Stochastic Optimal Control for an Energy Storage

example: smoothing Ocean Wave Energy

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Lab seminar with Bart De Schutter,
November 20, 2014

Based on: P. Haessig, T. Kovaltchouk, B. Multon, H. Ben Ahmed, S. Lascaud
"Computing an Optimal Control Policy for an Energy Storage", EuroSciPy 2013
http://arxiv.org/abs/1404.6389

Outline of the presentation

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My background

Pierre Haessig

- Assistant professor at Supélec since September 2014
- PhD on Electricity Storage in relation to Wind Energy (control & sizing), with SATIE lab (ENS Rennes) and EDF R&D.

StoDynProg: a software package for Dynamic Opt.

Working on the management of Energy Storage with Wind Power, I've progressively discovered that:

- my problems fall in the class of *Dynamic Optimization* (a quite specific problem structure)
- the *Dynamic Programming* approach exists to solve them.
- basic DP algorithms are "too simple to be worth implementing" !!

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So I've started a generic code to solve all *my* problems and hopefully other Dynamic Optimization problems as well.

I wanted to challenge this "genericity claim" by trying it on a *different* problem: I took it from a topic of interest of my research group: Ocean Power Smoothing (with an Energy Storage).

Outline of the presentation

Ocean Wave Energy Harvesting

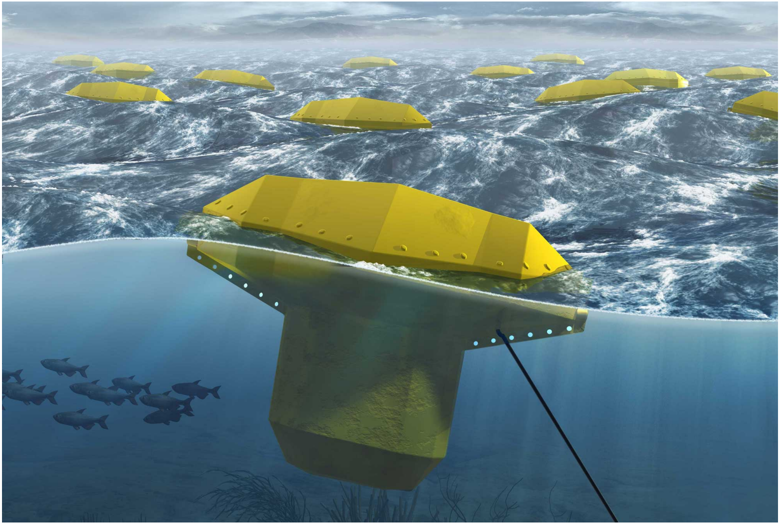
(CC-BY-NC picture by polandeze)
www.flickr.com/photos/polandeze/3151015577

Harvesting electric power from Ocean Waves with "big machines" is an active area of Research & Development.

There are no industrialized devices yet (unlike for wind & sun), but rather *a wide variety of prototypes machines:*
Wave Energy Converters

E.ON P2 Pelamis, July 2011 http://www.pelamiswave.com

Ocean Energy Converter: the SEAREV

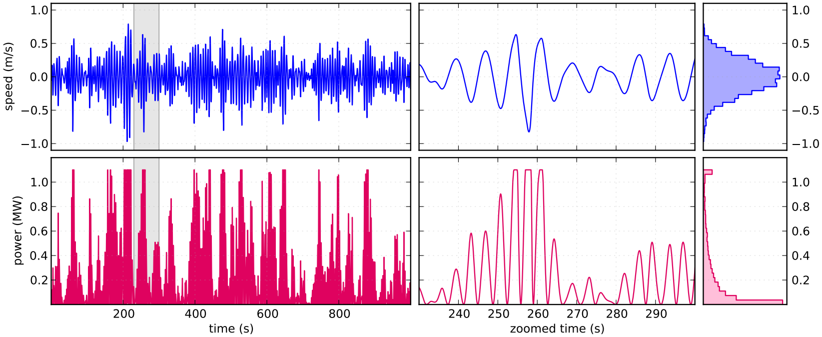


Hydro-mechanical design from Centrale Nantes.

