PES meeting

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

Jonathan Dumas, Bertrand Cornélusse, Antonello Giannitrapani «, Simone Paoletti «, Antonio Vicino «

*Dipartimento di Ingegneria dell'Informazione e Scienze Matematiche Universita` di Siena, Italy

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Capacity firming context

Where ?

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

What ?

-> The variable, intermittent power output from a renewable power generation plant, such as wind or solar, can be **maintained at a committed level** for a period of time.

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 <u>https://www.cre.fr/</u>.

Summary

- 1. Literature review
- 2. Capacity firming process
- 3. Capacity firming formulations
- 4. PV scenarios
- 5. Case study
- 6. Conclusions & perspectives

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Literature review

The optimal day ahead bidding strategies of a plant composed of **only a production device** have been addressed in, e.g., [1]–[4].

Incorporating an energy storage in the framework is still an open problem.

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.
 E. Y. Bitar, R. Rajagopal, P. P. Khargonekar, K. Poolla, and P. Varaiya, "Bringing wind energy to market," IEEE Transactions on Power Systems, vol. 27, no. 3, pp. 1225–1235, 2012.
 A. Giannitrapani, S. Paoletti, A. Vicino, and D. Zarrilli, "Bidding strategies for renewable energy generation with non stationary statistics," IFAC Proceedings Volumes, vol. 47, no. 3, pp. 10 784–10 789, 2014.
 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.

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Capacity firming process

The system considered is a **grid-connected PV** plant with a battery energy storage system (**BESS**).

At the tendering stage the offers are selected on the electricity selling price.

At the operational stage the electricity is exported to the grid at the contracted selling price according to a well-defined **daily nomination and penalization scheme**.

Capacity firming process

The capacity firming process is decomposed into a **day ahead nomination** and a **real-time control** process.

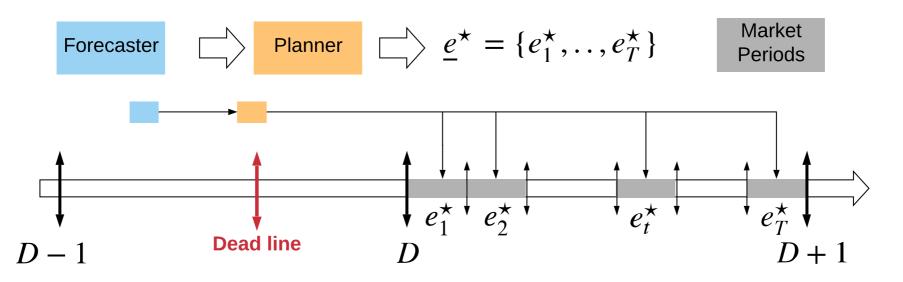


Figure 1: Day ahead nomination process.

The nominations are accepted if they satisfy the ramping power constraints

$$\frac{|e_{\tau}^{\star} - e_{\tau-1}^{\star}|}{\Delta_{\tau}} \leq \Delta P^{\star}, \,\forall \tau \in \mathcal{T} (1)$$

Capacity firming process

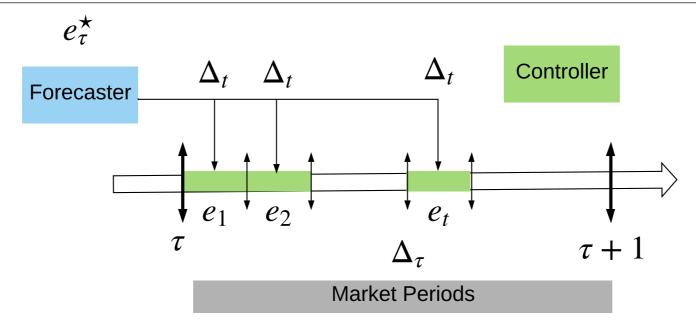


Figure 2: Real-time control process.

