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Individual Thermal Generator and Battery Storage Bidding Strategies Based on Robust Optimization

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ABSTRACT Bidding in the day-ahead market encompasses uncertainty on market prices. To properly address this issue, dedicated optimal bidding models are constructed. Traditionally, these models have been derived for generating units, in particular thermal generators. Recently, optimal bidding models have been updated to account for specifics of energy storage, foremost battery storage. Batteries are significantly different devices than generators. On one hand, a battery can both purchase and sell electricity with practically instant change in its output power. On the other hand, a battery is energy-limited, which makes its profit very sensitive to optimal scheduling. In this paper, we examine the existing and derive new robust optimization-based optimal bidding models individually for a thermal generator and a battery storage. The models are examined in terms of the expected profit by applying the obtained bidding curves and (dis)charging schedules to actual realizations of uncertainty. Moreover, we examine the effect of the range of uncertainty caused by the selection of input scenarios. Based on the presented case studies, we form conclusions on the effectiveness of the robust optimization approach for this type of problems.

INDEX TERMS Optimal bidding, thermal generator, battery storage, robust optimization.

I. INTRODUCTION

Robust optimization technique has gained a lot of attention in the power system research community since the introduction of the linear reformulation method proposed by Bertsimas and Sim [1]. It has been applied to both the power system planning, e.g. [2], [3], and operation problems, e.g. [4], [5], to address uncertainty of market prices, output of renewables and long-term uncertainties. This paper focuses on optimal price-taker bidding problems of a thermal generator and a battery storage individually. We derive appropriate robust optimization-based models, solve them, and derive conclusions based on the performed case studies. To properly motivate our work, in subsections I-A and I-B we first review these two topics and then articulate the research gaps identified in the literature, finalizing with our contribution to the body of knowledge.

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A. BACKGROUND AND CONTRIBUTION ON THERMAL GENERATOR BIDDING USING ROBUST OPTIMIZATION

Ever since the introduction of competitive electricity markets, generation asset owners have been interested in maximizing the benefit of their market participation. Generators whose capacity is low as compared to the market size (i.e., overall electricity consumption) generally cannot affect market prices. This paper focuses on such generators, i.e. the price-takers. The only relevant uncertainty these generators face is the uncertainty on the market prices. At first, this uncertainty might seem trivial as a generator can offer to sell electricity at its marginal production cost to protect against losses. Furthermore, most day-ahead energy markets today operate on the basis of a single market clearing price (as opposed to pay-as-bid markets), where a price taker's optimal bidding strategy is to offer electricity at its marginal generation cost. Additionally, even the convex generation cost curve can be accommodated in the bidding strategy as some markets allow bidding a curve instead of only a price-quantity pair [6]. However, generators' operation accommodates intertemporal dependencies, such as ramp up and down limits, minimum up and down times and startup costs. While startup costs only need to be internalized in the bidding strategy across a number of hours and at worst will reduce the generator's profit, poor modeling of ramp up and down limits as well as minimum up and down times can result in infeasible generator operating points. For example, a market clearing outcome indicating that a generator whose minimum down time is two hours is cleared at hour t, not scheduled at hour $t+1$, and scheduled to operate again at hour $t+2$ is unattainable for this generator. Even if the minimum down time limit would not be violated, the generator might prefer to operate at hour $t+1$ with a loss in order to avoid incurring the startup cost in the following hour.

A detailed model of a thermal generator acting in the day-ahead market is presented in [7]. The model includes minimum and maximum power output constraints, ramp limits, minimum up and down times, as well as stair wise formulation of the start-up cost function. Furthermore, [8] propose additional constraints on the upper bound and ramp limits in the self-scheduling formulation. These inequalities strengthen the linear-programming relaxation and speed up the calculation time. Dynamic programming algorithms that keep track of a set of functions that represent the overall cost of generator schedules until each time step is presented in [9]. The results of the case study show linear scaling characteristics that can speed up the state-of-the-art for piece-wise linear and quadratic generation cost curve. An accurate model of the detailed startup and shutdown cost of thermal generators is developed in [10]. This model simulates dynamic unit temperature and considers dynamic ramping and forbidden zones. An overview of various generator scheduling formulations and their impact on the unit commitment problem is available in [11].

Considering the physical generator limits and the economic framework described above, forecasting of market prices is essential for successful market participation of a thermal generator. A stochastic scheduling technique that maximizes a producer's profit taking into account the stochastic nature of power prices was considered in [12]. The results of the case study stress the importance of deriving proper scenarios and their respective probabilities. Another important work in this field is [13], where the authors present a forecasting framework for estimating the probability density functions of the day-ahead market clearing prices. The formulated bidding rule takes advantage of the expectations of hourly market price values to build and submit appropriate bidding curves into the market. The value of bidding curves, as opposed to single price-quantity pair bidding, has been proven in [14]. In many works, e.g. [15], uncertain prices are addressed by deriving explicit stochastic scenarios and obtaining expected profits. However, to quantify the risk and protect against unlikely events, more meticulous methods are used. Conditional value-at-risk is employed in [16] and [17] to quantify a tradeoff between the profit and the risk. Another approach that enables risk aversion by adjusting a robustness parameter is robust optimization. In [18], the authors propose a generator bidding strategy based on robust optimization. This framework solves a series of robust mixed-integer linear programming problems for different price uncertainty bounds. The solutions of these problems are then combined into a set offering curves for each hour. Similar to the robust optimization, which minimizes the cost of the worst-case realization of uncertainty, is the min-max regret model that minimizes the highest regret over all possible scenarios while ensuring robustness. The min-max regret model formulated in [19] is bilinear. After its conversion to a mixed-integer linear program, the problem is solved using the Benders' decomposition and generator bidding curves are derived. A multistage robust unit commitment model with non-fixed recourse is proposed in [20]. The proposed approach generates a least-cost generation schedule and ensures dispatch nonanticipativity by solving a trilevel program.

