Day-ahead Energy and Balancing Capacity Bidding Considering Balancing Energy Market Uncertainty

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***Abstract*—Decarbonization of the power system sparked the the liberalization of electricity systems, from wholesale energy to balancing services procurement. In Europe, wholesale energy markets are open, transparent, technology-neutral and coupled under internal market scheme. Balancing services markets are divided into balancing capacity and balancing energy markets. When bidding in the balancing capacity market, a market participant must consider the day-ahead energy market as well, as it serves as a reference market for all trades. It must also consider the balancing energy market which is uncertain in both the volumes and prices. In this paper we propose a bidding model for balancing capacity and, consequently, day-ahead energy market with a formulation robust towards balancing energy market prices.**

***Index Terms*—Battery Storage, Balancing Capacity, Balancing Energy, Frequency Restoration Reserve**

I. Introduction

Power systems are transforming. The century long hydro-thermal domination as both the main power generation units as well as the main system flexibility providers gradually vanishes. Power systems are pioneers when it comes to decarbonisation, which make sense as the generation of heat and electricity takes the highest share in the global greenhouse gas (GHG) emissions with 42% of the total emissions [1], where the coal power plants alone generate 30% of global GHG emissions [2]. Currently, more than one fourth of electricity comes from renewable energy sources (RES) [3], with the steepest increase in the future capacity additions [1]. In a nutshell, the controllable coal and other fossil units are being replaced with uncontrollable RES units.

To cope with such increase in variability and unpredictability as well as parallel loss of the main flexibility providers, the power system must evolve. It must attract new flexibility providers and enable them to participate in flexibility provision. During the past few years, there is a significant rise in new flexible technologies, where the lead is taken by battery storage systems (BSS). Germany alone had in 2018: 125 thousand home BSS (415 MW, 930 MWh), 700 industry scale BSS (27 MW, 57 MWh, these numbers represent only the registered projects), 59 utility-scale projects (400 MW, 550 MWh) [4]. In general, large projects are mostly installed to provide frequency services, whereas the behind-the-meter batteries are focusing on increasing the solar self-consumption and decreasing the overall electricity bill.

This work has been supported in part by the European Structural and Investment Funds under project KK.01.2.1.02.0063 SUPEER (System for optimization of energy consumption in households), as well as by the Croatian Science Foundation and European Union through the European Social Fund under project Flexibility of Converter-based Microgrids – FLEXIBASE (PZS-2019-02-7747).

The utility-scale BSS is mostly focusing on the frequency containment reserve (FCR), but since this market is becoming saturated (total volume in Germany FCR is below 600 MW), focus is transferred towards the frequency restoration reserves (FRR), primarily with automatic (aFRR) and less with manual activation (mFRR). A prerequisite to participate in any of these markets for a BSS (or any other participant such as demand response) is the change in regulations and market concepts. To name some of the changes: transparent pricing mechanism must be in place, the procurement horizons and the market resolution must decrease, gate closure times must come closer to real-time, the bid volumes must also decrease etc. The European Union set the foundation for these changes through package of energy measures [5]–[7] where internal European electricity market (including balancing services) is envisioned.

The novelty of this paper is the development of a bidding algorithm for BSS which trades on three markets: Balancing Capacity Market (BCM), Day-ahead Market (DAM) and Balancing Energy Market (BEM). The proposed bidding model is primarily used to acquire BCM and secondary DAM schedules. Their prices are considered as deterministic forecasts, while the BEM market is modeled through robust approach in order to find the worst case realisation of BEM prices and to check its influence on the BCM and DAM scheduling.

II. Methodology

The aFRR and mFRR markets have separate auctions for upward or positive direction and for downward and negative direction. The proposed bidding model will cover both directions. However, in the following text our explanations will mostly tackle the upward direction due to simplicity, but the similar reasoning applies for the downward direction as well.

Note that the prime goal of this paper is not to create bidding on DAM, but only to use it to better coupe with BCM and BEM bidding strategy. The bidding on DAM is, in a way, a collateral result. The DAM is pivotal market in European context and pose as a reference for all other trades, and this is valid for the proposed model as well.

A. Market Setup

BCM and BEM are dependent markets as the former allocates/reserves the flexible capacity to stand idle and to be available in the latter market. The reserved balancing capacity (BC) cannot be used for other purposes rather than providing balancing energy (BE) if the bid is awarded in the BCM. However, it may not even be used for balancing if the bid does not get awarded in the BEM. A bidder in the BCM must consider the uncertainty of the BEM process. While the volume to be procured in the BCM is a known value (set by the transmission system operator) the volume to be procured in the BEM is unknown until close to real-time and depends on the power system real-time conditions, i.e. on its imbalance. If the power system is in perfect balance, the BEM market volume would be zero and none of the bidders would trade in it. If an imbalance does exist, the volume in the BEM will be procured up to the volume of the imbalance. However, power system imbalance is highly variable and unpredictable in its value.