Multon & Ben Ahmed group (SATIE) involved in the electric generator design.

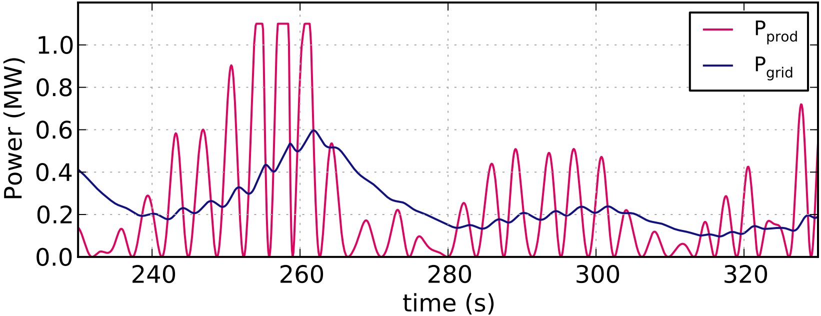
Ocean Energy Converter: the SEAREV

a highly fluctuating output



SEAREV is a giant double-pendulum that swings with the waves.
An electric generator “brakes” the inner wheel to generates power ($P_{prod} = T(\Omega) \times \Omega$).

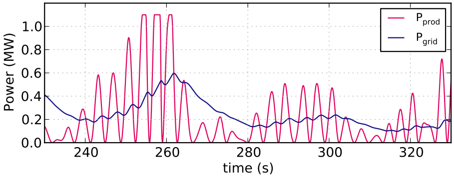
Power smoothing

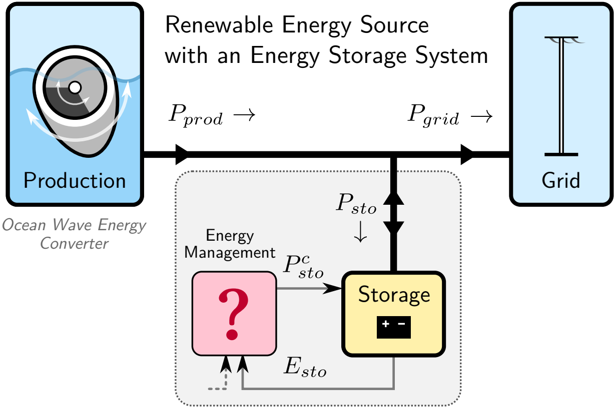


Objective of this application

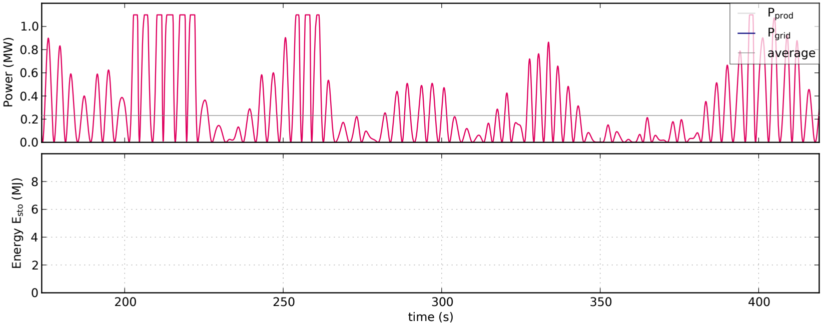
I want to *smooth out the variations* of the power production. This requires an **energy buffer** to store the difference $(P_{prod} - P_{grid})$.