The work presented in this paper related to the thermal generator's optimal bidding mainly extends the work from [18], which is based on the robust model presented in [1]. The robust formulation proposed in [18] assumes that in every hour $t \in T$ the actual market price λ_t lies within a known range $\lambda_t \in [\lambda_t^{\min}, \lambda_t^{\max}]$. This range is divided into K intervals, each having the same upper limit that corresponds to the most optimistic uncertainty realization, and the lower one equal to $\lambda_t^{\max} - \delta_k(\lambda_t^{\max} - \lambda_t^{\min})$, where $0 \leq \delta_k \leq 1$. The robust optimization problem at hand is solved K times, once for each uncertainty interval, and always for budget of uncertainty $\Gamma = 24$, which grants full protection but also the most conservative solution. Note that this procedure ignores the adjustment of the conservativeness level and always considers the worst-case realization of uncertainty. Since generating units always favor the high market prices, this model renders to a deterministic model with the market prices at the lower bound. This procedure results in K price–quantity pairs obtained for the lower price bound in each iteration. The resulting price–quantity pairs are used to construct thermal generator bidding curves for each hour. However, this procedure may result in infeasible operating schedule of a thermal generator since the price–quantity pairs used to construct the bidding curves are obtained independently without imposing ramp constraints between iterations. To this end, our paper contributes to the thermal generator optimal bidding problem in the following original ways:

- We formulate a robust optimization problem that constructs market bidding curves immune to infeasible ramping requirements between the consecutive hours.
- We obtain secure ramping optimal solutions by solving only once the robust optimization problem that incorporates and coordinates the results of all K iterations.

B. BACKGROUND AND CONTRIBUTION ON BATTERY STORAGE BIDDING USING ROBUST OPTIMIZATION

Although thermal generators still take an important role in power systems, we explore the implementation of the robust optimization tool to more recent market participants. The authors of [21] propose a robust optimization model to obtain the most rewarding bidding strategy of a smart home aggregator considering the uncertainty on the market prices, local load and local photovoltaic output. Robust scheduling of an EV aggregator aiming to maximize its profit and considering the electricity price uncertainty is proposed in [5]. Virtual power plant bidding using robust optimization was tackled in [22] and [23]. Similarly to [21], in [22] the robust optimization is used to address the uncertainty on market prices and local wind generation. In the proposed two-stage procedure the first stage decides on optimal bids in the day-ahead market, while the second stage optimizes the bidding strategy in the real-time market. This paper constructs bidding curves in the same fashion as [18]. An adaptive robust upgrade of the static virtual power plant model from [22] is presented in [23]. The adaptability of the model manifests by allowing adjustments of the virtual power plant variables after the worst-case realization of the wind power plant output. On the other hand, uncertainty of market prices is modeled via stochastic scenarios allowing for derivation of the bidding curves. Robust optimization was used in [24] to derive optimal bidding curves for a concentrating solar plant combined with thermal storage. The storage system provides an increased dispatchability for the concentrating solar plant, which significantly affects its overall profit. A two-stage adaptive robust program that captures collaborative operation of residential microgrids is constructed in [25] to derive a scheduling that minimizes the microgrids' operating cost under the worst realization of photovoltaics output.

Affinely adjustable robust optimization bidding model of a solar power plant paired with battery storage is proposed in [26]. This is a two-stage robust optimization model that considers uncertainty of the solar power plant output and prices in two consecutive markets. Affinely adjustable robust formulation was applied to the day-ahead scheduling of a multi-energy system in [27]. The proposed robust formulation includes piece-wise linear decision rules, stressing their potential use for real-time control. A microgrid robust optimization bidding model is presented in [28]. The uncertain output of intermittent distributed generation and day-ahead market prices are modeled using stochastic scenarios, while real-time market prices are addressed using robust optimization. Although [26] and [28] both use battery as a storage device, the presented models use only generic energy storage formulation and ignore specifics of battery energy storage, such as reduced charging capability at high states of energy.

Considering the literature on battery energy storage bidding using robust optimization, this paper delivers the following contributions:

- We formulate two robust optimal bidding models for battery storage. The first one uses two budgets of uncertainty, one for the discharging process and one for the charging process. This model is extremely optimistic for low values of uncertainty budgets and allows a finer control over the level of conservatism. The second one uses a single budget of uncertainty and relies on the average price as the best-case price. In this model both the upward and downward deviations are possible.
- Instead of using a generic energy storage model, we adopt a more detailed battery charging model that considers the reduced charging power at high battery state of energy. This results in an improved accuracy of the battery operation and quantifies the expected revenues more accurately.

C. PAPER ORGANIZATION

The rest of the paper is organized as follows. In Section II the robust thermal generator bidding problem is presented using two formulations, denoted by RobGen_1 and RobGen_2. This Section also presents a case study and compares results obtained using both formulations. Section III focuses on robust battery storage bidding problem and presents two different models, RobBat_2Γ and RobBat_Γ, which are compared in an additional case study. The relevant conclusions on usefulness of the robust optimization in optimal bidding problems are articulated in Section IV. Additionally, the Appendix presents a general bilevel robust formulation of the profit maximization problem used throughout this paper and its linear reformulation based on the work of Bertsimas and Sim [1].

II. ROBUST THERMAL GENERATOR BIDDING PROBLEM

A. NOMENCLATURE

1) SETS AND INDICES

- k Index of iterations running from 1 to K.
- l Index of generator output segments running from 1 to L.
- t Index of periods running from 1 to T.

2) PARAMETERS

c^{F}	Thermal generator fixed cost [€].
c^{SD}	Generator shutdown cost [€].
c^{SU}	Generator startup cost [€].
d_t^k	Price difference between the upper and lower bound in iteration k, calculated as $(\lambda_t^{\max} - \lambda_t^{\min}) \cdot k/K$ [€].
$N^{\mathrm{OFF/ON}}$	Number of hours the generator has been off/on prior to the first period.
$P^{\max}$	Generator power capacity [MW].
$P^{\min}$	Generator's minimum stable output [MW].
$R^{\mathrm{down/up}}$	Ramp down/up limit [MW].
$R^{\mathrm{SD/SD}}$	Shutdown/startup ramp limit [MW].
$T^{\mathrm{down/up}}$	Minimum down/up time [h].

u_0 Initial commitment status (value 0/1).
α_l Cost slope of generation block l [€/MW].
$\lambda_t^{\max}$ Upper price bound at hour t [€/MWh].
$\lambda_t^{\min}$ Lower price bound at hour t [€/MWh].
ρ_l Size of generator block l [MW].

