

# Energy management of a grid-connected PV plant coupled with a battery energy storage device using a stochastic approach

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*Extension of the paper submitted to PMAPS 2020*

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## Capacity firming context

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### System

-> **PV/wind generation + energy storage system**

### 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

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1. Literature review
2. Capacity firming process
3. Problem formulation
4. Case study
5. Conclusions & perspectives

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## Literature review: day ahead bidding

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The optimal bidding strategies with only a **production device**: [1,2].

[1] P. Pinson, C. Chevallier, and G. N. Kariniotakis, "Trading wind generation from short-term probabilistic forecasts of wind power," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1148–1156, 2007.

[2] A. Giannitrapani, S. Paoletti, A. Vicino, and Zarrilli, "Bidding wind energy exploiting wind speed forecasts," *IEEE Transactions on Power Systems*, vol. 31, no. 4, pp. 2647–2656, 2015.

Incorporating an **energy storage** and dealing with the **uncertainties**: SDDP/SDP [3]/[4], chanced-constrained [5], **2-stage stochastic** [6], robust optimization [7,8].

[3] M. V. Pereira, L. M. Pinto, *Multi-stage stochastic optimization applied to energy planning*, *Mathematical programming* 52 (1- 3) (1991) 359–375.

[4] P. Haessig, B. Multon, H. B. Ahmed, S. Lascaud, P. Bondon, *Energy storage sizing for wind power: impact of the autocorrelation of day-ahead forecast errors*, *Wind Energy* 18 (1) (2015) 43–57.

[5] F. Conte, S. Massucco, F. Silvestro, *Day-ahead planning and real-time control of integrated pv-storage systems by stochastic optimization*, *IFAC-PapersOnLine* 50 (1) (2017) 7717–7723.

[6] A. Parisio, E. Rikos, L. Glielmo, *Stochastic model predictive control for economic/environmental operation management of microgrids: An experimental case study*, *Journal of Process Control* 43 (2016) 24–37.

[7] D. Bertsimas, E. Litvinov, X. A. Sun, J. Zhao, T. Zheng, *Adaptive robust optimization for the security constrained unit commitment problem*, *IEEE transactions on power systems* 28 (1) (2012) 52–63.

[8] R. Jiang, J. Wang, Y. Guan, *Robust unit commitment with wind power and pumped storage hydro*, *IEEE Transactions on Power Systems* 27 (2) (2011) 800–810.

Mixed integer quadratic programming, simulation-based genetic algorithm, and expert-based heuristic are compared in [9].

[9] A. N'Goran, B. Daugrois, M. Lotteau, S. Demasse, *Optimal engagement and operation of a grid-connected PV/battery system*, in: *2019 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe)*, IEEE, 1–5, 2019.

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## Contributions: PMAPS 2020 paper + extension

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2 layers approach:

- **2-stage stochastic** planner scenario based approach -> **day-ahead** bidding;
- **deterministic** controller -> **real-time** set points.

Formulation:

- **Mix Integer Quadratic Programming (MIQP)**;
- linear constraints to approximate a non-convex penalty function, **compatible** with a **scenario approach**.

PV scenarios:

- **Gaussian copula** methodology based on the **parametric** PVUSA model using a weather **regional climate model**.

2-stage **stochastic** planner vs **deterministic** counterpart:

- oracle = using perfect knowledge of the future;
- PV point forecasts.

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## Day ahead engagement process

