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WORKING PAPER

The Value of Nuclear Power Plants Flexibility: A Multistage Stochastic Dynamic Programming Approach

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Nuclear power plants will increasingly need to follow uncertain loads in future power systems dominated by intermittent renewable generation. However, regulatory and technical constraints limit the frequency of load-following operations, making their efficient allocation crucial. This paper explores the economic value of nuclear flexibility by modeling it as a stock constraint within a stochastic dynamic programming framework. We show how non-convex constraints at the reactor scale translate to the fleet level through a linearized approximation, allowing for analyzing multiple reactors operating under flexibility constraints. Applying this model to the French electricity system in 2035 using the Stochastic Dual Dynamic Programming (SDDP) algorithm, we estimate a marginal value of EUR 100/MW for the current flexibility level of the French nuclear fleet. Our results show that increased nuclear flexibility enhances system-wide cost efficiency and improves the integration of renewables, with solar generation seeing the largest benefits. However, our findings suggest a potential misalignment with the profit-maximizing goals of individual nuclear operators, which may deter them from increasing flexibility despite its necessity for the system.

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Executive summary

The increasing integration of renewable energy sources in European power systems demands greater flexibility from conventional generation assets. Traditionally designed for baseload operation, nuclear power plants must adapt to load-following operations to ensure system reliability. This paper quantifies the economic value of nuclear flexibility in future power systems, focusing on France in 2035.

Key Findings

1. **Economic Value of Flexibility**: The marginal value of flexibility for the French nuclear fleet in 2035 is estimated at €100/MWh. This means increasing the amount of load-following operations performed by nuclear reactors can benefit the system significantly. In 2023, French nuclear plants performed 25 load-following operations and can theoretically vastly improve.
2. **Renewable Integration**: Greater nuclear flexibility reduces renewable curtailment significantly, especially for solar energy. Solar curtailment is cut by nearly 50% at the highest flexibility level, enhancing its economic viability.
3. **Profitability Misalignment**: While system efficiency improves with increased nuclear flexibility, the profit-maximizing goals of nuclear operators may not align with system-wide benefits. Profits peak at current flexibility levels, suggesting limited incentives for nuclear operators to enhance flexibility.
4. **System Cost Efficiency**: Enhanced nuclear flexibility reduces overall system costs by optimizing resource utilization and minimizing reliance on costly peaking plants.

Policy Recommendations

1. **Regulatory Incentives for Flexibility**: Regulators should closely monitor the performance of nuclear operators to bring flexibility to the system as a dominant player may be unwilling to maximize the flexibility of their plant to maximize their own profits. Mechanisms to align operator incentives with system-wide needs, such as flexibility bonuses or modified market designs, may be relevant.
2. **Integrated Resource Planning**: Strategic integration of nuclear flexibility with renewable expansion plans can maximize cost-efficiency and system reliability.
3. **Focus on Solar Complementarity**: Given the expected boom in solar generation, policies fostering coordination between nuclear and solar assets should be prioritized.

Conclusion

Nuclear flexibility is critical for integrating high shares of renewables in future energy systems. While system-wide cost reductions and renewable integration improve with flexibility, operator incentives remain misaligned. Addressing this gap through targeted policies will be essential for leveraging the full potential of flexible nuclear power.

1. Introduction

The transition toward low-carbon power systems goes hand-in-hand with an increased penetration of Variable Renewable Energy sources (VREs), such as solar and wind. Because of the intermittency of VREs, the provision of flexibility—which is commonly defined as the capacity to effectively and promptly adapt to unforeseen fluctuations in electricity demand or supply (Cochran et al., 2014; Perez-Arriaga and Batlle, 2012)—is becoming crucial for preserving the reliability of the power system. In power systems endowed with nuclear generation, operating a Nuclear Power Plant (NPP) in the so-called load-following mode—i.e., by varying the output as the residual load on the grid changes—is recurrently presented as a low-carbon flexibility option to accommodate VREs and preserve the reliability of the system (Troy et al., 2010; Jenkins et al., 2018). However, the fleet of existing nuclear reactors was primarily installed to provide baseload generation as these NPPs were designed to operate at maximum rated capacity with limited output changes whenever online. Though the NPP output can be varied, the power plant is subjected to specific constraints on safety or technology considerations (Khatib and Difiglio, 2016; Owen, 2011). In some regions, the aptitude of NPPs to operate flexibly is also mothballed by regulatory mandates or the absence of economic incentives since some plants do not face market prices and instead receive compensation based on predetermined rates. Assessing the economic value of nuclear flexibility can motivate law or market design change to unleash this potential. Given the controversies surrounding the future of nuclear generation,[1] an adequate representation and valuation of nuclear flexibility is crucial for analyzing the extent to which NPPs can complement VREs in future electric systems.

