Aging-aware NaS battery model in a stochastic wind-storage simulation framework

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session *Energy storage systems for power grids 1*

Outline of the presentation

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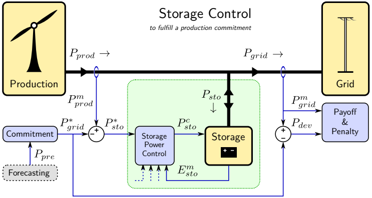
Wind Power Production with an Energy Storage System

an industrial application



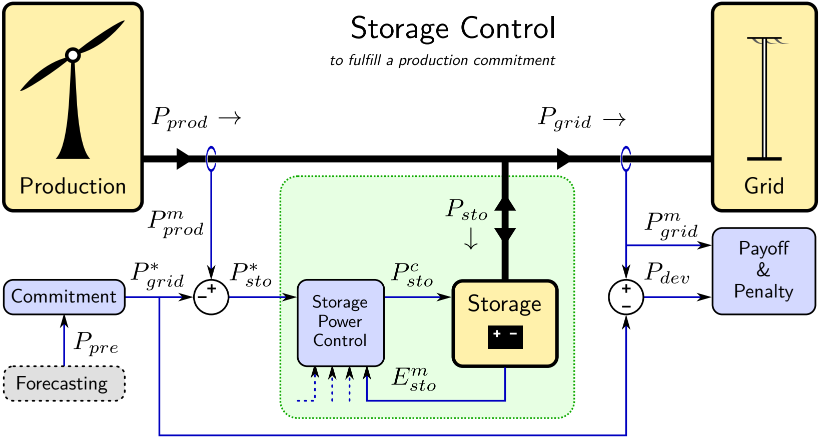
The French Commission for the Regulation of Energy (CRE) launched a call for tender for wind farms "with services" targeting French islands.

Key requirement

commitment on a day-ahead production plan, hour by hour.

Wind Power Production with an Energy Storage System

system overview



NaS battery testing

In parallel to the "wind-storage" call for tenders, the French utility EDF is testing a **1 MW/7 MWh** Sodium-Sulfur (NaS) battery in La Réunion.

Objective

We study the *sizing* and the *control* (energy management policy) of an Energy Storage System (ESS) to fulfill the day-ahead production commitment of a wind farm.

The specific storage technology being investigated here is NaS since it is currently tested on field.

For this purpose, we build a **simulation model** of a wind-storage system that should:

- *Assess the performance* of an Energy Storage System (NaS battery) to fulfill a day-ahead production commitment
- Run without need of wind power forecast data (limited availability).

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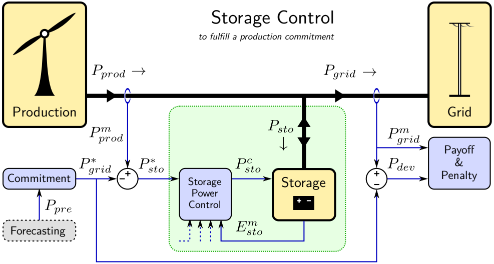
Commitment deviation: description

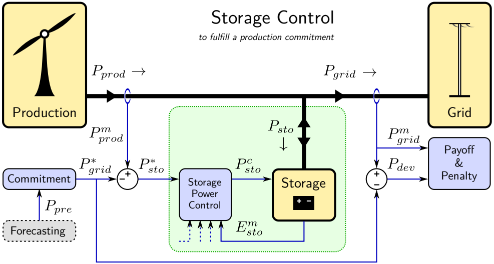


The wind operator should keep the production P_{grid} close to its commitment P_{grid}^*. We thus define the commitment deviation:

$$P_{dev} = P_{grid} - P_{grid}^*$$

. . . which should be kept *"small"* at all times.