As both markets are based on demand and supply curves intersections, the price acquired by all participants lies at the point of intersection – market clearing price. Since the volume to be procured in BEM is unknown at the gate-closure time of BCM, the point of intersection, i.e. the market clearing price, is also unknown and uncertain. The BSS doesn't have variable generation costs and it's only cost for discharge is the cost of prior energy purchases. Therefore it is highly important for BSS to consider all the prices during market horizon as they are the base for its successful trading.

There is a gap in the literature in addressing the balancing energy uncertainty. Deterministic modeling of balancing capacity activation [8], [9], [10], [11] can create problems to BSS [12]. Inability to adhere to the agreed DAM schedule causes additional balancing costs [13], whereas the inability to activate the scheduled balancing capacity leads to penalization [9], [11], [14] and eventually disqualification from the BCM/BEM participation [15]. One of the possible approaches is stochastic modeling of the balancing capacity activation, as pursued in [16], [17], [18], [14]. However, it is very difficult to efficiently couple such BC activation scenarios with the BEM price uncertainty. Papers [10], [19] and [20] took a different approach, as they modeled balancing capacity activation under a robust framework. Such approach showed promising results as a tool to grasp the BC activation uncertainty. However, all the reviewed papers observing relevant uncertainty modeled the uncertain BC activation but with BE price as known input. In other words, the BC activation is never modeled with an uncertain price and it is mostly observed as a ratio of the BC (even in the deterministic models). However, the real-world BEM holds not only the BC activation uncertainty, but also the BEM price uncertainty which is correlated with BE. It means that the BE is not a ratio of the BC, but the volume that is awarded based on its submitted price as on the any other market. In this paper we are bridging this gap where we used robust BC activation to calculate the uncertain BEM price and to re-position the BCM and DAM bids accordingly.

B. Mathematical Model

This paper leans on the previous work of authors [19] and [20] where uncertainty of reserve activation was robustly modeled without BEM modeling. In the cited papers, the BEM price uncertainty was not modeled but only used as a deterministic parameter. The robust formulation of reserve activation from [19] is used in this paper to model the uncertain system-wide BE needs and to calculate the uncertain BEM price. This approach allows bid submission on the worst-case BEM price scenario.

1) Objective Function: Objective function expressed in (1) has two terms: the deterministic day-ahead timeframe stated in (2) and the uncertain real-time timeframe stated in (3). The uncertain parameters are $\tilde{c}_t^{\text{BEM\_UP}}$ and $\tilde{c}_t^{\text{BEM\_DN}}$. The objective function is subjected to constraints (4) - (12).

$$\min_{\Xi_{\mathcal{O}}} \quad \{c^{\text{DAM\&BCM}} + \max[c^{\text{BEM}}(\tilde{c}_t^{\text{BEM\_UP}}, \tilde{c}_t^{\text{BEM\_DN}})]\}; \quad (1)$$

$$c^{\text{DAM\&BCM}} = \sum\nolimits_{t=1}^{N_t} (e_t^{\text{DAM}} \cdot C_t^{\text{DAM}} - bc_t^{\text{BSS\_UP}} \cdot C_t^{\text{BCM\_UP}} - bc_t^{\text{BSS\_DN}} \cdot C_t^{\text{BCM\_DN}}); \quad (2)$$

$$c^{\text{BEM}}(\tilde{c}_t^{\text{BEM\_UP}}, \tilde{c}_t^{\text{BEM\_DN}}) = \sum\nolimits_{t=1}^{N_t} (-be_t^{\text{BSS\_UP}} \cdot \tilde{c}_t^{\text{BEM\_UP}} + be_t^{\text{BSS\_DN}} \cdot \tilde{c}_t^{\text{BEM\_DN}}); \quad (3)$$

2) Primal Constraints: Equation (4) defines the non-negativeness of the bidding variables. Total allocated day-ahead power cannot exceed BSS invertor power limits as stated in (5) and (6). Equations (7) and (8) state that bid BSS BE bid, in the real-time, cannot be higher than the allocated BC volume. BSS state-of-energy (SOE) balance is expressed with (9), while (10) - (12) secure the sufficient energy to activate all allocated BC bids.

$$e_t^{\text{BSS\_BUY}}, e_t^{\text{BSS\_SELL}}, bc_t^{\text{BSS\_UP}}, bc_t^{\text{BSS\_DN}}, be_t^{\text{BSS\_UP}}, be_t^{\text{BSS\_DN}} \geq 0; \quad (4)$$

$$e_t^{\text{BSS\_SELL}}/\Delta - e_t^{\text{BSS\_BUY}}/\Delta + bc_t^{\text{BSS\_UP}} \leq P^{\text{BSS\_MAX}}, \quad (5)$$

$$-e_t^{\text{BSS\_SELL}}/\Delta + e_t^{\text{BSS\_BUY}}/\Delta + bc_t^{\text{BSS\_DN}} \leq P^{\text{BSS\_MAX}}; \quad (6)$$

$$be_t^{\text{BSS\_UP}}/\Delta \leq bc_t^{\text{BSS\_UP}}; \quad (7)$$

$$be_t^{\text{BSS\_DN}}/\Delta \leq bc_t^{\text{BSS\_DN}}; \quad (8)$$

$$soe_t^{\text{BSS}} = SOE^{\text{T0}} + \sum\nolimits_{\tau=1}^{t} (e_\tau^{\text{BSS\_BUY}} \cdot \eta^{\text{CH}} - e_\tau^{\text{BSS\_SELL}}/\eta^{\text{DCH}}); \quad (9)$$