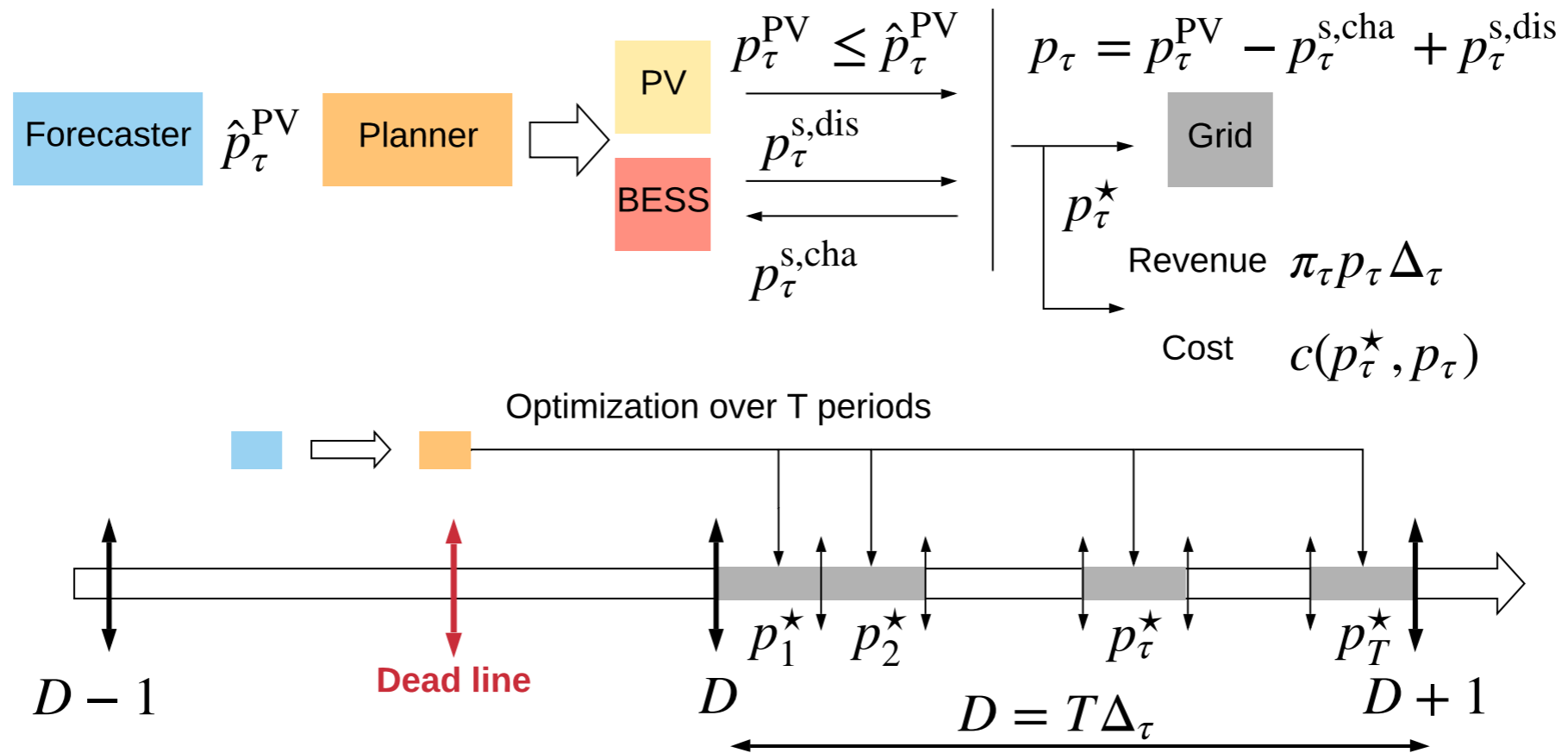


Figure 1: Day ahead engagement process.

The engagement plan is accepted if it satisfies **the constraints**

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

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

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

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## Real-time process

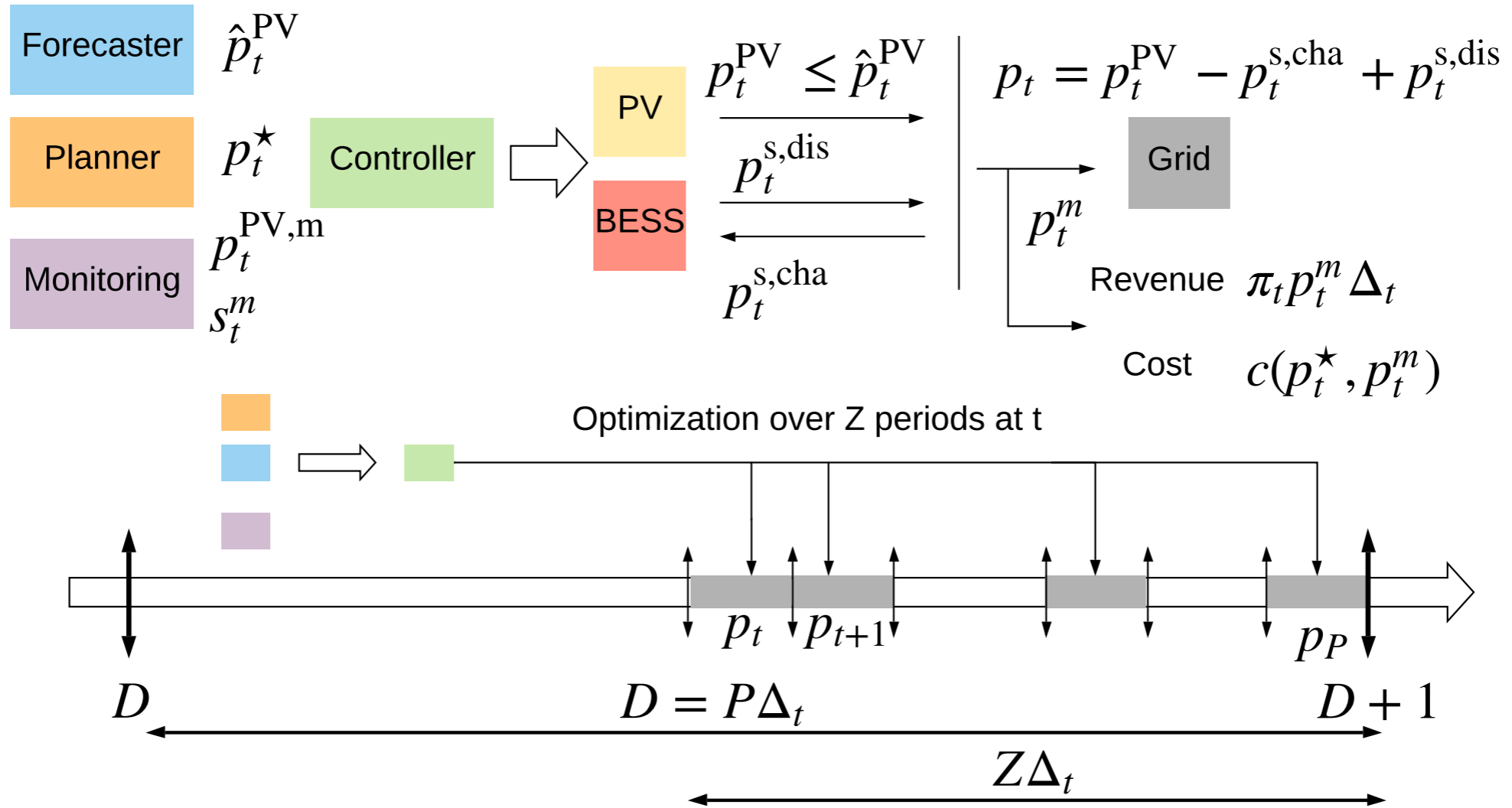
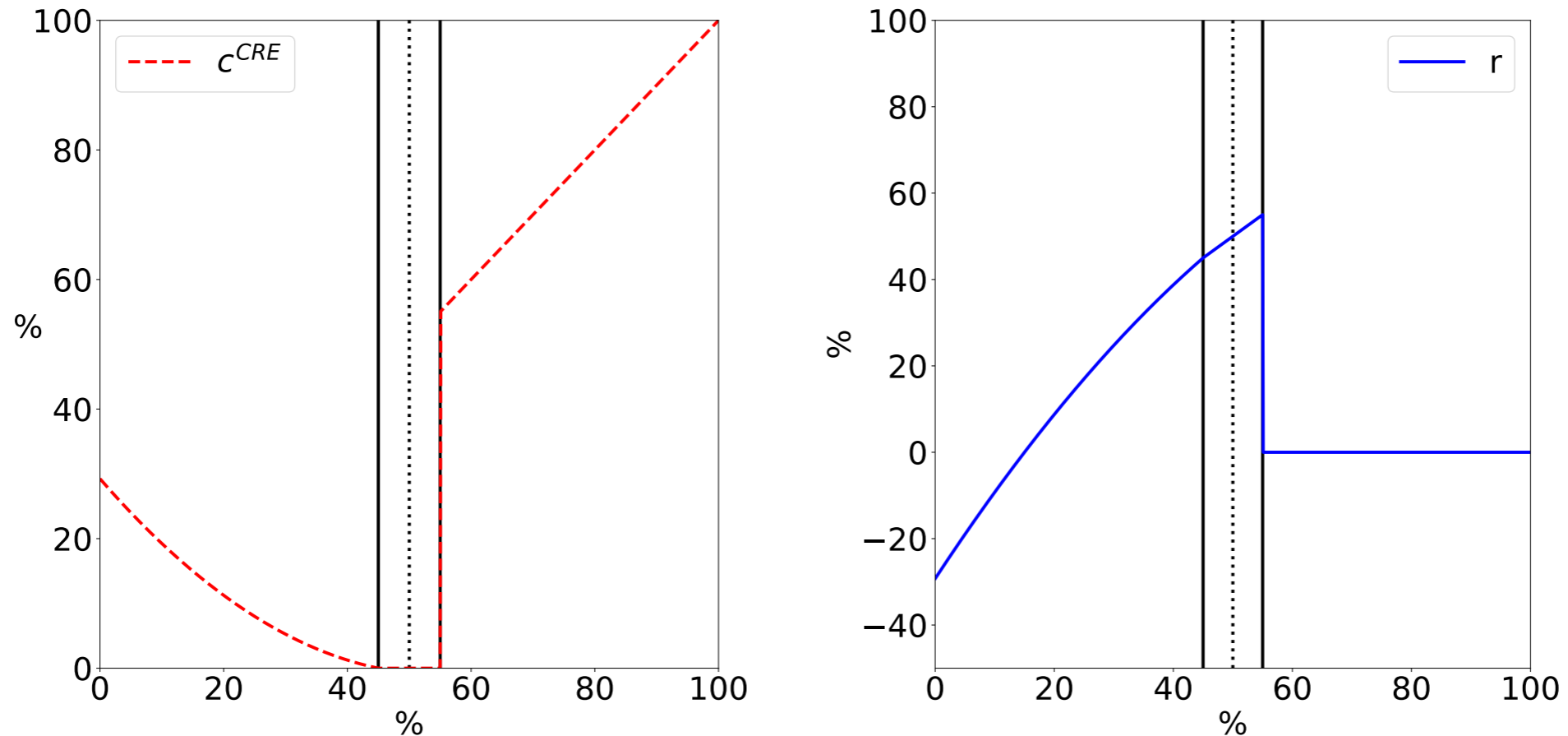