3) VARIABLES

c_t Operating costs in period t [€]
c_t^{p} Production costs in period t [€]
$c_t^{\mathrm{SD/SU}}$ Shutdown/startup costs in period t [€]
p_t Power output in period t [MW]
$p_{t,l}$ Power output within generation segment l in period t [MW]
u_t Binary variable (1 if unit is online at t, 0 otherwise)

B. RobGen_1 FORMULATION

RobGen_1 formulation is acquired from [18] and used as a baseline robust model. The problem is solved K times, where every iteration uses different prices. It suggests that in each hour the price lies inside the interval $[\lambda_t^{\min}, \lambda_t^{\max}]$, where $\lambda_t^{\max}$ is the upper bound and is constant in all iterations, while $\lambda_t^{\min}$ is the lower bound that decreases linearly in each iteration. In all iterations the robustness parameter Γ is set to 24, representing full conservativeness, which results in prices equal to $\lambda_t^{\min}$ in all time periods as this is the worst case for a generator bidding in the market. RobGen_1 problem is formulated as follows for each iteration k:

$$\text{Max} \sum_{t=1}^{T}[\lambda_t^{\max} \cdot p_t - c_t(p_t)] - z \cdot \Gamma - \sum_{t=1}^{T} q_t \tag{1.1}$$

$$\text{subject to}: \ z + q_t \geq d_t \cdot y_t \quad \forall t \leq T \tag{1.2}$$

$$z,\ q_t,\ y_t \geq 0 \quad 1 \leq t \leq T \tag{1.3}$$

$$p_t \geq y_t \quad 1 \leq t \leq T \tag{1.4}$$

$$c_t(p_t) = c_t^{\mathrm{p}} + c_t^{\mathrm{SU}} + c_t^{\mathrm{SD}} \quad \forall t \leq T \tag{1.5}$$

$$c_t^{\mathrm{p}} = c^{\mathrm{F}} \cdot u_t + \sum_{l=1}^{L} \alpha_l \cdot p_{l,t} \quad \forall t \leq T \tag{1.6}$$

$$p_t = \sum_{l=1}^{L} p_{l,t} + P^{\min} \cdot u_t \quad \forall t \leq T \tag{1.7}$$

$$p_{l,t} \leq \rho_l - \rho_{l-1} \quad \forall t \leq T, 2 \leq l \leq L \tag{1.8}$$

$$p_{l,t} \geq 0 \quad \forall t \leq T, l \leq L \tag{1.9}$$

$$c_t^{\mathrm{SU}} \geq c^{\mathrm{SU}} \cdot (u_t - u_{t-1}) \quad \forall t \leq T \tag{1.10}$$

$$c_t^{\mathrm{SD}} \geq c^{\mathrm{SD}} \cdot (u_{t-1} - u_t) \quad \forall t \leq T \tag{1.11}$$

$$c_t^{\mathrm{SD}}, c_t^{\mathrm{SU}} \geq 0 \quad \forall t \leq T \tag{1.12}$$

$$p_t \leq P^{\max} \cdot u_t \quad \forall t \leq T \tag{1.13}$$

$$p_t \leq p_{t-1} + R^{\mathrm{up}} \cdot u_{t-1} + R^{\mathrm{SU}} \cdot (u_t - u_{t-1}) + P^{\max} \cdot (1 - u_t) \quad \forall t \leq T \tag{1.14}$$

$$p_t \leq P^{\max} \cdot u_{t+1} + R^{\mathrm{SD}} \cdot (u_t - u_{t+1}) \quad \forall t \leq T-1 \tag{1.15}$$

$$p_{t-1} - p_t \leq R^{\mathrm{down}} \cdot u_t + R^{\mathrm{SD}} \cdot (u_{t-1} - u_t) + P^{\max} \cdot (1 - u_{t-1}) \quad \forall t \leq T \tag{1.16}$$

$$\sum_{t=1}^{M}(1 - u_t) = 0 \tag{1.17}$$

$$\sum_{n=t}^{t+T^{\mathrm{up}}-1} u_n \geq T^{\mathrm{up}} \cdot (u_t - u_{t-1}) \quad \forall t : M+1 \leq t \leq T - T^{\mathrm{up}} + 1 \tag{1.18}$$

$$\sum_{n=t}^{T}[u_n - (u_t - u_{t-1})] \geq 0 \quad \forall t : T - T^{\mathrm{up}} + 2 \leq t \leq T \tag{1.19}$$

$$\sum_{t=1}^{H} u_t = 0 \tag{1.20}$$

$$\sum_{n=t}^{t+T^{\mathrm{down}}-1} (1 - u_n) \geq T^{\mathrm{down}}(u_{t-1} - u_t) \quad \forall t : H + 1 \leq t \leq T - T^{\mathrm{down}} + 1 \tag{1.21}$$

$$\sum_{n=t}^{T}[1 - u_n - (u_{t-1} - u_t)] \geq 0 \quad \forall t : T - T^{\mathrm{down}} + 2 \leq t \leq T \tag{1.22}$$

where:

$$M = \mathrm{Min}\ \{N_{\mathrm{T}}, (T^{\mathrm{up}} - N^{\mathrm{ON}}) \cdot u_0\},$$
$$H = \mathrm{Min}\ \{N_{\mathrm{T}}, (T^{\mathrm{down}} - N^{\mathrm{OFF}}) \cdot (1 - u_0)\}.$$

Derivation of robust constraints (1.2)–(1.4) is explained in Appendix at the end of the paper. Thermal generator total operating costs in eq. (1.1) consist of production costs, startup costs and shutdown costs, where production costs, defined in (1.5), consist of the no-load costs and piecewise linear approximation of variable costs with monotonically increasing slopes.