$$soe_t^{\text{BSS}} + e_{t+1}^{\text{BSS\_BUY}} \cdot \eta^{\text{CH}} - e_{t+1}^{\text{BSS\_SELL}}/\eta^{\text{DCH}} - \Lambda \cdot \Delta/\eta^{\text{DCH}} \cdot bc_{t+1}^{\text{BSS\_UP}} \geq SOE^{\text{MIN}}, \quad \forall t \in \mathcal{T}_{(t \neq Nt)}; \quad (10)$$

$$soe_t^{\text{BSS}} + e_{t+1}^{\text{BSS\_BUY}} \cdot \eta^{\text{CH}} - e_{t+1}^{\text{BSS\_SELL}}/\eta^{\text{DCH}} + \Lambda \cdot \Delta \cdot \eta^{\text{CH}} \cdot bc_{t+1}^{\text{BSS\_DN}} \leq SOE^{\text{MAX}}, \quad \forall t \in \mathcal{T}_{(t \neq Nt)}; \quad (11)$$

$$SOE^{\text{T0}} \leq soe_t^{\text{BSS}} \leq SOE^{\text{MAX}}, \text{ for } t = N_t; \quad (12)$$

3) Uncertainty Set: The maximisation subproblem stated in (1) is subject to robust uncertainty set $\mathcal{C}$ which has three main parts: the one-time-step balancing energy limits eqs. (15) - (20), the one-horizon-window balancing energy limits eqs. (21) - (26) and the balancing energy price limits eqs. (27) - (30). All the right-hand-side parameters (expressed with Capital Greek Letters) are calculated from historical data. Inputs for equations (15) - (20) are the individual time-step boundaries for UP/DN BE activation, while inputs for equations (21) - (26) are daily activated balancing energy boundaries for UP/DN. The algorithm will generate the worst BE activation distribution throughout day constrained with the historical BE activation data. The position of BE activation variables ($be_{\tau,t}^{\text{SYS\_UP}}, be_{\tau,t}^{\text{SYS\_DN}}$) triggers BE price positioning ($c_{\tau,t}^{\text{BEM\_UP}}, c_{\tau,t}^{\text{BEM\_DN}}$) through eqs. (27) - (30). Inputs for those equations are historical BE aggregated bids taken form [21]. Aggregated bids are piece-wise linearised as explained in Section III.

$$\mathcal{C} = \Big\{ be_t^{\text{SYS\_UP}}, be_t^{\text{SYS\_DN}}, c_t^{\text{BEM\_UP}}, c_t^{\text{BEM\_DN}} \quad |$$

$$be_t^{\text{SYS\_UP}}, be_t^{\text{SYS\_DN}} \geq 0; \tag{13}$$

$$c_t^{\text{BEM\_UP}}, c_t^{\text{BEM\_DN}} \quad \text{free}; \tag{14}$$

$$be_t^{\text{SYS\_UP}} + be_t^{\text{SYS\_DN}} \geq A_t : \alpha_t; \tag{15}$$

$$be_t^{\text{SYS\_UP}} + be_t^{\text{SYS\_DN}} \leq B_t : \beta_t; \tag{16}$$

$$be_t^{\text{SYS\_UP}} \geq \Pi_t : \pi_t; \tag{17}$$

$$be_t^{\text{SYS\_UP}} \leq M_t : \mu_t; \tag{18}$$

$$be_t^{\text{SYS\_DN}} \geq X_t : \chi_t; \tag{19}$$

$$be_t^{\text{SYS\_DN}} \leq N_t : \nu_t; \tag{20}$$

$$\sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_UP}} + \sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_DN}} \geq \Phi : \phi; \tag{21}$$

$$\sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_UP}} + \sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_DN}} \leq \Psi : \psi; \tag{22}$$

$$\sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_UP}} \geq E : \epsilon; \tag{23}$$

$$\sum\nolimits_{t=1}^{N_t} be_t^{SYS\_UP} \leq \Gamma : \gamma; \tag{24}$$

$$\sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_DN}} \geq \Upsilon : \upsilon; \tag{25}$$

$$\sum\nolimits_{t=1}^{N_t} be_t^{\text{SYS\_DN}} \leq \Omega : \omega; \tag{26}$$

$$c_t^{\text{BEM\_UP}} - I_{t,i}^{\text{SL}} \cdot be_t^{\text{SYS\_UP}} \geq I_{t,i}^{\text{IN}} : \iota_{t,i}; \tag{27}$$

$$c_t^{\text{BEM\_UP}} \leq K_t : \kappa_t \tag{28}$$

$$c_t^{\text{BEM\_DN}} - \Theta_{t,i}^{\text{SL}} \cdot be_t^{\text{SYS\_DN}} \leq \Theta_{t,i}^{\text{IN}} : \theta_{t,i}; \tag{29}$$

$$c_t^{\text{BEM\_DN}} \geq P_t : \rho_t \tag{30}$$

4) Reformulated Model: To create the solvable problem we rewrite the objective function form (1) to its robust counterpart in (31) and (32).

