Energy Markets & Policy
BERKELEY LAB

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July 2023

This is a pre-print version of conference proceedings published in the *2023 IEEE Power & Energy Society General Meeting (PESGM).*
DOI: https://doi.org/10.1109/PESGM52003.2023.10252335

This work was supported by the U.S. Department of Energy's Office of Energy Efficiency & Renewable Energy and the Office of Electricity under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

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***Abstract*—This paper proposes a stochastic model for hybrid power plants participation in day-ahead electricity markets, considering uncertainty in market prices and renewable generation. Additionally, it presents a methodology to incorporate this hybrid participation into existing production cost models (PCM), allowing the analysis and market design of future systems with high penetration of hybrids. These developments are illustrated using a wind-battery hybrid located in New York Independent System Operator (NYISO) footprint.**

I. Introduction

In the quest to deeply decarbonize electricity sources, storage technologies can increase grid flexibility to balance the variability and uncertainty of renewable generation. One option for deploying an energy storage resource ("ESR") is to install it alongside a variable renewable energy generator ("VRE"). So-called hybrid power plants ("hybrids") have drawn interest from developers and policy-makers. In the US, at the end of 2021, almost 36 GW of generation and 3.2 GW (8.1 GWh) of ESRs were operating as hybrids across nearly 300 plants [1]. These projects are the first wave of 285 GW of solar, 17 GW of wind, and 207 GW of storage proposed as hybrids in interconnection queues [2].

Therefore, to simulate future markets, hybrids must be represented in standard software simulation tools, such as production cost models (PCMs). PCMs are widely used to evaluate the economic impact of generation dispatch decisions. A key challenge of representing hybrids in PCMs is determining ESRs' marginal operation costs. Different from fuel-based generators, where marginal costs are tied to commodity prices, and from VREs, where they are near zero, ESRs have an effective marginal cost based on expectations of future prices.

This paper aims to develop a model representing the participation of hybrids in electricity markets and to establish a process for executing it in existing PCM tools. In the near term, this work can be used to simulate future markets with ESRs and hybrids and, in the long-term, to generate real market bids for these resources. Today, hybrids and ESRs are still an emergent reality in bulk power systems and the historical data on prices, bids, and agent decisions is limited. Therefore, our approach intends to create bids consistent with those a hybrid participant would submit, without the knowledge of historical market outcomes. Developing this capability is one step toward enabling future electricity market designs with high penetrations of hybrids.

Funded by the U.S. Department of Energy, contract DE-AC02-05CH11231.

A spectrum of market participation models for hybrids has been proposed [3] from "separate independent resources" ("2R") to "single, self managed resource" ("1R") [4]. This work focuses on the latter, in which a hybrid appears as a single entity to markets, submitting price-quantity bidding curves and managing its own operational limits. Hybrids in a 1R model which self-schedule, that is, offer price-independent quantity bids, are a special case of our approach.

A. Literature Review

Numerous approaches to market participation for hybrids and related resources have been proposed in the literature. Hydro storage systems with stochastic inflows are modeled similarly to hybrids, making medium term bidding strategies for hydro-electric assets, surveyed in [5], relevant to this setting. Virtual power plants also consist of multiple resources jointly bid into the market, though they differ from hybrids in their physical coupling. An overview of ~ 50 works pertaining to hybrid or ESR bidding or scheduling is compiled in [6].

Several approaches in this literature contribute to our stated goals, but none satisfy all necessary criteria. Among the leading candidates, [7] and [8] require more information than is available in the simulation environments we consider. The former employs a distribution of prices given the current environmental state, and a model of how this state evolves over time. The latter requires scenarios on the ESR's operation, information our bidder cannot predict in advance of solving this scheduling problem. Other candidates do not guarantee valid market bids, since decreasing offer curves may be produced by [9], and neither [10], [8], nor [11] limits the number of price steps in the bid curve.

B. Contributions

This work presents two main contributions to represent hybrids participation in day-ahead wholesale electricity markets via a 1R model. The first addresses the challenge of decision-making under uncertainty of market prices and VRE production, by developing a stochastic optimization model for hybrid operations in day-ahead markets to deliver price-quantity hourly bid curves with a limited number of non-decreasing marginal price steps. The second addresses the incorporation of this decision-making model into PCM simulations to analyze future systems with high penetrations of hybrids. The approach includes scenario generation, selection of modeling parameters, and a heuristic to address potential price spikes not reflected in the scenarios.