For a given control period, the **net remuneration** of the plant is proportional to the **export** minus a **penalty**

$$r_t^n = \pi_t^{exp} e_t^m - f^e(e_t^{\star}, e_t^m), \,\forall t \in \mathscr{P} (2)$$

The penalty function depends on the specifications of the tender. In this study, is approximated as

$$f^{e}(e_{t}^{\star}, e_{t}^{m}) = \pi^{e} \left(\max\left(0, \left|e_{t}^{\star} - e_{t}^{m}\right| - \Delta E\right) \right)^{2} (3)$$

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Capacity firming formulations: day ahead nomination

The deterministic (D) objective function to minimize is

$$J_D = \sum_{\tau \in \mathcal{T}} - \pi_\tau^{exp} e_\tau + f^e(e_\tau^\star, e_\tau)$$
(4)

The stochastic (S) objective function to minimize is

$$J_{S} = \sum_{\omega \in \Omega} p_{\omega} \sum_{\tau \in \mathcal{T}} \left[-\pi_{\tau}^{exp} e_{\tau,\omega} + f^{e}(e_{\tau}^{\star}, e_{\tau,\omega}) \right]$$
(5)

They are **Quadratic Problems** (QP). The D formulation uses point forecasts of PV production and the S formulation PV scenarios.

See paper submitted to PMAPS for all the equations and constraints available on orbi: <u>https://orbi.uliege.be/handle/2268/246270</u>

Capacity firming formulations: real-time control

The oracle assumes perfect knowledge of PV and uses nominations

$$J^{oracle} = \sum_{t \in \mathscr{P}} -\pi_t^{exp} e_t + f^e(e_t^{\star}, e_t)$$
(6)

The myopic controller uses the last PV measured value and nominations

$$J^{myopic} = -\pi_t^{exp} e_t + f^e(e_t^{\star}, e_t)$$
(7)

The **real-time controller** (RT) uses the last PV measured value, the PV point forecasts, and nominations

$$J^{real-time} = \sum_{t \in \mathscr{P} \setminus \{1, \dots, t-1\}} - \pi_t^{exp} e_t + f^e(e_t^{\star}, e_t)$$
(8)

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PV scenarios

The Gaussian copula methodology has already been used to generate wind and PV scenarios in, e.g., [5]–[8].

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

[5] 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 Inter- national Journal for Progress and Applications in Wind Power Conversion Technology 12 (1) (2009) 51–62.

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

[7] 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.

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

PV scenarios

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

Method based on Gaussian copula

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

$$u_i = \phi(g_i)$$

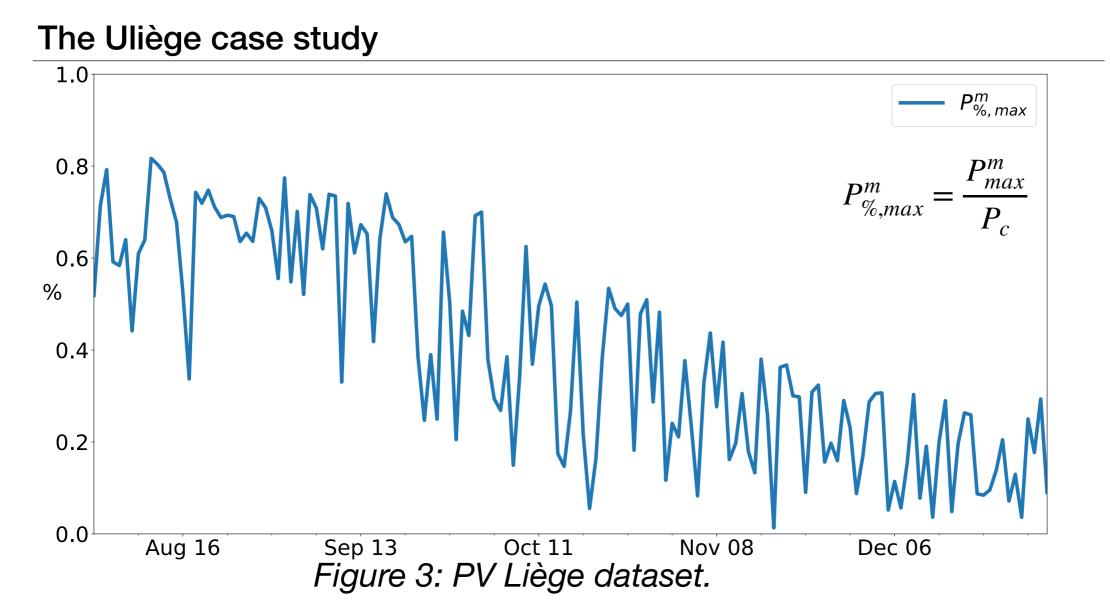
3: Apply to each entry u_i the inverse marginal *cdf* of Z_i

