint. Another barrier exists to the computation of optimal offering strategies over a larger number of time steps: the time required for computing the

solution. As shown in the following section, augmenting the time resolution by a factor 3 would have critical consequences on the solution time.

Alternatively, the expression of risk preferences may be enhanced by strategic design of offering prices, as well as the combination of offers from multiple clusters of flexible assets, represented by independent saturation curves. This is the subject of future work.

D. Computational performance

Computational complexity of the proposed model is mostly sensitive to the number of integer variables. As shown in Fig. 5, the number of integer variables grows substantially with the number of time steps. However, the number of price scenarios does not affect the number of integer variables.

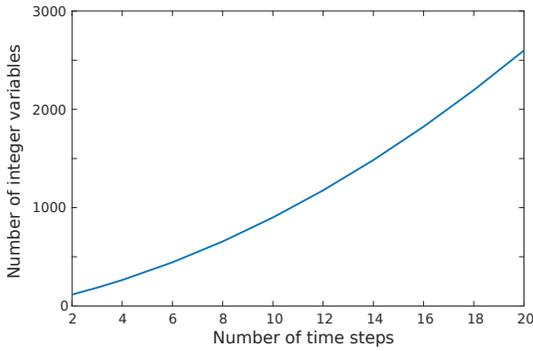


Figure 5. Integer variables in the problem versus number of time steps.

Fig. 6 shows the time required to solve the problem as a function of the number of time steps and price scenarios. These results were obtained in GAMS 24.6.1 using Gurobi solver on a 64-bit Windows computer with an Intel(R) Core(TM) i5-5300U CPU @ 2.30 GHz. The analysis shows a low sensitivity of computational time with respect to the number of scenarios while a high sensitivity to the number of time steps.

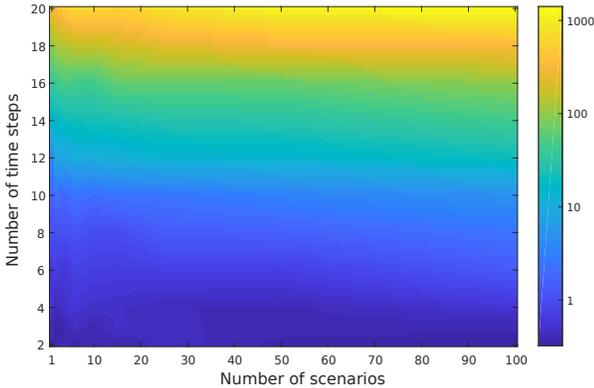


Figure 6. Effect of the number of time steps and scenarios on the computational time, expressed in seconds on a logarithmic color scale.

In particular, a problem defined on 8 time steps corresponds to an optimization horizon of 2 hours with a 15-minute resolution, in line with the specifications in the EcoGrid 2.0

balancing market [14]. In this case, an optimal solution was found in a matter of seconds. If the problem was to be solved every 15 minutes, this would be a feasible solution time.

V. CONCLUSIONS

This paper presents a stochastic mixed-integer linear optimization problem for the offering strategy of a flexibility aggregator participating in a balancing market using asymmetric block offers. The flexibility of the aggregated load is modelled using a saturation curve, and balancing market price forecast scenarios are used for deriving an optimal solution under uncertainty. Risk-aversion of the aggregator is accounted for using the CVaR risk metric.

A case study is used to derive the offering strategy of the aggregator using sample saturation curve and price scenarios. The effect of different risk preferences is demonstrated and analysed, and the role of asymmetries and non-linearities in the load-shifting characteristics is discussed. Computational performance is also analysed, and it shows that using the offering strategy tool for participating in a real-time balancing market is feasible without heavy computational requirements.

We showed however that the expression of risk preferences is limited in the study case that was analysed. Limiting factors were identified as: the reduced amount of offering options due to the small amount of time steps in the optimization horizon, the lack of strategic design of offering prices, as well as the reduction of the aggregated flexible loads to a single cluster. Future work may thus include extensions of the problem to derive price-quantity offer curves, which would allow aggregators to offer different levels of quantity at increasing prices. The effect of dividing the portfolio of flexible assets in multiple clusters may also be investigated, as well as alternative solution methods for reducing the computational time of the problem with a substantially higher number of time steps.

In addition, the potential price-making behavior of a strategic aggregator in an imperfect competitive balancing market is of interest to investigate. Uncertainty in the characteristics of the flexible assets may also be considered, and the effect of asymmetries and non-linearities in the load-shifting specifications could be analysed in further detail. Finally, real-life implementation of this offering strategy tool will yield interesting insights.

APPENDIX

MIXED-INTEGER LINEAR EQUIVALENTS

Equations (2a) and (2b) are implemented with the following mixed-integer linear constraints, using auxiliary binary variables defined in (10), and with \bar{P} the maximum instant regulation power that can be provided by the aggregator, in absolute values:

$$q_{tt'}^{\text{resp}} - p_{t'}^{\text{resp}} \leq \bar{P} (1 - u_{tt'}^0 + u_{tt'}^1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9a)$$

$$q_{tt'}^{\text{resp}} - p_{t'}^{\text{resp}} \geq \bar{P} (u_{tt'}^0 - u_{tt'}^1 - 1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9b)$$

$$q_{tt'}^{\text{resp}} \leq \bar{P} (u_{tt'}^0 - u_{tt'}^1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9c)$$

$$q_{tt'}^{\text{resp}} \geq \bar{P} (u_{tt'}^1 - u_{tt'}^0), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9d)$$

$$q_{tt'}^{\text{reb}} - p_{t'}^{\text{reb}} \leq \bar{P}(1 - u_{tt'}^1 + u_{tt'}^2), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9e)$$

$$q_{tt'}^{\text{reb}} - p_{t'}^{\text{reb}} \geq \bar{P}(u_{tt'}^1 - u_{tt'}^2 - 1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9f)$$

$$q_{tt'}^{\text{reb}} \leq \bar{P}(u_{tt'}^1 - u_{tt'}^2), \quad \forall (t, t') \in \mathcal{T}^2, \quad (9g)$$

$$q_{tt'}^{\text{reb}} \geq \bar{P}(u_{tt'}^2 - u_{tt'}^1), \quad \forall (t, t') \in \mathcal{T}^2. \quad (9h)$$