$$\min_{\Xi_{\mathcal{O}}} \quad (z); \tag{31}$$

$$\max_{\Xi_{\mathcal{C}}} [c^{\text{BEM}}(\tilde{c}_t^{\text{BEM\_UP}}, \tilde{c}_t^{\text{BEM\_DN}})] \leq z - c^{\text{DAM\&BCM}} \tag{32}$$

To solve the min-max problem, the inner maximisation sub-problem form (32) is transformed to its dual counterpart and connected with the main problem through strong-duality equaiton. The final one-level problem is stated in (33) - (45). Equation (33) represents new objective function, while the primal constraints from the main problem are rewritten as (34). Equation (35) represents strong duality equation , while the dual constraints are stated in (36) - (45).

$$\min_{\Xi_{\mathcal{O}}} \quad (z); \tag{33}$$

$$(2), (4) - (12) \tag{34}$$

$$\begin{aligned} &\sum\nolimits_{t=1}^{N_t} [A_t \cdot \alpha_t + B_t \cdot \beta_t + \Pi_t \cdot \pi_t + X_t \cdot \chi_t + M_t \cdot \mu_t + N_t \cdot \nu_t \\ &+ K_t \cdot \kappa_t + P_t \cdot \rho_t + \sum\nolimits_{i=1}^{N_i} (I_{t,i}^{\text{IN}} \cdot \iota_{t,i} + \Theta_{t,i}^{\text{IN}} \cdot \theta_{t,i})] \\ &+ \Phi \cdot \phi + \Psi \cdot \psi + E \cdot \epsilon + \Upsilon \cdot \upsilon + \Gamma \cdot \gamma + \Omega \cdot \omega \\ &\leq z - c^{\text{DAM\&BCM}}; \end{aligned} \tag{35}$$

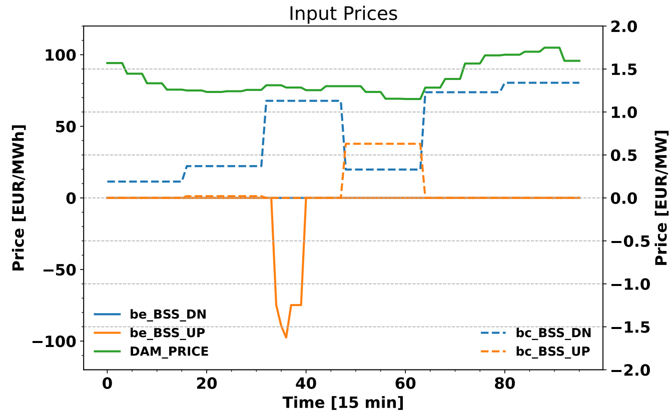


Fig. 1: Input prices for case studies

$$\begin{aligned} &\alpha_t + \beta_t + \pi_t + \mu_t + \phi + \psi + \epsilon + \gamma \\ &- \sum\nolimits_{i=1}^{N_i} I_{t,i}^{\text{SL}} \cdot \iota_{t,i} \geq 0 \quad : be_t^{\text{SYS\_UP}}; \end{aligned} \tag{36}$$

$$\sum\nolimits_{i=1}^{N_i} \iota_{t,i} + \kappa_t = - \, be_t^{\text{BSS\_UP}} \quad : c_t^{\text{BEM\_UP}}; \tag{37}$$

$$\begin{aligned} &\alpha_t + \beta_t + \chi_t + \nu_t + \phi + \psi + \upsilon + \omega \\ &- \sum\nolimits_{i=1}^{N_i} \Theta_{t,i}^{\text{SL}} \cdot \theta_{t,i} \geq 0 \quad : be_t^{\text{SYS\_DN}}; \end{aligned} \tag{38}$$

$$\sum\nolimits_{i=1}^{N_i} \theta_{t,i} + \rho_t = be_t^{\text{BSS\_DN}} \quad : c_t^{\text{BEM\_DN}}; \tag{39}$$