Power smoothing using an Energy Storage





Power smoothing: control of the Energy Storage



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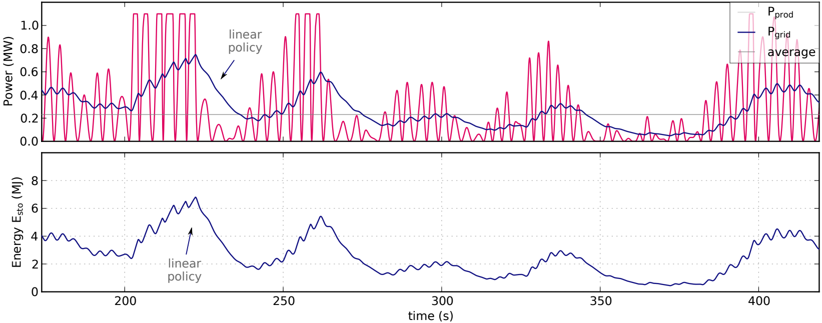
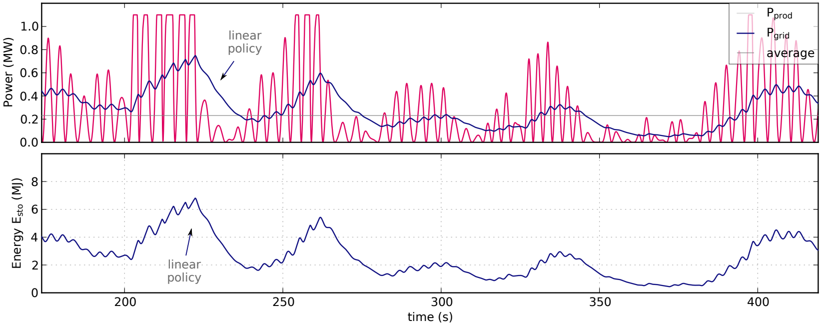


First, using a simple control law (∼policy)

$$P_{grid}(t) = \frac{P_{max}}{E_{rated}} E_{sto}(t)$$

…quite good result but storage is underused → could do better.

Power smoothing: control of the Energy Storage



“Doing better” is defined with an additive cost function which penalizes P_{grid} variations:

$$J = \frac{1}{N}\mathbb{E}\left\{\sum_{k=0}^{N-1} cost(P_{grid}(k) - P_{avg})\right\} \quad \text{with } N \to \infty$$

cost J should be minized.

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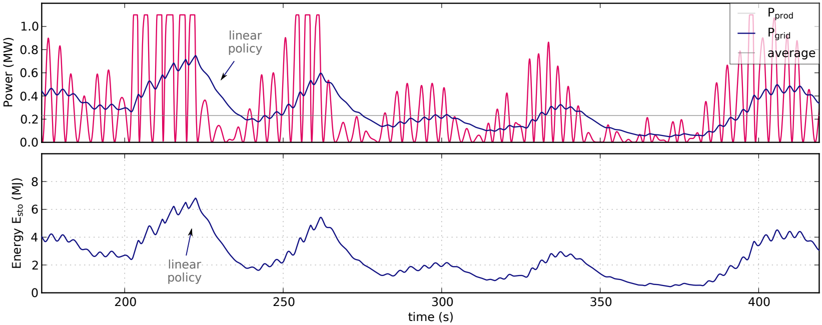

Controlling the storage (choosing P_{grid} at each time step) in order to minimize a cost function is a ***Stochastic*** **Dynamic Optimization** problem

(also called Stochastic Optimal Control)

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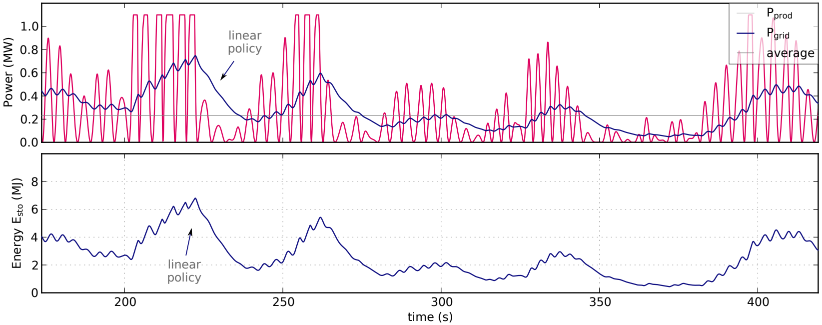

