Energy Storage for Wind Power

Storage technologies, Energy management and Sizing

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Outline of the presentation

1. Storage for the grid
2. Context of wind-storage in French islands
3. Modeling of stochastic inputs
4. Energy management of the storage
5. Sizing of the energetical capacity
6. Conclusions

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1. Storage for the grid
   - Energy storage introduction
   - Application examples, for renewables
   - Important modeling aspects
   - Conclusion

2. Context of wind-storage in French islands

3. Modeling of stochastic inputs

4. Energy management of the storage

5. Sizing of the energetical capacity

6. Conclusions

Power/Energy: order of magnitudes

Power and Energy of some common objects:

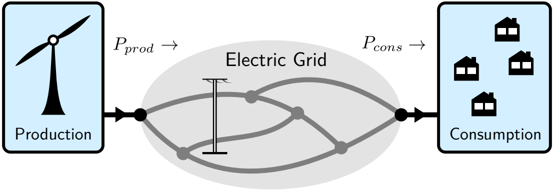
- **Smartphone**: 5 W (charging power), 5 Wh (battery)
- **Water boiler**: 2 kW, 100 Wh (1 ℓ of water from 15 to 100°C)
- **Electric car**: 100 kW (134 hp, peak), 25 kWh

Most of the talk: storage for the grid, in the **MW/MWh** scale.

Storage on the grid

On the grid, **production and consumption are equal**.

Therefore, any "source of variability" must then be balanced by a "source of flexibility". Many levels of **controls** are present to control the many degrees of freedom, to keep the system within a safe operating area.



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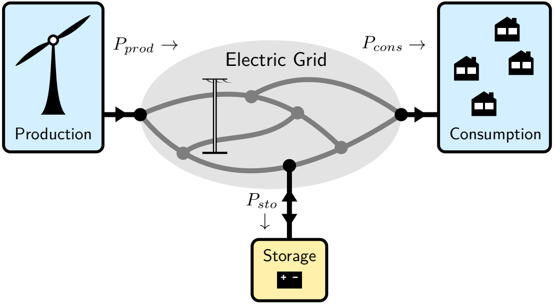

Energy storage is one such source of (pure) flexibility.

Sources of variability

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The effect of weather

Many of the above are related to weather variability (ex: icing on transmission line).

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- Scheduling of dispatchable generation
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Actually, energy storage is *already there*. . .

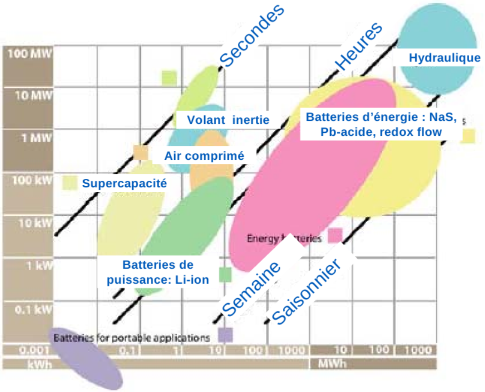
Energy storage in the present grid

Hydro power (with or without pumping) is, by far, the main storage technology in used today (for decades).

and demand side management for **heating** is a kind of storage as well.

Energy and Power ratings

Many different technology, with different Energy/Power ratings



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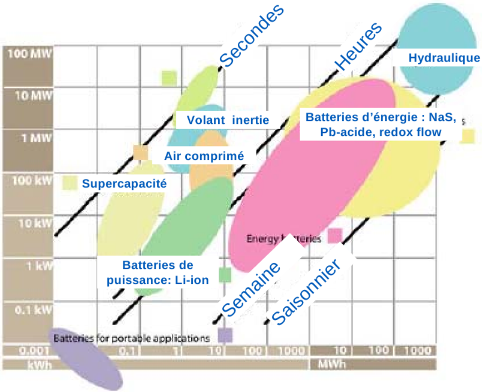


"Time constant" of a storage

$T = E_{rated}/P_{rated}$, technology dependent.

Different applications

A quick tour of storage field applications, connected to wind/solar generation.

- different goals, different codes
- different time constants, technologies

Flywheels (small time constants)

Beacon Power: "frequency regulation" plants, as a service for system operators. 20 MW/5 MWh (15 minutes).

http://beaconpower.com/hazle-township-pennsylvania/

Also used in some Uninterruptible Power Supplies (UPS).
Ex: Piller flywheels can deliver several MW during 10 seconds.
http://www.piller.com/205/energy-storage

Wind power smoothing in Hawaï

In Kahuku Wind Power project (2011), energy storage helps wind integration in a weak grid (200 MW).

System:

- 15 MW/10 MWh Xtreme Power (high power lead-acid)
- 30 MW wind farm in Hawaï
- controls ramps to ±1 MW/min
- (fire in 2011)

Image: Xtreme Power

Futamata NaS-Wind farm (2009)

A huge pilot plant for reducing wind power variability (possible operation at **constant output**!).

Ratings:

- 51 MW wind farm at Futamata, Japan
- 34 MW sodium sulfur (NaS) batteries
- storage time constant: **7 hours**

(Kawakami 2010)

NaS technology: promising battery technology for grid scale storage.

Hot temperature operation (300°C). Deals with Terna (Italy) and EDF (France).

Small PV-storage systems

off-grid area

In off-grid remote area, millions of people rely on PV-storage systems for their daily electricity consumption.
(Diesel backup also possible).

Typical system (New Caledonia):

- 1 kW PV (peak)
- 17 kWh battery

Lead-acid battery are used, for robustness, low price and high energy/power ratio.

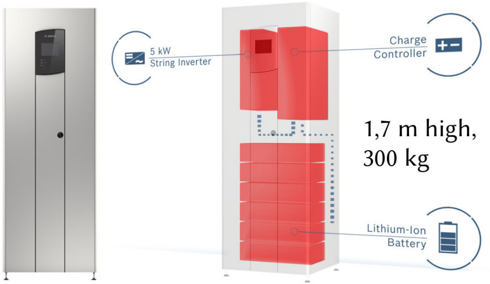
(Multon, 2011)

Picture: `http://www.sunzil.nc`

Small PV-storage

grid connected houses

Recent offers for storage as a home appliance (e.g. German market).
Goal: increasing the **self-consumption** of PV energy.



Ex: Bosch BPT-S 5 kW solar inverter, with lithium-ion battery (4 to 13 kWh).
Li-ion chosen for high efficiency and long lifespan (20 years expected).

Picture: `http://bosch-solar-storage.com`

El Hierro wind-hydro

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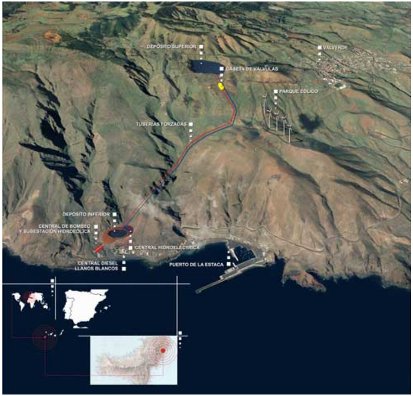
Power plant inaugurated in 2014:

- 11 MW of wind
- 11 MW of hydro generation
- 6 MW of pumping

Cost: 80 M€ (i.e. 7 €/W).

