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Energy management of a grid-connected photovoltaic plant coupled with a battery energy storage device using a robust approach

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Context

System

-> **PV+ energy storage system** connected to the **grid**

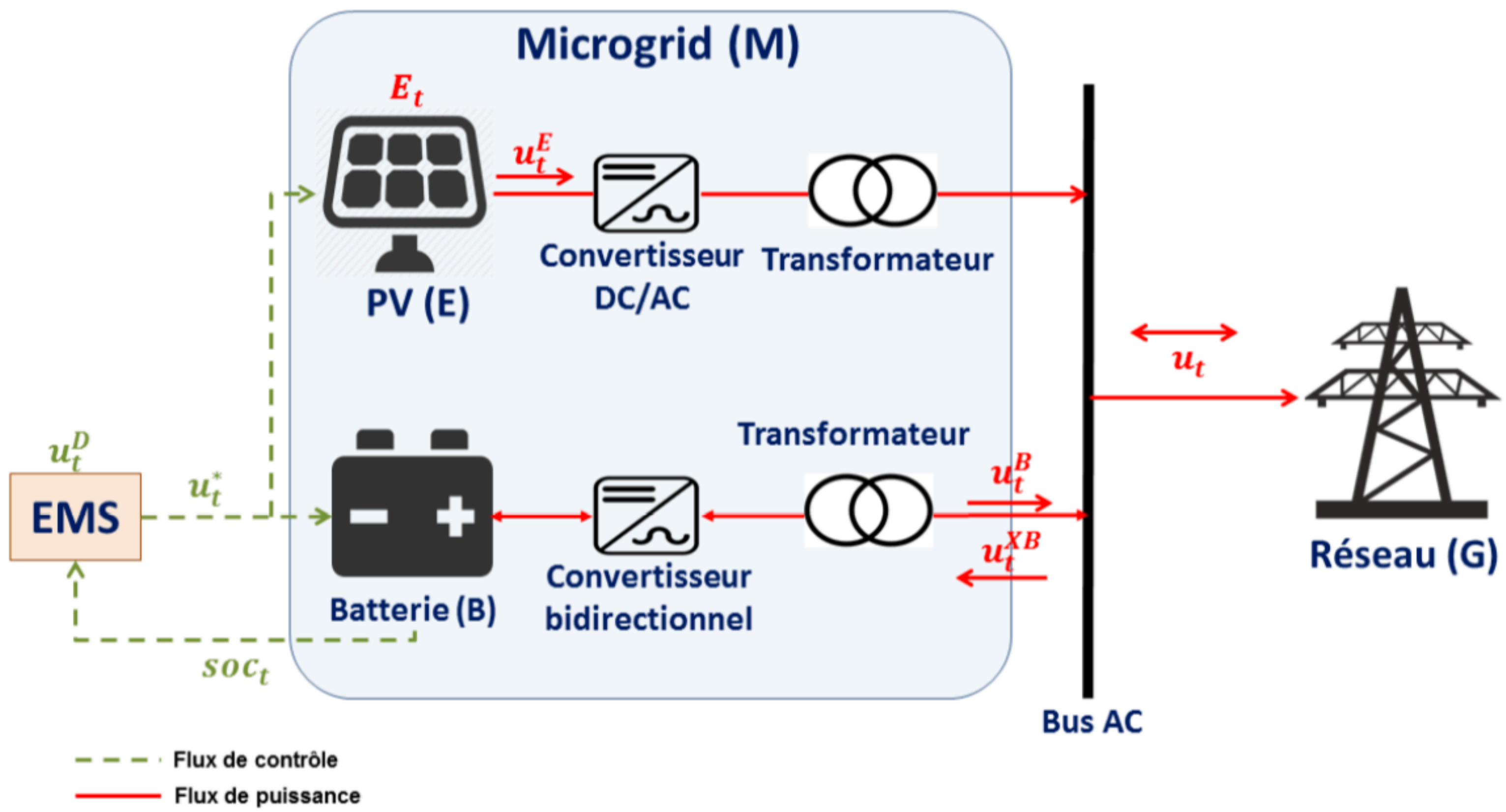

Figure 1: System = PV + battery connecte to the grid

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Context

Where ?

-> Remote areas: French islands (Réunion, Corse, Guadeloupe, etc)

Goal

-> The **intermittent power** from a PV/wind plant has to be **maintained at a committed level**.

How ?

-> The **energy storage system smoothes** the output and controls the ramp rate (MW/min).

Who ?

-> The French Energy Regulatory Commission defines the **specifications** of the tenders *https://www.cre.fr/*.

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Summary

1. Capacity firming vs day ahead market
2. Problem formulation
3. Case study
4. Conclusions & perspectives

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Day-ahead energy market

- producers **bid** (level & price) **before 12 am** (deadline) at D for D+1
- **1 pm at D** -> day ahead **prices** for D+1 are **cleared** based on the **uniform pricing principle ->** *the agents have the incentive to bid at their marginal cost*
- producers can **adjust bids** on the **intraday market** up to 15 min prior delivery

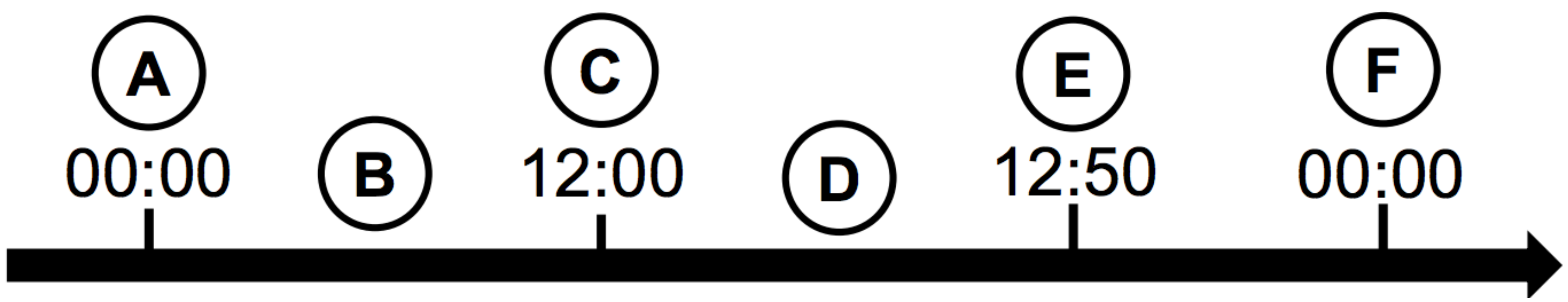

Figure 2: Day ahead market

A: opening day-ahead market
B: bid submissions
C: closing gate
D: market clearing-also is executed
E: notification of the market clearing outcomes
F: beginning of the delivery

Energy market lesson: Thibaut Théate Antoine Dubois Adrien Bolland
http://blogs.ulg.ac.be/damien-ernst/teaching/elec0018-1-energy-markets/
See also P. Pinson teaching: http://pierrepinson.com/index.php/teaching/

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Capacity firming energy market

- producers **bid** (level only !) **before 4 pm** (deadline) at D for D+1
- the **bidding** price is **known** ! With a peak price during peak hours (7-9pm)
- it is **not possible to adjust the bid on a intraday market** !!!
- **penalties** if deviation from the schedule

