Day-ahead decision making in electricity markets

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- 1. Introductory example from the French non-interconnected zones (NIZ)
- 2. Resolution methods
- 3. Numerical results from the French NIZ example
- 4. Conclusion and Perspectives

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1. Introductory example from the French non-interconnected zones (NIZ)

Rules for solar plant management in the French NIZ

Optimization problem formulation

Market rules for solar plants in the French NIZ

 We operate a solar plant over one day with discrete time steps t ∈ {0, 1, ..., T}



- For every operating day
 - In the day-ahead stage, producers must supply a power production profile $p \in \mathbb{R}^{T}$
 - In the intraday stage, producers manage the power plant and deliver a power profile d ∈ ℝ^T

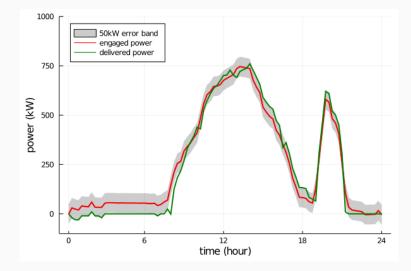
During the **intraday** stage, the **delivered power** *d* is compared with the **engaged power** *p* to compute the stage cost

$$C_t(d_t, \mathbf{p_t}) = \underbrace{-c_t \Delta_t d_t}_{\text{reward}} + \underbrace{C_t^{\mathsf{p}}(d_t, \mathbf{p_t})}_{\text{penalty}}$$

where

$$C_t^{\mathbf{p}}(d_t, \mathbf{p}_t) = \begin{cases} c_t \Delta_t \left[\frac{\left(d_t - \underline{d}(\mathbf{p}_t) \right)^2}{\overline{p}} - 0.2 \left(d_t - \underline{d}(\mathbf{p}_t) \right) \right], & \text{if } d_t < \underline{d}(\mathbf{p}_t) \\ 0, & \text{if } \underline{d}(\mathbf{p}_t) \le d_t \le \overline{d}(\mathbf{p}_t) \\ c_t \Delta_t \mathbf{p}_t, & \text{if } \overline{d}(\mathbf{p}_t) < d_t \end{cases}$$

Engaged power vs delivered power

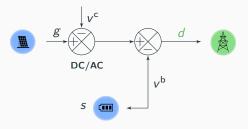


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Rules for solar plant management in the French NIZ

Optimization problem formulation

Schematic organization of the solar plant



- $s \in [0, \overline{s}]^{T+1}$ state of charge (state)
- $g \in [0, \overline{p}]^T$ generated power (uncertainty)
- $v^{c} \in [0,g]^{T}$ curtailed power (control)
- $v^{\mathsf{b}} \in [\underline{v}, \overline{v}]^{\mathcal{T}}$ battery power (control)
- $d = g v_b v_c$ delivered power

Stochastic optimal control framework

• We introduce the the state, control and noise variables

$$x = \begin{pmatrix} s \\ g \end{pmatrix}$$
, $u = \begin{pmatrix} v^{b} \\ v^{c} \end{pmatrix}$, $w = \epsilon$

 $\bullet\,$ The state process ${\bf X}$ is ruled by the dynamics

$$\mathbf{X}_{t+1} = f_t(\mathbf{X}_t, \mathbf{U}_t, \mathbf{W}_{t+1}) = \begin{pmatrix} \mathbf{S}_t + \rho_c \mathbf{V}_t^{\mathbf{b}^+} - \frac{1}{\rho_d} \mathbf{V}_t^{\mathbf{b}^-} \\ \alpha_t \mathbf{G}_t + \beta_t + \epsilon_{t+1} \end{pmatrix}$$

• The stage costs formulate as

$$L_t(\mathbf{X}_t, \mathbf{U}_t, \mathbf{W}_{t+1}, \mathbf{p}_t) = C_t(\mathbf{G}_{t+1} - \mathbf{V}_t^{\mathsf{b}} - \mathbf{V}_{t+1}^{\mathsf{c}}, \mathbf{p}_t)$$