The purpose of this paper is to examine the economics of flexible nuclear generation in a VRE-intensive power system. From a modeling perspective, our point of departure is an analogy with managing hydropower resources. Indeed, in contrast with most technologies of thermal power plants that run on coal or gas, one major flexibility limitation for NPPs stems from a limit on the number of load-following operations the reactor can undergo rather than on ramping capacity (Cany et al., 2016). The decision to allocate nuclear flexibility resources over time resembles the optimal scheduling for hydropower generation from reservoirs.

[1] Recall that some countries (e.g., France or Sweden) envision a nuclear renaissance (Vaillancourt et al., 2008; Hong et al., 2018) whereas others either consider NPPs only as one marginal technology within a portfolio of other options (Bruninx et al., 2013) or have decided to phase out nuclear completely as in Germany.

The operation of these reservoirs typically involves inter-temporal arbitrages whereby one must (i) weigh the immediate opportunity gain that can be yielded by using the stored water now and (ii) compare it with the value of storing the water for subsequent periods. As the future is cursed by uncertainty, that value is also uncertain, and a risk-neutral agent should consider it using an expected value perspective. By modeling flexibility as a predefined stock of load-following operations to be decided throughout the year given uncertain VRE generation, we propose that we take advantage of this analogy with hydropower and model the resource scheduling problem at hand as an instance of a stochastic dynamic programming problem.

We analytically show how flexibility constraints at the reactor scale translate to the fleet scale and how to efficiently model this complex, non-convex problem. We then build a numerical model of the French electricity system dispatch as a cost-minimization problem. The "curse of dimensionality" often complicates solving such multistage stochastic optimization problems. To address this, the Stochastic Dual Dynamic Programming (SDDP) algorithm, proposed by Pereira and Pinto (1991), offers an effective solution by decomposing the problem into simpler subproblems. Unlike traditional dynamic programming, which relies on discretizing the values taken by the state variables, SDDP uses a piecewise linear approximation of the Bellman function with Benders' cuts, allowing for continuous state variables and efficient computation. In the past decade, significant contributions in Operational Research have facilitated the widespread adoption of the SDDP algorithm, extending its use beyond hydrothermal problems. Shapiro (2011) improved understanding of algorithm convergence, Shapiro et al. (2013) explored risk aversion, and Soares et al. (2017) enhanced stability under variable water inflows. Dowson's recent Julia package further simplified SDDP implementation.(Dowson and Kapelevich, 2021) These advancements have enabled SDDP applications in various contexts, such as managing pumped hydro resources (Papavasiliou et al., 2018), integrating hydropower with wind (Bodal et al., 2016), gas storage valuation in incomplete markets (Löhndorf and Wozabal, 2021), microgrid management under renewable uncertainty (Bhattacharya et al., 2018), day-ahead electricity dispatch (Lu et al., 2020), and optimal farm management under uncertainty (Dowson et al., 2019).

Our study uncovers several key findings regarding the value of nuclear flexibility. First, maintaining the current flexibility level of the French nuclear fleet in 2035 yields an economic value of around EUR 100/MW, emphasizing a strong incentive to enhance flexibility. Technically, nuclear reactors are flexible enough to accommodate large shares of renewable energy without hitting operational limits. From a profitability standpoint, renewable energy—especially PV—benefits significantly from reduced curtailment, though wind turbine profits remain largely unchanged. Lastly, nuclear profits peak before reaching the socially optimal flexibility level, indicating possible misalignment between operator incentives and overall system welfare.