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

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PV dataset:

- August 2019 December 2019: 4 months
- 1 min resolution
- Pc = **466,4** kWp

BESS parameters:

- capacity = **500 kWh** with perfect efficiencies
- charging and discharging power = 500 kW
- initial state of charge = 0 kWh each day
- state of charge of the last period = 0 kWh each day

The Uliège case study

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

 $\hat{P} = a\hat{I} + b\hat{I}^2 + c\hat{I}\hat{T} (9)$

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 [9], <u>http://climato.be/cms/index.php?climato=fr_previsions-meteo</u>.

[9] 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.

[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.

[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.

The Uliège case study

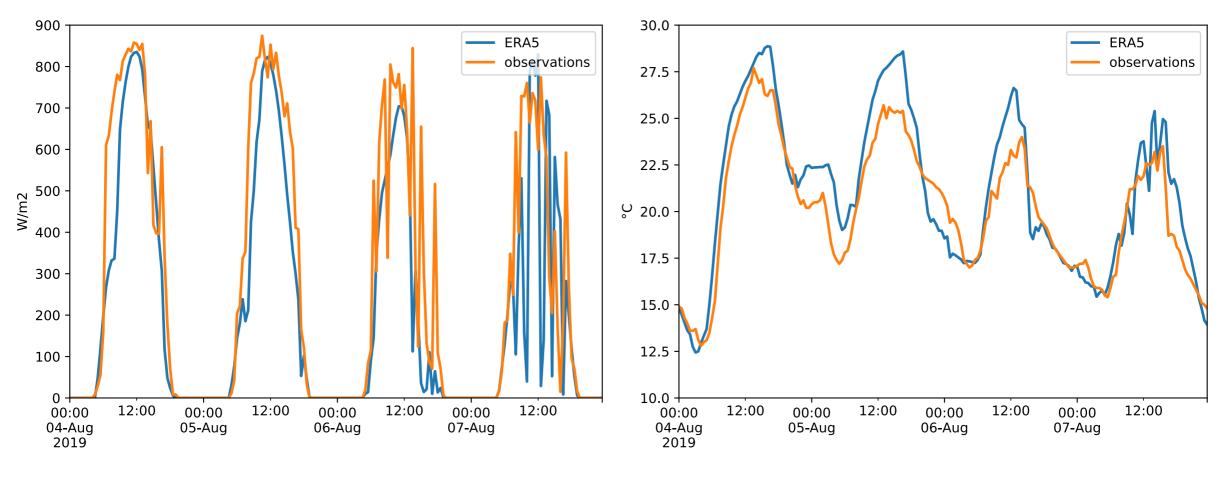
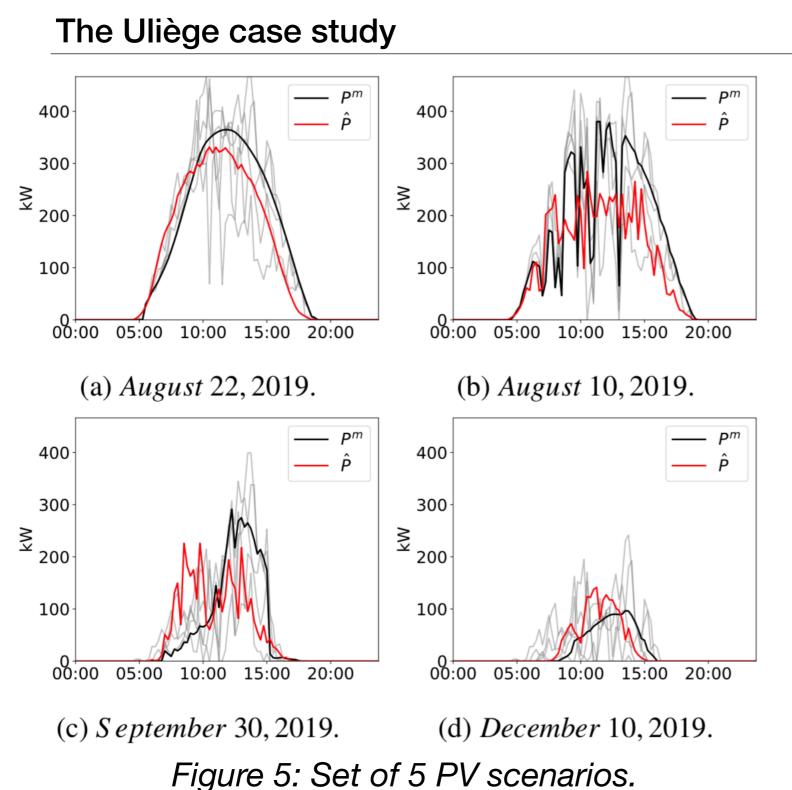