Ideal storage request



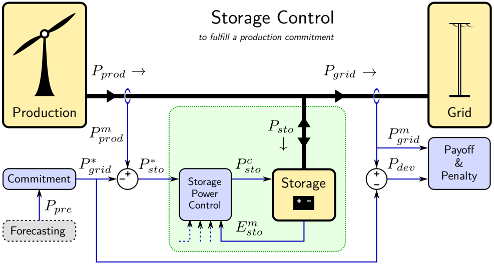
To perfectly fulfill the commitment ($P_{dev} = 0$), the ESS should absorb the “ideal storage request”:

$$P^*_{sto} = P_{prod} - P^*_{grid}$$

Energy management policy

Store $P_{sto} = P^*_{sto}$, whenever the ESS is neither full nor empty.

Ideal storage request

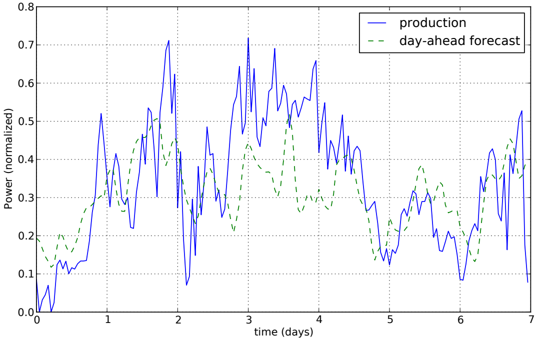


This ideal request P^*_{sto} is equal to the *forecast error* (assuming the commitment is taken equal to the forecast)

. . . thus the interest of studying and *modeling* forecast errors.

A look at wind power forecasting

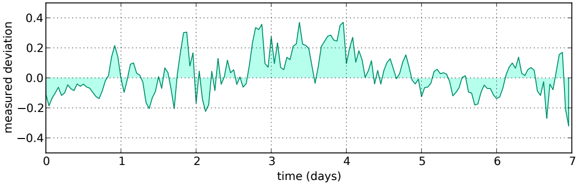
One week of a wind farm production and forecast/commitment:



We focus on the *difference* between production and forecast because P^*_{sto} is the input of the storage control.

Modeling forecast errors

One week of forecast errors (i.e. P^*_{sto}):

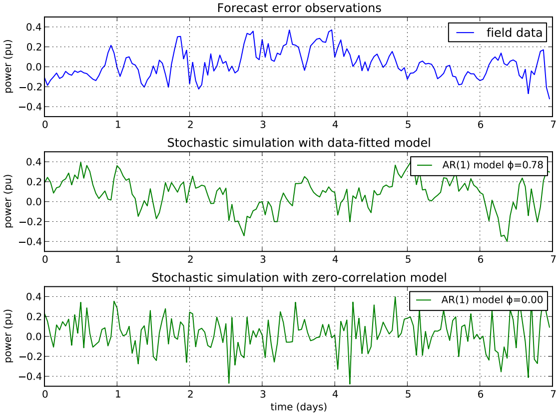


Available time series are not long enough (∼few months), we need a **forecast error simulation model** (a "noise generator").

Autoregressive modeling of forecast errors

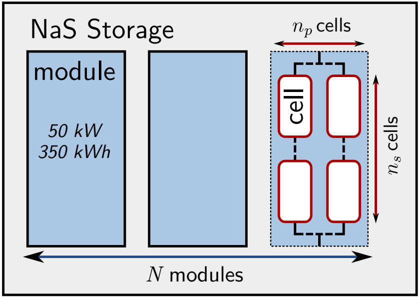
An AR(1) model captures the *autocorrelation* of forecast errors:

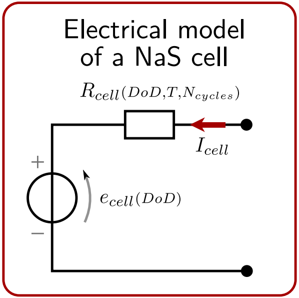
$$P^*_{sto}(k+1) = \phi P^*_{sto}(k) + \sigma_P \sqrt{1-\phi^2}\varepsilon(k+1)$$



NaS battery modeling

Sodium-Sulfur (NaS) batteries are designed for stationnary grid-scale storage of electricity (manufactured by NGK, Japan).