This paper contributes to the growing literature on the interplay between nuclear and renewable energy by focusing on the economic value of nuclear flexibility, which is key to the relevance of NPPs in future systems. Green and Léautier (2015) indeed demonstrate that flexibility is paramount for determining the optimum level of investment in NPPs, as shown in their analysis of the UK. Similarly, Shirizadeh and Quirion (2021) emphasize the importance of flexibility assumptions in determining the optimal electricity mix in France by 2050. Engineering studies, such as those by Cany et al. (2016) and Loisel et al. (2018), explore the compatibility between VREs and flexible nuclear operations in Europe. They find that VRE deployment challenges the profitability of NPPs, although they remain economically viable when operated flexibly. Denholm et al. (2012) stress the impacts of nuclear flexibility on the economics of nuclear generation in future electricity systems dominated by renewables. By operating flexibly, NPPs will achieve smaller load factors than those observed historically, affecting their revenues and ability to recoup the large capital expenditures required to build them. Lynch et al. (2022) and Jenkins et al. (2018) use MILP models to optimize nuclear flexible operations and highlight the benefits for both VREs and NPPs revenues. Perrier (2018) adopts a robust decision-making framework to propose an optimal pathway for retrofitting French reactors. Much of the existing literature on nuclear flexibility overlooks key aspects of how nuclear-specific constraints, like cycling limitations, affect power systems dominated by VRE. Indeed, the uncertainty of VRE production is generally not considered, and the economic value of nuclear flexibility is not properly defined. By addressing this question through a stochastic dynamic programming lens, we intend to bridge this gap as well as contribute to the expanding use of SDDP by applying it for the first time to the scheduling of load-following operations in nuclear power plants.

The paper is organized as follows. The next section provides a concise overview of the technological constraints restricting the operations of a nuclear power plant and the SDDP framework. Next, Section 3 presents our analytical model and first results. Sections 4 and 5 present the implementation of the numerical model on the French case study in 2035. Section 6 presents and discusses the results, and the last section offers a summary and some concluding remarks. For clarity, Appendix 7 presents proofs and data assumptions.

2. Background & motivation

2.1. A changing market environment for nuclear generation

Most NPPs currently in use worldwide are light water reactors, of which a particular type, the Pressurized Water Reactor (PWR), accounts for more than two-thirds of the world's nuclear capacity. These plants were built in the 1980s and 1990s as part of the nuclear programs decided in the aftermath of the oil shocks (Toth and Rogner, 2006). Their design was thus primarily driven by the need to conserve oil used in baseload thermoelectric generation in order to shield energy-importing nations from potential supply disruptions. The specific economics of NPPs also favored their use as a source of baseload generation. The capital expenditures account for approximately 70% of the total Levelized Cost of Electricity (LCOE), reaching up to 85% when considering all fixed costs and decommissioning (Khatib and Difiglio, 2016). Maintaining a high load factor by continuously generating an output close to nameplate capacity was necessary to recoup these upfront and fixed costs. During the last three decades, these nuclear plants thus represented the cornerstone of baseload generation: they were operated at rated capacity and supplemented by peak-or mid-merit units (e.g., thermal power plants or hydropower dams) that absorbed variations in the load.

However, the market environment is radically changing as VREs are becoming prevalent in power systems. VRE technologies have low-to-zero marginal costs, so it is economically optimal to enroll renewable production in the system when available. In good weather conditions, VREs thus compete with nuclear generation and can even displace it. Consequently, the historical consensus that regarded NPPs as the unmatched option for baseload generation needs to be reconsidered (Lévêque, 2013). This changing landscape has deep implications for the role assigned to nuclear plants. In a VRE-dominated power system, nuclear power may still be considered a relevant source of low-carbon generation during low VRE production. A fundamental issue for the future of nuclear energy is, therefore, its ability to complement VREs by varying the output of existing NPPs to match the residual demand, that is, the difference between the load and the generation from intermittent renewables.