The overall thermal generator output in eq. (1.7) consists of the sum of piecewise outputs and minimum stable generation if the generator is online. Constraint (1.8) limits piecewise power outputs for the first and the remaining output segments, while (1.9) imposes nonnegativity on power output variables. Startup and shutdown costs are modeled using a single binary variable in (1.10)–(1.12). Constraints below represent the feasible operating region. Constraint (1.13) limits the power output, while constraints (1.14)–(1.16) impose operational, startup and shutdown ramp limits. Constraints (1.17)–(1.19) model generator minimum up times, while constrains (1.20)–(1.22) model generator minimum down times.

C. ROBGEN_2 FORMULATION

In order to eliminate the risk of obtaining offering curves that violate ramp constraints, we propose an alternative approach in which the K individual robust counterparts considered in RobGen_1 model are linked together. Specifically, we propose to solve one single robust counterpart:

$$\text{Max} \sum_{k=1}^{K}\sum_{t=1}^{T}(\lambda_t^{\max} - d_t^k) - c_t(p_t^k) \tag{2.1}$$

$$p_t^{k_1} \le p_{t-1}^{k_2} + R^{\text{up}} \cdot u_{t-1}^{k_2} + R^{\text{SU}} \cdot (u_t^{k_2} - u_{t-1}^{k_2}) + P^{\max} \cdot (1 - u_t^{k_2}) \quad \forall k_1, k_2 \le K : k_1 \ne k_2, t \le T \tag{2.2}$$

$$p_{t-1}^{k_2} - p_t^{k_1} \le R^{\text{down}} \cdot u_t^{k_2} + R^{\text{SD}} \cdot (u_{t-1}^{k_2} - u_t^{k_2}) + P^{\max} \cdot (1 - u_{t-1}^{k_2}) \quad \forall k_1, k_2 \le K : k_1 \ne k_2, t \le T \tag{2.3}$$

$$\text{Constraints} \quad (1.2) - (1.22) \tag{2.4}$$

where all the variables have additional dimension k that denotes the iterations. Different iterations have different input parameter d_t^k, setting the height of the uncertainty range. Constraints (2.2) and (2.3) disallow ramp violations between the power output of different iterations, i.e. protect against infeasible production schedules caused by deriving bidding curves based on results of independently obtained solutions. Therefore, instead of solving multiple robust problems and obtaining unrelated solutions (RobGen_1 formulation), we solve the entire problem in a single shot and obtain a ramp-limit-safe solution.

D. CASE STUDY

This case study compares RobGen_1 and RobGen_2 on the same input data used in [18]. We compare both the objective function values and the shape of the obtained bidding curves. Generator data are provided in Table 1, while Figure 1 shows energy price data obtained as lower and upper bounds of the EPEX spot prices on Mondays from March 19 to June 25, 2018 [29]. All scenarios are grouped relatively close together except the outlier for April 30, 2018, when the prices were negative for the most of the day. The price range is divided in 100 intervals, which means that model RobGen_1 is solved 100 times, while model RobGen_2 imposes ramp constraints among the output of all 100 intervals.

TABLE 1. Generator technical and economic data.

Fixed cost (c^{F})	824 €/MWh
Shutdown cost (c^{SD})	100 €/MWh
Startup cost (c^{SU})	1500 €/MWh
Capacity ($P^{\max}$)	294 MW
Minimum power output ($P^{\min}$)	112 MW
Startup ramp limit (R^{SU})	170 MW/h
Shutdown ramp limit (R^{SD})	160 MW/h
Ramp-up limit (R^{up})	60 MW/h
Ramp-down limit (R^{down})	70 MW/h
Minimum up time (T^{up})	4 h
Minimum down time (T^{down})	4 h

A selection of generated bidding curves is displayed in Figure 2. Generally, bidding curves obtained using the RobGen_1 model cover a wider output range than the ones obtained using the RobGen_2 model and they are mostly spread across the entire operating range of the thermal generator. This may cause infeasible hourly transitions in case of fluctuating prices. For instance, if the price changes from €54/MWh in hour 17 to €39/MWh in hour 18, the thermal generator would need to change its output from the maximum 294 MW to 179 MW. However, this would violate its ramp-down limit of 70 MW/h. On the other hand, the RobGen_2 model produces more narrow bidding curves. Its output in hour 17 will be in the range 112–162 MW, depending on the price. In the following hour, its output range slightly extends to the range 112–172 MW (note that ramp-up limit is 60 MW). In hour 19, the prices keep increasing and the RobGen_2 formulation moves the lower output bound to 142 MW and keeps the upper one at 172 MW, as otherwise the ramp-up constraint with respect to the previous hour might not be satisfied. In hour 20, the offering curve of RobGen_2 model is very narrow with offers ranging from 192 to 202 MW, which enables it to further increase the output range in hour 21 to 174–252 MW, still respecting the ramp-up constraint. After hour 21, the RobGen_2 bidding curves slowly move to the left again as the market prices decrease.

