
Modelling Flexible Nuclear Generation in Low-Carbon Power Systems: *A Stochastic Dual Dynamic Programming approach*

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01

Introduction

Nuclear power and flexibility

Motivation

- With rising share of Renewables, **flexibility is needed**
- Nuclear is a low-carbon and dispatchable energy source... but it comes with **specific technical constraints**.
- Some nuclear intensive systems already use nuclear to dampen variations of supply and/or demand (France). ***To what extent ?***



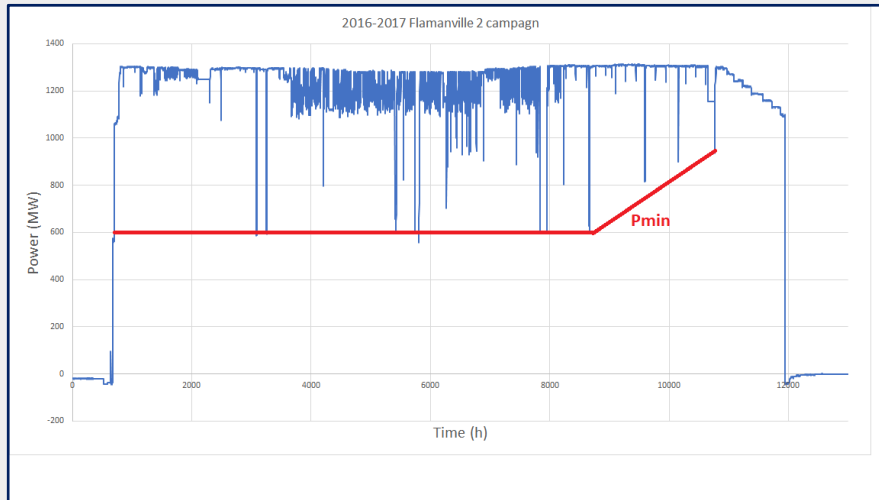
A dark blue-tinted photograph of a nuclear power plant. In the foreground, a green field with a fence contains a herd of cows grazing. In the background, several large, cylindrical cooling towers and various industrial buildings of the power plant are visible, along with several high-voltage power line towers and their associated cables stretching across the sky. The overall scene is dimly lit, suggesting dusk or dawn.

02

Nuclear Power plants

Specific constraints on flexibility

Constraints



Nuclear is submitted to several constraints narrowing its flexibility potential, mainly **Mechanical stress & Atomic considerations (Xenon effect)**.

Number of cycling operations limited to **200 per year**, 5 per week and 2 per day (IAEA).

Constraints are enounced as limitation on virtual **stocks**

Relevant literature

Previous works on Nuclear flexibility generally use MILP to model cycling operations in a deterministic framework.

- In Loisel *et al.* (2018), the number of cycles is limited and the whole European system is depicted.
- In Jenkins *et al.* (2018), ramping constraints and moments of imposed stable power are modelled.
- In Cany *et al.* (2016), different scenarios of energy production are compared and nuclear flexibility is modelled through ramping rates only.
- Lynch *et al.* (2022) accounts for the change in flexibility for each reactor induced by atomic considerations.

No stochasticity involved !



03

Modelling
approach

SDDP for modelling opportunity costs

SDDP *literature*

The Stochastic Dual Dynamic Programming algorithm, originally developed by Pereira & Pinto (1991) for **hydropower** scheduling purposes.

Benders cut to fasten SDP algorithms, suited for **storage management** (water, batteries... a stock of nuclear cycling operations ?)

Recent application: Papavasiliou et al. (2018) for real-time storage dispatch under Renewable supply uncertainty.