Figure 2: Real-time control process.



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## Penalty and revenue



*Figure 3: Penalties (left) and net revenues (right).  
Engagement = 50 % of PV installed capacity, deadband tolerance = 5%.*

$$r_t = \Delta_t \pi_t p_t^m - c(p_t^*, p_t^m), \quad \forall t \in \mathcal{P}. \quad (2)$$

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## Formulation: day ahead nomination

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The objective **2-stage stochastic** (S) programming using a **scenario approach** is

$$J_S = \sum_{\omega \in \Omega} \alpha_{\omega} \sum_{\tau \in \mathcal{T}} \left[ \underbrace{-\Delta_{\tau} \pi_{\tau} p_{\tau, \omega}}_{\text{Revenue}} + \underbrace{c(p_{\tau}^{\star}, p_{\tau, \omega})}_{\text{Penalty}} \right] \quad (3)$$

The objective **deterministic** (D=S with one scenario) counterpart is

$$J_D = \sum_{\tau \in \mathcal{T}} -\Delta_{\tau} \pi_{\tau} p_{\tau} + c(p_{\tau}^{\star}, p_{\tau}) \quad (4)$$

(3)-(4) are **Mix Integer Quadratic Problems** (MIQP). The S formulation uses PV scenarios, and the D formulation uses PV point forecasts.

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## Formulations: real-time control

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The **oracle** (= D planner) assumes **perfect knowledge** of PV and uses day ahead **engagements** as **inputs**

$$J^{oracle} = \sum_{t \in \mathcal{P}} -\Delta_t \pi_t p_t + c(p_t^*, p_t) \quad (5)$$

The **real-time controller** (RT) uses the **last PV measured** value, the **PV point forecasts**, and day ahead **engagements**, for  $t$  in  $[1, P]$

$$J^{RT} = \sum_{t \in \mathcal{P} \setminus \{1, \dots, t-1\}} -\Delta_t \pi_t p_t + c(p_t^*, p_t) \quad (6)$$

**WARNING:** RT should use **intraday PV point forecasts** updates to compute re-engagements (not available in the case study).