2.2. *Flexible nuclear generation: What limitations?*

2.2.1. *Nuclear-specific constraints, a concise review*

NPPs face constraints like other thermal plants, such as ramping rates and warm-up delays. However, modern NPPs in Europe can reduce output by up to 100% of their nameplate capacity within an hour, meaning they are not limited by ramping rates on an hourly scale (IAEA, 2018). Yet, NPPs must adhere to specific restrictions. Although they can adjust output between a minimum threshold and the rated capacity using control rods or boric acid concentration (Cany, 2017), sudden output changes induce thermal and mechanical stress, particularly affecting fuel pellets and claddings due to temperature variations (Jenkins et al., 2018; IAEA, 2018). Another constraint is the "Xenon effect", which occurs as Xenon-135 concentration increases when reactor power decreases, complicating fission reactions and narrowing output modulation capabilities, especially after two-thirds of the fuel cycle (Lynch et al., 2022). A typical irradiation cycle profile is displayed in Figure 1, presenting the rise in minimal power due to the Xenon effect and the cycling operations performed for load-following purposes.

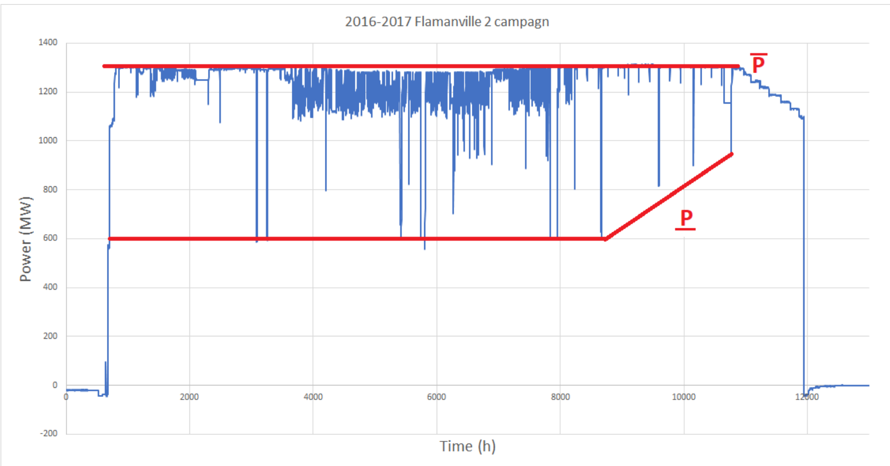

Figure 1: Illustration of a typical nuclear reactor's fuel cycle.

Although cycling operations can accelerate wear and tear and increase maintenance costs, experiences in France and Germany show minimal impacts on costs, reliability, or safety when these operations are well-managed. (IAEA, 2018; Cany, 2017)

2.2.2. Implications for load-following operations

To account for these concerns, international standards limit the frequency of load-following operations for PWR designs to two per day, five per week, and two hundred per year (IAEA, 2018). These limits have been set by European nuclear operators since 1990 to ensure safety, performance, and flexibility in new reactor designs. With the rise of VREs, these limits have not been fully tested yet, as load-following operations have remained below the maximum thresholds (e.g., the maximum load-following operations observed in French reactors by 2018 was 155 according to Cany et al. (2018)). However, regulations differ across the globe. In the US, nuclear plants are restricted to a maximum of one cycle per day (EPRI, 2014). In China, the business model of NPPs does not incentivize flexible operation, as they are remunerated based on controlled tariffs rather than being exposed to wholesale prices (Andrews-Speed, 2023). Similarly, the Hinkley Point C nuclear plant in the UK will benefit from a predefined sell price through a Contract-for-Difference scheme. Yet, the system impacts of these regulatory frameworks remain to be assessed.

3. The value of nuclear flexibility: analytical intuitions

When the cap on annual load-following operations is binding, load-following operations become scarce, necessitating their efficient allocation over time. The challenge is intertemporal: deciding whether to reduce NPP output now, such as during high wind production in spring, or to save this flexibility for future periods, like a summer day with high solar output. Prioritizing immediate curtailment avoidance may lead to future overproduction issues if flexibility is depleted. The methodology presented next addresses this allocation problem.