$$\beta_t, \mu_t, \nu_t, \kappa_t \geq 0; \tag{40}$$

$$\theta_{t,i} \geq 0; \tag{41}$$

$$\psi, \gamma, \omega \geq 0; \tag{42}$$

$$\alpha_t, \pi_t, \chi_t, \rho_t \leq 0; \tag{43}$$

$$\iota_{t,i} \leq 0; \tag{44}$$

$$\phi, \epsilon, \upsilon \leq 0; \tag{45}$$

III. Input Data

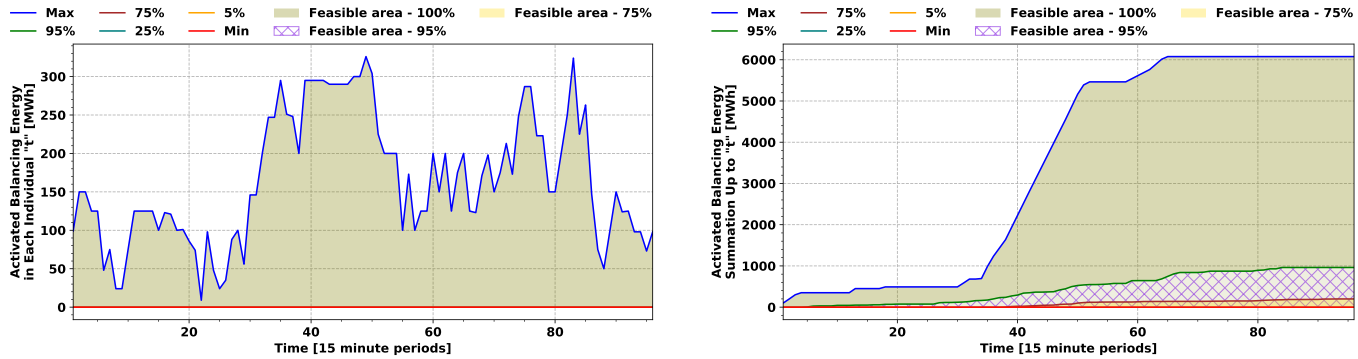
The input data can be divided into data used in objective function (2), primal limits in . (4) - (12), uncertainty set limits for BE activation volumes in eqs. (15) - (26) and prices in eqs. (27) - (30). Due to conciseness reasons only mFRR data is observed in this paper.

A. Objective Function and Primal Constraints

The DAM and BCM prices are modeled as deterministic where Germany's historical data from [22] has been used. Used prices in case studies are shown on Figure 1. For the case study we will use a battery of 10 MW ($P^{\text{BSS\_MAX}}$) and 10 MWh (SOE^{MAX}) with charging and discharging efficiencies of 0.92. The time-step is equal to Germany Imbalance Settlement Period of 15 minutes ($\Delta = 0.25$) and the worst duration of one BE activation is equal to time-step ($\Lambda = 1$).

B. Balancing Energy Volumes

To model uncertainty of balancing energy activated volumes historic data with 15 minute resolution through two years, 2020-2021, for Germany is taken from [22]. The principle how to create such uncertainty set and what are all the datasets used can be found in [19] and [20]. Due to conciseness of the paper,



(a) Data for mFRR Up One-time-step Upper Limit - Parameter M

(b) Data for mFRR Up Daily Upper Limit - Parameter Γ

Fig. 2: mFRR BE Input Parameters, from years: 2020-2021

we will only briefly explain and visualise two datasets used to model parameters: M in (18) and Γ in (24). All the other one-time-step parameters are conceptually the same as M, and all the other one-horizon-window parameters are conceptually the same as Γ. Figure 2 visualises the used 15-min data for M (left) and Γ (right).

On the left subfigure, each time-step represents the statistical view on individual mFRR UP BE activations. It can be seen that only maximal activations are different from zero, because in more than 98% of time, the mFRR BE activation is zero. Also, daily distribution of activations is not uniform but the activations are higher during the day, especially in morning and evening peak hours. For example, in time-step 50 (13:00 - 13:15) the peak activation happened of 326 MWh.

On the right subfigure, each time-step represents the statistical view on the up-to-that-time-step summation of activations (from $\tau = 0 to \tau = t$). Once again, this plot shows how the maximal activation curve is significantly higher than, e.g. 95% percentil curve. We can again see how the significant increase in maximal curve during the morning peak hours after which saturation occurs.

C. Balancing Energy Prices

To model uncertainty of balancing energy prices historic data (aggregated bids) with 4-hour resolution through one month, June 2021, for Germany is taken from [21]. Figure 3 visualised the used 4-hour data (for period 16:00-20:00) for up (left) and down (right) products. The figure 3 is divided into three parts which are following our thought process to get the right data format: subfigures 3a and 3b are showing the real data curves accepted at BEM for 30 days, subfigures 3c and 3d are showing monthly statistical properties of the curves, while the subfigures 3e and 3f are showing the piecewise linearized min/max and median price curves.

The first step was to visualise and understand the price curves. From subfigures 3a and 3b it can be seen that the curves are always monotonically increasing/decreasing, but also they are often increasing with higher gradient as the volume increases (convex curves). The second step was to compress all the curves into several families of curves which can later on act as different uncertainty budgets in the simulations. We created those families as a percentiles of the real curves as shown on subfigures 3c and 3d. The behaviour of those curves is similar to those from subfigures 3a and 3b.