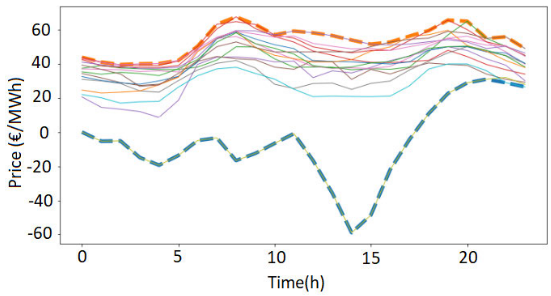
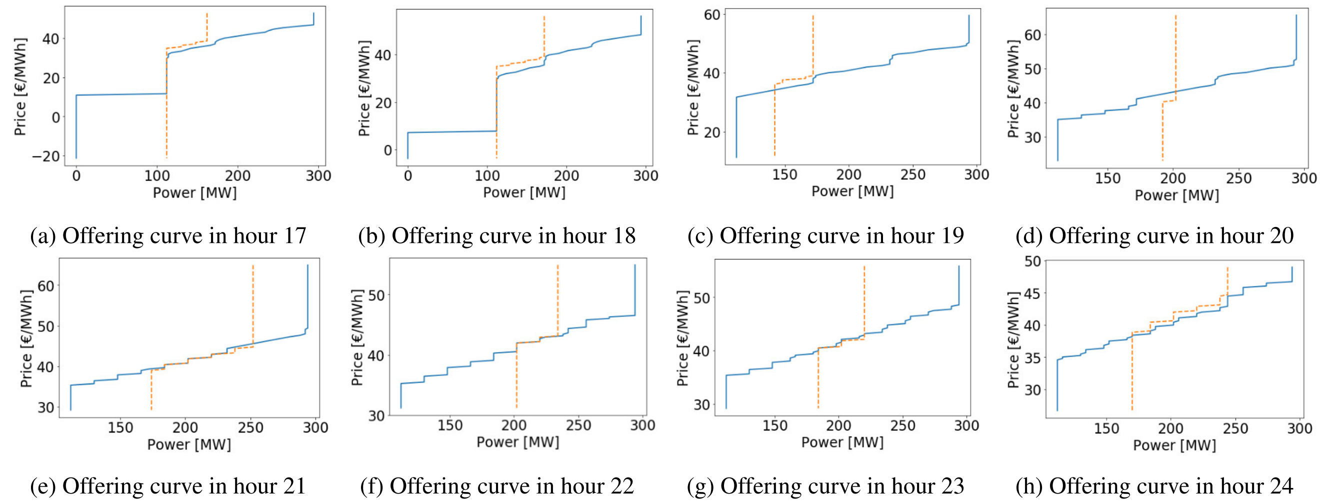


FIGURE 1. Fifteen market price scenarios used to create the upper (thick dashed orange line) and the lower (thick dashed blue line) price bounds.

In order to quantify the difference between RobGen_1 and RobGen_2 models and assess how often the ramp constraints would actually be violated, we apply the generator bidding curves obtained by both formulations on the actual price curves used to define the robust bounds. The resulting profit as well as the number of ramp-constraint violations per scenario are shown in Figure 1. Generally, generator's profit for RobGen_1 is always higher than for RobGen_2 model. While for scenarios 3, 4, 6 and 8 these differences are rather low, in the remaining scenarios they are more significant. Furthermore, scenario 7, which is the outlier since its prices are very low and actually negative for the most of the day, incurs negative profit for the RobGen_2 model, while RobGen_1 model allows the generator to stop producing electricity when the prices are low or negative. On the other hand, RobGen_2 prevents the generator to shut down because of the ramp constraints. For example, in hour 17, electricity price ranges from -48.6 € /MWh in scenario 7 to 51.5 € /MWh in scenario 13. Since the output across all scenarios must be feasible, the generator cannot just shut down or reduce its output, as it can in RobGen_1.



(a) Offering curve in hour 17 (b) Offering curve in hour 18 (c) Offering curve in hour 19 (d) Offering curve in hour 20

(e) Offering curve in hour 21 (f) Offering curve in hour 22 (g) Offering curve in hour 23 (h) Offering curve in hour 24

FIGURE 2. Offering curves obtained using RobGen_1 (in blue) and RobGen_2 (in orange) formulations for hours 17–24.

The expected profit across all 15 scenarios for the RobGen_1 model is €106,141 with standard deviation €11,250. On the other hand, the expected profit for RobGen_2 model is 12% lower, €93,665, with standard deviation €9,683. The higher expected profit obtained using the RobGen_1 model is a result of ramp-constraints violations in 11 out of 15 scenarios. The ramp constraints in some scenarios are violated quite frequently, up to five times, as shown in Figure 3.

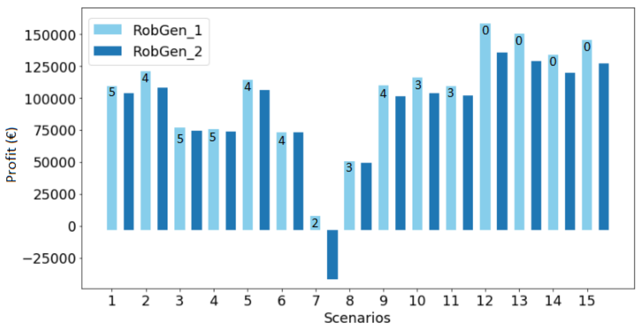


FIGURE 3. Profits and number of ramp-constraint violations per scenario for RobGen_1 and RobGen_2 models.

Introducing additional ramp constraints in RobGen_2 and simultaneously solving the problem does not increase the overall solution time. Actually, on a computer equipped with a 4-core i7 processor clocking at 1.8 GHz and 16 GB RAM solving the RobGen_1 model 100 times take 45 seconds, while solving the RobGen_2 model once takes under 5 seconds.

III. ROBUST BATTERY STORAGE BIDDING PROBLEM

As opposed to a thermal generator, which only sells electricity and thus prefers high prices at all time periods, battery storage in some time periods purchases electricity, acting as a consumer, in some time periods it sells electricity, acting as a generator, and in time periods with average daily prices it usually remains idle. Thus, when it sells electricity it prefers upward deviation from the average price, while the downward deviation is preferred when it purchases electricity. Having this in mind, we formulate two types of robust battery storage bidding models. The first one considers that the most favorable prices are located at the upper bound when selling electricity and at the lower bound when purchasing electricity. This model thus includes two budgets of uncertainty, Γ^{dis} and Γ^{ch}, one is the downward deviation from the upper bound when discharging and selling, and the other one is the upward deviation from the lower bound when charging and purchasing electricity. We refer to this model as RobBat_2Γ. The second model we formulate assumes that the best-case scenario is when the price of electricity moves along the points equally distant from the upper and the lower bound at each time period. This formulation, denoted RobBat_Γ, uses a single budget of uncertainty indicating in how many hours the prices deviate from this assumed middle scenario in an unfavorable way for the battery storage. Both models are formulated in the following subsections after the nomenclature.