And, the engagement plan is accepted if it satisfies **the constraints**

$$|p_\tau^\star - p_{\tau-1}^\star| \leq \Delta_{p,\tau}^\star \quad (1a)$$

= Ramping power constraints

$$-p_\tau^\star \leq -P_\tau^{\star,-} \quad (1b)$$

$$p_\tau^\star \leq P_\tau^{\star,+}, \quad (1c)$$

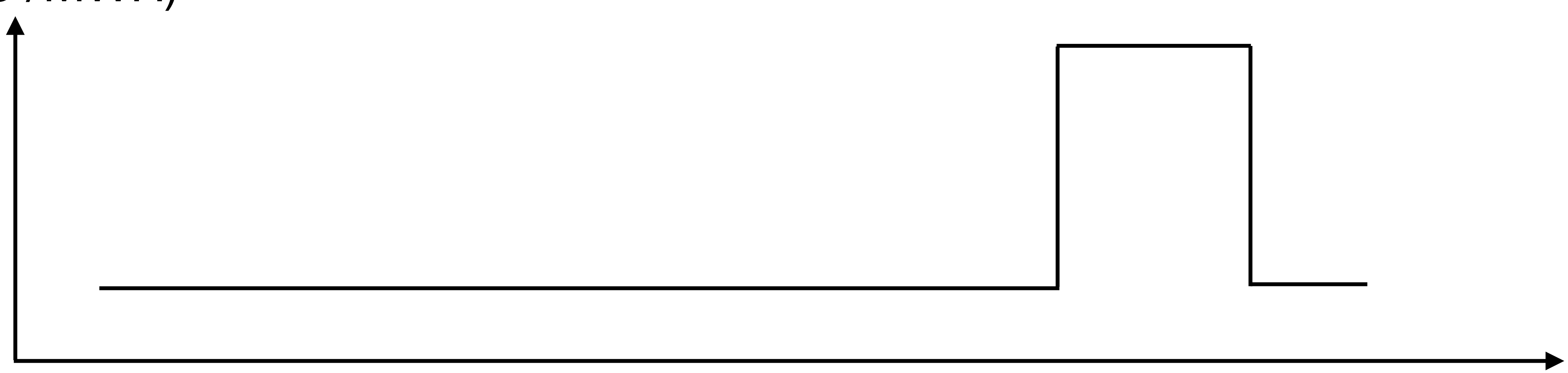

Figure 3: Selling price

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Penalty and revenue

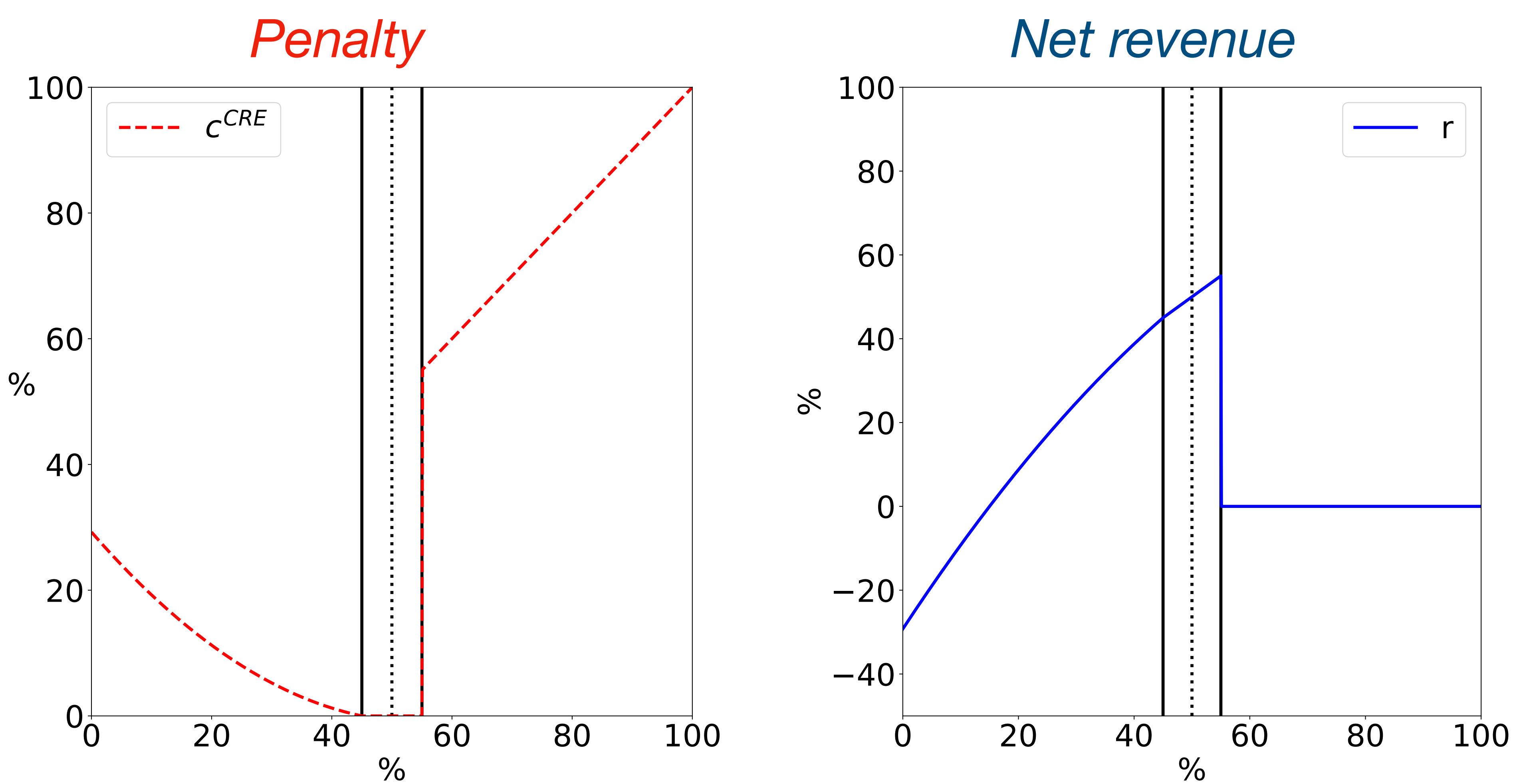

Figure 4: Penalty (left) and net revenue (right).
Engagement = 50 % of PV installed capacity, deadband tolerance = 5%.