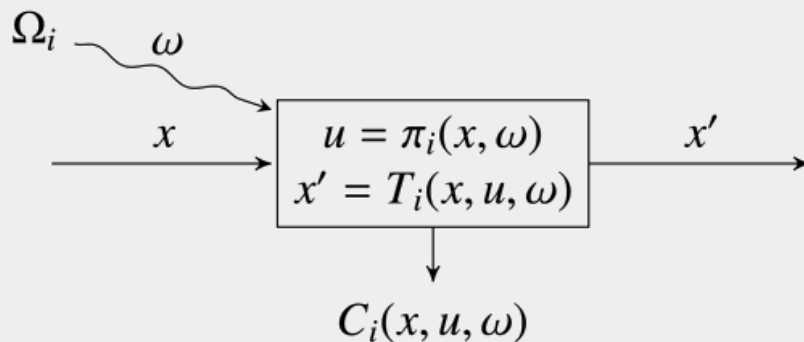
How to use a stock optimally ?

$$\underset{\pi}{\text{minimize}} \quad \mathbb{E}_{i \in \mathbb{R}^+, \omega \in \Omega_i}(V_i^\pi(x_0, \omega))$$

$$V_i^\pi(x, \omega) = \min_{x, x', u} C_i(x, u, \omega) + \mathbb{E}_{j \in i^+, \phi \in \Omega_j}(V_j(x', \phi))$$

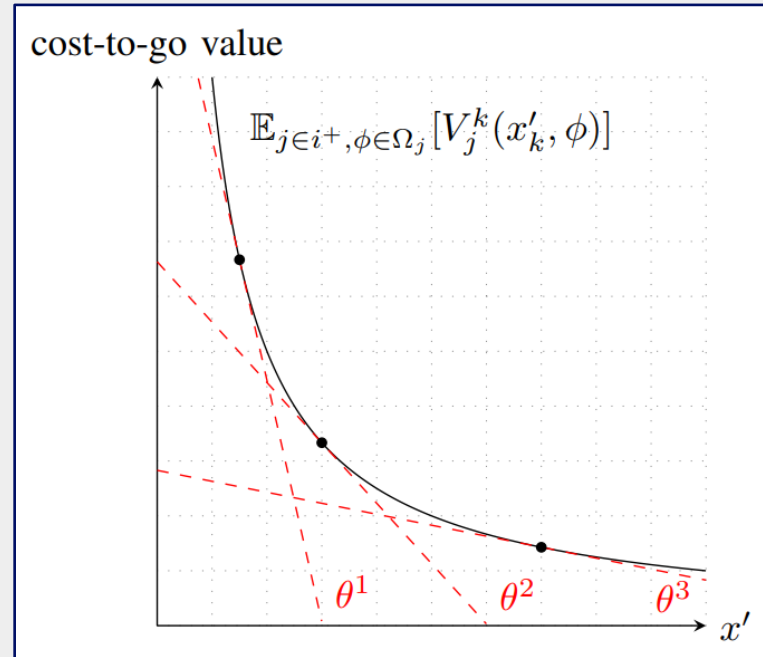
subject to

$$x' = T_i(x, u, \omega),$$
$$u = \pi_i(x, \omega) \in U_i(x, \omega)$$



How to use a stock optimally ?

- Approximation of the cost-to-go term with **Benders cuts**
- Back & Forth iterations for building the **convex envelope** of the function
- Once training ends, we get a « **policy** » to be run over hundreds of simulations

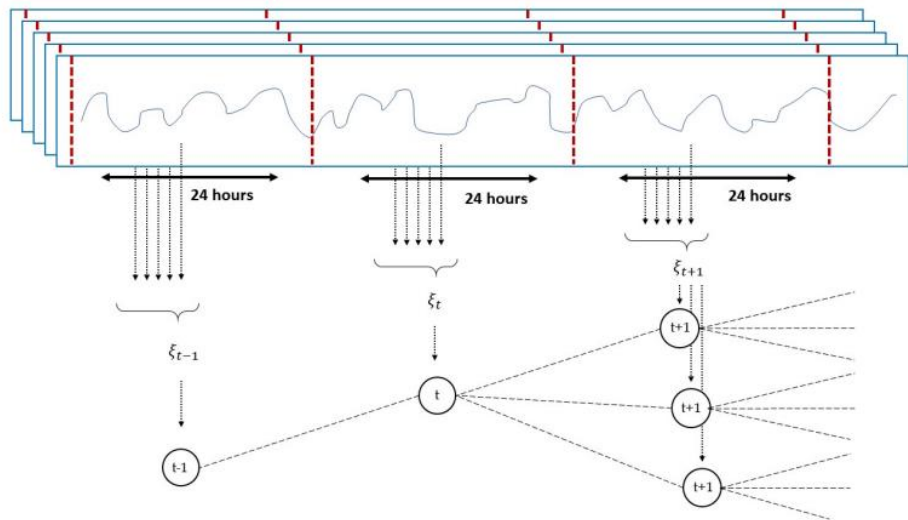




Application 04

What benefits from an increased nuclear flexibility of French reactors in 2035 ?