A. NOMENCLATURE

1) SETS AND INDICES

- j Index of breakpoints of the battery charging curve running from 1 to J.
- t Index of hours running from 1 to T.

2) PARAMETERS

- d_t Market prices uncertainty range (difference between the upper and the lower bound) [€/MWh].
- F_j Maximum amount of energy that can be charged at specific state of energy breakpoint R_j as a portion of $P^{\max}$.
- $P^{\max}$ Maximum battery power [MW].

R_j	Capacity of each state of energy segment j as a portion of the maximum state of energy $SoE^{\max}$.
SoE^{init}	Initial state of energy [MWh].
$SoE^{\max}$	Maximum state of energy [MWh].
$SoE^{\min}$	Minimum state of energy [MWh].
λ_t^{av}	Average of the upper and lower price bounds at hour t [€/MW].
$\lambda_t^{\max}$	Upper price bound at hour t [€/MW].
$\lambda_t^{\min}$	Lower price bound at hour t [€/MW].

3) VARIABLES

p_t^{ch}	Charging power in period t [MW].
p_t^{dis}	Discharging power in period t [MW].
SoE_t	Battery state of energy in period t [MWh].
$SoE_{t,j}^{\text{seg}}$	State of energy of segment j in period t [MWh].
u_t	] Binary variable equal to 1 if battery is charging at t and 0 otherwise.

B. FORMULATION OF THE RobBat_2Γ MODEL

The robust optimal battery bidding problem with two budgets of uncertainty, one for selling electricity and one for purchasing electricity, is formulated as follows:

$$\text{Max} \sum_{t=1}^{T}\{[\lambda_t^{\min} + d(t)] \cdot p_t^{\text{dis}} - \lambda_t^{\min} \cdot p_t^{\text{ch}}\}$$
$$- z^{\text{ch}} \cdot \Gamma^{\text{ch}} - z^{\text{dis}} \cdot \Gamma^{\text{dis}} - \sum_{t=1}^{T} q_t^{\text{ch}} - \sum_{t=1}^{T} q_t^{\text{dis}} \tag{5.1}$$

$$\text{subject to: } z^{\text{dis}} + q_t^{\text{dis}} \geq d_t \cdot y_t^{\text{dis}} \quad \forall t \leq T \tag{5.2}$$
$$p_t^{\text{dis}} \leq y_t^{\text{dis}} \quad \forall t \leq T \tag{5.3}$$
$$z^{\text{dis}},\ q_t^{\text{dis}},\ y_t^{\text{dis}} \geq 0 \quad \forall t \leq T \tag{5.4}$$
$$z^{\text{ch}} + q_t^{\text{ch}} \geq d_t \cdot y_t^{\text{ch}} \quad \forall t \leq T \tag{5.5}$$
$$p_t^{\text{ch}} \leq y_t^{\text{ch}} \quad \forall t \leq T \tag{5.6}$$
$$z^{\text{ch}},\ q_t^{\text{ch}},\ y_t^{\text{ch}} \geq 0 \quad \forall t \leq T \tag{5.7}$$
$$p_t^{\text{ch}} \leq P^{\max} \cdot u_t \quad \forall t \leq T \tag{5.8}$$
$$p_t^{\text{dis}} \leq P^{\max} \cdot (1 - u_t) \quad \forall t \leq T \tag{5.9}$$
$$SoE_t = SoE^{\text{init}} + p_t^{\text{ch}} \cdot \eta - p_t^{\text{dis}}/\eta \quad t = 1 \tag{5.10}$$
$$SoE_t = SoE_{t-1} + p_t^{\text{ch}} \cdot \eta - p_t^{\text{dis}}/\eta \quad \forall t : 2 \leq t \leq T \tag{5.11}$$
$$SoE^{\min} \leq SoE_t \leq SoE^{\max} \quad \forall t \leq T \tag{5.12}$$
$$SoE_T \geq SoE^{\text{init}}, \tag{5.13}$$
$$SoE_t = \sum_{j=1}^{J-1} SoE_{t,j}^{\text{seg}} \quad \forall t \leq T \tag{5.14}$$
$$SoE_{t,j}^{\text{seg}} = (R_{j+1} - R_j) \cdot SoE^{\max} \quad \forall j \leq J-1,\ t \leq T \tag{5.15}$$
$$p_t^{\text{ch}} \cdot \eta \leq F_1 \cdot SoE^{\max} + \sum_{j=1}^{J-1} SoE_{t-1,j}^{\text{seg}} \cdot \frac{F_{j+1} - F_j}{R_{j+1} - R_j},\ t \leq T \tag{5.16}$$

The objective function (5.1) maximizes the battery storage profit by selling electricity at maximum price, $\lambda_t^{\min} + d(t)$, and purchasing it at minimum price, $\lambda_t^{\min}$. The second line in the objective function (5.1) contains robust counterparts of the charging and discharging processes. When there is a deviation from the best-case price related to charging, the corresponding two negative terms take values and thus deteriorate the objective function value. Similarly, an undesired deviation from the upper-bound price when discharging causes the two terms related to discharging to take values.

Variables $z^{\text{dis/ch}}$, $q_t^{\text{dis/ch}}$, $y_t^{\text{dis/ch}}$ and constraints (5.2)–(5.7) are a result of the dualization adopted to eliminate the robust subproblem according to [1]. Constraints (5.8) and (5.9) limit the charging and discharging power and disable simultaneous charging and discharging. State of energy for the first and the remaining time periods is calculated using eqs. (5.10) and (5.11). Minimum and maximum state of energy are imposed by the constraints (5.12), while constraint (5.13) ensures that the battery at the end of the optimization horizon is at least equally charged as at the beginning.