Net revenue: $$r_t = \Delta_t \pi_t p_t^{\mathrm{m}} - \boxed{c(p_t^\star, p_t^{\mathrm{m}}),} \ \forall t \in \mathcal{P}. \qquad (2)$$

Penalty

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Capacity firming energy market

Two steps:

- **Day ahead**: compute the **optimal bid** taking into account PV uncertainty
- **Intraday**: **minimize deviation** from the bid

Use the battery (BESS) to:

- store energy to **export** during **peak hours** !!!
- deal with PV **uncertainty ….**

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Capacity firming energy market

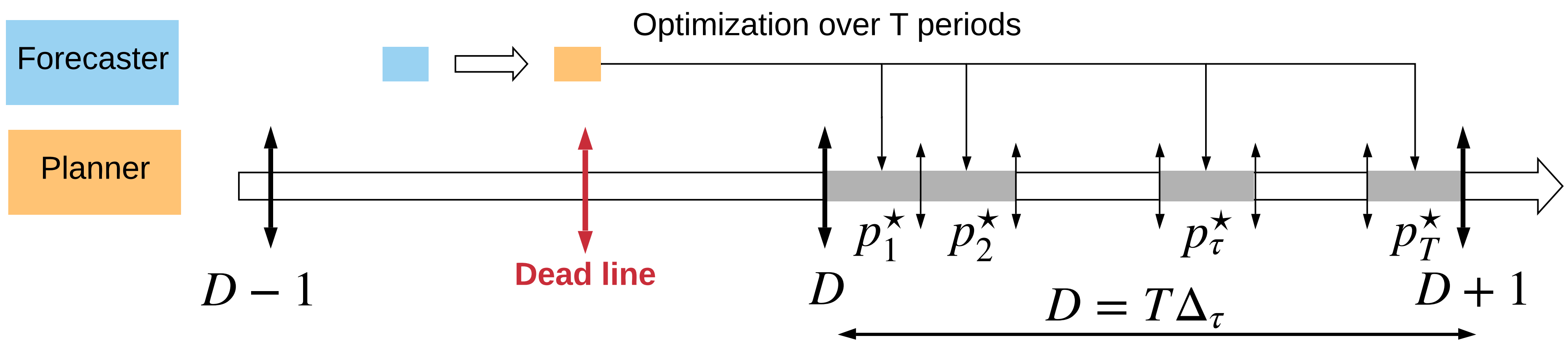

Figure 5: Day ahead bidding = STEP 1: compute the optimal bid

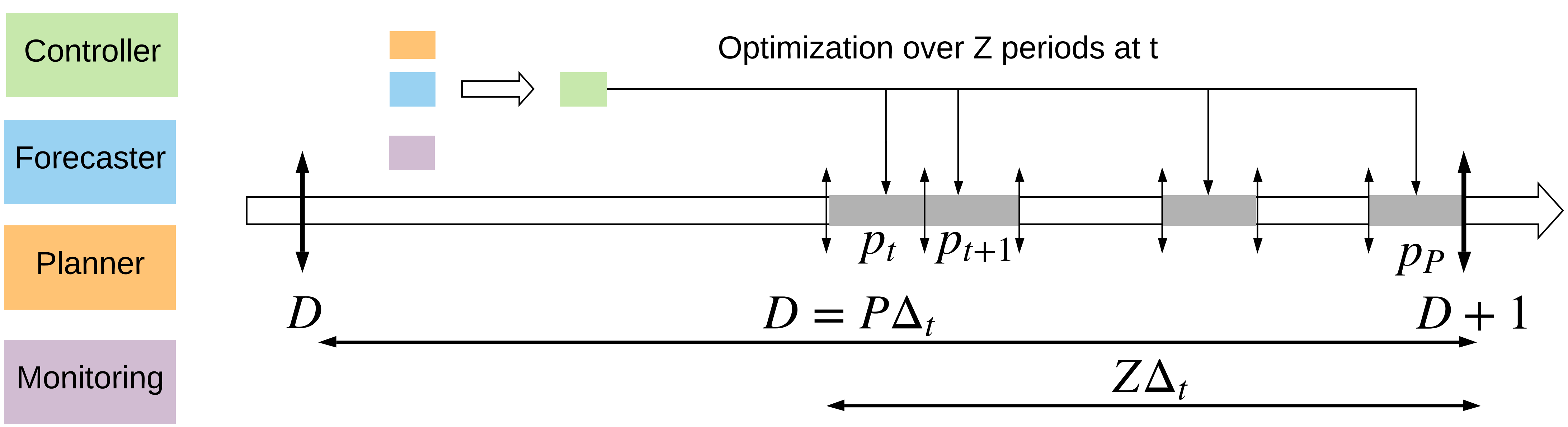

Figure 6: Intraday control = STEP 2: minimize deviation

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Summary

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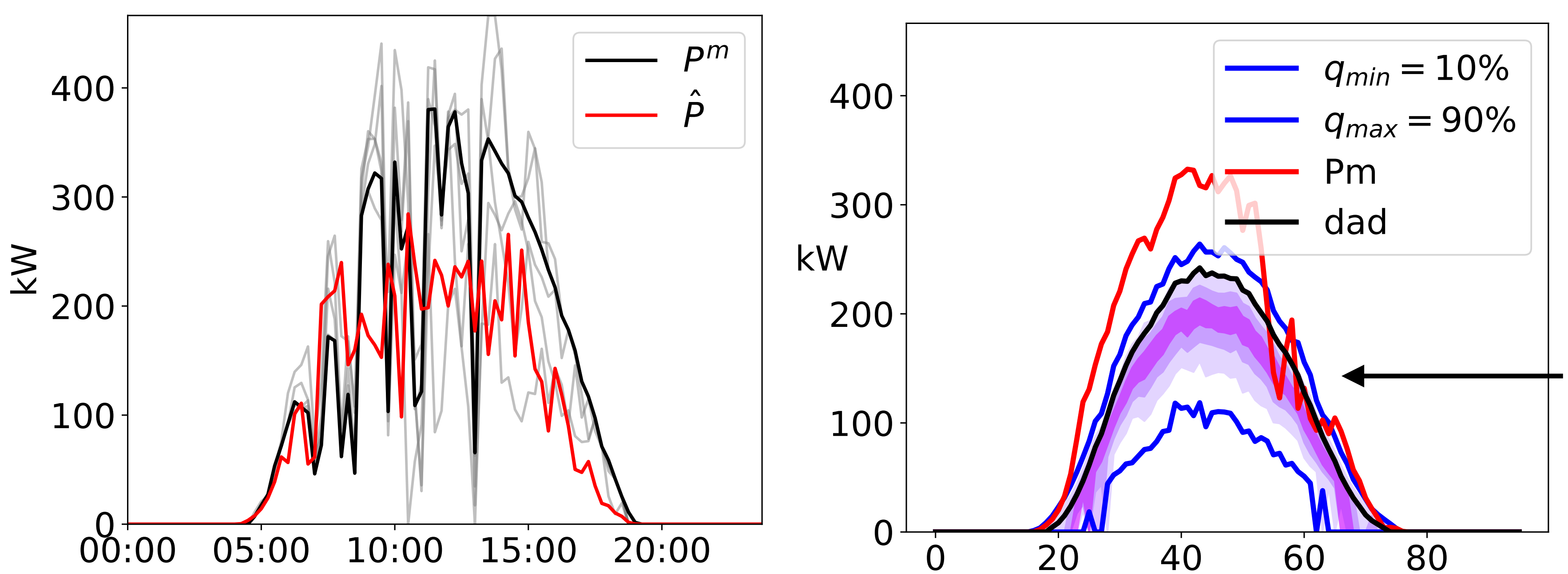
Formulation: day ahead nomination

How to manage the PV uncertainty ???

-> three approaches:

- **deterministic**: using PV *point* forecasts
- **stochastic**: using PV *scenarios*
- **robust:** using PV *uncertainty sets* (prediction intervals based on *quantiles*)



Uncertainty set between quantiles 10% & 90%

Figure 7: PV scenarios (left) & PV quantiles (right)

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Deterministic day ahead formulation

First-stage variables (x_t) = *engagement*.