II. Hybrid Bidding Problem Formulation

A. Model Notation and Nomenclature

The key variables (occasionally also used as superscripts) are the following: state of charge (C), power (E) and mode of operation ($MODE$) of the ESR; generator power output (G) and curtailment ($\bar{G}$); net hybrid production (H); positive/negative ($\epsilon^{+/-}$) and total (ϵ) deviations of the hybrid from its schedule; volume component of the (y, x) price-volume pairs defining a bidding curve, as illustrated in Fig. 1 (x).

The key parameters notations are: generator output potential (gen); market-clearing price (ρ); deviation penalty (η); ESR efficiency (μ); risk factors (σ, ψ); operating cost (O); point of interconnection capacity (poi); ability to charge from the grid (ψ); intraday participation factor (Λ); probability (π); price component of price-volume bidding pairs (y).

Other nomenclature: cha and dis indicate the ESR's charging and discharging modes; a time step t and the time period $\mathcal{T} = \{1, \dots, N_T\}$ will at times be referred to as an "hour" and "day"; each bid is limited to N_B marginal price steps.

B. Hybrid Power Plant Bidding Model Formulation

The goal of the price-taker hybrid operator is to maximize total operating profits while managing risk due to uncertainty. Uncertainty is modeled by a set of scenarios, where any given scenario $s \in \mathcal{S}$ consists of

$$\pi_s, \left\{gen_{t,s}, \rho_{t,s}^{\{DA,IN\}}, \eta_{t,s}^{\{+/-\}}, \mu_{t,s}^{\{cha,dis\}}, C_{t,s}^{\{max,min\}}\right\}_{t\in\mathcal{T}}.$$

If other plant parameters are not deterministic, it is straightforward to index these quantities by s too. The hybrid's objective is formulated linearly as

$$\max_{\Gamma}\sum_{s\in\mathcal{S}}\left(\pi_s\big(\underbrace{rev_s - cost_s}_{profit_s}\big)\right)+\zeta\underbrace{\left(\theta-\frac{1}{1-\sigma}\sum_{s\in\mathcal{S}}\pi_s\phi_s\right)}_{CVaR}, \quad (1)$$

$$\text{where } rev_s := \sum_{t=1}^{N_T}\rho_{t,s}^{DA}H_{t,s}^{DA}+\rho_{t,s}^{IN}H_{t,s}^{IN}+\rho_{t,s}^{+}\epsilon_{t,s}^{+}, \quad (2)$$

$$cost_s := \sum_{t=1}^{N_T}\rho_{t,s}^{-}\epsilon_{t,s}^{-}+O_t^{E^{cha}}E_{t,s}^{SC,cha}+O_t^{E^{dis}}E_{t,s}^{SC,dis}+O_t^{G}G_{t,s}^{SC}, \quad (3)$$

$$\begin{aligned}\Gamma := \Big\{&\{x_{t,b}\}_{t=1,\, b=1}^{t=N_T,\, b=N_B}, \theta, \{\phi_s\}_{s=1}^{N_S}, \{H_{t,s}^{DA,IN,SC}, \bar{G},\\ &G_{t,s}^{DA,IN,SC}, E_{t,s}^{DA,IN,SC}, E_{t,s}^{SC,dis}, E_{t,s}^{SC,cha}, C_{t,s}^{SC},\\ &MODE_{t,s}^{dis,cha}, \epsilon_{t,s}^{+}, \epsilon_{t,s}^{-}, \epsilon_{t,s}\}_{t=1,\, s=1}^{t=N_T,\, s=N_S}\Big\},\end{aligned} \quad (4)$$

and the deviation prices are defined as follows:

$$\rho_{t,s}^{+} = \begin{cases}\eta_{t,s}^{+}\cdot\min\{\rho_{t,s}^{DA},\rho_{t,s}^{IN}\}, & \min\{\rho_{t,s}^{DA},\rho_{t,s}^{IN}\}\geq 0\\ \eta_{t,s}^{-}\cdot\min\{\rho_{t,s}^{DA},\rho_{t,s}^{IN}\}, & \text{otherwise}\end{cases} \quad (5)$$

$$\rho_{t,s}^{-} = \begin{cases}\eta_{t,s}^{+}\cdot\max\{\rho_{t,s}^{DA},\rho_{t,s}^{IN}\}, & \max\{\rho_{t,s}^{DA},\rho_{t,s}^{IN}\}\leq 0\\ \eta_{t,s}^{-}\cdot\max\{\rho_{t,s}^{DA},\rho_{t,s}^{IN}\}, & \text{otherwise.}\end{cases} \quad (6)$$