French electric system



365
nodes

Day ahead modelling
for uncertainty

9
technologies

One cluster for nuclear,
solar and wind
exogenous

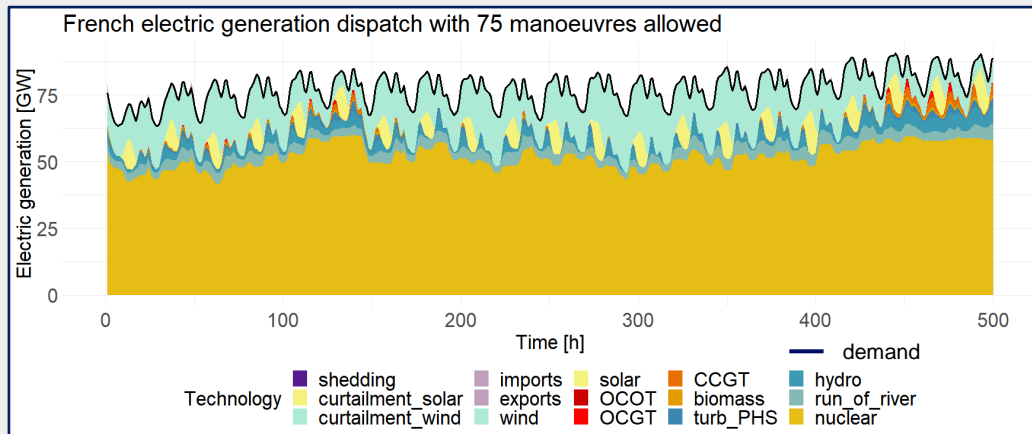
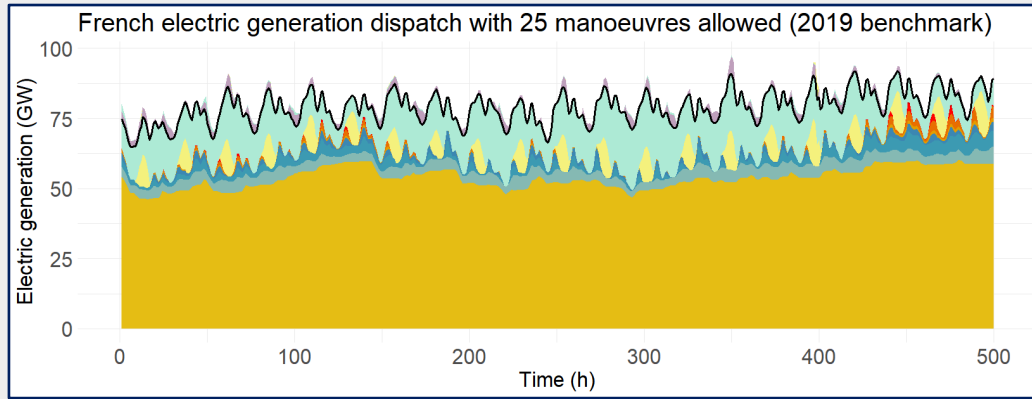
8760
Time steps