EDF commissioned a 7.2 MWh battery ($N = 20$ modules).
But the *model is fully sizable* in terms of rated energy (by setting N to an arbitrary number).

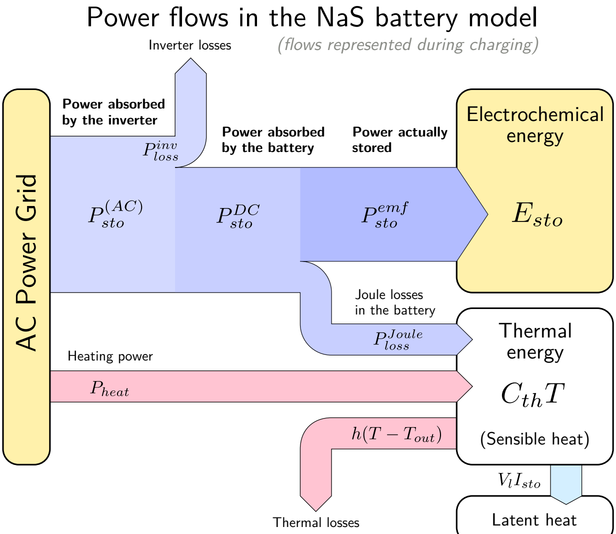
NaS battery modeling

requirements of the model

Because NaS batteries are *hot* (operating at 300 – 350 ℃), the *thermal modeling* is important. Temperature impacts the cell resistance, thus efficiency.

Losses of electrical energy need to be computed to evaluate their cost.

NaS battery model: power flows



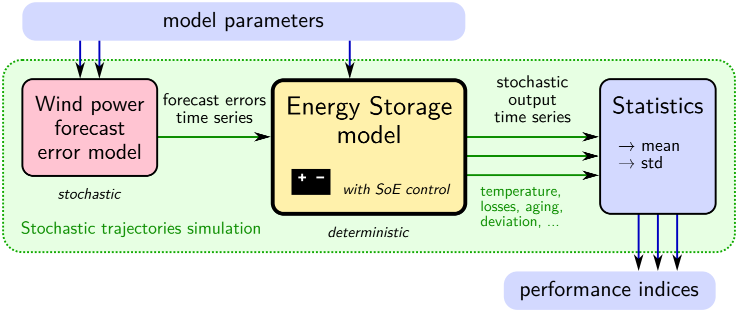
Outline of the presentation

Combining the forecast and ESS models

For given model parameters, the wind-storage simulation generates stochastic trajectories.

Model parameters are:

- for the forecast error: RMS error σ_P and correlation ϕ
- for the NaS battery: the rated energy E_{rated}



Case study
a typical wind farm in La Réunion island

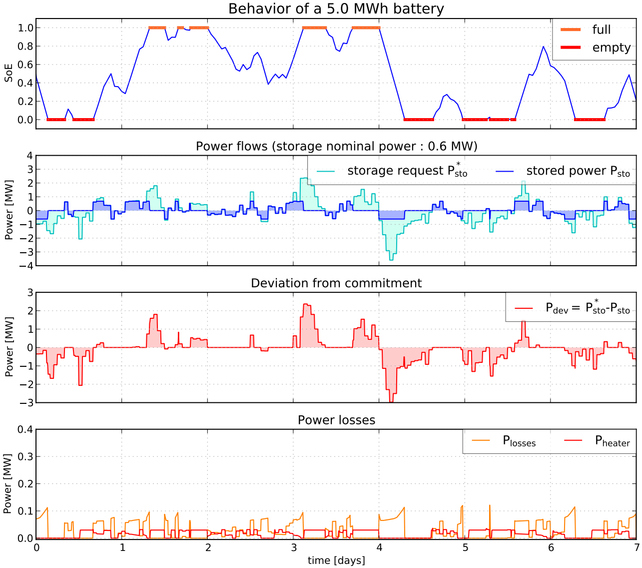
We consider a wind farm with a rated power $P_{nom} = 10$ MW. For the forecast error model, we consider:

- an RMS forecast error of 10 %: $\sigma_P = 1$ MW
- an inter-hour correlation of 80 %: $\phi = 0.8$

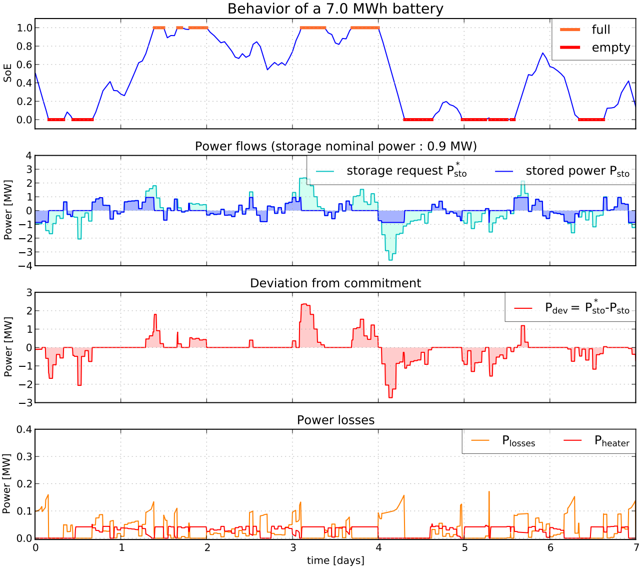
Before looking at the performance statistics, we first observe the *trajectories* (samples of stochastic time series).

We will look at the effect of increasing the storage capacity E_{rated} from 5 to 20 MWh. Rated power rises accordingly since the "E/P ratio" is fixed with the NaS technology at *7.2 hours*.

Stochastic trajectories from the simulation



Stochastic trajectories from the simulation



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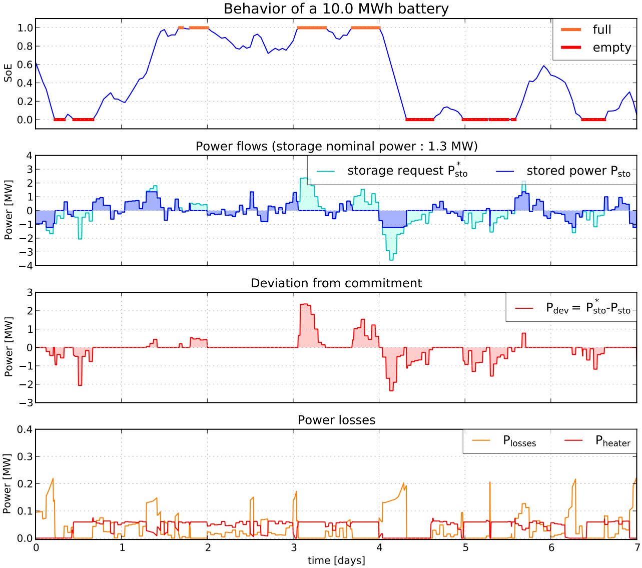