Picture, and more info:

`http://www.goronadelviento.es`



Important modeling aspects

For storage control or sizing, models are necessary. Here are some important aspects that should be taken into account in such studies:

- dynamics (e.g. State of Energy evolution)
- energy losses (rarely negligible)
- investment cost (often huge)
- aging (which can lead to replacement, so re-investment)

Storage dynamics

Simple **energy-based description**:

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- power: $-P_{discharge} \leq P_{sto} \leq P_{charge}$
  (limitations can depend on State of Energy)

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State of Energy

$SoE = E_{sto}/E_{rated}$, between 0 and 1.

Losses (efficiency)

Storage losses depend on the **technology**, but also on the **operating conditions**:

- State of Energy (ex: battery series resistance)
- Charge/discharge rate
- Temperature (for batteries)

Either model structure or model data is often hard to find.
Simplified linear losses model often used in design study:

$$P_{losses} = \alpha |P_{sto}|$$

Litterature often gives **roundtrip efficiency** η_{cycle}, i.e. efficiency on a charge/discharge cycle, for *some* cycling conditions.
(warning: $\eta_{cycle} \approx 1 - 2\alpha$)

Losses of auxilliaries

The consumption or the losses of **auxilliary systems** should not be forgotten.

Examples of auxilliaries:

- Losses of power electronics converters
- Air conditionning (quite usual for Lithium-ion batteries)
- Heating, for hot batteries (Sodium-Sulfur)

These can become the main sources of losses if the storage itself is highly efficient (like lithium-ion).

Storage investment cost

Storage investment cost is often evaluated by taking a unit price, from manufacturer or litterature:

- price in **€/kWh** for "energy applications" (most batteries)
- price in **€/kW** for "power applications" (super-capacitors)

Examples:

- Lead-acid : 200 €/kWh (?)
- Lithium-ion: 500 to 1000 €/kWh (?)

Storage investment cost

extra costs

Extra costs (sometimes unexpected) can be important.

Example 1:

- simple battery *cell*, versus
- battery *module*, which include measurements, protections and a Battery Management System (BMS) which are require for a safe operation.

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Example 2: EDF in La Réunion, for a 7 MWh NaS battery:

- planned to cost 2 M€ (270 €/kWh)
- eventually cost 3 M€ (420 €/kWh), due to additional *civil engineering* required for chemical hazard.

Aging modeling

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Typical value for Li-ion batteries: 1000 – 3000 *deep* cycles (more *small* cycles).

Aging + price: the usage cost

Combining the aging with capacity price, one can make simple *lifecycle cost analysis*.

Application

For Li-ion battery at 1000 €/kWh, that can perform 3000 cycles, what is the lifecycle usage cost discharging 1 kWh of electricity ?

(not taking into account the price to buy electricity).

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Comparison: the price of electricity from grid is about 0.10 €/kWh (France)

Energy storage on electricity grids
a conclusion attempt

Energy storage on electricity grids:

- already in use, in contexts where it makes sense (lots of niches)
- many field experminents, to test both the *business model*, and the technical *reliability* (several cases of fire...).
- not economical for large scale artitrage/energy shifting.

Outline of the presentation

Renewables in French islands

Islands (Guadeloupe, La Réunion) have weak grids (< 1 GW), with expensive and high-CO_2 electricity (Diesel : 130 €/MWh).
→ Wind power at 110 €/MWh is economically interesting, but...

Island grids are particularly sensitive to the **variability** of intermittent renewable energies (wind and PV).

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Today treatment of variability:

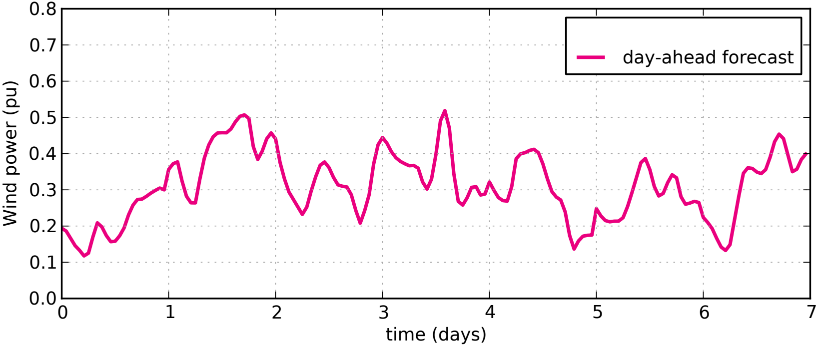
- Production: flexible, but expensive units (combustion turbine at 300 €/MWh).
- Grid code: a "30 % limit" (at each time) of intermittent productions ("non dispatchable")

→ The growth of renewables is severely reduced

Overview of wind power variability

Day-ahead production forecast

Wind power can be forecasted one day in advance, using **meteorological and statistical** tools.



one week of forecast/production (1h means), in Guadeloupe

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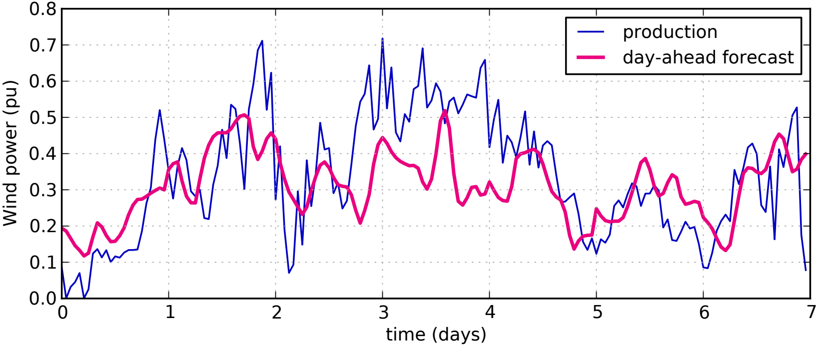

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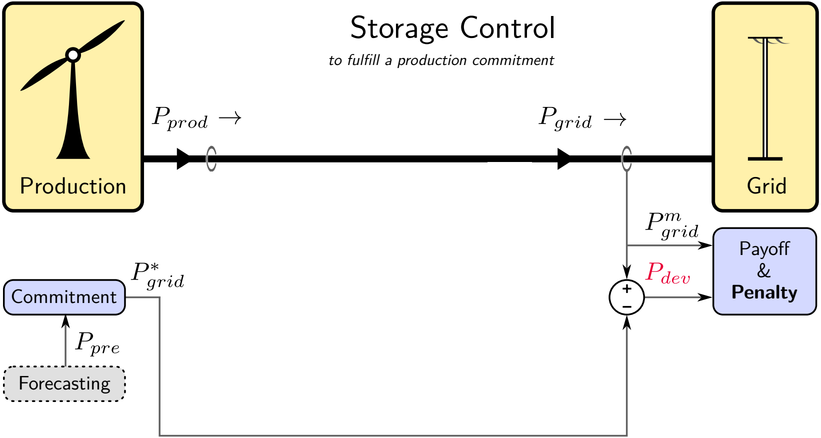
Day-ahead forecast is not perfect → errors to compensate...