Within a day, hourly
resolution

5
Possible profiles

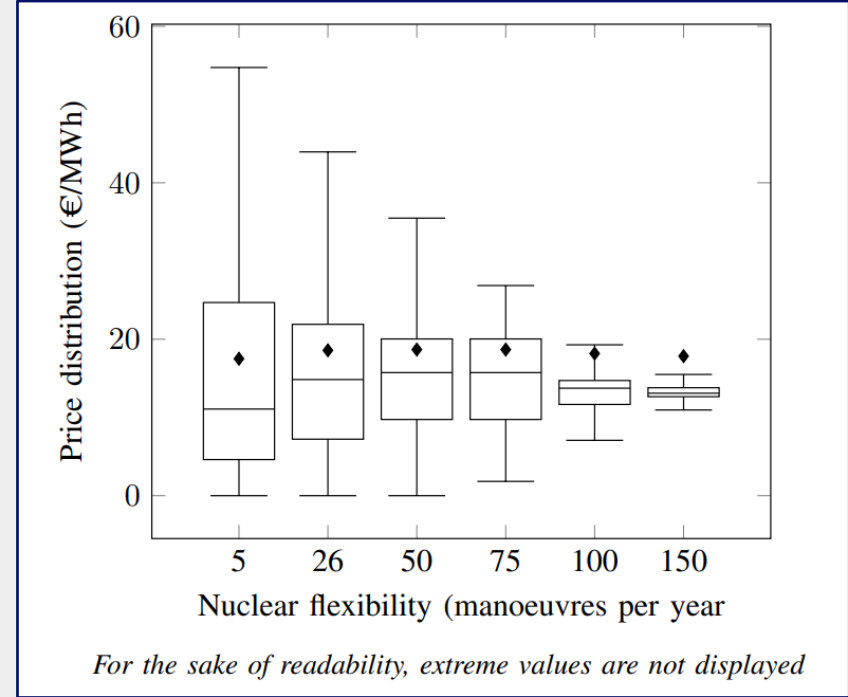
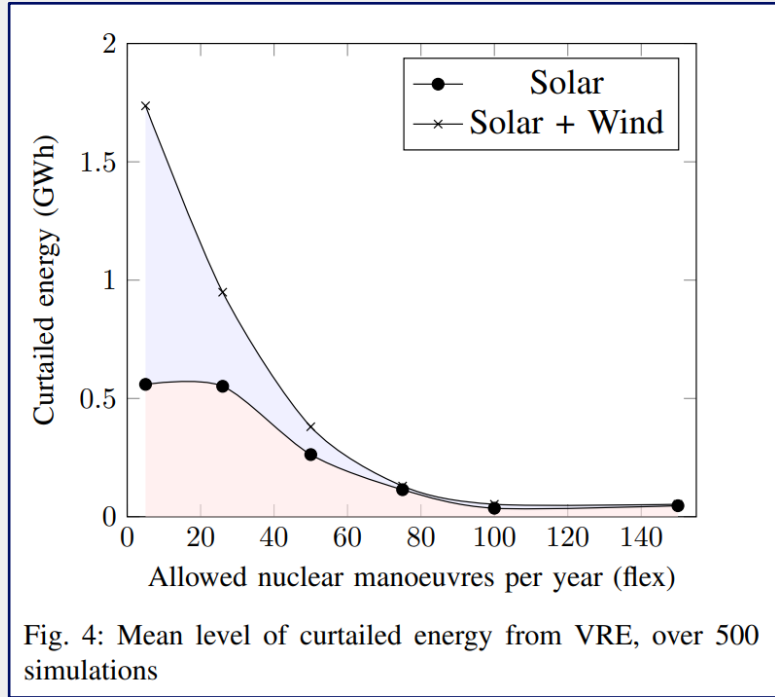
Each day, we pick out
time series from a set of
5 renewables profiles

Power dispatch



- **2035**, French TSO projections
- Curtailment is clearly **reduced**
- With 75 manoeuvres, nuclear **dampens solar variations**