Second-stage variables (y_t) = dispatch variables: *charge*, *discharge*, *state of charge*, etc.

Objective function to **minimize** = J(x_t, y_t) = **-Net revenue** over the entire day.
-> **Net revenue** = revenue - penalty.

$\mathcal{X}$ = **set** of constraints on the **engagement** (ramping constraints).

$\Omega(x_t, \hat{d}_t)$ = **set** of constraints on the **dispatch** variables

$\hat{d}_t$ = **PV** point forecasts

The **deterministic** formulation is (MIQP)

$$\min_{x_t \in \mathcal{X}, y_t \in \Omega(x_t, \hat{d}_t)} J\left(x_t, y_t\right) \quad (3)$$

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Stochastic day ahead formulation

First-stage variables (x_t) = *engagement*.

Second-stage variables (y_{t,w}) = dispatch variables: *charge*, *discharge*, *state of charge*, etc.

Minimization of the **expected profit over all PV scenarios** !

$\hat{d}_{t,\omega}$ = **PV** scenarios

The **stochastic** formulation is (MIQP)

$$\min_{[x_t \in \mathcal{X}, y_{t,\omega} \in \Omega(x_t, \hat{d}_{t,\omega})\ \forall \omega]} \sum_{\omega} \alpha_{\omega} \cdot J\left(x_t, y_{t,\omega}\right) \quad (4)$$

α_{ω} = probability of scenario w

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PV uncertainty set

Robust approach: PV uncertainty set.

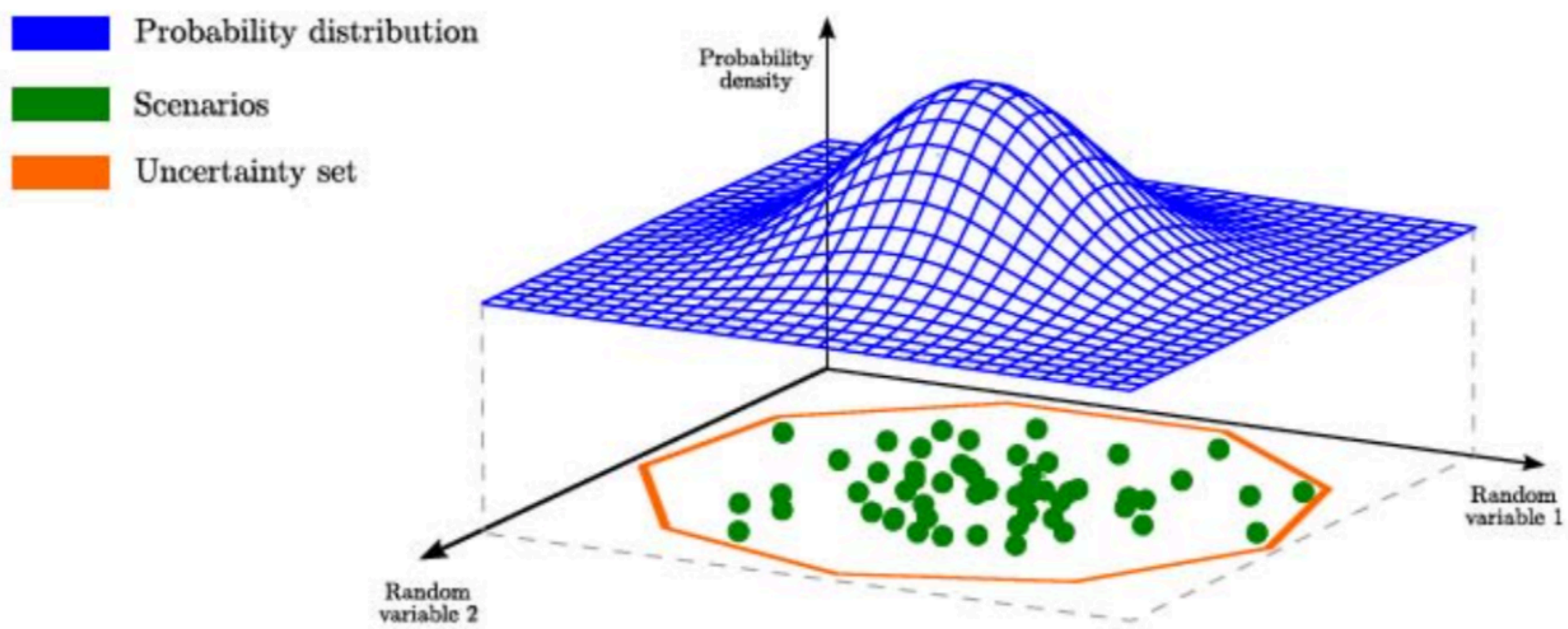

Figure 8: PV uncertainty set

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PV uncertainty set

PV **uncertainty set** D defined by PV **quantile forecasts.**

$$\mathcal{D} = \Big\{ d_t \in \mathbb{R}^T : \sum_{t \in \mathcal{T}} z_t^- + z_t^+ \leq \Gamma,$$
$$0 \leq z_t^- + z_t^+ \leq 1 \quad \forall t \in \mathcal{T},$$
$$d_t = \bar{d}_t - z_t^- d_t^{min} + z_t^+ d_t^{max} \Big\}.$$

$$0 \leq \Gamma \leq 96$$

Uncertainty budget:

- 0 -> no uncertainty
- 96 -> full uncertainty

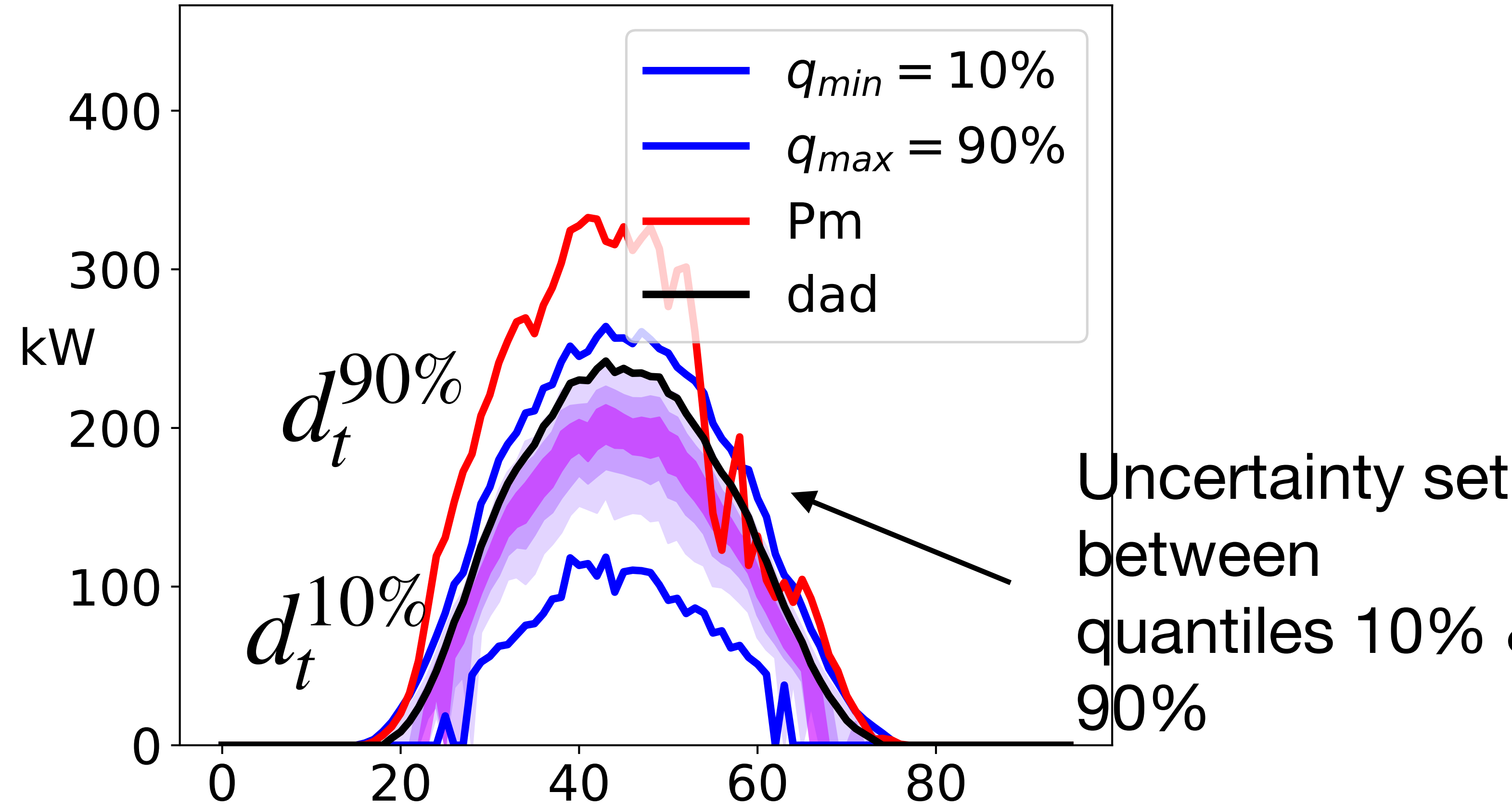

Figure 9: PV uncertainty set

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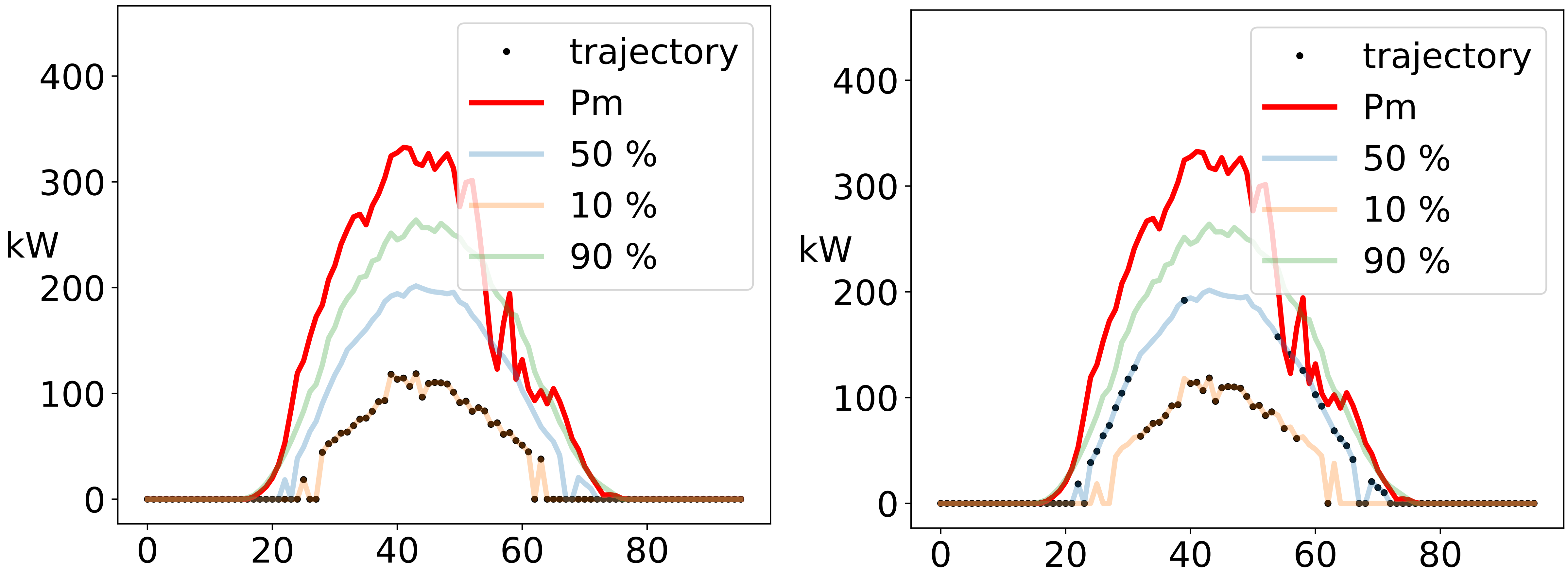
PV uncertainty set



$\Gamma = 48$ $\quad\quad$ $\Gamma = 24$

Figure 10: PV worst trajectories.

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Robust day ahead formulation

$$\min_{x_t \in \mathcal{X}, y_t \in \Omega(x_t, \hat{d}_t)} J(x_t, y_t) \Rightarrow \min_{x_t \in \mathcal{X}} \min_{y_t \in \Omega(x_t, \hat{d}_t)} J(x_t, y_t)$$

Robust: $d_t \in \mathscr{D} \Rightarrow y_t(d_t)$ Minimize over the **worst** PV **trajectory** into D.

The **two-stage robust formulation** is (**NON LINEAR**)

$$\min_{x_t \in \mathcal{X}} \boxed{\max_{d_t \in \mathscr{D}} \min_{y_t \in \Omega(x_t, \hat{d}_t)} J(x_t, y_t)} \quad (5)$$

= **worst-case dispatch cost ! For a given x**

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Robust day ahead formulation

The **two-stage robust** formulation is (**NON LINEAR**)

$$\min_{x_t \in \mathscr{X}} \max_{d_t \in \mathscr{D}} \min_{y_t \in \Omega(x_t, \hat{d}_t)} J\left(x_t, y_t\right) \quad (5)$$

D**uality** !
(still **NON LINEAR ...**)

$$\min_{x_t \in \mathscr{X}} \max_{d_t \in \mathscr{D}, \phi_t \in \mathscr{P}} J^{dual}\left(x_t, d_t, \phi_t\right) \quad (6)$$

with **ϕ the dual variables** of constraints in $\Omega(x_t, \hat{d}_t)$

Robust day ahead formulation

$$\min_{x_t\in\mathscr{X}} \boxed{\max_{d_t\in\mathscr{D},\phi_t\in\mathscr{P}} J^{dual}\left(x_t, d_t, \phi_t\right)} \tag{6}$$

$$R(x_t) = \max_{d_t\in\mathscr{D},\phi_t\in\mathscr{P}} J^{dual}\left(x_t, d_t, \phi_t\right) \tag{7}$$

EUREKA !!! -> **Convex piece-wise linear function** in x !!!

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Robust day ahead formulation

Benders decomposition !!!!!