3.1. A stylized model

Consider a simple analytical model where the NPP operator intends to maximize profit over two time periods, considering the flexibility constraints that limit the change in power output between periods. Let q_1 and q_2 denote the power output of the nuclear plant at periods $t = 1$ and $t = 2$, respectively. The prices at each period are given by p_1 and p_2. The operator's profit each period is given by revenue minus generation costs, thus the profit function for each period can be expressed as:

$$\Pi_t = p_t q_t - C(q_t),$$

with $C(q_t)$ the cost of generating q_t units of power. In the following, we assume $C(q_t) = c \times q_t$, with c the variable cost of the NPP. In this simplified framework, the NPP's flexibility constraint is captured by a linear limit on the permissible change in output between two consecutive periods. This constraint is expressed as follows:

$$|q_1 - q_2| = \Delta \qquad (\mu) \tag{1}$$

where Δ is the maximum allowed deviation between the production levels of the two periods, and μ is the shadow price associated with this constraint. For this analysis, we assume the constraint to be binding, effectively making the inequality an equality—a condition central to our study. The problem is formulated within a stochastic dynamic programming framework, where the price at time $t = 2$ follows a probability density function $f(\cdot)$. The value function at time $t = 2$ is given by:

$$V_2(q_2, p_2) = \max_{q_2 \in \mathbb{R}^+} \quad (p_2 - c)q_2 \tag{2}$$

Here, the Bellman term—or cost-to-go function—$V_2(q_2, p_2)$ represents the maximum profit achievable at time $t = 2$ for a given realization of price p_2. The problem at time 1 writes:

$$\begin{aligned} \max_{q_1 \in \mathbb{R}^+} \quad & (p_1 - c)q_1 + \mathbb{E}_{p_2}(V_2(q_2, p_2)) \\ \text{s.t.} \quad & (1) \end{aligned} \tag{3}$$

The Lagrange function reads:

$$\mathcal{L}(q_1, q_2, \mu) = (p_1 - c)q_1 + \mathbb{E}_{p_2}(V_2(q_2, p_2)) - \mu(|q_2 - q_1| - \Delta).$$

Solving the Karush-Kuhn-Tucker (KKT) conditions for this setup, and extending to a multistage framework, yields the following proposition.

Proposition 1. *Under the given assumptions, the value of nuclear flexibility is determined by the maximum absolute expected value of the price, adjusted for the variable cost, across all considered timeframes:*

$$\mu = \max_{t \in \mathcal{B}} \left(|\mathbb{E}[p_t] - c| \right),$$

where p_t represents the price at time t, c is the variable generation cost, and $\mathcal{B}$ is the set of timeframes where the flexibility constraint is binding.

Proof. See Appendix A.

3.2. Nuclear flexibility at the fleet scale

To properly assess the value of nuclear flexibility in future energy systems, we need a system-wide model that considers the aggregate behavior of nuclear power plants rather than individual reactors. While nuclear flexibility constraints are inherently non-linear and non-convex at the reactor scale—each reactor makes a binary decision when deciding to operate or not a load-following cycle—these constraints become computationally challenging when modeling large fleets of reactors. As suggested in the literature, one solution is to cluster reactors, reducing the number of integer variables and making the problem more tractable (Langrene et al., 2011; Palmintier and Webster, 2014; Meus et al., 2018). However, clustering may not fully capture the flexibility potential of the entire fleet, which can respond more fluidly when reactors are considered individually. Indeed, we demonstrate how the flexibility constraints of individual reactors can be aggregated at the fleet level. We show that, as the number of reactors increases, a linearized flexibility constraint at the fleet scale closely approximates the behavior of a fleet governed by non-convex, integer-based constraints.