The objective function (1) maximizes the expected profit from all three settlements - day-ahead market (DA), intraday market (IN), and deviations - plus the weighted conditional value-at-risk (CVaR), which is equal to the expected profit of the least profitable $(1-\sigma)\times 100\%$ of scenarios [12]. In general, it is desirable to limit exposure to deviation costs, which are used to settle differences between the scheduled and delivered power. This model maintains the property that deviations always close against the participant if $\eta_{t,s}^{+} < 1$ and $\eta_{t,s}^{-} > 1$.

The hybrid operator is subject to constraints imposed by physical infrastructure, market rules, and their risk management strategy. We formulate these limitations as linear equations and inequalities and integer constraints. The first set of constraints primarily pertain to the hybrid's physical infrastructure. For all $s \in \mathcal{S}$ and all $t \in \mathcal{T}$:

$$\max\{-\psi E_t^{cha,max}, -poi\} \leq H_{t,s}^{SC} \leq poi \quad (7)$$

$$H_{t,s}^{SC} = H_{t,s}^{DA} + H_{t,s}^{IN} \quad (8)$$

$$H_{t,s}^{k} = G_{t,s}^{k} + E_{t,s}^{k} \qquad \forall k \in \{SC, DA, IN\} \quad (9)$$

$$0 \leq G_{t,s}^{SC} \leq G_t^{max} \quad (10)$$

$$G_{t,s}^{SC} = G_{t,s}^{DA} + G_{t,s}^{IN} \quad (11)$$

$$-E_t^{cha,max} \leq E_{t,s}^{SC} \leq E_t^{dis,max} \quad (12)$$

$$E_{t,s}^{SC} = E_{t,s}^{DA} + E_{t,s}^{IN} \quad (13)$$

The constraints also ensure the hybrid schedule accounts for its activity in day-ahead and intraday markets (8, 11, 13), respects the physical bounds in the combined-market schedule (7, 10, 12), and keeps the integrity of the hybrid configuration (9).

The second set of constraints define a realistic ESR operating schedule for for each scenario $s \in \mathcal{S}$:

$$MODE_{t,s}^{k} \in \{0, 1\} \qquad \forall k \in \{cha,\, dis\}, \forall t \in \mathcal{T} \quad (14)$$

$$MODE_{t,s}^{cha} + MODE_{t,s}^{dis} \leq 1 \qquad \forall t \in \mathcal{T} \quad (15)$$

$$0 \leq E_{t,s}^{SC,k} \leq E_t^{k,max} MODE_{t,s}^{k} \qquad \forall k \in \{cha,\, dis\}, \forall t \in \mathcal{T} \quad (16)$$

$$E_{t,s}^{SC} = E_{t,s}^{SC,dis} - E_{t,s}^{SC,cha} \qquad \forall t \in \mathcal{T} \quad (17)$$

$$C_{t,s}^{min} \leq C_{t,s}^{SC} \leq C_{t,s}^{max} \qquad \forall t \in \mathcal{T} \cup \{final\} \quad (18)$$

$$C_{t,s}^{SC} = C_{t-1,s}^{SC} + \mu_{t-1,s}^{cha} E_{t-1,s}^{SC,cha} - \frac{1}{\mu_{t-1,s}^{dis}} E_{t-1,s}^{SC,dis} \qquad \forall t = 2, \dots, N_T \quad (19)$$

$$C_{final,s}^{SC} = C_{N_T,s}^{SC} + \mu_{N_T,s}^{cha} E_{N_T,s}^{SC,cha} - \frac{1}{\mu_{N_T,s}^{dis}} E_{N_T,s}^{SC,dis} \quad (20)$$

Constraints (14-15) prevent simultaneous charge and discharge, (16-17) decompose the ESR's schedule and (18-20) manage the state-of-charge at the start of each time interval.