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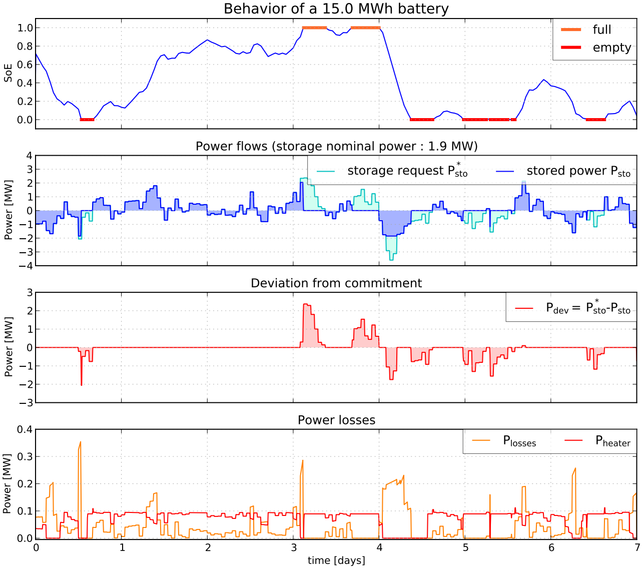
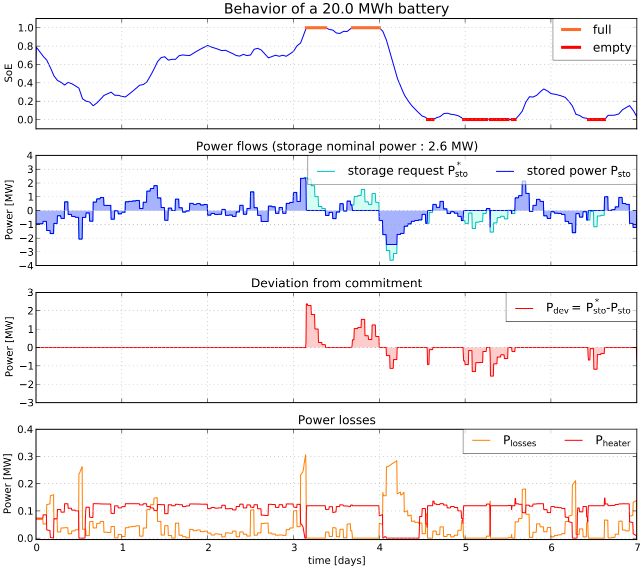
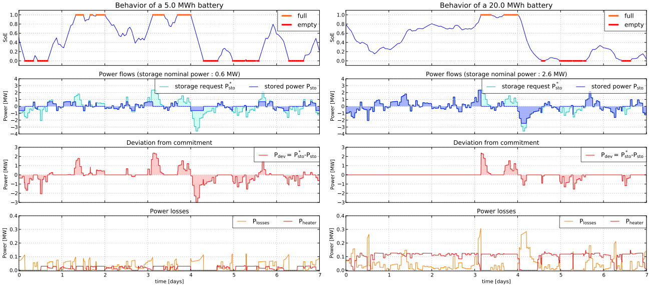


Stochastic trajectories from the simulation



Stochastic trajectories from the simulation



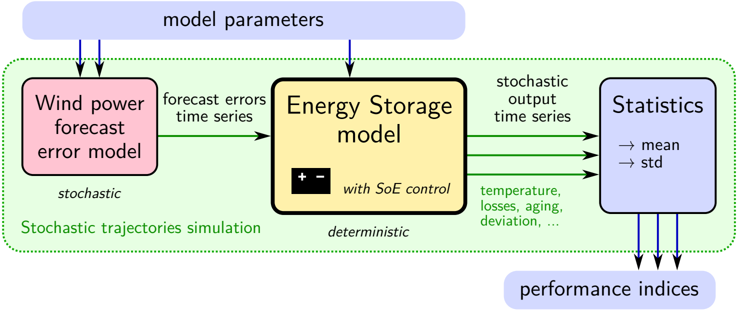
Observations:

- a bigger battery “absorbs” better the forecast error
- a smaller battery consumes less heating power.

We want now to compute *quantitative* performance indices. . .

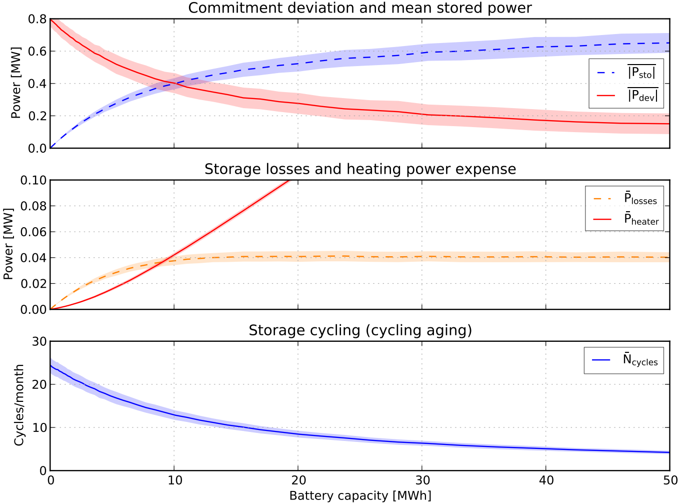
Statistics of performance

The stochastic simulations are *repeated* to collect many (1000) trajectories on which to compute *statistics* of performance indices like losses and commitment deviation.