Minimizing the **intraday** operating cost formulates as a **multistage stochastic optimization problem** parametrized by *p*

$$\min_{\mathbf{U}_{0},...,\mathbf{U}_{T-1}} \mathbb{E} \Big[\sum_{t=0}^{T-1} L_{t}(\mathbf{X}_{t}, \mathbf{U}_{t}, \mathbf{W}_{t+1}, \mathbf{p}_{t}) + \mathcal{K}(\mathbf{X}_{T}, \mathbf{p}_{T}) \Big]$$
$$\mathbf{X}_{0} = x_{0}$$
$$\mathbf{X}_{t+1} = f_{t}(\mathbf{X}_{t}, \mathbf{U}_{t}, \mathbf{W}_{t+1}), \quad \forall t \in \{0, ..., T-1\}$$
$$\mathbf{U}_{t} \in \mathcal{U}_{t}(\mathbf{X}_{t}, \mathbf{p}_{t}), \quad \forall t \in \{0, ..., T-1\}$$
$$\sigma(\mathbf{U}_{t}) \subseteq \sigma(\mathbf{W}_{1}, ..., \mathbf{W}_{t}), \quad \forall t \in \{0, ..., T-1\}$$

Coupled day-ahead and intraday problem

The optimal management of the solar plant over one operating day formulates as

 $\begin{array}{c} \underset{\boldsymbol{p}\in\mathcal{P}}{\text{intra-day value } \Phi(\boldsymbol{p})} \\ \hline \\ \overbrace{\boldsymbol{u}_{0},\ldots,\boldsymbol{U}_{T-1}}^{\text{min}} \mathbb{E}\Big[\sum_{t=0}^{T-1} L_{t}(\boldsymbol{X}_{t},\boldsymbol{U}_{t},\boldsymbol{W}_{t+1},\boldsymbol{p}_{t}) + \mathcal{K}(\boldsymbol{X}_{T},\boldsymbol{p}_{T})\Big] \\ \\ \boldsymbol{X}_{0} = x_{0} \\ \boldsymbol{X}_{t+1} = f_{t}(\boldsymbol{X}_{t},\boldsymbol{U}_{t},\boldsymbol{W}_{t+1}), \quad \forall t \in \{0,\ldots,T-1\} \\ \\ \boldsymbol{U}_{t} \in \mathcal{U}_{t}(\boldsymbol{X}_{t},\boldsymbol{p}_{t}), \quad \forall t \in \{0,\ldots,T-1\} \\ \\ \sigma(\boldsymbol{U}_{t}) \subseteq \sigma(\boldsymbol{W}_{1},\ldots,\boldsymbol{W}_{t}), \quad \forall t \in \{0,\ldots,T-1\} \end{array}$

1. Introductory example from the French non-interconnected zones (NIZ)

2. Resolution methods

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For $p \in \mathcal{P}$ we may compute by **dynamic programming**

$$\Phi(\mathbf{p}) = V_0(x_0, \mathbf{p})$$

where for $t \in \{0, ..., T\}$ and $x \in X_t$ we define the **parametric value functions**

$$V_{T}(x, \mathbf{p}) = \mathcal{K}(x, \mathbf{p})$$
$$V_{t}(x, \mathbf{p}) = \min_{u \in \mathcal{U}_{t}(x, \mathbf{p}_{t})} \mathbb{E} \Big[L_{t}(x, u, \mathbf{W}_{t+1}, \mathbf{p}_{t}) + V_{t+1} \big(f_{t}(x, u, \mathbf{W}_{t+1}), \mathbf{p} \big) \Big]$$

Descent method for the day-ahead problem

- We consider applications where the value function Φ and the constraint set P are convex
- We want to apply a first order descent algorithm

Projected (sub)gradient algorithm

input: $p^0 \in \mathcal{P}, \{\alpha_k\}_{k=1...K} \in \mathbb{R}_+^K$ for k = 1...K do compute y^k as a (sub)gradient of Φ at p^k update $p^{k+1} = \prod_{\mathcal{P}} (p^k - \alpha^k y^k)$ end output: p^K

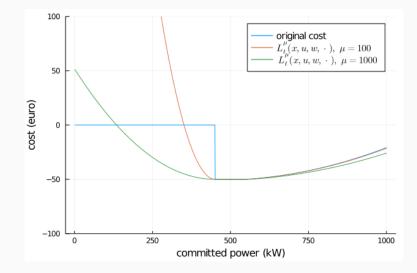
how do we compute a (sub)gradient of Φ at p^k ??