In addition, we define:

$$u_{tt'}^0 = \begin{cases} 1 & \text{if } t \geq t' \\ 0 & \text{otherwise,} \end{cases} \quad \forall (t, t') \in \mathcal{T}^2, \quad (10a)$$

$$u_{tt'}^1 = \begin{cases} 1 & \text{if } t \geq t' + \tau_{t'}^{\text{resp}} \\ 0 & \text{otherwise,} \end{cases} \quad \forall (t, t') \in \mathcal{T}^2, \quad (10b)$$

$$u_{tt'}^2 = \begin{cases} 1 & \text{if } t \geq t' + \tau_{t'}^{\text{resp}} + \tau_{t'}^{\text{reb}} \\ 0 & \text{otherwise,} \end{cases} \quad \forall (t, t') \in \mathcal{T}^2, \quad (10c)$$

$$u_{tt'}^3 = \begin{cases} 1 & \text{if } t \geq t' + \tau_{t'}^{\text{resp}} \\ & + \tau_{t'}^{\text{reb}} + T_{\text{rec}} \\ 0 & \text{otherwise,} \end{cases} \quad \forall (t, t') \in \mathcal{T}^2. \quad (10d)$$

Equation (11) below provides a mixed-integer linear equivalence for (10a)-(10d), with μ a relatively small value defined as $(T+1)^{-1}$:

$$u_{tt'}^0 \geq \mu(t - t' + 1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11a)$$

$$(1 - u_{tt'}^0) \geq \mu(t' - t), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11b)$$

$$u_{tt'}^1 \geq \mu(t - t' - \tau_{t'}^{\text{resp}} + 1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11c)$$

$$(1 - u_{tt'}^1) \geq \mu(t' + \tau_{t'}^{\text{resp}} - t), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11d)$$

$$u_{tt'}^2 \geq \mu(t - t' - \tau_{t'}^{\text{resp}} - \tau_{t'}^{\text{reb}} + 1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11e)$$

$$(1 - u_{tt'}^2) \geq \mu(t' + \tau_{t'}^{\text{resp}} + \tau_{t'}^{\text{reb}} - t), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11f)$$

$$u_{tt'}^3 \geq \mu(t - t' - \tau_{t'}^{\text{resp}} - \tau_{t'}^{\text{reb}} - T_{\text{rec}} + 1), \quad \forall (t, t') \in \mathcal{T}^2, \quad (11g)$$

$$(1 - u_{tt'}^3) \geq \mu(t' + \tau_{t'}^{\text{resp}} + \tau_{t'}^{\text{reb}} + T_{\text{rec}} - t), \quad \forall (t, t') \in \mathcal{T}^2. \quad (11h)$$

Equations (12) are mixed-integer linear equivalent of (4):

$$\sum_{s \in \mathcal{S}} v_{ts}^{\text{resp}} = 1, \quad \forall t \in \mathcal{T}, \quad (12a)$$

$$\sum_{s \in \mathcal{S}} v_{ts}^{\text{reb}} = 1, \quad \forall t \in \mathcal{T}, \quad (12b)$$

$$p_t^{\text{resp}} = \sum_{s \in \mathcal{S}} (v_{ts}^{\text{resp}} P_s), \quad \forall t \in \mathcal{T}, \quad (12c)$$

$$p_t^{\text{reb}} = \sum_{s \in \mathcal{S}} (v_{ts}^{\text{reb}} P_s), \quad \forall t \in \mathcal{T}, \quad (12d)$$

$$\tau_t^{\text{resp}} = \sum_{s \in \mathcal{S}} (v_{ts}^{\text{resp}} T_s), \quad \forall t \in \mathcal{T}, \quad (12e)$$

$$\tau_t^{\text{reb}} = \sum_{s \in \mathcal{S}} (v_{ts}^{\text{reb}} T_s), \quad \forall t \in \mathcal{T}. \quad (12f)$$

Finally, (6)-(7) are replaced by the following mixed-integer linear constraints, with $\tau_t^{\text{resp}}, \tau_t^{\text{reb}} \in \mathbb{N}^+$:

$$\tau_t^{\text{resp}} + \tau_t^{\text{reb}} \leq (T - t + 1) \left(1 - \sum_{t'=1}^{t-1} (1 - u_{tt'}^3) \right), \quad \forall t \in \mathcal{T}. \quad (13)$$

It is worth mentioning that constraint (13) may perform poorly if the parameter T_{rec} takes a value above 1, due to the construction of the state variables $u_{tt'}^3$ in the set of constraints (11). An alternative formulation would be to define T_{rec} as dependent on the shape of the blocks' parts, so that it takes the value zero for a block that follows an empty shape.

ACKNOWLEDGEMENTS

We thank Charalampos Ziras, Henrik W. Bindner and all other EcoGrid 2.0 partners for their insightful comments.

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