Wind-storage call for tenders

a new treatment for variability

Call for tenders of the French Energy Regulation Commission (CRE) for wind farms with a *production commitment*:



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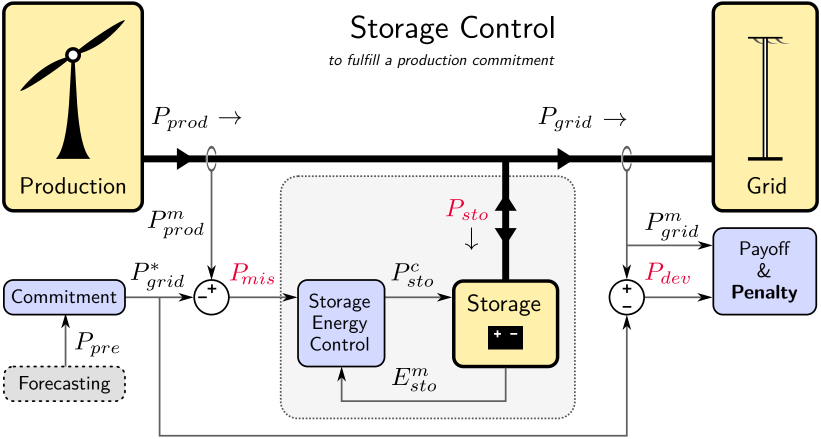

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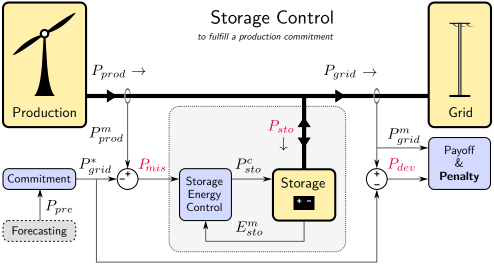
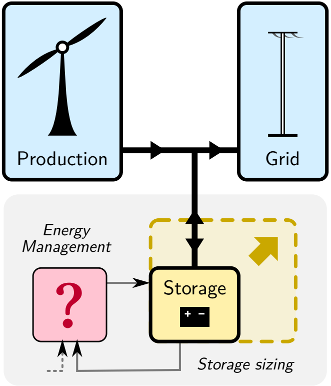


Services required by the Commission:

- frequency regulation (10 % of rated power should be adjustable during 15 minutes)
- limitation of power variations (ramps)
- **commitment** to a day-ahead production schedule.

Problem statement



How to *size* and
how to *manage*
the wind-storage system?

A double optimization problem:

- Which storage sizing
  (capacity E_{rated} et power P_{rated})
  enables to *optimally* fullfill
  a day-ahead production commitment?
- Which control policy to use,
  at a given sizing, to make the best use of the energy stock?

Problem specifics
beyond wind-storage context

Storage sizing

Optimization

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Energy management

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Storage sizing
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Coupling

Sizing and
Energy management are
coupled optimizations.

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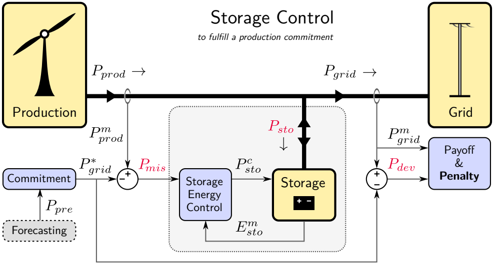
Outline of the presentation

Importance of the forecast error

The storage is there to *mitigate forecast errors*.



(hypothesis "day-ahead commitment = day-ahead forecast")

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

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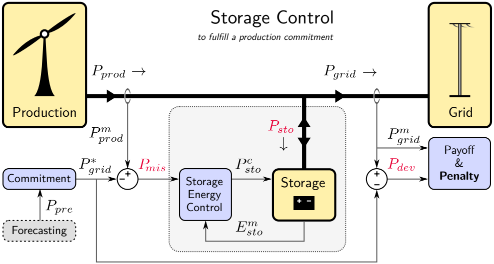

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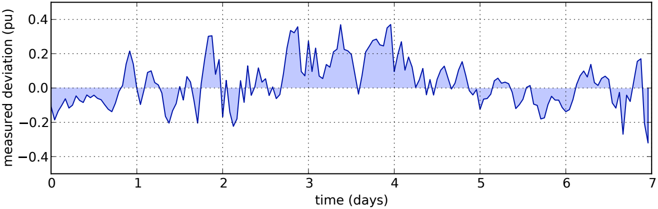
The need for modeling P_{mis}

Day-ahead forecast error is the main input of the problem.
Thus the importance to **characterize** it.

Characterizing forecast error

Forecast quality depends on the terrain complexity, and forecast horizon, ...

Example of a wind farm in Guadeloupe: standard deviation is **15%** of the rated power.



Temporal structure : day-ahead forecast errors, at a hourly time step, are not *independent*...

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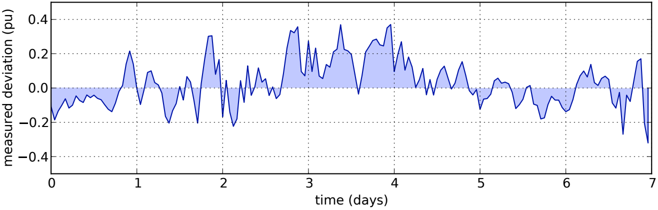
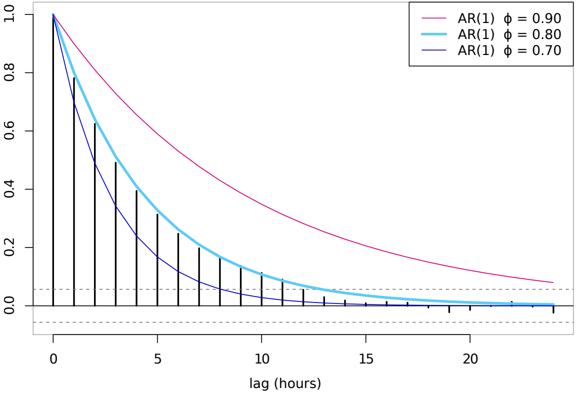


Temporal structure : day-ahead forecast errors, at a hourly time step, are not *independent*. . .

. . . sometimes *forgotten/neglected* in litterature on storage!

Autocorrelation of forecast errors

Temporal dependency (autocorrelation) decays exponentially



This shape corresponds to an AR(1) stochastic process.

