

# Bidding stochastic demand for ancillary services: the P90 rule

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## Equations

Sets:

- $\mathcal{H} = \{1, 2, \dots, 24\}$
- $\mathcal{M} = \{1, 2, \dots, 1440\}$
- $\mathcal{M}_h = \{h \times 60 + m \mid m \in \{0, 1, 2, \dots, 59\}\}$
- $\mathcal{I} = \{1, 2, \dots, \text{Number of samples}\}$

Definitions:

**Definition 1** (Energinet's P90 rule [2]). *This means, that the participant's prognosis, which must be approved by Energinet, evaluates that the probability is 10% that the sold capacity is not available. This entails that there is a 90% chance that the sold capacity or more is available. This is when the prognosis is assumed to be correct.*

*The probability is then also 10%, that the entire sold capacity is not available. If this were to happen, it does not entail that the sold capacity is not available at all, however just that a part of the total capacity is not available. The available part will with high probability be close to the sold capacity.*

Simple optimization problem where bids,  $p_h^{\text{cap}}$ , must adhere to uncertain available flexibility,  $P_m^{\text{B}}(\xi)$ .

$$\max_{p_h^{\text{cap}}} \sum_h \lambda_h p_h^{\text{cap}} \quad (1a)$$

$$\text{s.t. } \mathbb{P}(p_h^{\text{cap}} \leq P_m^{\text{B}}(\xi), \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}) \geq 1 - \epsilon \quad (1b)$$

## DRJCC

Converting (1) to DRJCC for distributions within some ambiguity set defined by Wasserstein distance  $\theta$ :

$$\max_{p_h^{\text{cap}}} \sum_h \lambda_h p_h^{\text{cap}} \quad (2a)$$

$$\text{s.t. } \mathbb{P}(p_h^{\text{cap}} \leq P_m^{\text{B}}(\xi), \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}) \geq 1 - \epsilon \quad \forall \mathbb{P} \in \mathcal{F}(\theta) \quad (2b)$$

A tractable formulation of (2) is given by [1, Proposition 2]:

$$\max_{p_h^{\text{cap}}, q_i, s_i \geq 0, t} \sum_h \lambda_h p_h^{\text{cap}} \quad (3a)$$

$$\text{s.t.} \quad \epsilon |\mathcal{I}| t - \sum_{i \in \mathcal{I}} s_i \geq \theta |\mathcal{I}| \quad (3b)$$

$$P_m^{\text{B}}(\xi_i) - p_h^{\text{cap}} + M \cdot q_i \geq t - s_i, \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}, \forall i \in \mathcal{I} \quad (3c)$$

$$M(1 - q_i) \geq t - s_i \quad (3d)$$

$$q_i \in \{0, 1\}, \quad \forall i \in \mathcal{I} \quad (3e)$$

Let the set of flexible demands be denoted by  $d \in \{\mathcal{D}\}$ . Then TSO profit is described by the following bi-level problem:

$$\max_{\epsilon, \theta} \sum_h \lambda_h p_{h,d}^{\text{cap}} - \sum_h \sum_d \frac{1}{|\mathcal{I}|} \sum_i \nu_{h,i,d} \quad (4a)$$

$$\text{s.t.} \quad \text{Problem (3)}, \quad \forall d \quad (4b)$$

$$\nu_{h,i,d} = \left( p_{h,d}^{\text{cap}} - P_m^{\text{B}}(\xi_i) \right)^+, \quad \forall i, \forall h, \forall d \quad (4c)$$

## ALSO-X

Inspired by [3, 4], the reformulation of (1) is:

$$\max_{p_h^{\text{cap}}, y_{m,i}} \sum_h \lambda_h p_h^{\text{cap}} \quad (5)$$

$$\text{s.t.} \quad -(1 - y_{m,i})M \leq p_h^{\text{cap}} - P_m^{\text{B}}(\xi_i) \leq y_{m,i}M, \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}, \forall i \in \mathcal{I} \quad (6)$$

$$\sum_{i \in \mathcal{I}, m \in \mathcal{H}} y_{m,i} \leq q \quad (7)$$

$$y_{m,i} \in \{0, 1\}, \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}, \forall i \in \mathcal{I} \quad (8)$$

Here,  $q = \lfloor \epsilon \cdot |\mathcal{I}| \cdot |\mathcal{M}| \rfloor$  and  $y_{m,i}$  is a binary variable indicating an overbid in minute  $m$  and sample  $i$ . The ALSO-X algorithm as listed in Algorithm 1 iteratively conducts an exponential search for the best value of  $q$  such that the frequency of violations is less than  $\epsilon$  by solving a relaxed version of (5) with respect to  $y_{m,i}$ . Thus, ALSO-X does not consider the magnitude of violation - as opposed to CVaR - but only the frequency of violations. It is therefore expected that ALSO-X is less conservative than CVaR which was also the motivation behind its incarnation [3].

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**Algorithm 1** ALSO-X

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**Require:** Relax the integrality of  $y$  Input: Stopping tolerance parameter  $\delta$

- 1:  $q \leftarrow 0, \bar{q} \leftarrow \lceil -\epsilon \rceil$
  - 2: **while**  $q \neq \bar{q}$  **do**
  - 3:   Set  $q_a \leftarrow (q + \bar{q})/2$  and retrieve  $\Theta^*$  as an optimal solution to (4).
  - 4:   Set  $q \leftarrow q_a$  if  $P(y^* = 0) \geq 1 - \epsilon$ ; otherwise,  $\bar{q} \leftarrow q$
  - 5: **end while** Output: A feasible solution of model (5).
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## CVaR

First, let  $\mathcal{I}$  denote the number of samples for the empirical distribution. The CVaR formulation of the JCC in (1) is then [3]:

$$\max_{p_h^{\text{cap}}, \beta \geq 0, \zeta_{m,i}} \sum_h \lambda_h p_h^{\text{cap}} \quad (9)$$

$$\text{s.t. } p_h^{\text{cap}} - P_m^{\text{B}}(\xi_i) \leq \zeta_{m,i}, \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}, \forall i \in \mathcal{I} \quad (10)$$

$$\frac{1}{|\mathcal{M}| \cdot |\mathcal{I}|} \sum_{i \in \mathcal{I}, m \in \mathcal{H}} \zeta_{m,i} - (1 - \epsilon) \cdot \beta \leq 0 \quad (11)$$

$$\beta \leq \zeta_{m,i}, \quad \forall m \in \mathcal{M}_h, \forall h \in \mathcal{H}, \forall i \in \mathcal{I} \quad (12)$$

The CVaR approximation in (9) is a simple LP. The JCC is now approximated such that expected value of the  $\epsilon$  worst samples and minutes is attenuated.

# Bibliography

- [1] Zhi Chen, Daniel Kuhn, and Wolfram Wiesemann. “Data-driven chance constrained programs over Wasserstein balls”. In: *Operations Research* (2022).
- [2] “Energinet: Prequalification and Test”. In: *Energinet* (2023). Accessed: 2023-11-24. URL: <https://en.energinet.dk/electricity/ancillary-services/prequalification-and-test/>.
- [3] Nan Jiang and Weijun Xie. “ALSO-X and ALSO-X+: Better convex approximations for chance constrained programs”. In: *Operations Research* 70.6 (2022), pp. 3581–3600.
- [4] Álvaro Porras et al. “Integrating Automatic and Manual Reserves in Optimal Power Flow via Chance Constraints”. In: *arXiv preprint arXiv:2303.05412* (2023).