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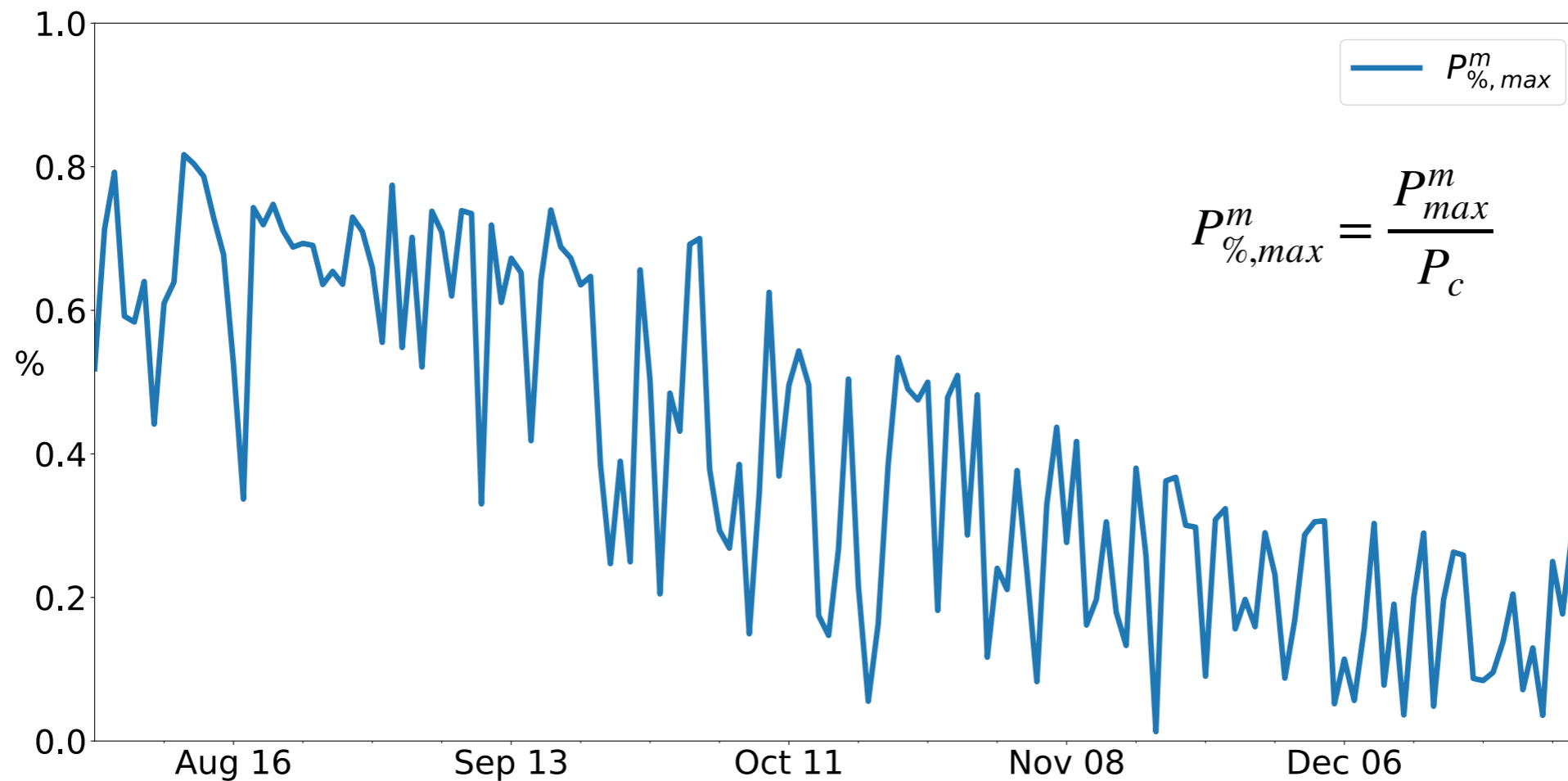
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## The Uliège case study: dataset

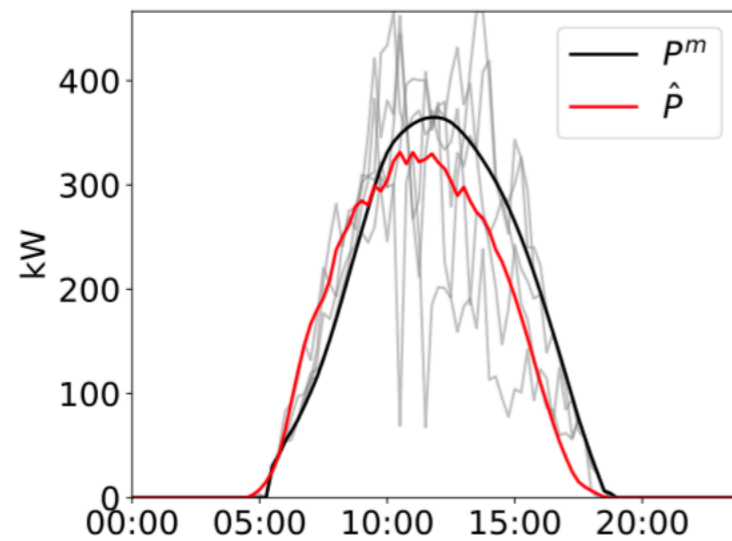


*Figure 4: PV max per day of the Liège dataset.*

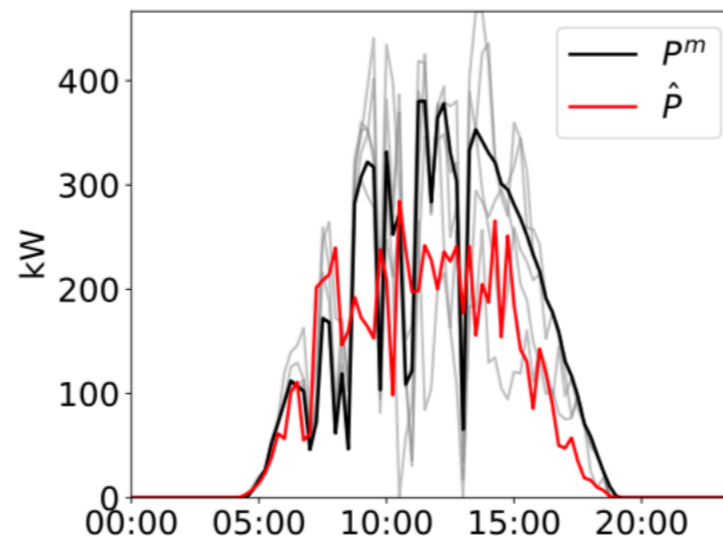
- 08-12/2019: **4 months**
- **1 min** resolution monitored on site
- $P_c = 466,4$  kWp