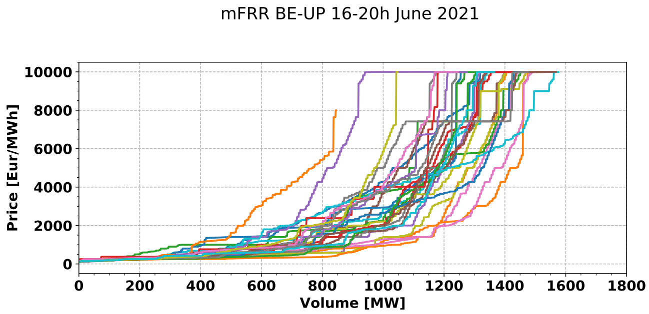
Finally, for our model we need to have linear boundaries for BE prices. Therefore we need to linearise the prices. Due to monotonic and convex nature of the curves, we can piecewise linearise the curves without the need of binaries. As an example, we chose two curves from statistical observation: minimal/maximal (for up and down reserve, respectively) and median. Those two curves (min/max - black and med - red) and their piecewise linear conuterparts (the purple and green lines) are shown on subfigures 3e and 3f. From our model standpoint, the worst case of BE price forming is lowest price for BE up, and the highest price for BE down. This means that purple or green lines are acting as lower/upper (for up/down direction) boundary for BE price which is modeled in eqs. (27) and (29). Additionally, the upper/lower (for up/down direction) boundary for BE price are min and max prices shown as blue and orange lines and modeled with eqs. (28) and (30).

IV. Results and Discussion

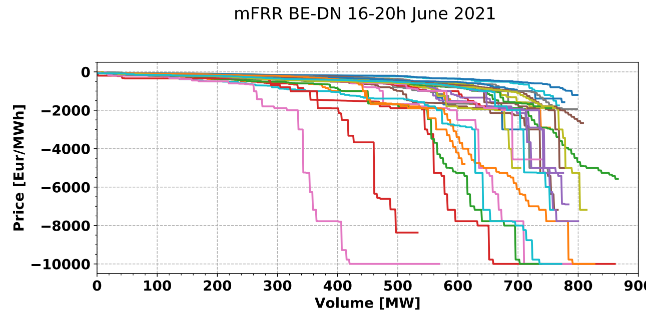
We conduced the results for one day at the beginning of July 2021 (Sunday July 4th). Used prices are shown on Figure 1. Four case studies are devised:

1) Case study 1: BEM prices are not considered in objective function (deterministic prices $\tilde{c}_t^{\text{BEM\_UP}}$ and $\tilde{c}_t^{\text{BEM\_DN}}$ with value zero)
2) Case study 2: BEM prices are taken from one exact date (deterministic prices $\tilde{c}_t^{\text{BEM\_UP}}$ and $\tilde{c}_t^{\text{BEM\_DN}}$ with real value). On Figure 1 it can be seen that $\tilde{c}_t^{\text{BEM\_DN}}$ appears from 09:30-11:00, while $\tilde{c}_t^{\text{BEM\_UP}}$ is zero throughout day as there is no activation in that direction.
3) Case study 3: BEM prices are robustly modeled with min/max curves (black) from Figures 3e and 3f.
4) Case study 4: BEM prices are robustly modeled with median curves (red) from Figures 3e and 3f.

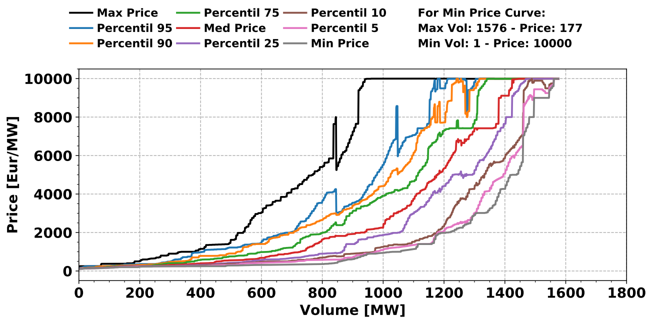
Figure 4 show all bidding variables results. Figure 4b shows different behavior around the hours when down mFRR activation happens. This can be seen as preparing of BCM and DAM bidding for known real-time activation and its prices. This case is not realistic and can negatively impact the day-ahead bidding. Figure 4c shows that BEM up bidding from



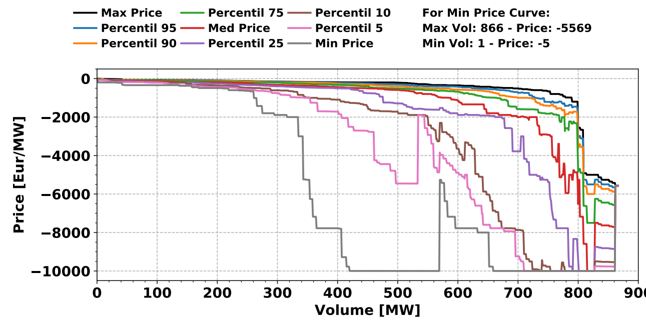
(a) Real mFRR Up BE Curves for 30 Days (June 2021)



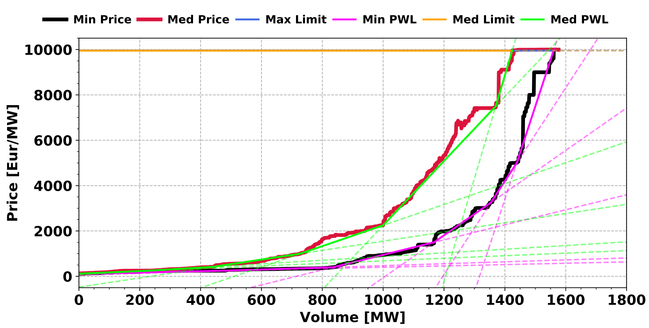
(b) Real mFRR Down BE Curves for 30 Days (June 2021)