- *Master problem*: solve $\min_{x_t \in \mathcal{X}} \hat{R}_i(x_t)$

Iteration = i

- *Sub problem*: compute $\hat{R}_i(x_t) \approx \max_{d_t \in \mathcal{D}, \phi_t \in \mathcal{P}} J^{dual}\left(x_t, d_t, \phi_t\right)$

How to compute $\hat{R}_i(x_t)$???

See J. Kazempour (DTU) teaching: *https://www.jalalkazempour.com/teaching*

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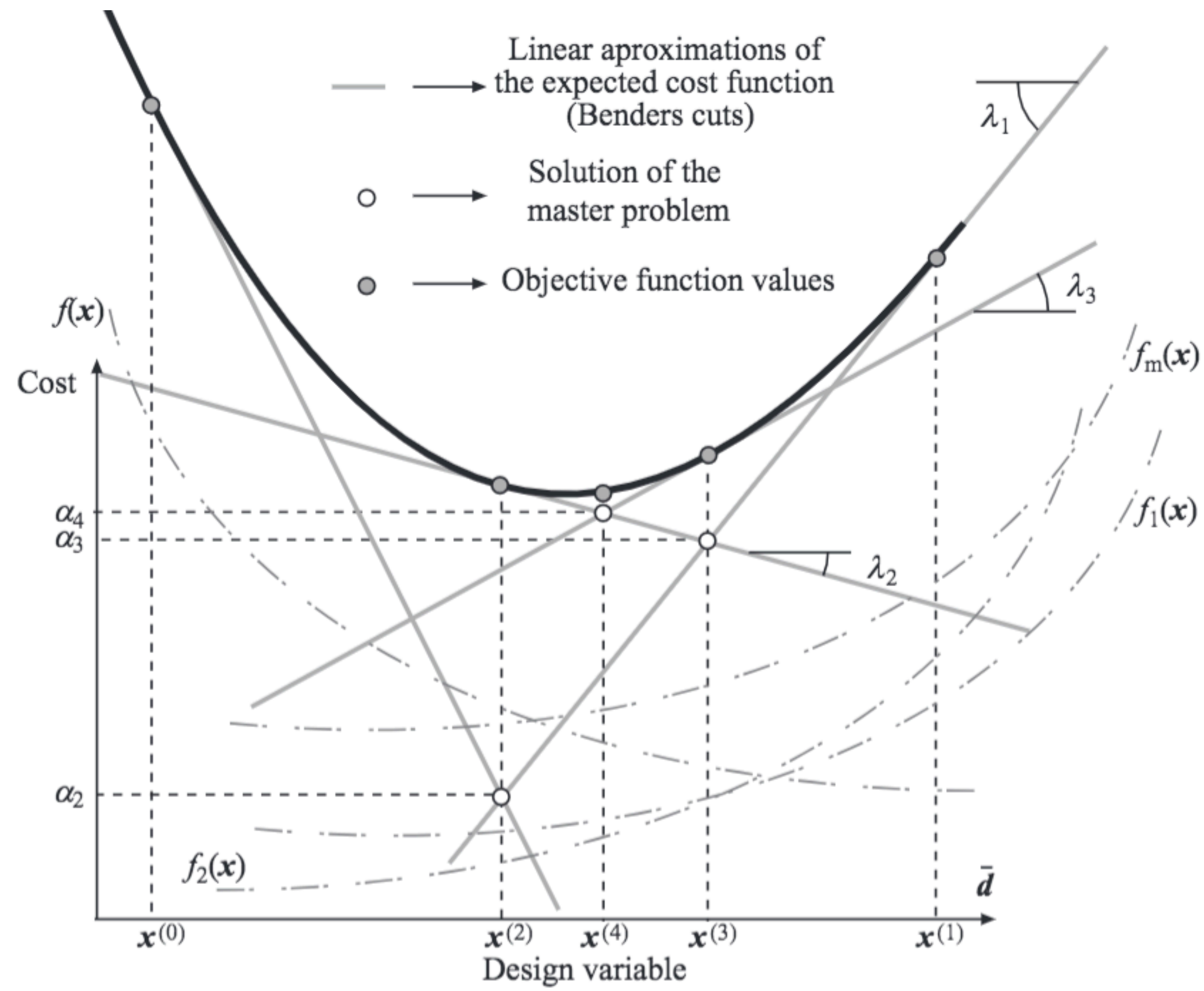
Robust day ahead formulation

Cutting plane algorithm !!! -> each iteration adds a cut !

$$\hat{R}_i(x_t) \approx \max_{d_t \in \mathscr{D}, \phi_t \in \mathscr{P}} J^{dual}\left(x_t, d_t, \phi_t\right)$$

$\hat{R}_i(x_t) =$ Set of inequalities !!! Computed by the Sub Problem



https://www.jalalkazempour.com/teaching

Figure 11: Cutting planes.