2. Resolution methods

Lower smooth approximations

Lower polyhedral approximations

Smoothing the cost function with the Moreau envelope



When the value functions are **convex** and **differentiable** with respect to p we compute the gradient $\nabla_p \Phi(p^k)$ where for $t \in \{0, ..., T\}$ and $x \in \mathbb{X}_t$

$$u^* \in \underset{u \in \mathcal{U}_t(x)}{\operatorname{arg min}} \mathbb{E} \Big[L_t^{\mu}(x, u, \mathbf{W}_{t+1}, \boldsymbol{p}_t^k) + V_{t+1} \big(f_t(x, u, \mathbf{W}_{t+1}), \boldsymbol{p}^k \big) \Big]$$
$$\nabla_{\boldsymbol{p}} V_t(x, \boldsymbol{p}^k) = \mathbb{E} \Big[\nabla_{\boldsymbol{p}} L_t^{\mu}(x, u^*, \mathbf{W}_{t+1}, \boldsymbol{p}_t^k) + \nabla_{\boldsymbol{p}} V_{t+1} \big(f_t(x, u^*, \mathbf{W}_{t+1}), \boldsymbol{p}^k \big) \Big]$$

2. Resolution methods

Lower smooth approximations

Lower polyhedral approximations

When the value functions are **convex** and **non-differentiable** with respect to p we apply the SDDP algorithm to obtain **polyhedral lower apporximations**

- After each **forward-bakward** iteration $n \in \{1, ..., N\}$ we add a new cut $\langle \cdot, \alpha_t^n \rangle + \beta_t^n$
- Under convexity assumptions we have convergence guarantees of the polyhedral approximate

$$\underline{V}_{t}^{N}(x, \boldsymbol{p}^{k}) = \max_{1 \leq n \leq N} \left(\left\langle \left(x, \boldsymbol{p}^{k} \right), \alpha_{t}^{n} \right\rangle + \beta_{t}^{n} \right) \leq V_{t}(x, \boldsymbol{p}^{k})$$

We can evaluate an approximate subgardient of $\partial \Phi(p^k)$ by taking $y^k \in \partial \underline{V}_0^N(x, p^k)$ as a **dual variable** of the constrained problem

$$\min_{x,p} \quad \underline{V}_0^N(x, p^k)$$

s.t. $p = p^k \quad [y^k]$

Since $\underline{V}_0^N(x, p^k)$ is polyhedral the above problem is a LP

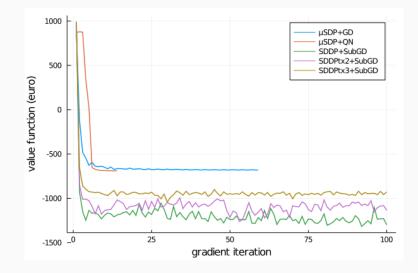
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3. Numerical results from the French NIZ example

Numerical results for a single day

Numerical results for one year

Numerical results of the day-ahead optimization $\min_{\mathbf{p}\in\mathcal{P}} \Phi(\mathbf{p})$



	Steps	Avg. time / (sub)gradient	Avg. time / iteration	Avg. number of cuts /
		call (seconds)	(seconds)	iteration
μ SDP+GD	35	2.55	2.71	-
μ SDP+QN	12	2.55	10.17	-
SDDP+SubGD	100	2.55	2.68	17
$SDDPt \times 2+SubGD$	100	5.10	5.23	37
$SDDPt \times 3+SubGD$	100	7.65	8.02	55

3. Numerical results from the French NIZ example

Numerical results for a single day

Numerical results for one year

Intraday simulation: experimental context

- We use PV forecast and observed data from Schneider Electric's EMSx dataset
- We use 1 year of data for calibration
- We another 1 year of data for simulation
- We simulate the management of 365 consecutive days
- We apply the French ZNI market rules **but** we do not consider intraday profile re-submission

We consider two methods

- Stochastic method based on μ SDP+QN
 - **day-ahead** : we use our gradient method with a smoothing of the cost to compute daily profiles
 - intraday : we perform intraday simulation with Stochastic Dynamic Programming

• Deterministic method based on MPC

- **day-ahead** : we use forecasts and a deterministic MIQP solver to compute daily profiles
- intraday : we perform intraday simulation with Model Predictive Control

Method	Total yearly gain (\in)
Deterministic (MPC)	560 410
Stochastic (µSDP+QN)	611 681

Our stochastic method gives 8% of gain versus a deterministic one

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- Our approach gives promising results: 8% of gain on the (simplified) NIZ use case
- **Question 1** : how does it perform on the complete NIZ use case ?
- **Question 2** : extension of the method to other energy markets ?