AR(1) autoregressive model

discrete time model, with time step $\Delta_t = 1\,\mathrm{h}$

Model based on the low-pass filtering of a white noise $\varepsilon(k)$:

$$P_{mis}(k+1) \;=\; \phi\, P_{mis}(k) \;+\; \sigma_P \sqrt{1-\phi^2}\, \varepsilon(k+1)$$

"autoregressive": each value depends on the previous one (with ϕ)

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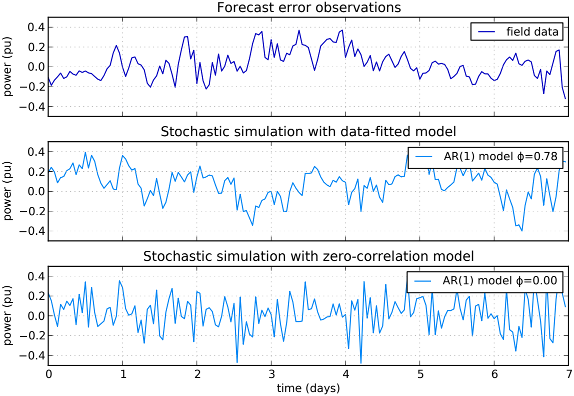


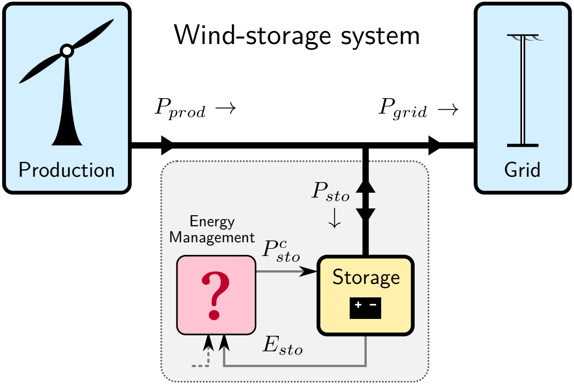
field data $\rightarrow$ estim. $\hat{\phi} = 0.78$
$\hat{\sigma}_P = 0.15\,\mathrm{pu}$

simulation **with** autocorrelation
$\phi = 0.78$ ($\sigma_P = 0.15$)

simulation **without** autocorrelation
$\phi = 0.0$ ($\sigma_P = 0.15$)

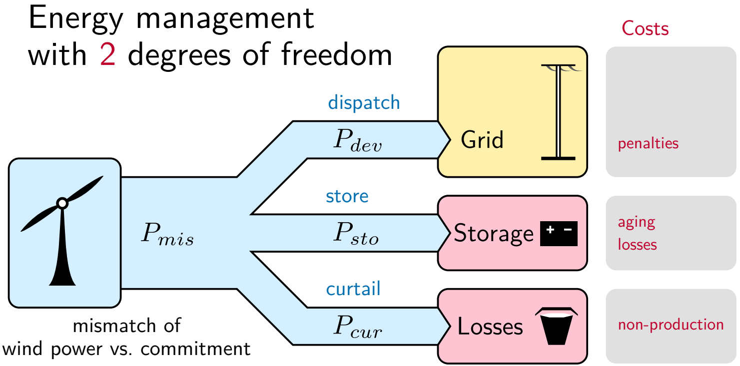
Outline of the presentation

Description of the control problem



How to management the energy storage?

Description of the control problem



We want to **allocate** the forecast error$^{(*)}$ P_{mis} between : the grid, a storage and a curtailment setpoint, at **the least cost**.

$^{(*)}$ hypothesis "day-ahead commitment = day-ahead forecast"

Presentation of Dynamic Programming

The optimization of energy management is a **dynamic** et **stochastic** optimization problem.

Dynamic programming (Bellman, ~1950) is the natural method to address this kind of problem.

Usage in energy management:

- management of hydro-electric dams (ex. EDF).
- management of hybrid electric vehicles (litterature).

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Often used for *deterministic* optimizations,...

ex.: predetermined mission profile for a vehicle.

...but more rarely in a *stochastic* context

ex.: hybrid electric vehicles [Lin 2004], elevators+supercapacitors [Bilbao 2012].

Objective of Dynamic Programming

Minimize a penalty $c(\dots)$, in **temporal average**, in **expectation**:

$$J = \frac{1}{K}\,\mathbb{E}\Big\{ \sum_{k=0}^{K-1} c(x_k, u_k, w_k) \Big\} \quad \text{with } K \to \infty$$

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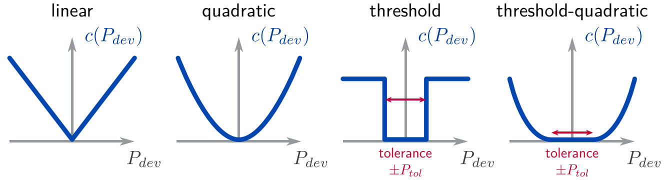
and the choice of the instantaneous penalty function $c()$ is **free**.
$\rightarrow$ We want to penalize in particular the deviation P_{dev} :

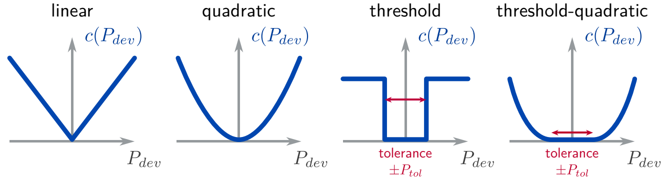


Objective of Dynamic Programming

Minimize a penalty $c(\ldots)$, in **temporal average**, in **expectation**:

$$J = \frac{1}{K}\mathbb{E}\left\{\sum_{k=0}^{K-1} c(x_k, u_k, w_k)\right\} \quad \text{with } K \to \infty$$

and the choice of the instantaneous penalty function $c()$ is **free**.
→ We want to penalize in particular the deviation P_{dev} :



Shape *to be chosen* depending the desired behavior
(→ **reflection** on the rules of the wind-storage call for tenders)

Dynamics of the System

in discrete time, with time step $\Delta_t = 1\,\mathrm{h}$

A dynamics function $f(x_k, u_k, w_k)$ models
the **evolution of the state** x_k: "memory, inertia" of the system.