Constraints (5.14)–(5.16) model the dependency of the battery charging power on its state of energy. This dependency manifests as reduced battery charging capacity at higher states of energy, which is a consequence of its operation in the constant-voltage part of the charging curve. This convex curve is piecewise linearized using the breakpoints (F_i, R_i) at which the maximum battery charging power further reduces. In order to model this linearization, we use battery state of energy linear segments $SoE_{t,j}^{\text{seg}}$, which constitute battery's overall state of energy SoE_t, in a same way that piecewise linear thermal generator output segments $p_{l,t}$ constitute overall generator output p_t (see [30] for details on this battery charging model).

C. FORMULATION OF THE RobBat_Γ MODEL

This formulation considers average prices λ_t^{av} for both battery discharging and charging as the most optimistic scenario, i.e. for $\Gamma = 0$. However, once Γ takes positive values, at least one of the remaining two terms in (6.1) take value different than zero and deteriorate the objective function value. Constraints (6.2)–(6.4) are derived directly from the robust subproblem, while the remaining constraints are identical to the RobBat_2Γ model.

$$\text{Max} \sum_{t=1}^{T}[\lambda_t^{\text{av}} \cdot (p_t^{\text{dis}} - p_t^{\text{ch}})] - z \cdot \Gamma - \sum_{t=1}^{T} q_t \tag{6.1}$$
$$\text{subject to: } z + q_t \geq \Delta d_t \cdot y_t \quad \forall t \leq T \tag{6.2}$$
$$- y_t \leq p_t^{\text{dis}} - p_t^{\text{ch}} \leq y_t \quad \forall t \leq T \tag{6.3}$$
$$z,\ q_t \geq 0 \quad \forall t \leq T \tag{6.4}$$
$$\text{Constraints (5.8)} - \text{(5.16)} \tag{6.5}$$

D. CASE STUDY

We conduct four different analysis where the RobBat_2Γ and RobBat_Γ models are applied to two sets of prices, one using the full uncertainty range from Table 2 and Fig. 1 and the other using a reduced uncertainty set that omits the outlier scenario (the one at the lower bound, far below all the other scenarios). Objective function values for all four cases and $\Gamma = 0$ are provided in Table 2. Objective function values both with and without the outlier scenario are approximately five times higher for the RobBat_2Γ model as its initial assumptions on purchasing and selling prices are much more optimistic than the ones of the RobBat_Γ model, i.e. selling at the upper-bound prices and purchasing at the lower-bound prices as opposed to both buying and selling at the average prices. However, as the obtained objective function values in robust optimization generally do not reflect the expected profits, we obtain charging and discharging schedules for both models under both the full and reduced uncertainty range for all values of Γ and apply those schedules on the available market price scenarios. As a result, the optimal value of the uncertainty budget is not known ahead of the bidding process. Instead, it is assumed based on the historical data. In this case study, we evaluate the expected profit for individual uncertainty budgets on a number of realizations of uncertainty, i.e. scenarios.

TABLE 2. Objective function values in the battery case study for $\Gamma = 0$.

Model	All scenarios	Without outlier
RobBat_2Γ	166,049	70,711
RobBat_Γ	30,782	14,571

Expected profits over all scenarios for the RobBat_2Γ model with and without the outlier scenario are presented in Figures 4 and 5. The highest expected profit when the outlier scenario is considered is achieved for $\Gamma^{ch} = 0$ and Γ^{dis} in the range from 19 to 23. The expected profit equals €9,235. However, 76 out of 576 combinations of Γ^{ch} and Γ^{dis} result in a negative profit. This means that a poor selection of uncertainty budgets would cause losses to the battery storage. The highest loss equal to -€11,648 is obtained for $\Gamma^{ch} = 7$ and $\Gamma^{dis} = 24$. This poor performance is caused by the

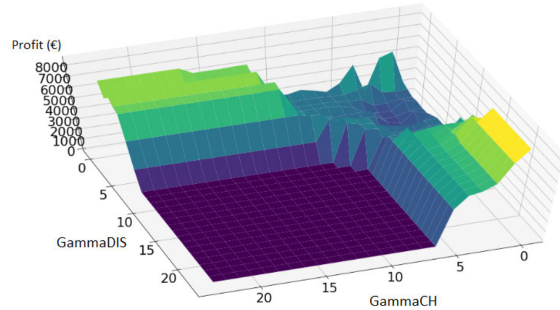


FIGURE 5. Expected profit over all scenarios for the RobBat_2Γ model when the outlier scenario is not considered.

outlier scenario having an opposite gradient as compared to the remaining scenarios over most hours. For instance, in hours 8–11 the prices of the outlier scenario are increasing, while the prices of all the other scenarios are decreasing (see Figure 1). This causes a poor selection of hours for battery to discharge and charge and results in massive losses.

When observing the reduced uncertainty range with no outlier scenario, profit is positive for all combinations of uncertainty budgets. The highest expected profit €8601.32 is achieved for $\Gamma^{ch} = 0$ and Γ^{dis} in the range from 17 to 24. The lowest profit is 0, when the battery storage never charges nor discharges.

Figure 6 shows profit per scenario (red dots) for the RobBat_Γ model for all values of Γ resulting in at least some battery charging/discharging activity (profit per scenario for values of Γ higher than presented is always zero), while the blue line shows the expected profit, i.e. the weighed average of all scenarios (red dots). In case when outlier scenario is taken into account (Figure 6a), for all Γ values higher than 7 the objective function is zero, thus the profit is zero as no charging or discharging is scheduled. The highest profits are achieved for the outlier scenario (top row of red dots). The schedule for $\Gamma = 0$ results in €56,384 profit. While in RobGen models the outlier scenario brings losses, in RobBat_Γ the outlier brings maximum profit. That is because at negative prices the battery can charge and be paid for it, making further profit when selling this electricity at positive prices. However,