The next set of constraints determines the imbalances to be settled using deviation prices. For all $s \in \mathcal{S}$ and all $t \in \mathcal{T}$:

$$\epsilon_{t,s} = gen_{t,s} - G_{t,s}^{SC} - \bar{G}_{t,s} \quad (21)$$

$$0 \leq \bar{G}_{t,s} \leq gen_{t,s} \quad (22)$$

$$0 \leq \epsilon_{t,s}^{k} \qquad \forall k \in \{+, -\} \quad (23)$$

$$\epsilon_{t,s} = \epsilon_{t,s}^{+} - \epsilon_{t,s}^{-} \quad (24)$$

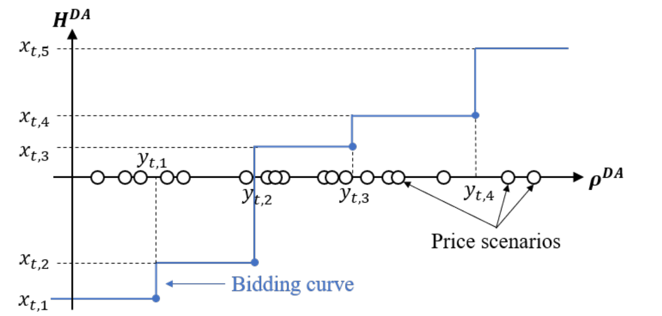

Fig. 1: Bidding curve illustration for hour t highlighting the role of price points in the grouping of scenarios.

While market rules vary, the following constraints reflect universal market principles to be satisfied at every time $t \in \mathcal{T}$:

$$H_{t,s}^{DA} = x_{t,b} \ \text{ if } \ y_{t,b-1} < \rho_{t,s}^{DA} \leq y_{t,b} \qquad \forall s \in \mathcal{S} \quad (25)$$

$$x_{t,b} \leq x_{t,b+1} \qquad \forall b = 1, \ldots, N_B - 1 \quad (26)$$

$$\max\{-\psi E_t^{cha,max}, -poi\} \leq H_{t,s}^{DA} \leq \min\{E_t^{dis,max} + G_t^{max}, poi\} \quad \forall s \in \mathcal{S} \quad (27)$$

$$-\Lambda G_{t,s}^{DA} \leq G_{t,s}^{IN} \leq \Lambda G_{t,s}^{DA} \qquad \forall s \in \mathcal{S} \quad (28)$$

$$-\Lambda E_t^{cha,max} \leq E_{t,s}^{IN} \leq \Lambda E_t^{dis,max} \qquad \forall s \in \mathcal{S} \quad (29)$$

Constraint (25) ensures scenarios are assigned to a bid curve segment based on their day-ahead price for that time. The *if* statement in this constraint does *not* affect its linearity, because y_{tb} are parameters set in advance using the strategy in section II-C. Determining prices and volumes simultaneously would create a nonconvex decision problem [7]. The requirement that the bids be non-decreasing and non-anticipative is enforced by (26). The physical operating limits for the hybrid day-ahead bids are presented in (27), while constraints (28) and (29) limit the degree of participation in the intraday market. This may be enforced by a market operator to ensure that the bulk of transactions are settled in the day-ahead market, or it could be imposed by the hybrid operator to limit exposure to the more volatile intraday market in a coarse way.

The final two constraints help to calculate the CVaR:

$$0 \leq \phi_s \quad \text{and} \quad \theta - \phi_s - profit_s \leq 0 \qquad \forall s \in \mathcal{S}. \quad (30)$$

C. Selecting Price Points Based on Jenks Natural Breaks

The above model selects the optimal volume components of price-volume bidding pairs based on their coupled price point parameters, $\{y_{t,b}\}_{t \in \mathcal{T}, b \in \mathcal{B}}$. As described in Fig. 1 and constraint (25), these price points partition the scenarios, such that all scenarios within a partition class plan the same hybrid power output. Price points for each time t are selected before solving the problem in Section II-B – they are input parameters to the model – through the following three-phase process that utilizes the day-ahead price scenarios:

1) **Partition Phase:** Using Jenks natural breaks algorithm ("Jenks") [13], partition the day-ahead price scenarios $\{\rho_{t,s}^{DA}\}_{s \in \mathcal{S}}$ into classes $\{P_{t,b}\}_{b \in \mathcal{B} = \{1,\ldots,N_B\}}$, that are ordered for every $t \in \mathcal{T}$ in the sense that,

$$\bar{P}_{t,b} := \max_{\rho \in P_{t,b}} \rho < \min_{\rho \in P_{t,b+1}} \rho := \underline{P}_{t,b+1}, \ \forall b \in \mathcal{B} \setminus N_B. \quad (31)$$

Jenks minimizes the within-class variation so that the price scenarios forced to share a common bid quantity via constraint (25) are as similar as possible.