Figure 4a: Irradiation.

MAE = 70 (W/m2) RMSE = 128 (W/m2) Figure 4b: Air temperature.

MAE = 1.29 (°C) RMSE = 1.56 (°C)



A set of PV scenarios is generated using the Gaussian copula approach based on the PVUSA point forecasts

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

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

NMAE = 4.25 % NRMSE = 9.20 %

The Uliège case study

Table 1: Nomination average computation times.

Ω	1	5	10	50	100
# variables	769	3457	6817	33697	67297
# constraints	1248	5092	9897	48337	96387
\overline{t}_{CPU} S (S)	_	0.3	0.8	3	7
$\overline{t}_{CPU} D^*$ (s)	0.1	-	-	-	-

CPLEX 12.9, on an Intel core i7-8700 3.20 GHz based computer with 12 threads and 32 GB of RAM.

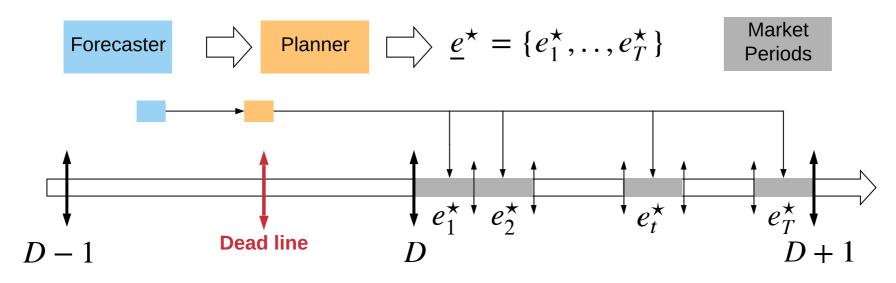


Figure 1: Day ahead nomination process.

The Uliège case study

Table 2: RT controller average computation times.

$ \mathcal{P} $	1440	720	360
# variables	10081	5048	2528
# constraints	15842	7933	3973
$\overline{t}_{\mathrm{CPU}} \operatorname{RT}$ (s)	0.8	0.4	0.2

CPLEX 12.9, on an Intel core i7-8700 3.20 GHz based computer with 12 threads and 32 GB of RAM.

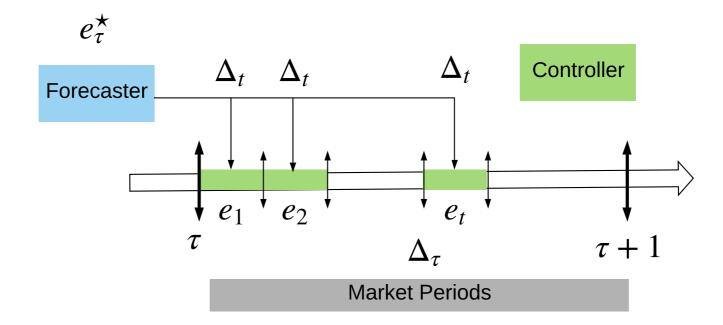


Figure 2: Real-time control process.