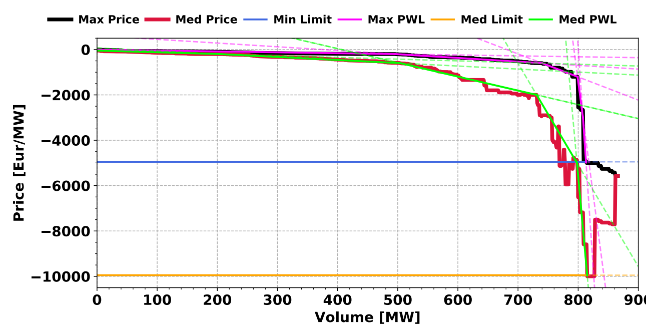
(c) Statistical View on mFRR Up BE Bidding Curves



(d) Statistical View on mFRR Down BE Bidding Curves



(e) Piece-wise Linearized mFRR Up BE Bidding Curves



(f) Piece-wise Linearized mFRR Down BE Bidding Curves

Fig. 3: mFRR BE Bid Plots for June 2021 for 4-hour Bidding Period: 16:00-20:00

17:00-20:00 is advisable even for the worst-case BEM price evolution. It accordingly prepares the BCM and DAM bidding around that period. Figure 4d shows that bidding with median vs worst price evolution do not introduce much differences in BCM and DAM bidding as we change the price inputs for all bidding periods in a rather similar fashion and the scheduling stays the same.

V. Conclusion

The proposed approach shows promising results as it can be used to better value the uncertainty of BEM prices in a day-ahead timeframe. As a future direction, such uncertainty modeling should be tested on a larger number of case studies (different prices and balancing services) to adequately asses its applicability. The second point in future work is adding BE volume uncertainty in state-of-energy equation to create models tackling both price and volume uncertainty.

References

[1] Resource Watch, "Energy — Resource Watch," 2021.

[2] International Energy Agency, "Emissions – Global Energy & CO2 Status Report 2019," 2019.

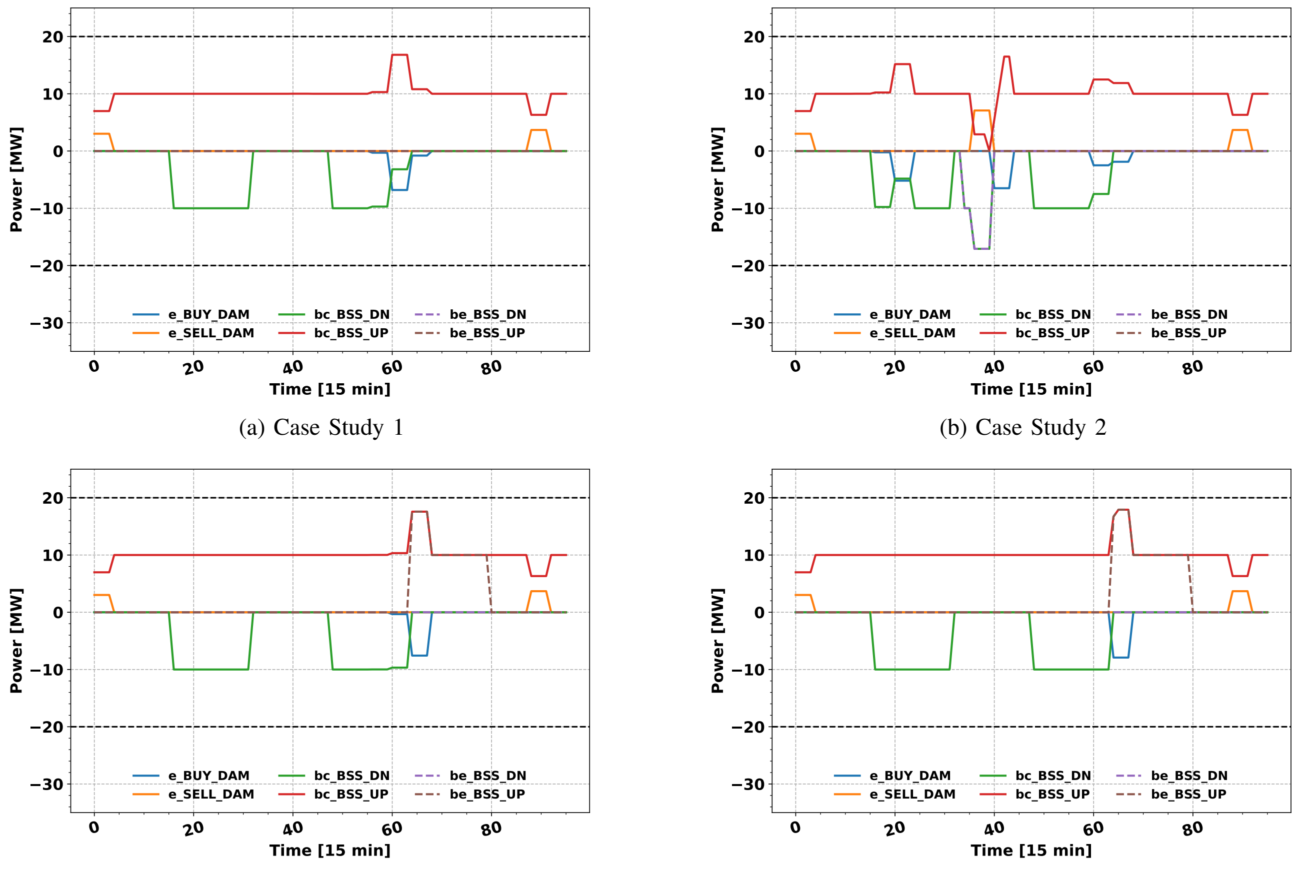
[3] Hannah Ritchie and Max Roser, "Electricity Mix - Our World in Data," 2021.