Example for the wind-storage system :

$$E(k+1) = E(k) + P_{sto}(k)\Delta_t \quad \text{(storage)}$$

$$P_{mis}(k+1) = \phi P_{mis}(k) + w(k) \quad \text{(AR(1) process)}$$

state	command	stochastic perturbation
$x = E, P_{mis}$	$u = P_{sto}$	$w = \sqrt{1-\phi^2}\,\varepsilon$

Constraint on the command P_{sto}:

$$0 \leq E + P_{sto}\Delta_t \leq E_{rated} \quad \text{(limit of the storage capacity)}$$

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The dynamic equation $x_{k+1} = f(x_k, u_k, w_k)$ creates
a **coupling between the instants** $\rightarrow$ "dynamic optimization"

(Stochastic) Dynamic Programming

the optimization procedure

Resolution with a backward **recursive minimization**: ("Bellman eq.")

$$J_k(x_k)^* = \min_{u_k \in U(x_k)} \mathop{\mathbb{E}}_{w_k} \Big\{ \underbrace{c(x_k, u_k, w_k)}_{\text{instant cost}} + \underbrace{J^*_{k+1}\big(\overbrace{f(x_k, u_k, w_k)}^{\text{future state } x_{k+1}}\big)}_{\text{future cost}} \Big\}$$

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This minimization produces an optimal **control law** (or policy):

$$u_k = \mu^*(x_k)$$

Closed-loop Control

Important property of dynamic programming:

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This optimal control law μ^*:

1. is computed **off-line**, once for all: **heavy** computation (table $x_k \mapsto u_k^*$ on a grid over the state space),
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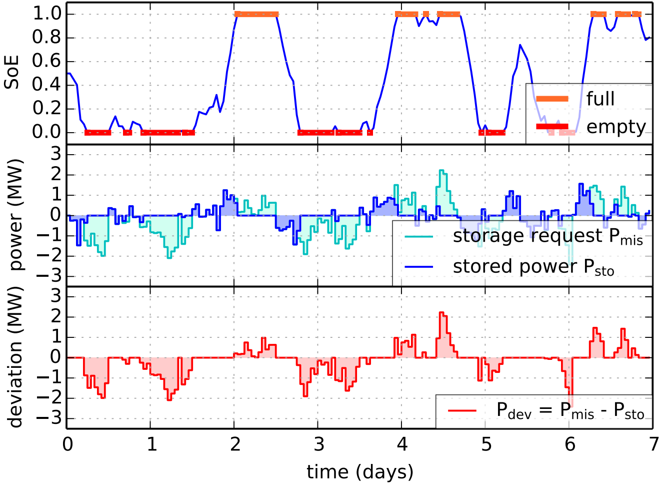
$\rightarrow$ Now, let's observe storage simulations of an optimally controled storage, with different shapes of penalization $c(\dots)$.

Trajectories for different shapes of penalization



Capacity:
$E_{rated} = 5\,\mathrm{MWh}$

Input P_{mis}:
$\sigma_P = 1\,\mathrm{MW}$.

before optimization

(optimal for a linear penalty)

empirical control "$P_{sto} = P_{mis}$ as long as feasible"

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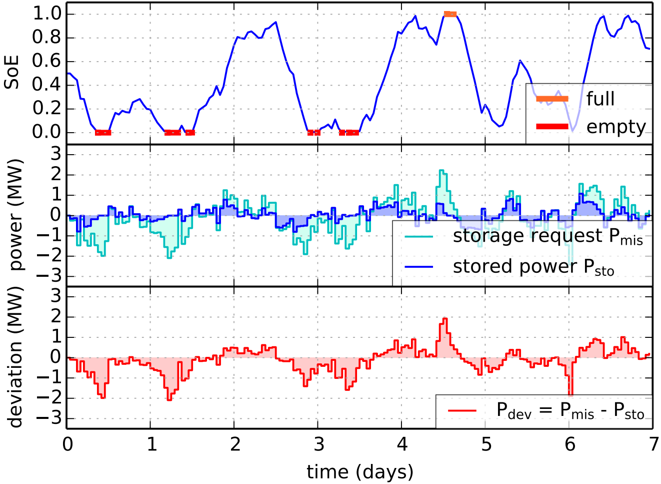

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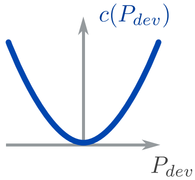
quadratic



optimal control for a **quadratic** cost

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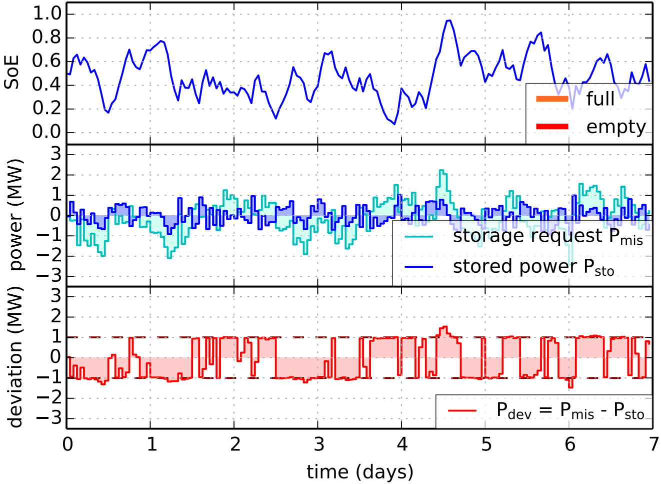

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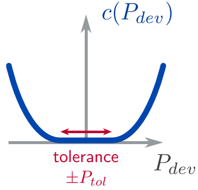
threshold-quadratic

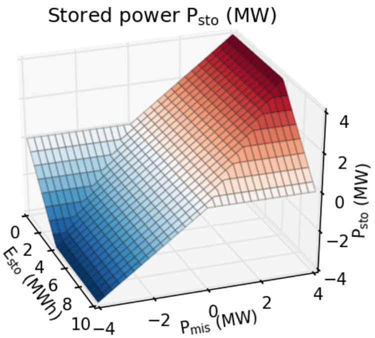


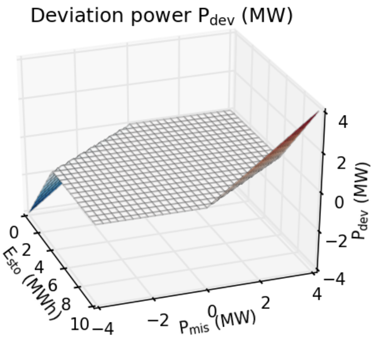
optimal control for a **threshold-quadratic** cost at ± 1 MW

Control law for different shapes of penalization

Storage: $P_{sto} = \mu^*(E_{sto}, P_{mis})$

Deviation: $P_{dev} = P_{mis} - P_{sto}$





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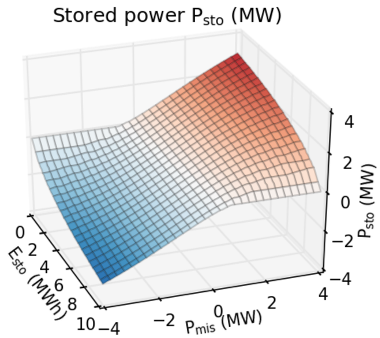

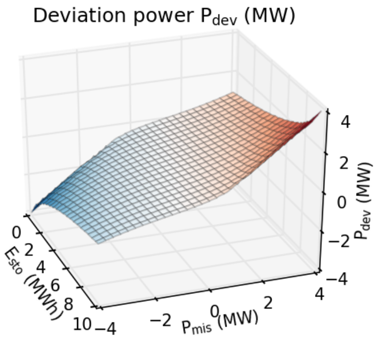

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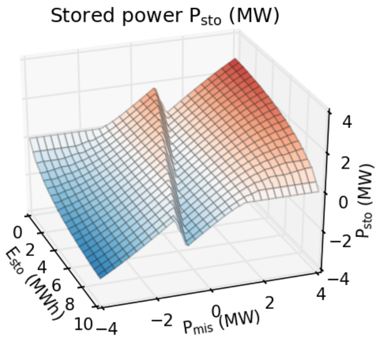

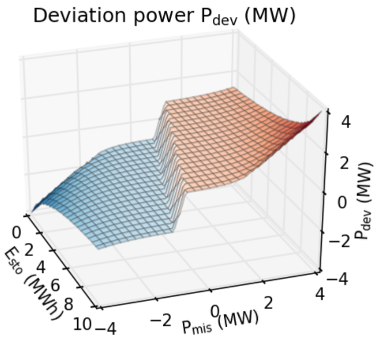

optimal control for a **threshold-quadratic** cost at ± 1 MW

Effect of the choice of deviation penalization shape

Stochastic Dynamic Programming (SDP) can address a *wide range* penalty functions.