The Uliège case study

Case study parameters

Nomination step

$$\Delta P^{\star} = 0.5 \% P_{c} = 2.32 \ (kW)$$

$$\Delta E = 1 \% P_{c} \Delta_{\tau} = 5.83 \ (kWh)$$

$$E^{cap} = P_{c} = 466.4 \ (kW)$$

$$\pi^{exp} = 45 \ (\pounds/MWh)$$

$$\pi^{e} = 1 \% \pi^{exp} = 0.45 \ (\pounds/MWh^{2})$$

$$\Delta_{\tau} = 15 \ (min)$$

Control step

- $\Delta P^{\star} = \ (kW)$
- $\Delta E = 1 \% P_c \Delta_t = 0.389 \ (kWh)$

$$E^{cap} = P_c = 466.4 \ (kW)$$

$$\pi^{exp} = 45 \ (\texttt{E}/MWh)$$
$$\pi^{e} = 1 \% \ \pi^{exp} = 6.75 \ (\texttt{E}/MWh^{2})$$
$$\Delta_{t} = 1 \ (min)$$

Planners and controllers combinations:

- D*/D/S oracle
- D*/D/S myopic
- D*/D/S RT
- **D* oracle = reference**

The Uliège case study

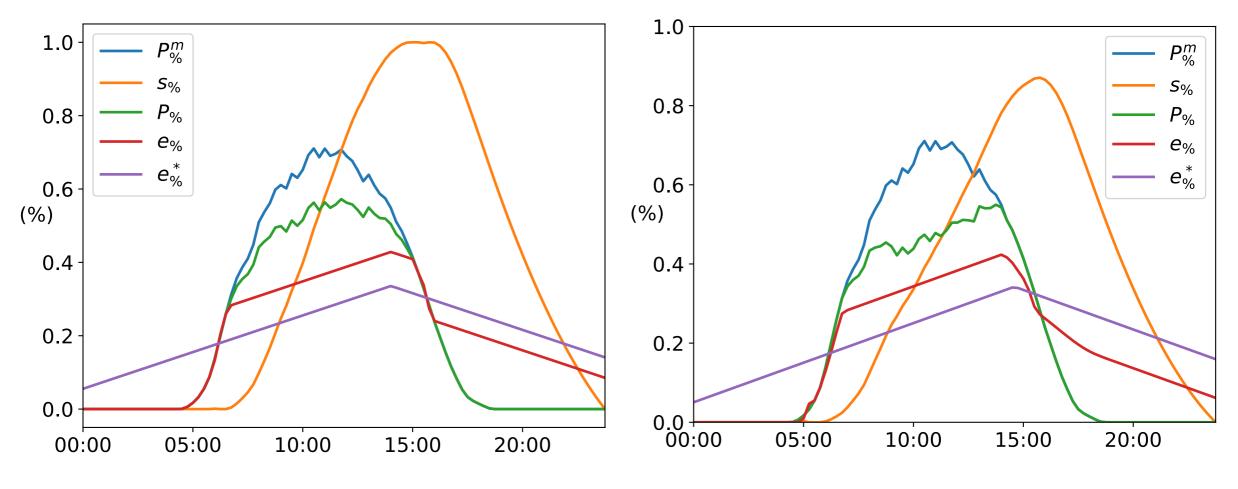


Figure 6a: **D*** - oracle on 22-08-2019.

Figure 6b: **S^20 - RT** on 22-08-2019.

$$P_{\%}^{m} = \frac{P^{m}}{P_{c}} \qquad P_{\%} = \frac{P}{P_{c}} \qquad e_{\%} = \frac{e}{\Delta_{t}P_{c}} \qquad e_{\%}^{*} = \frac{e^{*}}{\Delta_{t}P_{c}} \qquad s_{\%} = \frac{s}{\overline{S}}$$

The Uliège case study

Table 4: Results.