2) **Adjustment Phase:** There is a critical difference between prices above and below the generator's operating cost. If prices are above O_t^G, the VRE will rarely be curtailed. If prices are below O_t^G, curtailment may occur if it is not possible or profitable to charge the ESR. This phase adjusts the Jenks partition, if necessary, to ensure prices within the same class are uniformly above or below O_t^G.

3) **Selection Phase:** Select prices $y_{t,b}$ that divide the classes, i.e., that satisfy the following inequalities for every $t \in \mathcal{T}$:

$$y_{t,0} < \underline{P}_{t,1} \text{ and } \bar{P}_{t,b} \leq y_{t,b} < \underline{P}_{t,b+1}, \ \forall b \in \mathcal{B} \setminus N_B. \quad (32)$$

Specifically, we set the price points equidistant between adjacent classes, except when dividing the class immediately above O_t^G from the one immediately below it.

$$y_{t,b} = \begin{cases} \underline{P}_{t,1} & b = 0 \\ \bar{P}_{t,N_B} & b = N_B \\ O_t^G & \bar{P}_{t,b} < O_t^G \leq \underline{P}_{t,b+1} \text{ and } b \geq 1 \\ (\bar{P}_{t,b} + \underline{P}_{t,b+1})/2 & \text{otherwise} \end{cases} \quad (33)$$

III. Simulating Hybrid Bids Within a Future Electricity Market: A Case Study

Obtaining bids from the stochastic optimization model in section II for use in a PCM requires the development of scenarios and choice of model hyperparameters. This section presents a case study in setting key model inputs while discussing various trade-offs, focusing on a hypothetical wind-battery hybrid located in Zone E of the New York Independent System Operator (NYISO) footprint. The hybrid's ESR has power capacity equal to 50% of the VRE's and a duration of 4 hours. The approach is designed to reflect the accuracy of information typically available to a market participant, even if we, as researchers implementing the PCM, have additional knowledge. Further, the approach aims to consistently produce bids which perform well and are not overly sensitive to small changes in the model inputs.

A. Generation Scenarios (gen)

Generation potential scenarios are constructed to reflect the range of plausible generation levels and their relative likelihood. In this case study, the researcher has the maximum generation levels which will be used in the PCM and day-ahead forecasts of these values for one year. The bidder is allowed access to the day-ahead forecast for the optimization horizon (periods $t = 1, 2, \ldots, N_T$) and the empirical distribution of forecasts and forecast errors for two consecutive periods for the full data set. Scenarios are constructed sequentially around the day-ahead forecast by uniformly sampling from the

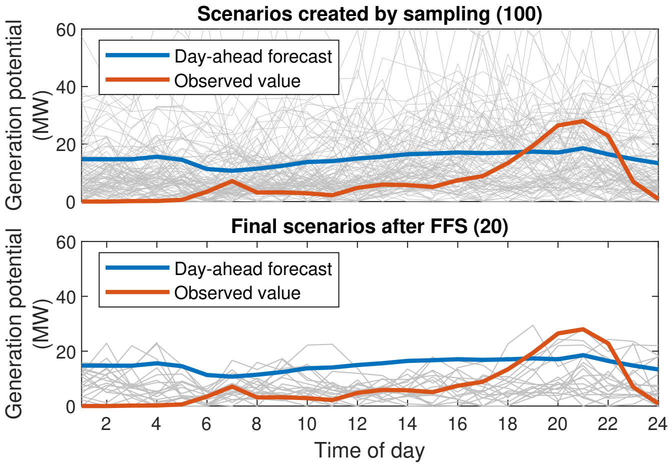

Fig. 2: Created and selected generation scenarios (grey) compared with the day-ahead generation forecast (blue line) and the realized generation level (orange line).

empirical distribution of errors in periods with similar forecast values and similar error values in the preceding period.