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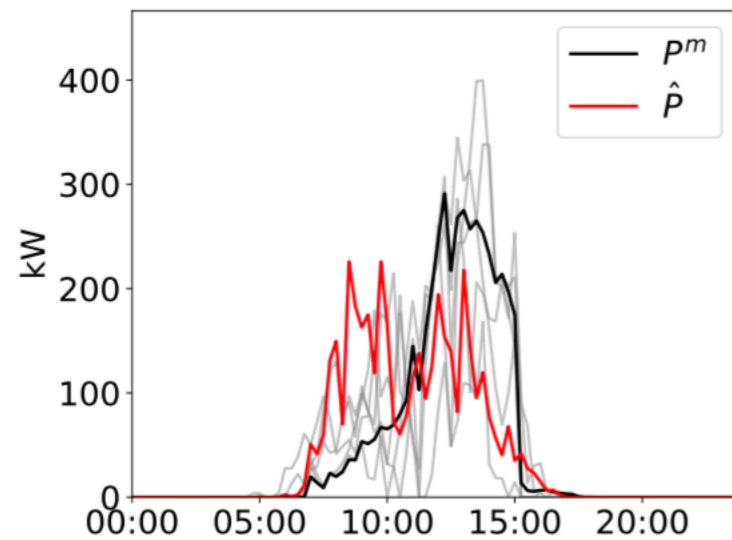
## PV scenarios



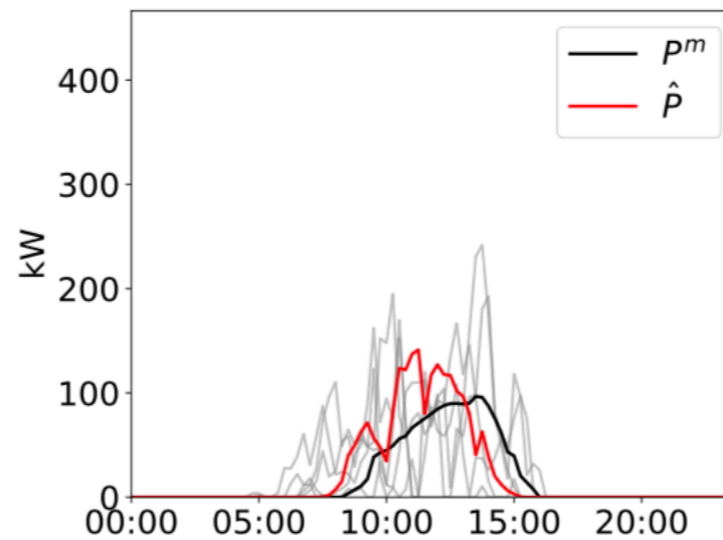
(a) *August 22, 2019.*



(b) *August 10, 2019.*



(c) *September 30, 2019.*



(d) *December 10, 2019.*

Red = **PVUSA** point forecast  
Black = PV measurement  
Grey = 5 PV scenarios

PVUSA:  
NMAE = 4.25 %  
NRMSE = 9.20 %

*Figure 5: Set of 5 PV scenarios.*

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## Simulation parameters

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### Simulation parameters:

- $P_c = 466,4$  kWp
- Planning and controlling periods = **15 min**
- Peak hours: **7 - 9 pm**
- Selling price = **100** €/MWh (**300** during peak hours)
- Deadband engagement tolerance = **5 %  $P_c$**
- Engagement ramping constraints = **7.5 %  $P_c/15min$**

### BESS parameters:

- capacity =  **$P_c * 1$  hour = 466.4 kWh**
- charging and discharging efficiencies = **0.95**
- charging and discharging power =  **$P_c = 466.4$  kW**
- initial state of charge = **0** kWh each day
- state of charge of the last period = **0** kWh each day



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## Computation times

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*Table 1: Computation times.*

$ \Omega $	1	5	20	50
# variables (k) $\approx$	1	4	15	40
# constraints (k) $\approx$	1.5	6	22	55
$\bar{t}_{\text{CPU}}$ (s)	0.1	0.5	3	10
$t_{\text{CPU}}^{\text{max}}$ (s)	0.3	1	7	30

Solver & software:

- **Cplex** (MIQP)
- **Pyomo python** library
- Ubuntu 18.04 LTS
- Intel core i7-8700 3.20 GHz based computer with 12 threads and 32 GB of RAM

Day ahead engagement **computation time is not an issue.**

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## Results

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*Table 2: Indicators.*

Name	Description	Unit
$J$	Daily objective.	k€
$c$	Penalty cost.	k€

*Table 3: Results.*

oracle	D*	D	S <sup>5</sup>	S <sup>20</sup>	S <sup>50</sup>
[ $J$ ]	-26.75	-26.38	-26.36	-26.41	-26.40
[ $c$ ]	0.02	0.23	0.25	0.20	0.23
RT	D*	D	S <sup>5</sup>	S <sup>20</sup>	S <sup>50</sup>
[ $J$ ]	-25.20	-24.88	-24.86	-24.88	-24.85
[ $c$ ]	-0.19	0.5	0.57	0.51	0.54

S<sup>20</sup> and D **achieved similar** results both with the oracle and RT controllers.

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## Conclusions & extensions

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The **2-stage stochastic** approach achieved **similar** results than its deterministic counterpart.

-> At least **one full year of data** are required to produce « good » PV scenarios (seasonality).

-> **Intraday weather forecast updates** are required to compute re-engagements and run « properly » the **RT** controller.

-> Extension to a **robust formulation** is currently underwork using quantile PV generation forecasts.