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ULiège case study

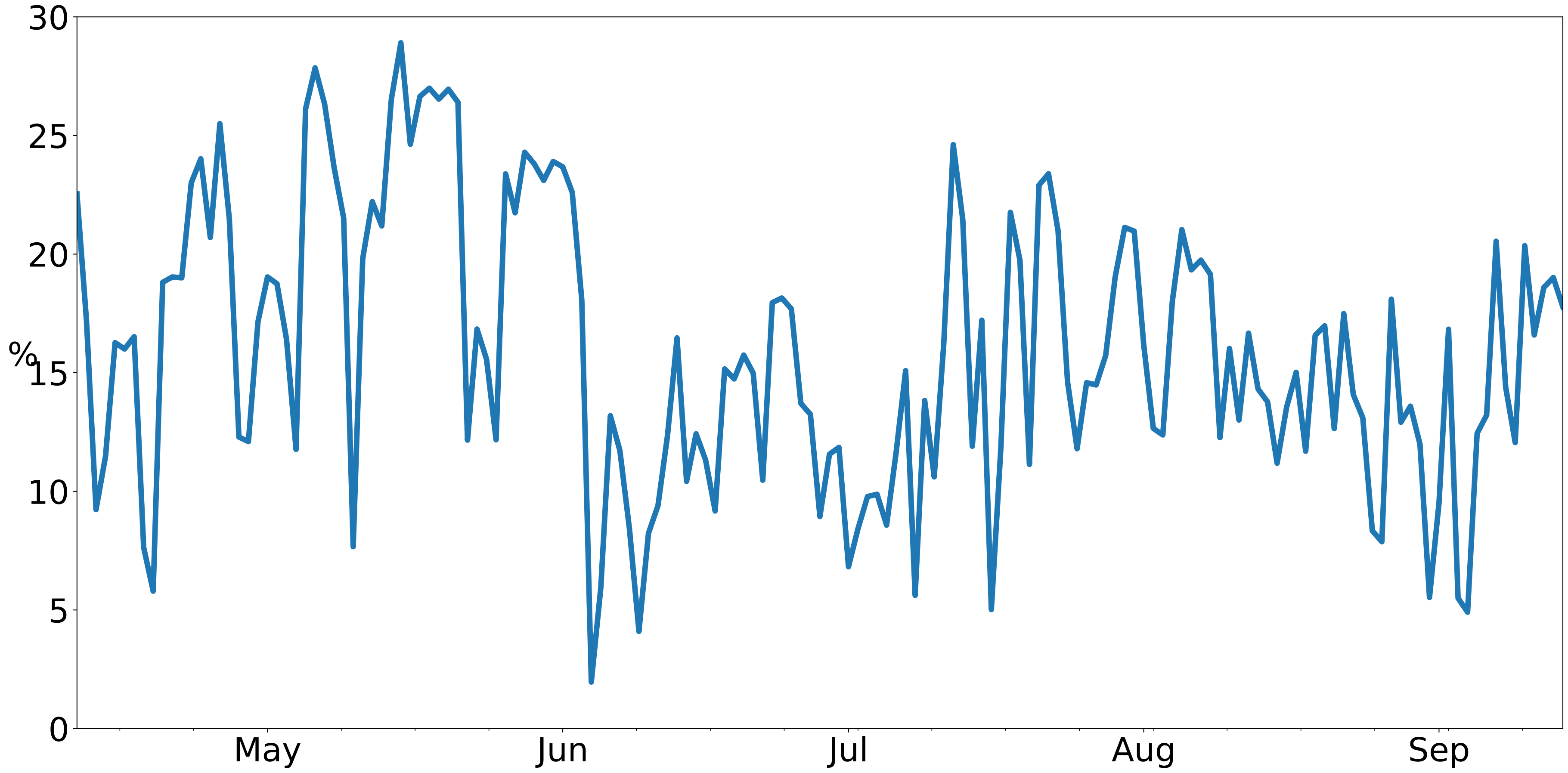

*Figure 12: Daily energy PV generation normalized by 466,4 * 24.*

Dataset = **350** days
15 min resolution
Pc = **466,4** kWp (installed capacity)

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Simulation parameters

Simulation parameters:
- Peak hours: **7 - 9 pm**
- Selling price = **100** €/MWh (**300** during peak hours)
- Deadband engagement tolerance = **5 % Pc**
- Engagement ramping constraints = **7.5 % Pc/15min**

Battery parameters:
- capacity = **466.4 kWh**
- charging/discharging efficiencies = **0.95**
- charging/discharging power **= 466.4** kW
- initial state of charge = **0** kWh each day
- state of charge of the last period = **0** kWh each day

Quantile forecasts: *https://orbi.uliege.be/handle/2268/252357*

Dumas, Jonathan, Xavier Fettweis, and Bertrand Cornélusse. "Deep learning-based multi-output quantile forecasting of PV generation." (2020).

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ULiège case study

$$\Gamma = 48$$

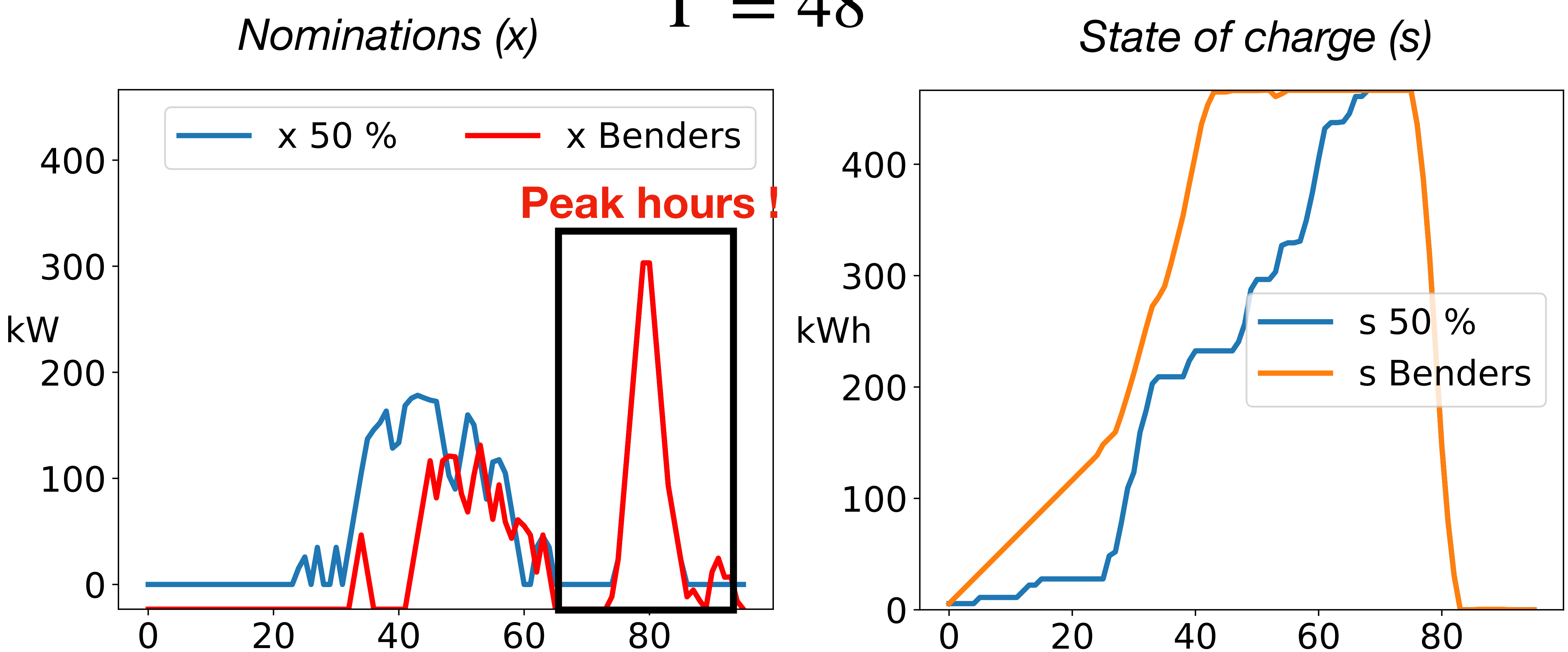

Figure 13: Nominations (left) and state of charge (right).

The robust approach (Benders) is more **conservative**.

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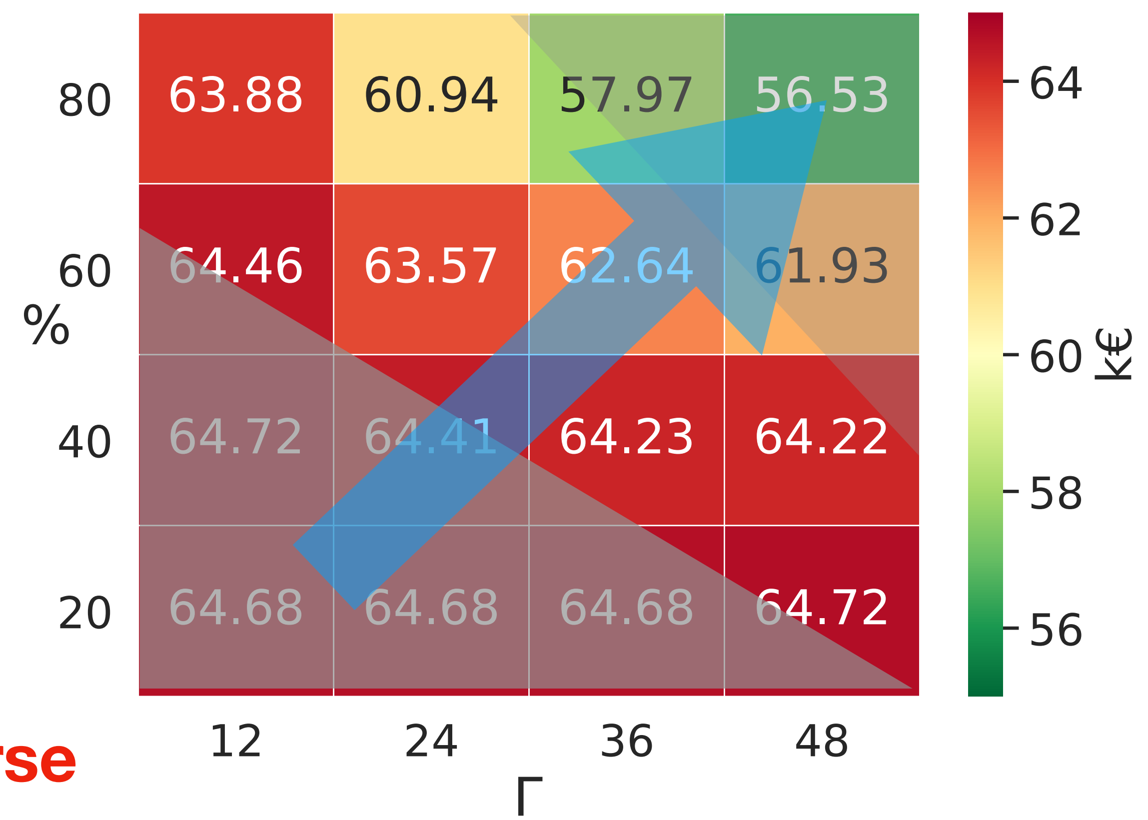
ULiège case study