I (1-C)								
$J_{\mathrm{tot}}~(\mathrm{k} \widehat{\in})$								
	D^{\star}	D	$S^{ \Omega =5}$	$S^{ \Omega =20}$	$S^{ \Omega =50}$			
Myopic	-2.80	-1.69	-1.93	-2.55	-2.31			
Real-time	-5.45	-5.14	-5.18	-5.33	-5.28			
Oracle	-5.94	-5.77	-5.78	-5.86	-5.83			
$C_{ ext{tot}}^{e}$ (k \in)								
Myopic	2.05	3.16	3.00	2.34	2.60			
Real-time	0.34	0.7	0.67	0.5	0.56			
Oracle	0.22	0.36	0.34	0.26	0.29			
R^{e}_{tot} (k \in)								
Myopic	4.85	4.85	4.93	4.89	4.91			
Real-time	5.79	5.84	5.85	5.82	5.84			
Oracle	6.15	6.13	6.13	6.11	6.11			

Reference = D* - oracle

S - RT with 20 scenarios
achieved 89 % of the reference.
D - RT with 20 scenarios
achieved 86 % of the reference.

$$J_{tot} = -R^e_{tot} + C^e_{tot} \ (11)$$

S - RT achieved **smaller penalty** than D - RT.

Gross revenue of S - RT & D - RT are equivalent.

BESS capacity sensitivity analysis

Sensitivity analysis on the BESS capacity to **determine its marginal value** and the **optimal BESS capacity** for a given BESS unit cost.

Inputs:

- selling price
- BESS CAPEX
- Net revenue over 15 years for several battery capacities (0, 100, 250, 500, ...) kWh

$$\Delta R_i^{n,e} = 15 \times \frac{12}{5} \times (R_i^{n,e} - R_1^{n,e}) \quad \forall i \in \{2,...,9\} . (12)$$

Output:

- Optimal battery capacity for a given CAPEX = 0.075 (€ / kWh)

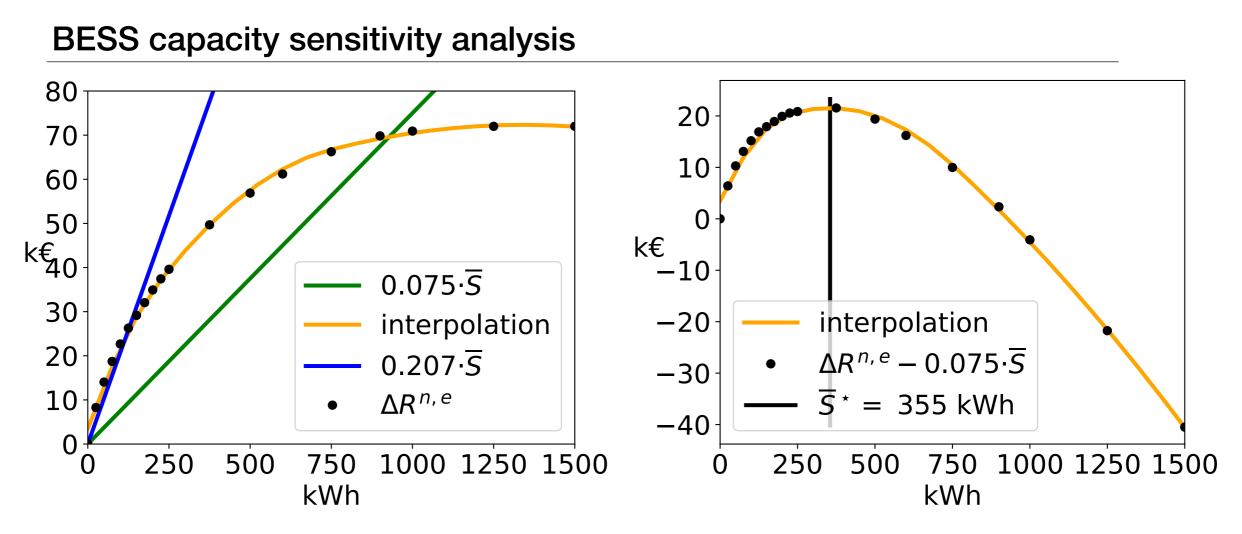


Figure 7a: Net revenue variation: **D* - oracle**.