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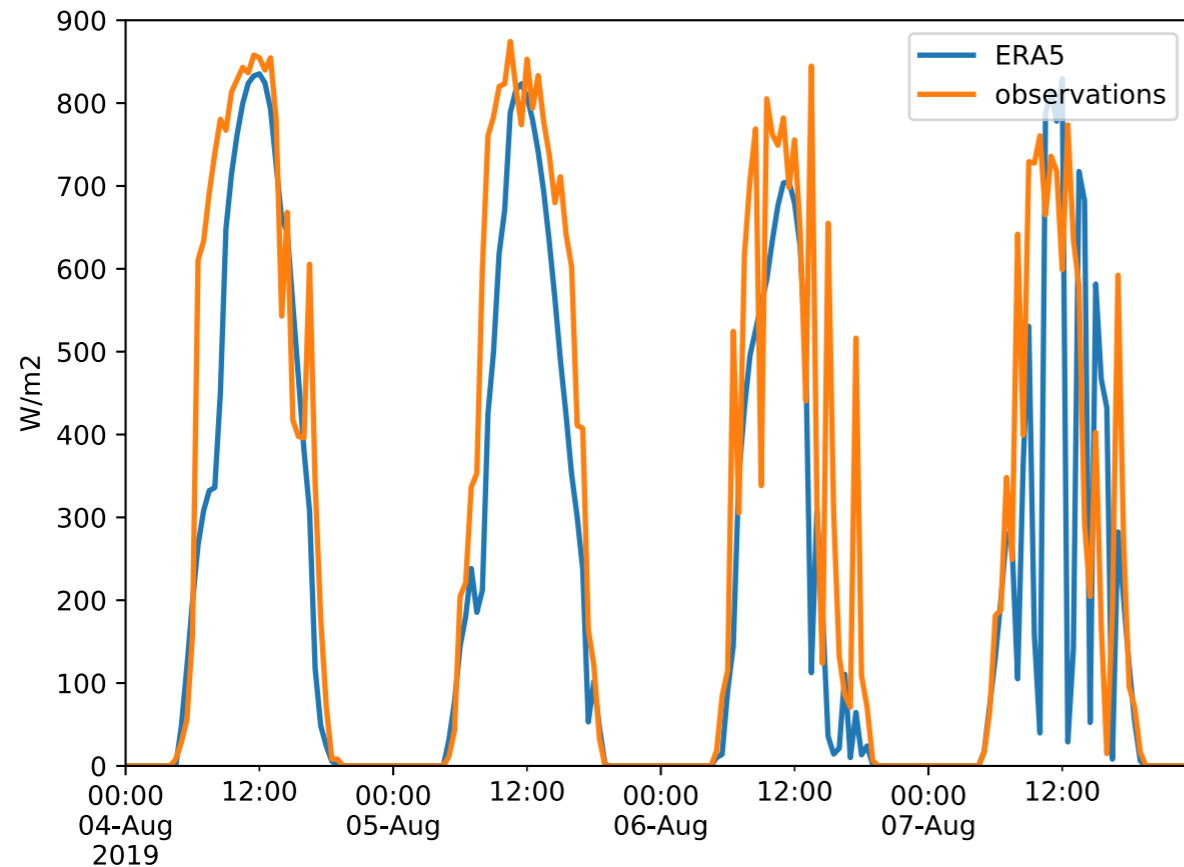
## Annex

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1. Weather forecasts
2. PV point forecasts
3. PV scenarios

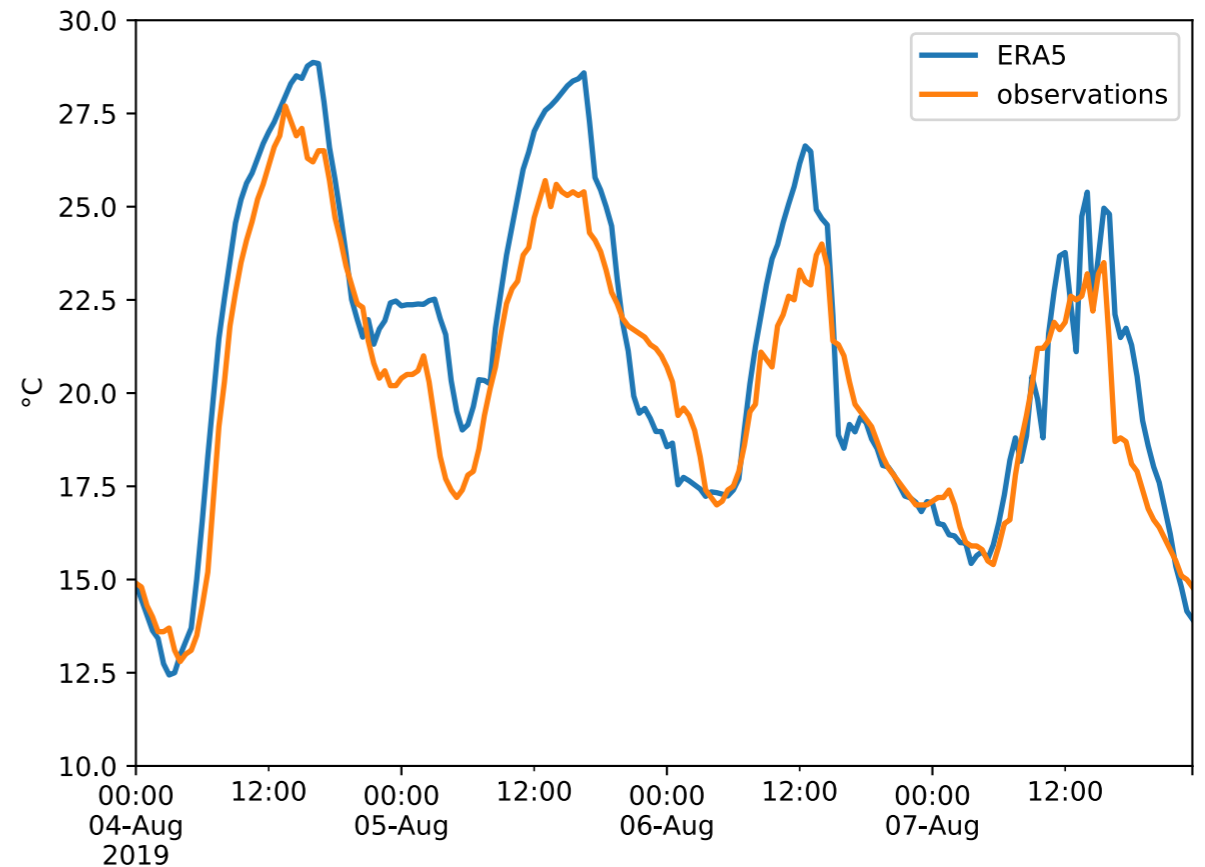
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## Weather forecasts: MAR regional climate model



*Figure 6a: Irradiation.*

MAE = 70 ( $W/m^2$ )  
RMSE = 128 ( $W/m^2$ )



*Figure 6b: Air temperature.*

MAE = 1.29 ( $^{\circ}C$ )  
RMSE = 1.56 ( $^{\circ}C$ )

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## PV point forecasts

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**PV point forecasts** are computed using the **PVUSA model** [10] which expresses the instantaneous generated power as a **function of irradiance and air temperature** according to the equation

$$\hat{P} = a\hat{I} + b\hat{I}^2 + c\hat{I}\hat{T} \quad (7)$$

[10] R.Dows, E.Gough, *PVUSA procurement, acceptance, and rating practices for photovoltaic power plants*, Tech. Rep., Pacific Gas and Electric Co., San Ramon, CA (United States). Dept. of ..., 1995.