[4] J. Figgener, P. Stenzel, K.-P. Kairies, J. Linßen, D. Haberschusz, O. Wessels, G. Angenendt, M. Robinius, D. Stolten, and D. U. Sauer, "The development of stationary battery storage systems in Germany – A market review," *Journal of Energy Storage*, vol. 29, p. 101153, jun 2020.

[5] THE EUROPEAN PARLIAMENT and THE COUNCIL OF THE EUROPEAN UNION, "DIRECTIVE (EU) 2019/944 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU," 2019.

[6] THE EUROPEAN PARLIAMENT and THE COUNCIL OF THE EUROPEAN UNION, "REGULATION (EU) 2019/943 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 5 June 2019 on the internal market for electricity," 2019.

[7] THE EUROPEAN COMMISSION, "COMMISSION REGULATION (EU) 2017/2195 of 23 November 2017 establishing a guideline on electricity balancing," 2017.



(a) Case Study 1

(b) Case Study 2

(c) Case Study 3

(d) Case Study 4

Fig. 4: Results for four observed case studies

[8] P. Sanchez-Martin, S. Lumbreras, and A. Alberdi-Alen, “Stochastic Programming Applied to EV Charging Points for Energy and Reserve Service Markets,” *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1–8, 2015.

[9] P. Hasanpor Divshali and C. Evens, “Optimum Operation of Battery Storage System in Frequency Containment Reserves Markets,” *IEEE Transactions on Smart Grid*, vol. 11, pp. 4906–4915, nov 2020.

[10] M. Kazemi, H. Zareipour, N. Amjady, W. D. Rosehart, and M. Ehsan, “Operation Scheduling of Battery Storage Systems in Joint Energy and Ancillary Services Markets,” *IEEE Transactions on Sustainable Energy*, vol. 8, pp. 1726–1735, oct 2017.

[11] M. R. Sarker, Y. Dvorkin, and M. A. Ortega-Vazquez, “Optimal participation of an electric vehicle aggregator in day-ahead energy and reserve markets,” *IEEE Transactions on Power Systems*, vol. 31, pp. 3506–3515, sep 2016.

[12] I. Pavic, H. Pandzic, and T. Capuder, “Electric vehicles as frequency containment reserve providers,” in *6th IEEE International Energy Conference, ENERGYCon 2020*, pp. 911–917, Institute of Electrical and Electronics Engineers Inc., sep 2020.

[13] ENTSO-E, “Balancing Report 2020,” tech. rep., ENTSO-E, Bruxelles, 2020.

[14] B. Han, S. Lu, F. Xue, and L. Jiang, “Day-ahead electric vehicle aggregator bidding strategy using stochastic programming in an uncertain reserve market,” *IET Generation, Transmission and Distribution*, vol. 13, pp. 2517–2525, jun 2019.

[15] C. Goebel and H.-A. Jacobsen, “Aggregator-Controlled EV Charging in Pay-as-Bid Reserve Markets With Strict Delivery Constraints,” *IEEE Transactions on Power Systems*, vol. 31, pp. 4447–4461, nov 2016.

[16] M. Alipour, B. Mohammadi-Ivatloo, M. Moradi-Dalvand, and K. Zare, “Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets,” *Energy*, vol. 118, pp. 1168–1179, jan 2017.

[17] M. Shafie-Khah, M. P. Moghaddam, M. K. Sheikh-El-Eslami, and J. P. Catalão, “Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets,” *Energy Conversion and Management*, vol. 97, pp. 393–408, jun 2015.

[18] S. I. Vagropoulos and A. G. Bakirtzis, “Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets,” *IEEE Transactions on Power Systems*, vol. 28, pp. 4031–4041, nov 2013.

[19] I. Pavić, H. Pandžić, and T. Capuder, “Tight Robust Formulation for Uncertain Reserve Activation of an Electric Vehicle Aggregator,” in *2021 IEEE PowerTech*, (Madrid), pp. 1–6, 2021.

[20] I. Pavic, H. Pandzic, and T. Capuder, “Electric vehicle aggregator as an automatic reserves provider under uncertain balancing energy procurement,” *IEEE Transactions on Power Systems*, pp. 1–1, 2022.

[21] Regelleistung.net, “Datacenter FCR/aFRR/mFRR,” 2021.

[22] Entso-e, “ENTSO-E Transparency Platform,” 2021.