Risk-**conservative**

$q^{min}, q^{max} = 10,\ 90\,\%$



$q^{min}, q^{max} = 40,\ 60\,\%$

Risk-**averse**

Figure 14: total profit (k€) per risk-aversion pair.

Total profit by using the **optimal pair** per day = **67.51** (k€) & **69.19** (k€) with the oracle.

How to select the optimal risk-aversion pair ??? $[q^{min}, q^{max}] \mid \Gamma$

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How to select the optimal risk-aversion pair ???

Assumption:

- a **risk-averse** strategy provides the best revenue for a **sunny/cloudy** day (where the **forecast error** should be **minimal**)
- a **risk-conservative** strategy provides the best revenue for a “**middle**” day (where the **forecast error** should be **maximal**)

Is true ????

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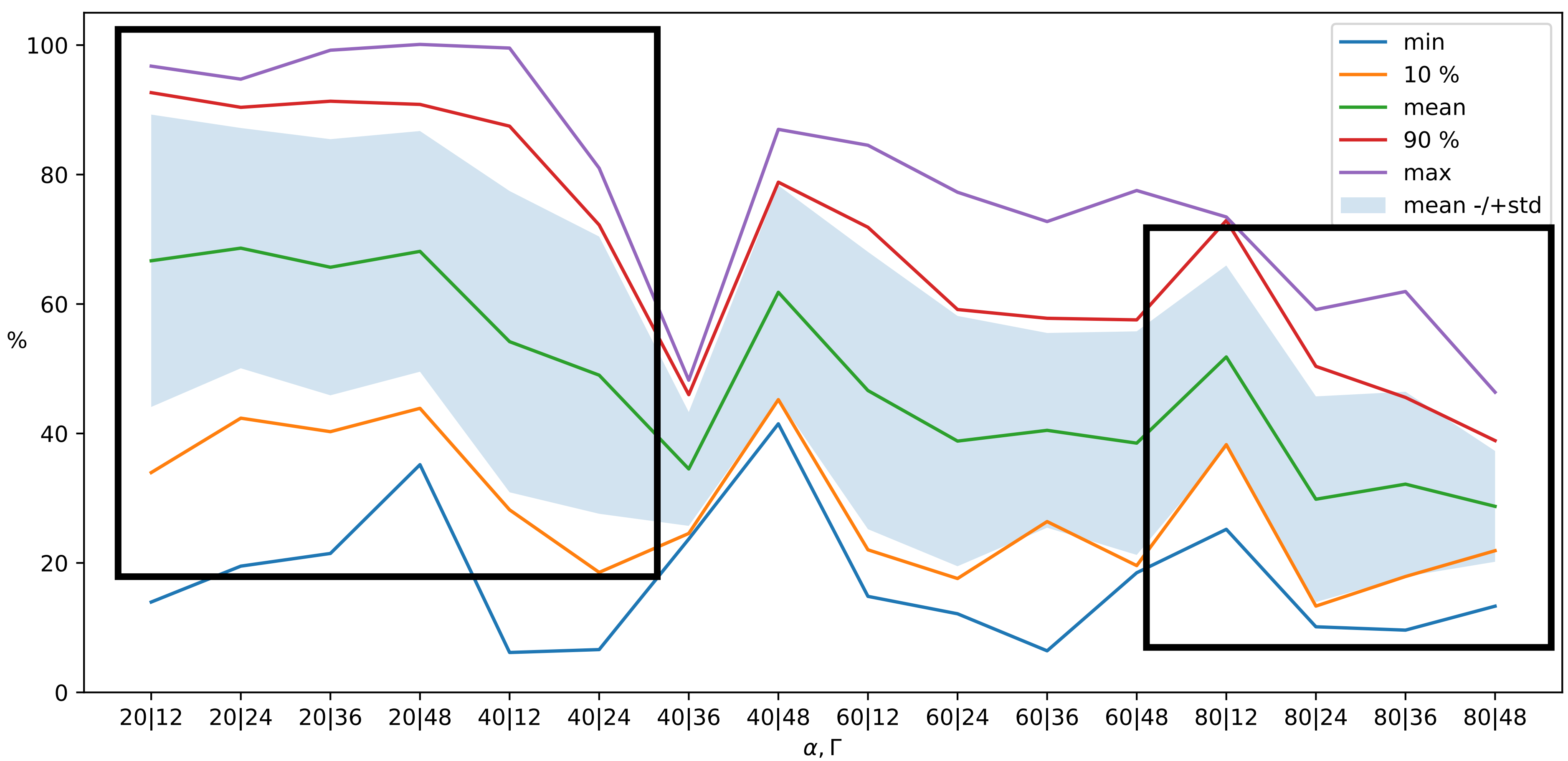
$$\bar{c}_p = \frac{\sum_{t \in \mathcal{T}} d_t^m}{\sum_{t \in \mathcal{T}} \hat{d}_t^{\textbf{cs}}}$$

Use the production under **clear sky condition** as normalizing factor -> **normalized capacity factor** !!!

$\bar{c}_p$



The assumption seems ok !!

$[q^{min}, q^{max}] \mid \Gamma$

Figure 15: Normalized capacity factor vs risk-aversion pair.

Risk-**averse** Risk-**conservative**

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ULiège case study

How to predict the optimal risk-aversion pair ???

-> use a **classifier/regressor** to **predict** the **optimal risk-aversion pair** based on the day ahead PV point forecasts;

-> use the **predicted risk-aversion** pair for robust optimization

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Conclusions & perspectives

- implement a **risk-aware algorithm** to optimize risk-aversion
- compare **deterministic**, **stochastic** & **robust** approaches
- use **Normalizing Flow** to compute PV scenarios, and quantiles
- **normalize** PV generation by PV generation with clear sky day to remove PV seasonality -> compute PV quantiles
- optimize **Benders convergence**