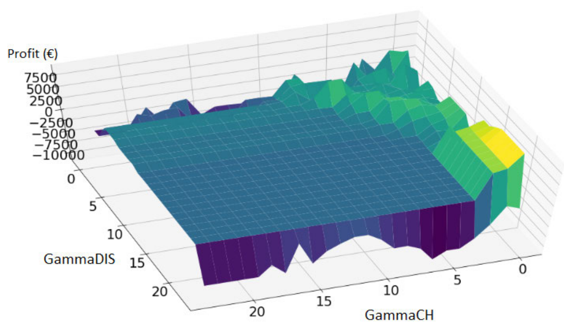
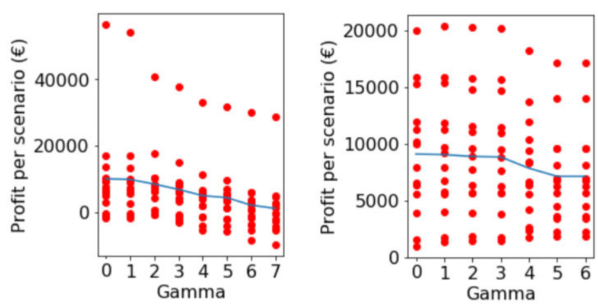


FIGURE 4. Expected profit over all scenarios for the RobBat_2Γ model when the outlier scenario is considered.



(a)With outlier scenario (b)Without outlier scenario

FIGURE 6. Profit per scenario and the expected profit for the RobBat_Γ model.

considering the outlier scenario has negative effects as well as it causes negative profits in 34 out of 120 scenario realizations for different uncertainty budgets. This effect increases for higher values of Γ.

When the outlier scenario is not considered (Figure 6b), the expected profit for all uncertainty budgets is lower, but no scenario realization results in losses. The highest expected profit €20,342 is achieved for $\Gamma = 1$. It is obvious the highest profit when considering the outlier scenario is significantly higher. The point of discussion is whether this higher profit is worth the risk of operating with losses. Overall, the expected battery profit with the outlier scenario is €6,012 and without it €8,284.

Both battery bidding models are solved very quickly, under 1 second. The solution times lower than for the thermal generator bidding models are a direct consequence of the reduced number of binary variables and constraints.

IV. CONCLUSION

The presented thermal generator and battery storage bidding strategies using robust optimization formulations were used to address the salient features of using these formulations in the day-ahead market. The following conclusions are drawn based on the case studies:

1) The RobGen_1 formulation from [18] results in more aggressive bidding and uses a wider range of output power than the proposed conservative RobGen_2 formulation. However, the violation frequency of generator ramp constraints is severe, which inflicts balancing costs. Therefore, risk-averse bidders should rely on the RobGen_2 model.
2) In the RobBat_2Γ model the best results are achieved for $\Gamma^{ch} = 0$ and high values of Γ^{dis}, indicating the importance of pinpointing the periods with lowest prices, regardless on how much those prices actually are. The realistic conservatism is achieved with the discharging prices descending from the upper bound using high Γ^{dis} values.
3) Regardless on the battery bidding formulation, scenarios used to set the price bounds should be carefully examined. An outlier scenario can significantly change the bidding strategy. Although the expected and maximum profits increase, the minimum profits decrease, which can often result in monetary losses.

To conclude, using robust optimization to produce optimal bidding strategy is a delicate task as the scenario characteristics are omitted. This is particularly the case for battery storage where it is imperative to choose the hours with the lowest prices to purchase electricity. Therefore, pure robust formulation without any uncertainty characterization should be avoided and some type of scenario-based approach should be used instead. Assuming that the market players pursue maximum expected profit, the stochastic optimization is a much more suitable tool for daily bidding schemes. Instead, robust formulation is appropriate for investment problems where the investors want to secure against the worst-case realization of uncertainty that could jeopardize their business venture.

APPENDIX

We briefly review here how to apply the methodology proposed in [1] to tackle uncertainty in the bidding problems we consider. A profit-maximization problem with a threat of maximizing the damage by altering the uncertain market prices is a bilevel problem with the following objective function containing the lower-level problem and its two constraints (dual variables of the lower-level problem constraints are separated by a colon):

$$\text{Max} \sum_{t=1}^{N_T} \lambda_t \cdot p_t - \text{Max} \sum_{t=1}^{N_T} \Delta\lambda_t \cdot |p_t| \cdot b_t \tag{A.1}$$

$$\text{subject to} \sum_{t=1}^{N_T} b_t \leq \Gamma \quad : z \tag{A.2}$$

$$0 \leq b_t \leq 1 \qquad \forall t \leq T \quad : w_t \tag{A.3}$$

Since the two maximizations in the objective function are contradictory (the lower-level problem maximization comes with a negative sign), the lower-level problem needs to be dualized. The resulting dual is:

$$\text{Max} \sum_{t=1}^{N_T} \lambda_t \cdot p_t - \text{Min} \left[z \cdot \Gamma + \sum_{t=1}^{N_T} w_t \right] \tag{A.4}$$

$$z + w_t \geq \Delta\lambda_t \cdot |p_t| \qquad \forall t \leq T \tag{A.5}$$

where $z \geq 0$ and $w_t \geq 0$. Now the two problems in the objective function have coinciding directions (negative minimization is identical to maximization), we can omit the lower-level minimization to achieve the final objective function (A.6) The only remaining issue is the absolute value in (A.5) since p_t is now a variable (it was a parameter when only the lower-level problem was observed). This is linearized as in (A.7) and (A.8). The final equivalent of problem (A.1)–(A.3) is thus:

$$\text{Max} \sum_{t=1}^{N_T} \lambda_t \cdot p_t - z \cdot \Gamma - \sum_{t=1}^{N_T} w_t \tag{A.6}$$

$$z + w_t \geq \Delta\lambda_t \cdot y_t \qquad \forall t \leq T \tag{A.7}$$

$$-y_t \leq p_t \leq y_t \qquad \forall t \leq T \tag{A.8}$$

with $z \geq 0$ and $w_t \geq 0$.

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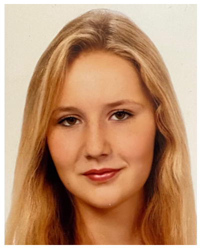

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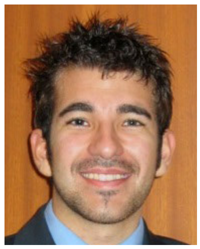

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