By comparing the optimization results, we observe that:

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By comparing the optimization results, we observe that:

- the penalization shape strongly impacts the **behavior** of the wind-storage system
- practical lesson learned:
  the grid code that shapes the penalties should be written for:
  - discouraging “pirate” strategies of wind operators,
  - encouraging “grid-friendly” behaviors
    (ex.: avoid hard thresholds, non-convex penalizations).

Effect of parameters

Just like the shape of the penalty function, the parameters of the problem also influence the optimal control law:

- Storage capacity: E_{rated}
  $\rightarrow$ the optimal control law depends on the sizing
- Autocorrelation coefficient of the input: ϕ
  $\rightarrow$ importance of a good estimation of ϕ (on field data)

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Beyond these observations:

Interest for sizing

If a **simple parametric form** can be deduced,
that takes into account the storage capacity,
one can avoid the repeated optimization of energy management.

Effect of the autocorrelation coefficient

Storage: $P_{sto} = \mu^*(E_{sto}, P_{mis})$

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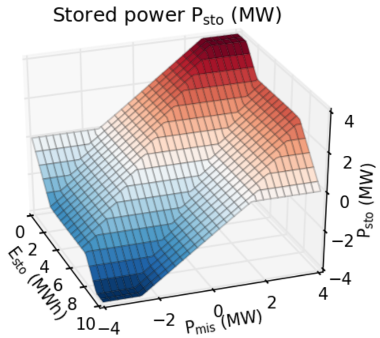

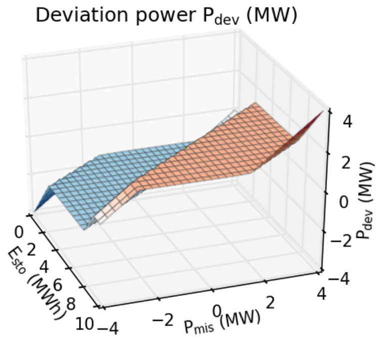

input autocorrelation: ϕ=0.0

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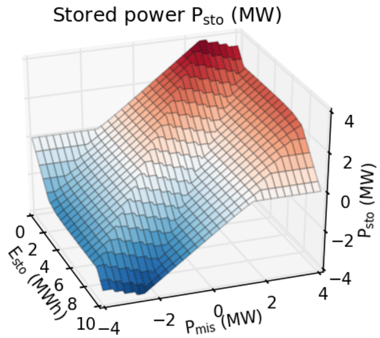
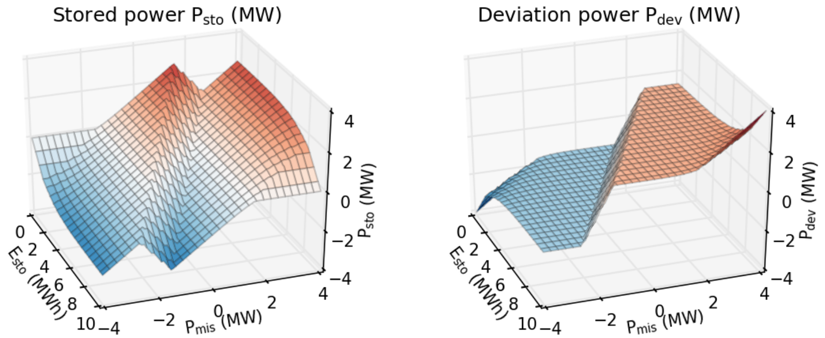


input autocorrelation: ϕ=0.3

Effect of the autocorrelation coefficient

Storage: $P_{sto} = \mu^*(E_{sto}, P_{mis})$ Deviation: $P_{dev} = P_{mis} - P_{sto}$



input autocorrelation: ϕ=0.6

Effect of the autocorrelation coefficient

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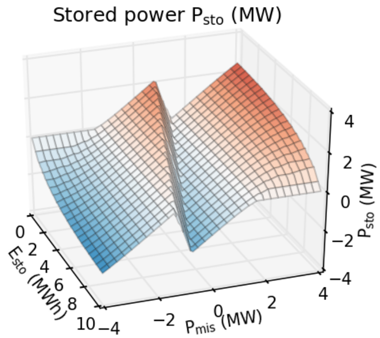

input autocorrelation: ϕ=0.8

→ the **persistence** of the error P_{mis} influences the control law.

Outline of the presentation

Sizing methodology

Storage sizing needs a *compromise* between:

- minimization of the storage capacity E_{rated}
- minimization of the commitment deviations $P_{dev}(k)$

$\rightarrow$ 2 *opposite/contradictory* objectives

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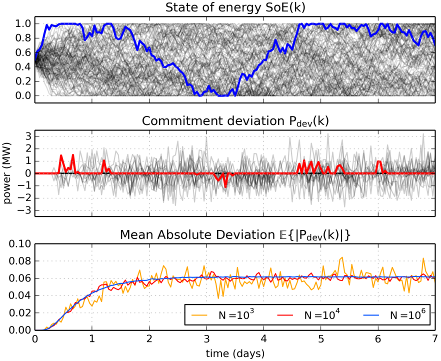
Possible solutions to come over this contradiction:

- minimization of the storage capacity, under a **constraint** of deviation performance
- minimization of a **weighted sum** of the two objectives (e.g. economic cost minimization)

Methodology of performance estimation

2 key issues for performance evaluation with simulations:

- **stochastic inputs** → *statistical* estimation, with many trajectories (Monte-Carlo)
- **dynamical system** → temporal simulations to "forget" the initial state and reach a *stationnary* state.



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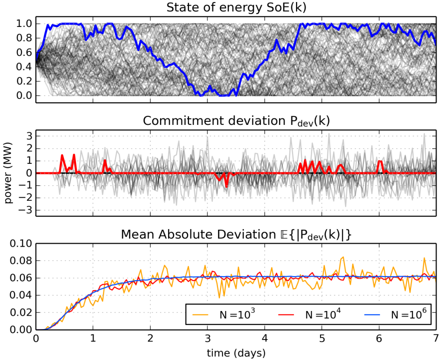

Example of performance criterion: commitment deviation, in **mean absolute value** $\|P_{dev}\|_1 = \mathbb{E}[|P_{dev}|]$.