It is straight-forward to create a large number of equally likely generation scenarios using this Monte Carlo approach. However, the optimization problem in section II will be computationally challenging if the number of scenarios is too large. The Fast Forward Selection (FFS) algorithm [14] is employed to perform scenario reduction. FFS is considered the "state-of-the-art" [15] and has been used in past research on energy storage bidding [16]. In this case study, the set of sampled scenarios and the day-ahead forecast were assigned probabilities of 0.2 and 0.8, respectively, based on experiments testing the relative accuracy of each. An example set of scenarios created with this procedure is shown in Fig. 2. Observe that, while there are wide-ranging values within the set of sampled scenarios at every hour, the scenarios which best represent this set (as determined by FFS) are similar to both the day-ahead forecast and the observed wind power.

B. Price scenarios (ρ^{DA}, ρ^{IN}, η^{+}, η^{-})

As discussed in the introduction, the absence of historical price data when simulating future markets is a key challenge. This section provides a methodology for creating price scenarios to inform hybrid bidding decisions from simulation results for a similar system and published electricity price forecasting metrics. The researcher has access to simulated day-ahead market prices for a system which is identical, other than that the hybrids are managed directly by the system operator (i.e., the hybrids do not submit bids) in a 2R participation model. Conducting these simulations does not require price forecasts. The resulting "2R prices" are available for the optimization horizon ($t=1, 2, \ldots, N_T$) and at least a few weeks prior.

Instead of using the day's 2R price profile directly in the bidding problem, a set of plausible scenarios is built around it. Scenarios are initialized as the price profiles of recent days – distinguishing between weekdays and weekends – then incrementally improved until they are representative of forecasts that a state-of-the-art price forecasting method could produce, with the 2R profile treated as the ground truth. State-of-the-art was defined as a 5% mean value of weekly-weighted mean absolute errors (WMAE), informed by the research in [17] and [18]. Fig. 3 provides an example of the final day-ahead price scenarios compared with the initial scenarios. This approach relies on assumptions that market prices will be similar under both participation models and that forecasting methods will have similar accuracy in future systems.

Only a day-ahead market was simulated, so $\Lambda = 0$ and $\rho^{IN}_{t,s} = 0$, for all $t \in \mathcal{T}$, $s \in \mathcal{S}$. Deviation price ratios of $\eta^{+}_{t,s} = 0.5$ and $\eta^{-}_{t,s} = 1.5$ for all $t \in \mathcal{T}$, $s \in \mathcal{S}$ were designed to generally limit deviations from the hybrid's scheduled output.

C. Combined Scenarios

A symmetric scenario tree was created to pair each generation scenario with each day-ahead price scenario. Since the day-ahead price scenarios are deemed equally likely, $\{\pi_s\}_{s\in\mathcal{S}}$ are proportional to the generation scenario probabilities.

D. Hyperparameters

This section will discuss the design of two key parameters:
1) Time horizon: $N_T = 48$ was chosen to provide a one-day look-ahead period in order to have a more complete view of ESR opportunity costs, particularly for hours late in the day. Hybrids with longer duration storage would benefit from modeling longer time horizons.
2) Number of generation scenarios: The number of scenarios, N_{FFS}, selected using FFS is a trade-off between bidding problem computation and the resulting strategy's robustness to generation uncertainty. We used $N_{FSS} = 20$ based on the analysis in Fig. 4 and a desire to typically be within 10-20% of bids based on 200 generation scenarios.

E. Resulting Bids

Solving the bidding problem in section II for the inputs developed in sections III-A, III-B and III-D, along with many parameters specific to the plant's technology and configuration, produces the bids in Fig. 5. The model was implemented in MATLAB and solved in, on average, 45 seconds using

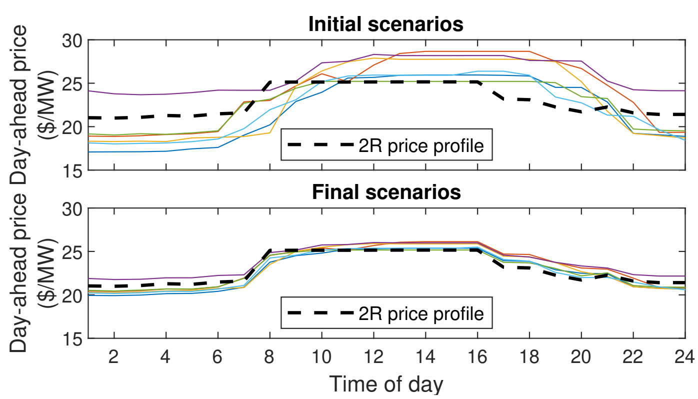

Fig. 3: The initial day-ahead price scenarios are improved until they, along with scenarios for each day of the month, correspond to a mean WMAE of 4.95%.