Parametric study of the performance
by varying the ESS capacity (0–50 MWh)

Performance metrics computed from 1000 trajectories of 30 days



Filled color intervals show the standard deviation among the different trajectories (i.e. *inter-month variability*).

Study of a cost model

We put a monetary weight (cost) on each performance metrics (commitment deviation, losses, aging), to find an optimal storage capacity.

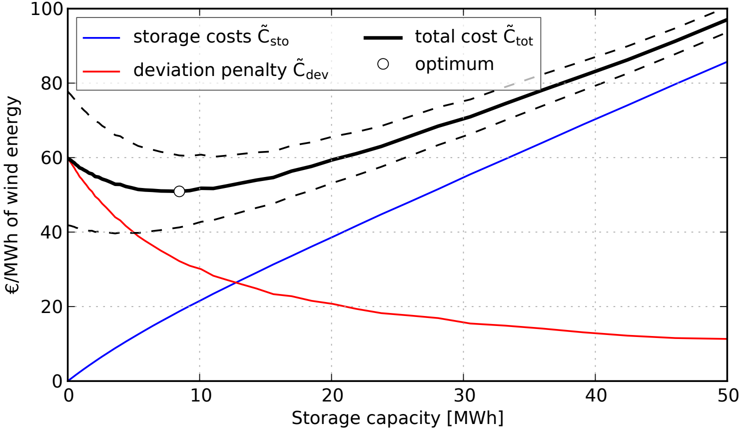
$$\tilde{C}_{tot} = \frac{1}{\bar{P}_{prod}}\Big(c_{batt}\big(\frac{\overline{|P_{sto}|}}{2N_{life}} + \frac{E_{rated}}{t_{life}}\big) \quad \text{cycling and calendar aging}$$
$$+c_{elec}(\bar{P}_{losses} + \bar{P}_{heat}) \quad \text{lost electricity}$$
$$+c_{dev}\overline{|P_{dev}|} \quad \text{commitment deviation}\Big)$$

Cost in €/MWh of produced wind energy.

Here, commitment deviation is penalized as Mean Absolute Deviation, but other choices are possible.

A look at the optimal capacity

With a penalty of 150 €/MWh$_{dev}$, the optimal capacity is 8.5 MWh, with an optimal cost of 50 €/MWh$_{prod}$ (30 for penalties, 20 for storage costs).



Dashed lines show the sensitivity to ± 30 % variations of the deviation penalty.

Outline of the presentation

Conclusion

From our simulations, we observe that:

- An Energy Storage System can indeed mitigate forecast errors to fulfill a day-ahead commitment.
- Battery cycling is kept below the allowed limit of 5000 cycles in 15 years.
- *Variability* of forecast errors generates a significant variability of performance metrics, like monthly penalty averages.
  This could impact day-to-day operation.

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From our simulations, we observe that:

- An Energy Storage System can indeed mitigate forecast errors to fulfill a day-ahead commitment.
- Battery cycling is kept below the allowed limit of 5000 cycles in 15 years.
- *Variability* of forecast errors generates a significant variability of performance metrics, like monthly penalty averages. This could impact day-to-day operation.

The case for Energy Storage (for day-ahead commitment):

- the cost function is quite "flat": not such a clear case for storage (high sensitivity to storage cost and penalty fee).
- but other penalty criterions may make the case clearer (like adding a tolerance deviation band).

Possible extensions

Additional degrees of freedom that should be taken into account to get a better performing system:

- *bidding strategy:* commitment power not necessarily equal to forecast power.
- *curtailment:* ability to lower the production level
- *energy management:* optimized control of storage power ($\rightarrow$ stochastic dynamic optimization)