Other criterions: energy losses, aging, ...

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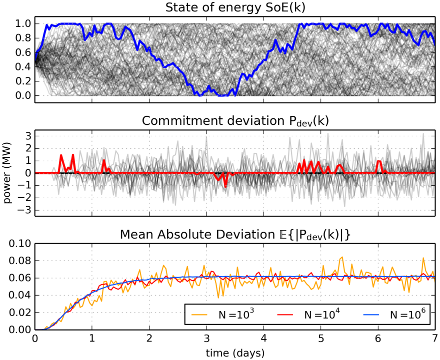

Example of performance criterion: commitment deviation, in **mean absolute value** $\|P_{dev}\|_1 = \mathbb{E}[|P_{dev}|]$.

Other criterions: energy losses, aging, . . .

To reduce the variance of estimation:

- more trajectories ($N = 10^x$), vectorizable
- longer trajectories, *not* vectorizable

Effect of autocorrelation on performance

We have seen that:

1. day-ahead wind power forecast errors are autocorrelated.
2. this autocorrelation influences the optimal energy management.

$\rightarrow$ Now we want to observe its **effect on sizing**
(autocorrelation sometimes *forgotten/neglected* in litterature)

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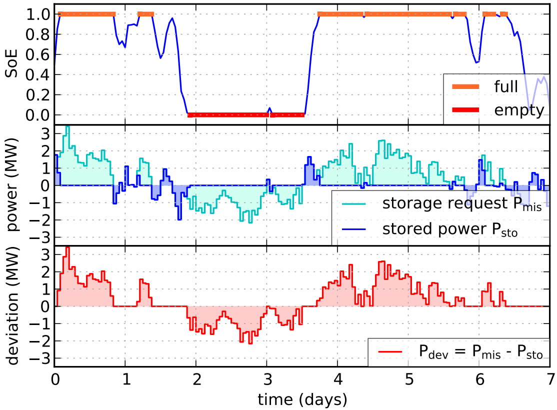
Simulations with:

- an model of ideal storage (no losses)
- an input stimulus P_{mis} simulated with an AR(1)

and we monitor the deviation $P_{dev} = P_{mis} - P_{sto}$

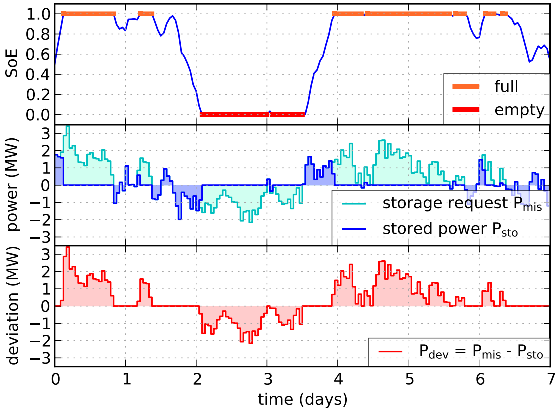
Effect of capacity on performance



capacity $E_{rated} = 05\,\mathrm{MWh}$

Fixed parameters: input amplitude $\sigma_P = 1\,\mathrm{MW}$, autocorrelation $\phi = 0.8$

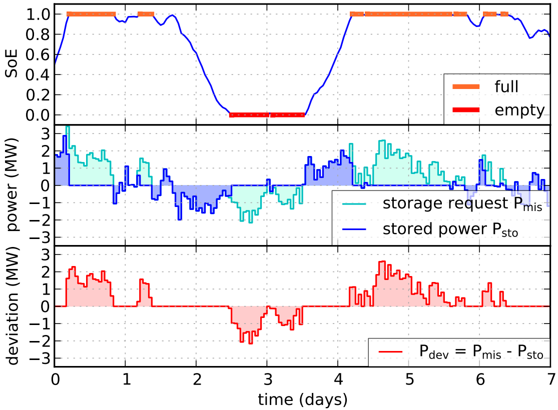
Effect of capacity on performance



capacity $E_{rated} = 10\,\mathrm{MWh}$

Fixed parameters: input amplitude $\sigma_P = 1\,\mathrm{MW}$, autocorrelation $\phi = 0.8$

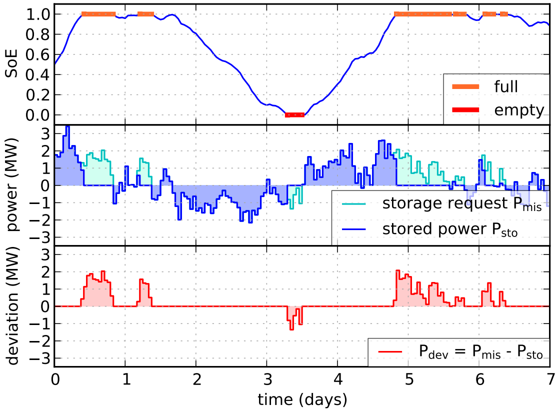
Effect of capacity on performance



capacity $E_{rated} = 20\,\mathrm{MWh}$

Fixed parameters: input amplitude $\sigma_P = 1\,\mathrm{MW}$, autocorrelation $\phi = 0.8$

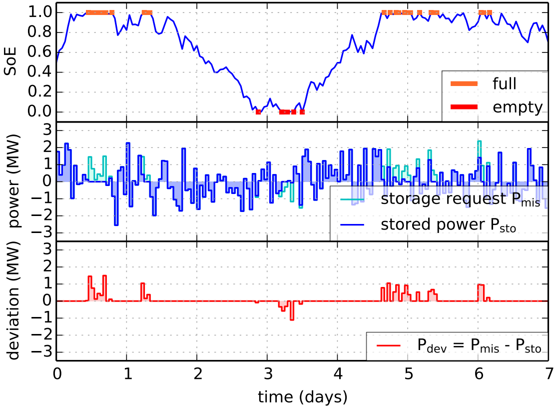
Effect of capacity on performance



capacity $E_{rated} = 40\,\text{MWh}$

Fixed parameters: input amplitude $\sigma_P = 1\,\text{MW}$, autocorrelation $\phi = 0.8$

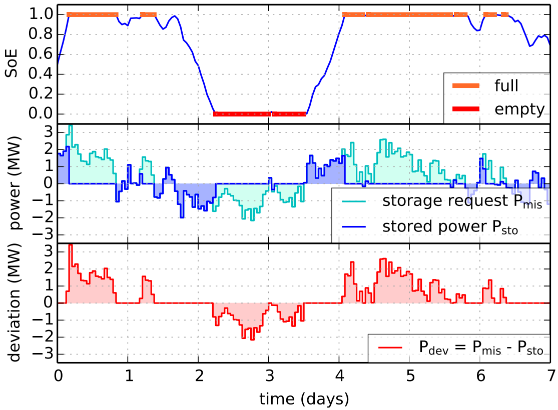
Effect of correlation on performance



autocorrelation $\phi = 0.0$

Fixed parameters: input amplitude $\sigma_P = 1\,\mathrm{MW}$, capacity $E_{rated} = 15\,\mathrm{MWh}$