Main results



Main results

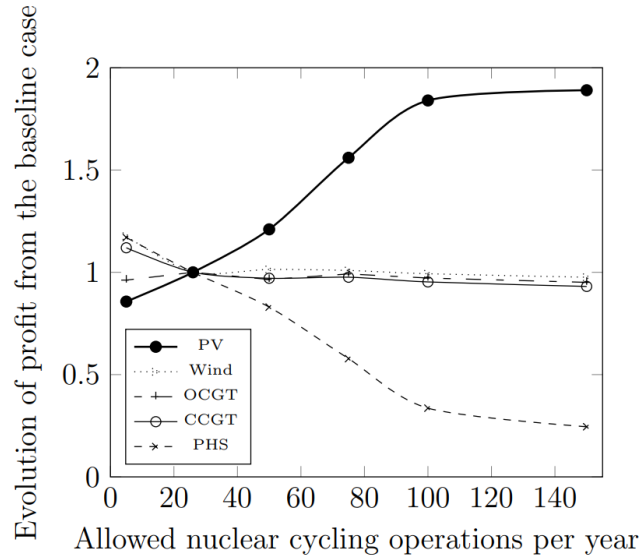
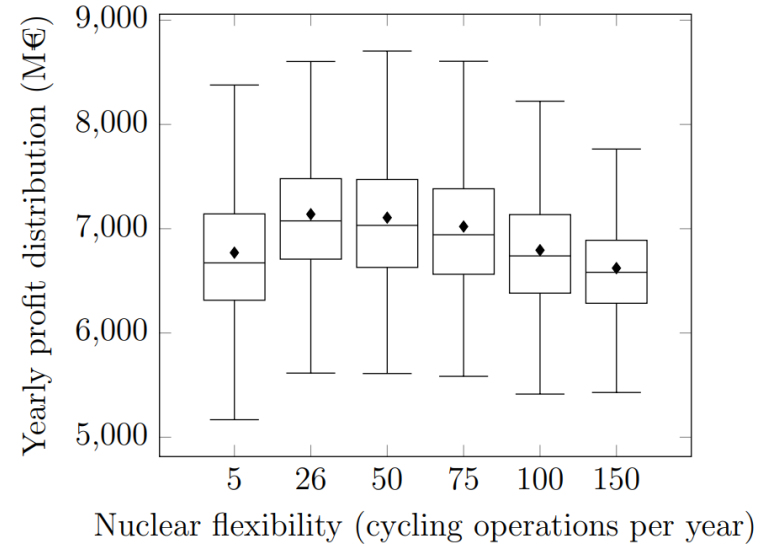


Figure 8: Mean level of profit for different technologies, over 500 simulations

Figure 9: NPPs profit distribution for different cycling constraints



A landscape photograph showing a hill with several wind turbines silhouetted against a twilight sky. The foreground is a body of water reflecting the scene. The overall color palette is dark blue and purple.

Conclusion

& further work

06

French nuclear flexibility by 2035

Technically feasible

- The need in cycling would be no more than **80-100/year**
- SDDP can be used for dispatching the cycling operations

Economically viable

- Nuclear profits plateau between **26-50 cycles**
- Solar profits **x1,5** for the same cycling range



Thanks

Questions ?

