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

> Ange Blanchard Olivier Massol

Table of contents

01	02	03
Introduction	Nuclear Power Plants	Modelling approach
Nuclear as a flexibility source ?	Specific flexibility constraints	The SDDP framework
04	05	06
04 Results	05 Insights	06 Conclusion



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 ?*



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 developped by Pereira & Pinto (1991) for **hydropower** schedulling purposes.

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

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



How to use a stock optimally?

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

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

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 costto-go term with **Benders** cuts
- Back & Forth iterations for building the **convex enveloppe** of the function
- Once training ends, we get a « **policy** » to be run over hundreads 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

8760

Time steps

Within a day, hourly resolution

9

technologies

One cluster for nuclear, solar and wind exogenous

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 manœuvres, nuclear dampens solar variations

Main *results*



Main *results*



Conclusion

& further work



French nuclear flexibility by 2035



- No need for more than 100 cycles per year
- SDDP can be used for dispatching the cycling operations



- 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	Ø	0
Wind	50	Ø	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	Ø	Ø	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