Effect of correlation on performance

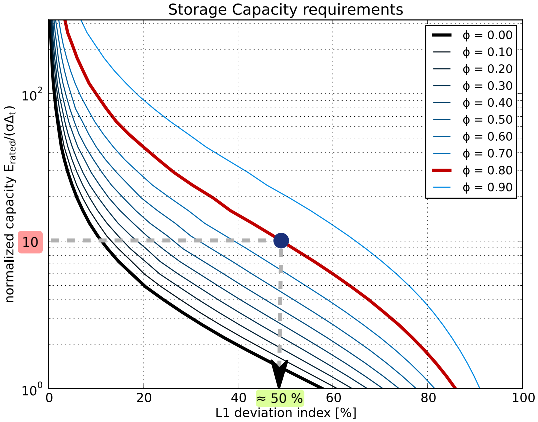


autocorrelation $\phi = 0.8$

Fixed parameters: input amplitude $\sigma_P = 1\,\text{MW}$, capacity $E_{rated} = 15\,\text{MWh}$

Effect of correlation on performance

We collect the statistic $\|P_{dev}\|_1 = f(E_{rated}, \phi)$ for 30×10 pts.



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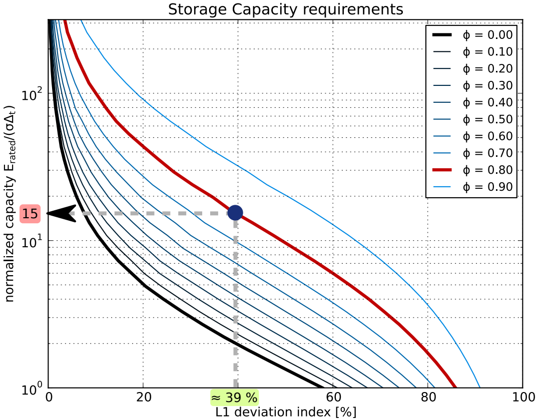

Reading as (pre-)sizing table: $E_{rated} = f(\|P_{dev}\|_1, \phi)$

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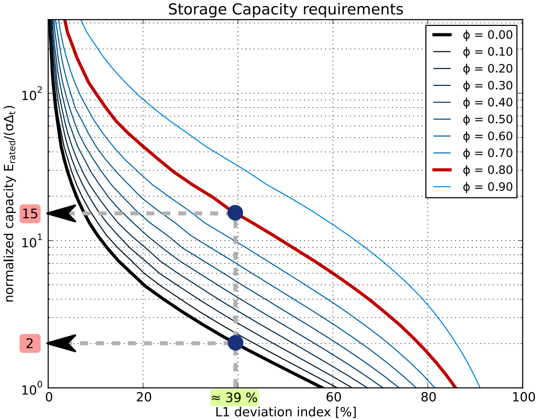

Reading as (pre-)sizing table: $E_{rated} = f(\|P_{dev}\|_1, \phi)$

autocorrelation strongly increases storage capacity need (~1 order of magnitude).

Economic sizing

Compromise between storage cost and reduction of deviation P_{dev}

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Needs of the economic sizing procedure

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estimation of losses and aging of the storage

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Needs of the economic sizing procedure

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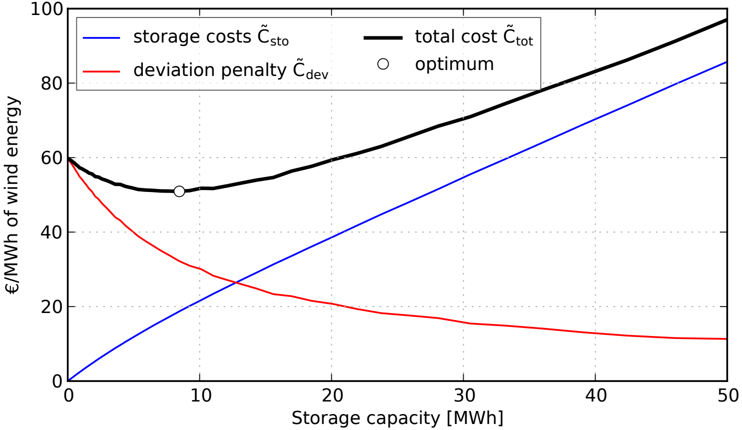
estimation of losses and aging of the storage

Ex.: sizing of a Sodium-Sulfur (NaS) battery:

1. Thermo-electrical model, including Joule losses and heating (hot battery at 350°C)
2. Performance evaluation, for different sizing choices: commitment deviation, losses, . . .
3. Compute the economic cost including: investment, aging and losses

Observations on the optimal sizing

With a penalty of 150 €/MWh_{dev}, the optimal capacity is 8.5 MWh, for a cost of 50 €/MWh_{prod} (30 for penalty, 20 for storage cost).



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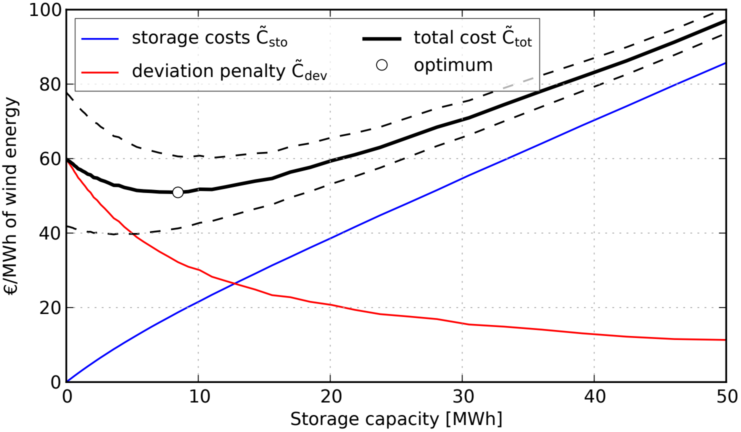

Dashed line: sensitivity to a variation of ± 30 % of the deviation penalty.

Outline of the presentation

Importance of models and data (e.g. weather forecast)

Modeling is instrumental to optimization (both sizing and energy management):

Input modeling

In particular model for the **dynamical behavior of weather-related stochastic inputs**
(For SDP: full probabilistic description, as a Markov process).

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Field data (production and forecast) is also important, for the validation of system performance (because the optimization models are always somewhat wrong).

Extensions

Extending the work on wind-storage for small islands:

- Evaluate **costs for the grid** (economic & environnemental)

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- Interactions **between farms** (global cost vision)
- **Other means of flexibility** (demand side management?)

Extensions

Extending the work on wind-storage for small islands:

- Evaluate **costs for the grid** (economic & environnemental)
- Interactions **between farms** (global cost vision)
- **Other means of flexibility** (demand side management?)
- Evaluate the **value of forecast**, from the point of view of a wind-storage system.

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