Dynamic Programming (Richard Bellman, ~1950) teaches us that the optimal control is a *state feedback* policy:

$$P_{grid}(t) = \mu(x(t)) \quad \text{with } x = (E_{sto}, other\ variables?)$$

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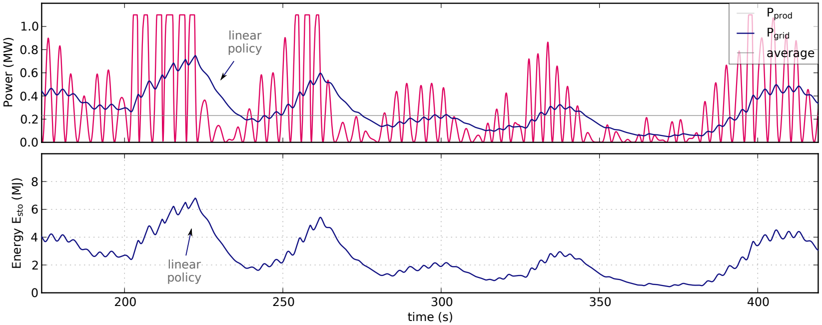

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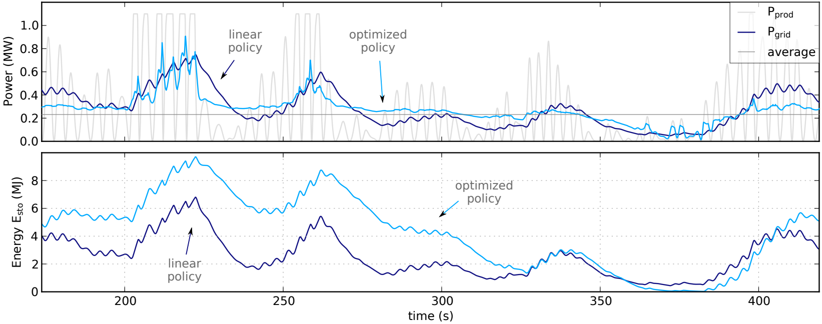
And DP gives us *methods to compute* this policy function μ...

Power smoothing: control of the Energy Storage



And now applying the optimal feedback policy μ^*, the standard deviation of the power injected to the grid is reduced by ∼20 % compared to the heuristic policy.

This improvement just comes from a smarter use of the stored energy.

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1. Energy storage dynamics is **deterministic**:

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   - Stochastic Autoregressive model for the pendulum speed Ω:

   $$\Omega(k) = \phi_1 \Omega(k-1) + \phi_2 \Omega(k-2) + w(k)$$

   - AR(2) $\rightarrow$ state space, with speed Ω and acceleration A
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Full state: $x = (E_{sto}, \Omega, A)$

Dynamic Programming equation

In the end, the optimization problem turns into solving the DP equation:

$$J^* + \tilde{J}(x) = \min_{u \in U(x)} \mathbb{E}_w \Big\{ \underbrace{cost(x,u,w)}_{\text{instant cost}} + \underbrace{\tilde{J}(f(x,u,w))}_{\text{cost of the future}} \Big\}$$

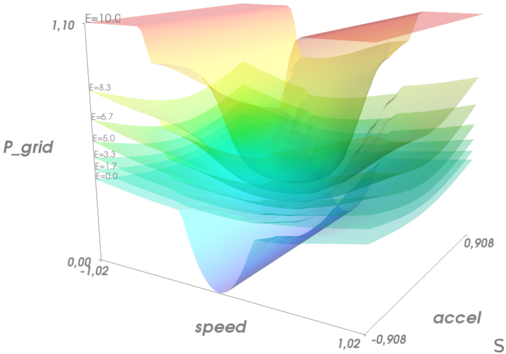
u is control and w is random perturbation, using generic notations

- It is a *functional* equation: should be solved for all x
- The optimal policy $\mu : x \mapsto u$ appears as the `argmin`.

The DP equation is solved on a **discrete grid** over the state space. With $x \in \mathbb{R}^n$, $\tilde{J}$ and μ are computed as n-dim. arrays.

The optimal policy $P_{grid}(E_{sto}, speed, accel)$

Optimal control is a $\mathbb{R}^3 \mapsto \mathbb{R}$ function (i.e. numerically, a 3D array)



surfaces

$P_{grid}(speed, accel)$, for different levels of energy E_{sto}

Conclusion

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Code and data openly available on GitHub

https://github.com/pierre-haessig/stodynprog/tree/master/examples/