The PVUSA parameters (a, b, and c) are estimated following the algorithm of [11]. **Weather forecasts** are provided by the Laboratory of Climatology of the university of Liège, based on the **MAR regional climate model** [12], [http://climato.be/cms/index.php?climato=fr\\_previsions-meteo](http://climato.be/cms/index.php?climato=fr_previsions-meteo).

[11] G.Bianchini, S. Paoletti, A. Vicino, F. Corti, F. Nebiacolombo, *Model estimation of photovoltaic power generation using partial information*, in: *IEEE PES ISGT Europe 2013*, IEEE, 1–5, 2013.

[12] X. Fettweis, J. Box, C. Agosta, C. Amory, C. Kittel, C. Lang, D. van As, H. Machguth, H. Galle'e, *Reconstructions of the 1900–2015 Greenland ice sheet surface mass balance using the regional climate MAR model*, *Cryosphere (The)* 11 (2017) 1015–1033.

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## PV scenarios

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The Gaussian copula methodology has already been used to generate wind and PV scenarios in, e.g., [13,16].

This approach is used to **sample PV error scenarios** (Z) based on a point forecast model.

[13] P. Pinson, H. Madsen, H. A. Nielsen, G. Papaefthymiou, B. Klöckl, *From probabilistic forecasts to statistical scenarios of short-term wind power production*, *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology* 12 (1) (2009) 51–62.

[14] P. Pinson, R. Girard, *Evaluating the quality of scenarios of short-term wind power generation*, *Applied Energy* 96 (2012) 12–20.

[15] G. Papaefthymiou, D. Kurowicka, *Using copulas for modeling stochastic dependence in power system uncertainty analysis*, *IEEE Transactions on Power Systems* 24 (1) (2008) 40–49.

[16] F. Golestaneh, H. B. Gooi, P. Pinson, *Generation and evaluation of space–time trajectories of photovoltaic power*, *Applied Energy* 176 (2016) 80–91.

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## PV scenarios

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- Multivariate random variable  $Z = \{Z_1, \dots, Z_r\}$
- Known quantities:
  - Marginal *cdfs*  $F_{Z_i}(\cdot)$ ,  $i = 1, \dots, r$
  - Correlation matrix  $R_Z$
- **Objective:** generate samples of  $Z$

### Method based on Gaussian copula

- 1: Generate a sample  $g = (g_1, \dots, g_r)$  from a Normal distribution  $\mathcal{N}(0, R_Z)$
- 2: Transform each entry  $g_i$  through the standard normal *cdf*  $\phi(\cdot)$

$$u_i = \phi(g_i)$$

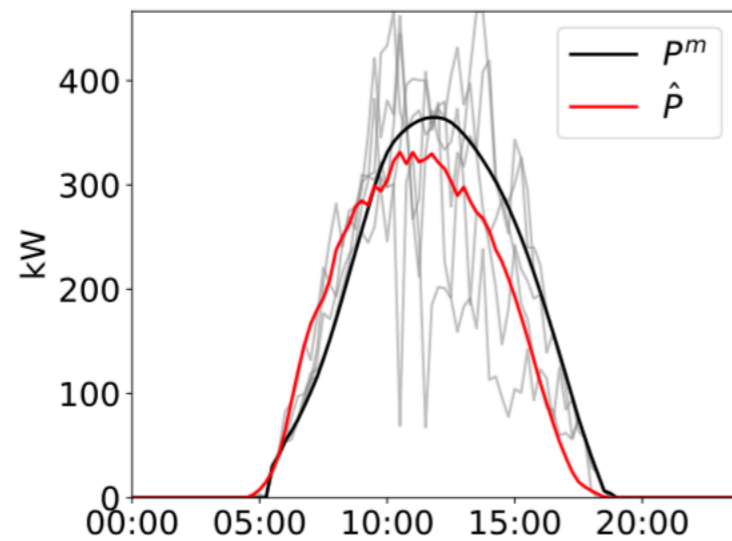
- 3: Apply to each entry  $u_i$  the inverse marginal *cdf* of  $Z_i$