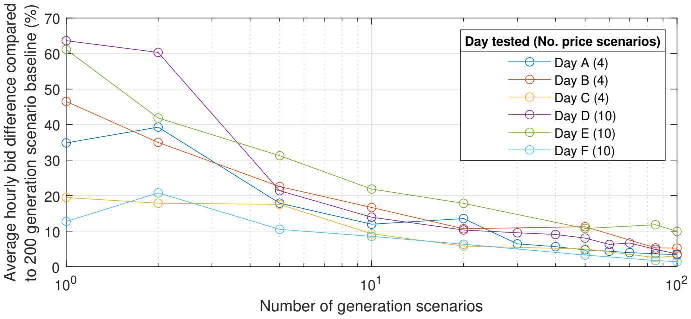

Fig. 4: Experimental results for 6 days comparing bid curves based on 1-100 generation scenarios to those based on 200 generation scenarios. Average hourly bid difference $:= \sum_{t=1}^{N_T} \|x_t^{(k)} - x_t^{(200)}\|_2 / \sum_{t=1}^{N_T} \|x_t^{(200)}\|_2$, where (k) indicates that the bid is based on k generation scenarios.

MATLAB's mixed-integer linear programming solver from its "optimization toolbox" and 24 seconds using Gurobi on a personal computer (for $|\mathcal{S}| = 200$). In most hours, including 1 and 16, bids take a self-schedule structure, that is, $x_{t,1} = x_{t,2} = \cdots = x_{t,5}$. The narrow range of price scenarios and the symmetric pairing of price and generation scenarios contribute to this outcome. However, in hours 11 and 13 the model does result in elastic bids with two distinct segments. If generation and price scenarios were correlated or price scenarios had more variation within each hour or across hours, we would expect to see the optimal solution make use of the available flexibility. The largest bids appear in the hours with the highest-priced scenarios, and the bids to charge from the grid occur at the start of the day when prices are lowest, as expected.

F. Heuristic to Add Elasticity for High- and Low-price Events

The advantage of bidding curves over self-scheduled bids is the ability to be dispatched differently if prices are higher or lower than expectations. The day-ahead price scenarios developed in section III-B allow for elasticity over a range of probable prices. However, prices may spike outside of this scenario range in ways that are difficult to predict, and the hybrid operator wants to capitalize on unexpectedly high and low prices. Thus we designed a heuristic which extends the

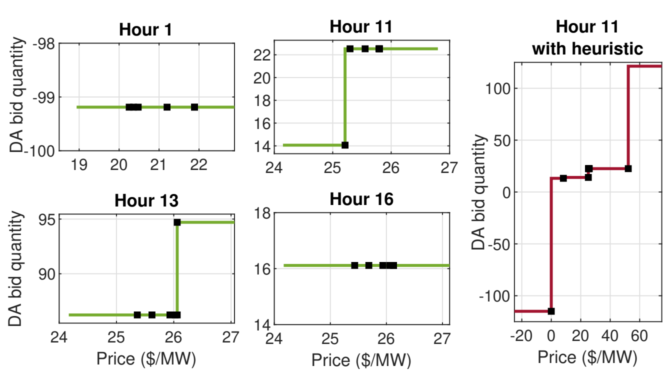

Fig. 5: Case study results for select hours: Black squares indicate (y, x) points, which together imply the depicted curve.

bids created by the section II-B model to offer more power when prices are exceptionally high and offer to charge the ESR when prices are exceptionally low, while reflecting the generator's cost of operation. The heuristic is demonstrated in Fig. 5; details are available in [6].

IV. Conclusion

As shown in the case study results, the proposed methods are able to generate bids which can be cleared centrally by a system operator, or by a PCM serving in that role. The bids are applicable not only if market prices are within the anticipated range, but also in the event of a price spike or dip. These methods can be used to represent the perspective and actions of hybrids and ESRs in models of future systems.

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