Further material

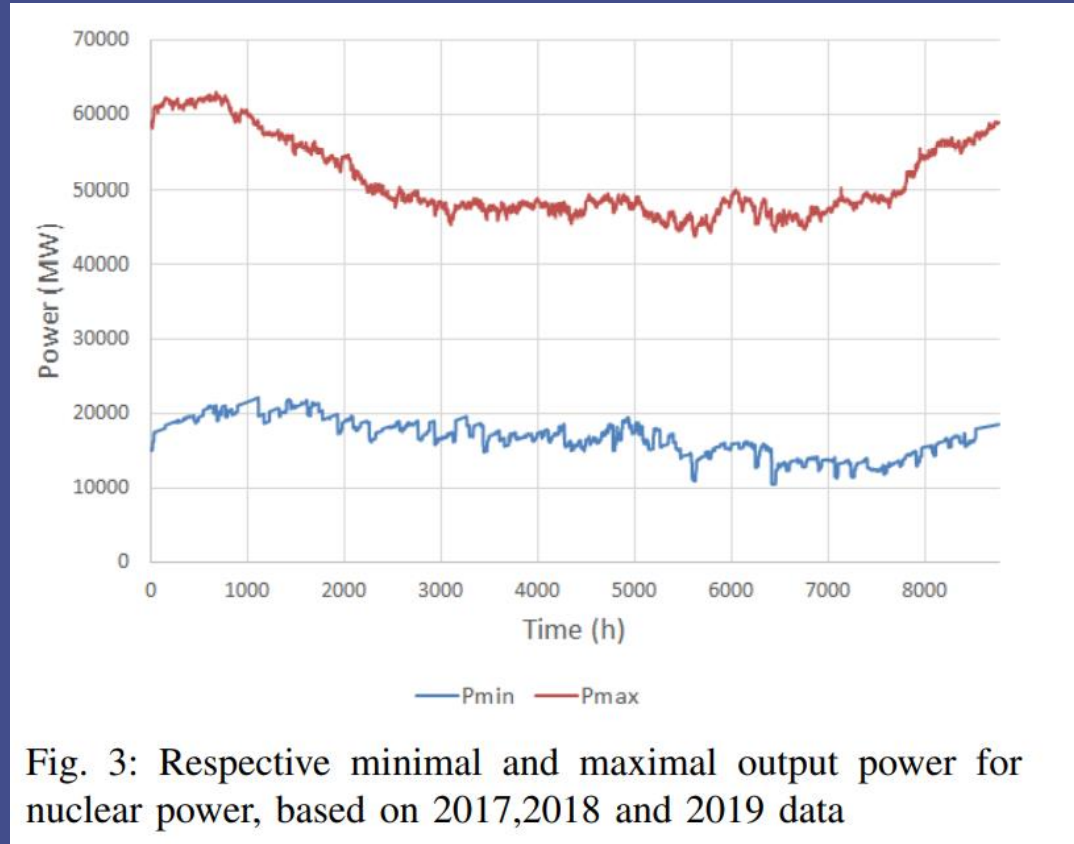


Fig. 3: Respective minimal and maximal output power for nuclear power, based on 2017,2018 and 2019 data

Further material

Technology	Capacity (GW)	Derating factor	Variable cost (€/MWh)
Solar	50	∅	0
Wind	50	∅	0
Hydro reservoir	8	0.86	0
PHS	7	0.54	0
Nuclear	63	$f(t)$	14
Biomass	2	0.9	99
CCGT	6.6	0.88	100
OCGT	4.7	0.94	151
OCOT	1	0.94	258
Imports	25	0.5	268
VoLL	∅	∅	10,000

TABLE II: Generation capacity installed in France in 2035, by technology

Further material

Scenario	Lower bound (G€)	Mean objective value (G€)	discrepancy
flex = 5	4.85	4.87	0.41%
flex = 26	4.54	4.55	0.29%
flex = 50	4.40	4.40	0.10%
flex = 75	4.31	4.33	0.38%
flex = 100	4.28	4.29	0.12%
flex = 150	4.27	4.27	-0.19%

TABLE III: Convergence data for different flexibility levels

Further material

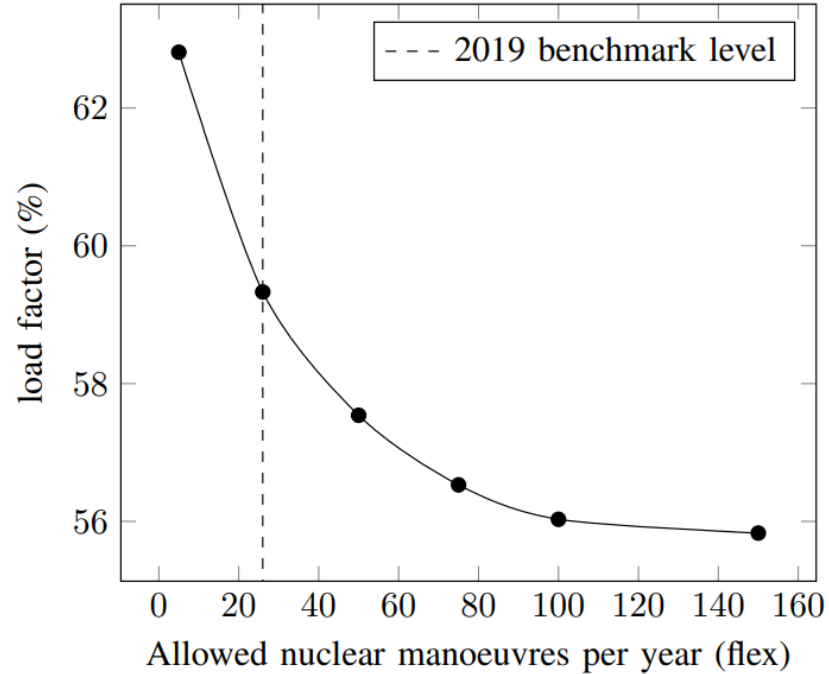


Fig. 5: Average load factor of NPPs as a function of the number of allowed manoeuvres