$$z_i = F_{Z_i}^{-1}(u_i)$$

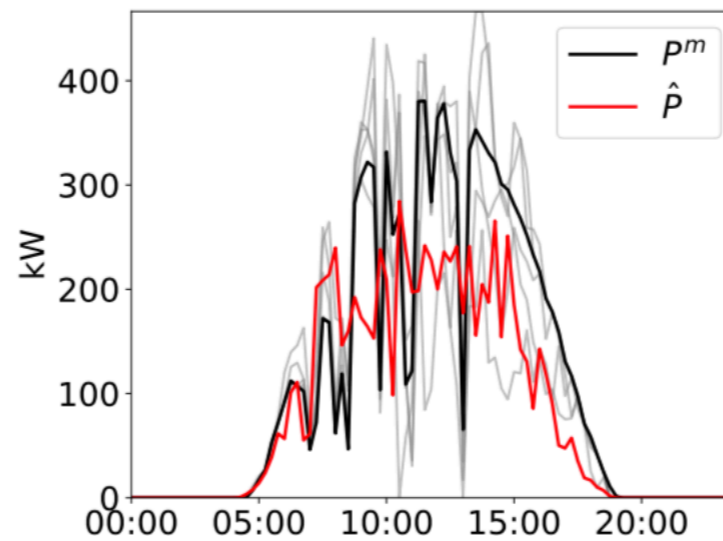


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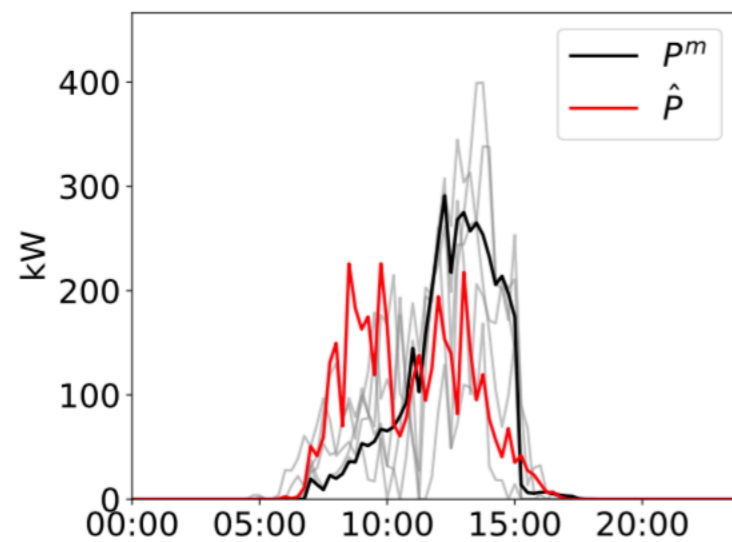
## PV scenarios



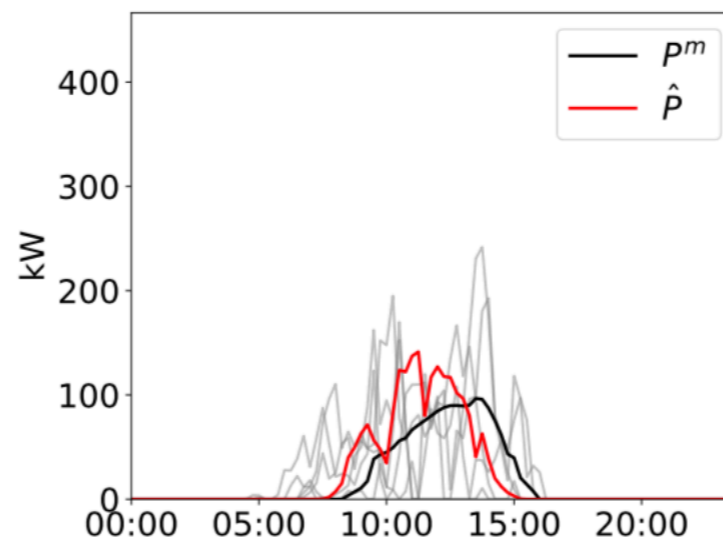
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$$\hat{P}_{i,\omega} = \hat{P}_i + z_{i,\omega} \quad i = 1, \dots, r. \quad (10)$$

Red = PVUSA point forecast  
 Black = PV measurement  
 Grey = 5 PV scenarios

NMAE = 4.25 %  
 NRMSE = 9.20 %

Figure 5: Set of 5 PV scenarios.

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## Limitations

The engagement follows the PV point forecasts.

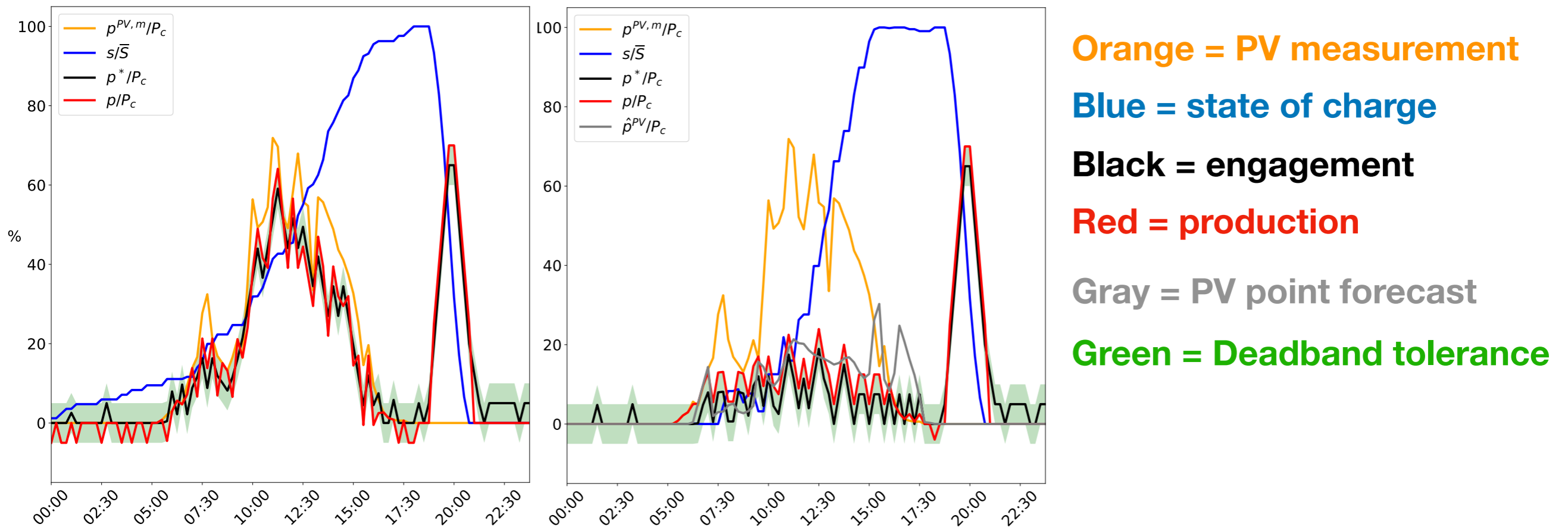


Figure 7: **D\* - oracle** vs **D - oracle** on 12-09-2019.

**Intraday PV point forecast** updates are required to compute **re-engagement** plans.