Computing an Optimal Control Policy for an Energy Storage

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Companion article: http://publications.pierreh.eu
Outline of the presentation

1. Intro
2. Example of Ocean Power Smoothing
3. solving Dynamic Optimization with Dynamic Programming
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3. solving Dynamic Optimization with Dynamic Programming
My background

- Curriculum in Electrical Engineering and Control Theory → *Matlab/Simulink kingdom*
- PhD student on Electricity Storage in relation to Wind Energy
- Python for all my simulation and visualisation work (and a bit of *R* for time series analysis)
StoDynProg: a Dynamic Optimization problem solving code

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”!!
StoDynProg: a Dynamic Optimization problem solving code

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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).
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Ocean Wave Energy Harvesting

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
Ocean Energy Converter: the SEAREV

Hydro-mechanical design from Centrale Nantes.
My group 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 ($P_{\text{prod}} = T(\Omega) \times \Omega$).
Objective of this application

I want to smooth out the variations of the power production. This requires an energy buffer to store the difference \((P_{\text{prod}} - P_{\text{grid}})\).
Power smoothing using an Energy Storage System

Renewable Energy Source with an Energy Storage System

\[ P_{\text{prod}} \rightarrow \quad P_{\text{grid}} \rightarrow \]

Production
Ocean Wave Energy Converter

Energy Management

Storage

\( P_{\text{sto}} \)
\( P_{\text{sto}}^c \)
\( E_{\text{sto}} \)
Power smoothing: control of the Energy Storage
Power smoothing: control of the Energy Storage

First, using a simple control law (~policy)

... 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:

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

cost $J$ should be minimized.
Power smoothing: control of the Energy Storage

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

(also called Stochastic Optimal Control)
Power smoothing: control of the Energy Storage

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

\[ P_{grid}(t) = \mu(x(t)) \quad \text{with} \quad x = (E_{sto}, speed, accel) \]
Power smoothing: control of the Energy Storage

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And DP gives us methods to compute this policy function \( \mu \ldots \)
Power smoothing: control of the Energy Storage

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

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

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

\[ J + \tilde{J}(x) = \min_{u \in U(x)} \mathbb{E}\left\{ \text{cost}(x, u, w) + \tilde{J}(f(x, u, w)) \right\} \]

\( u \) 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 \text{argmin}.

The DP equation is solved on a discrete grid over the state space. With \( x \in \mathbb{R}^n \), \( \tilde{J} \) and \( \mu \) are computed as \( n\)-d numpy arrays.
Equation solving, Multilinear interpolator

The resolution is done purely in Python. Basically a giant for loop with an `argmin` inside.

- `numpy` for handling arrays, with a good amount of vectorization
- `itertools` to iterate over the state space grid (of arbitrary dimension)
- (introspect for some signature analysis magic)
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**Extremely useful code reuse:** a multilinear interpolator by Pablo Winant (within its dolo project: github.com/albop/dolo). Uses Jinja templates to generate Cython code for dimension 1-5.

Learning of this project (on scipy ML) saved me weeks, if not months!
Conclusion

Code should be soon on GitHub (github.com/pierre-haessig). Decent Sphinx doc with examples (and complete code for SEAREV example), but ridiculous test coverage.