Figure 7b: Optimal BESS capacity.

D* - oracle Optimal capacity = 355 kWh Net revenue - CAPEX = **21.6 k€**

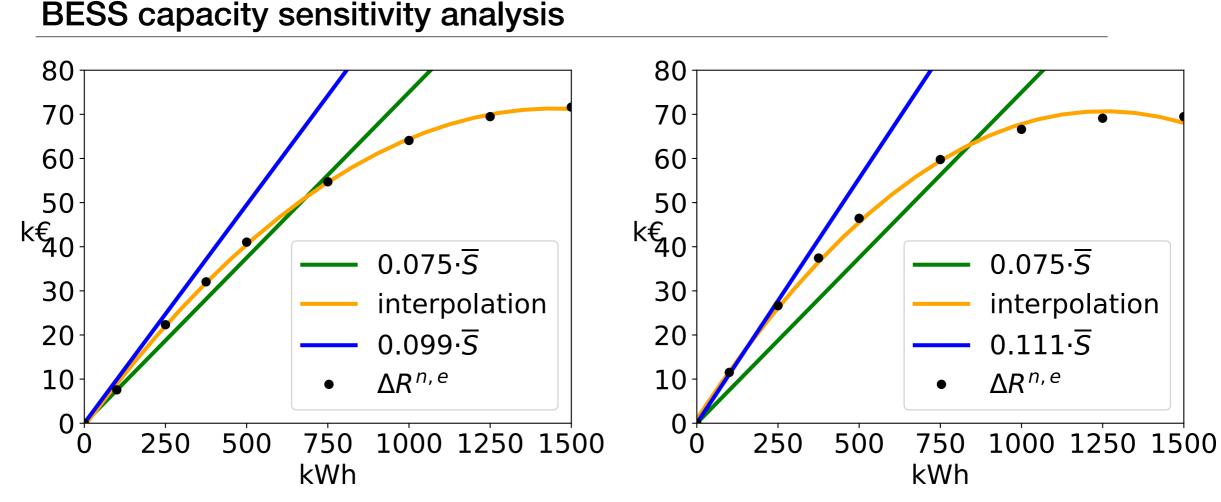


Figure 8a: Net revenue variation: **D** - **RT**.

D - RT Optimal capacity = **355 kWh** Net revenue - CAPEX = **3.7 k€** Figure 8b: Net revenue variation: **S^20 - RT**.

S^20 - RT Optimal capacity = **410 kWh** Net revenue - CAPEX = **8.5 k€**

Conclusions

The **stochastic** approach achieved **better results** than the deterministic one.

The BESS capacity sensitivity analysis demonstrate the **advantage of using a BESS** to optimize the bidding day ahead strategy.

A **trade-off** must be found between the marginal gain provided by the BESS and its investment and operational costs.

Perspectives

The planner behavior should be better assessed by using at least **a full year of data** to fully take into account the PV seasonality.

The PV plant **location** should be assessed.

The **non convex penalty function** of the French Energy Regulatory Commission should be considered*.

To be fully operational on the field, the controller should be able **to deal with control period of one second** for instance by adapting the approach implemented in [11].

[11] J.Dumas, S.Dakir, C.Liu, B.Cornélusse, Coordination of operational planning and real-time optimization in microgrids, in: XXI Power Systems Computation Conference, 2020. Available on orbi: <u>http://hdl.handle.net/2268/240076</u>

*The investigation is almost done: next PES meeting ?

Selling price calculation

Sensitivity analysis on the BESS capacity to determine the optimal selling price related to a system configuration.

Inputs:

- BESS / PV CAPEX & OPEX
- Exports for several battery capacities (0, 100, 250, 500, ...) kWh

Outputs:

- LCOE
- System configuration for an optimal selling price