Proposition 2. *Let N denote the number of reactors in a nuclear fleet, each subject to a non-convex flexibility constraint due to discrete load-following capabilities. When the flexibility of the aggregated fleet is approximated using a linearized model, the absolute deviation from the actual, discrete flexibility at the reactor level is bounded by $\frac{1}{N}$.*

Proof. See Appendix B.

We propose a numerical example to illustrate the convergence of the discrete approach (with integer variables) to the linearized aggregated approach as the number of nuclear reactors N increases. Consider a total fleet capacity of $Q =$ 63GW, that serves a given flexibility need at a certain timestep of $\delta = 10$GW. Consider a flexibility constraint for each reactor for the entire year of $\frac{\Delta}{N}$, with $\Delta = 0.8 \times 63 = 50.4$GW (i.e., each reactor can contribute up to 1 cycle of flexibility). In this setup, the ratio of the flexibility used at this timeframe to the total flexibility stock is $\frac{\delta}{\Delta}$, calculated as $\frac{10}{50.4} \approx 0.2$. For a given number of reactors N, the discrete approach uses n reactors to fulfill the flexibility need, where n is defined by:

$$n = \left\lceil \frac{\delta}{\Delta} \times N \right\rceil,$$

where $\lceil \cdot \rceil$ denotes the ceiling function (see Appendix B). The discrepancy between the discrete approach and the linearized approach is given by equation (4), and Figure 2 displays the value for a system of up to 10 reactors.

$$\eta = \frac{n}{N} - \frac{\delta}{\Delta}. \tag{4}$$

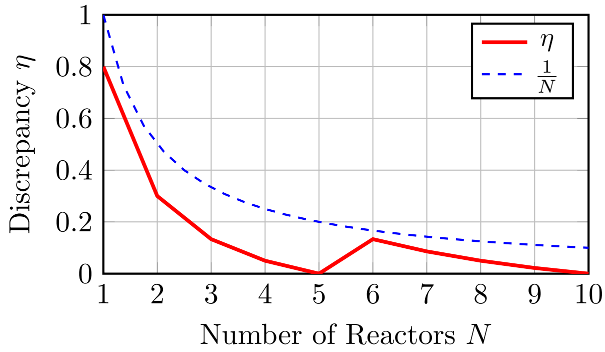

Figure 2: Error between the linearized aggregated model and the real non-convex problem, bounded by $\frac{1}{N}$.

In the numerical simulations, we consider the case of the French fleet, where the number of reactors (57 units) is sufficient to justify the use of a linearized and aggregated approach, greatly reducing tractability issues. In the following, we thus consider all the NPPs to be clustered into one unique cluster, approximating the real system's behavior.

4. Numerical Model

4.1. Overview

The numerical implementation of a multistage stochastic programming problem through Stochastic Dynamic Programming (SDP) has been well-studied in the literature (Shapiro et al., 2009). Conventional approaches are known to rapidly face tractability problems due to the so-called curse of dimensionality. We consider an alternative approach based on the Stochastic Dual Dynamic Programming (SDDP) algorithm to overcome it. Formally, the problem aims at minimizing the expected cost of operating the power system over one year. The problem includes an intertemporal constraint as the number of cycling operations that can be performed during the year is capped. Based on the nomenclature described in 4.3, the optimal policy (π) is the solution to the following problem:

$$\min_{\pi} \quad \mathbb{E}_{w \in R^{+}, \omega \in \Omega_w} \left[V_w^{\pi}(x_0, \omega) \right], \tag{5}$$

where the vector x_0 denotes the state variables at the initial stage $w = 0$ (which stands, for the present case, for the amount of NPPs cycling operations that remain usable), the vector ω denotes the observations of the random variables drawn from the sample space Ω_w. The objective function is thus given by the Bellman equation:

$$V_w^\pi(x, \omega) = C_w(x, u, \omega) + \mathbb{E}_{w' \in w^+, \phi \in \Omega_{w'}}[V_{w'}^\pi(x', \phi)], \tag{6}$$

where C_w is the cost of the system at stage w, and u is the action on the decision variables that is made. $\mathbb{E}_{w' \in w^+, \phi \in \Omega_{w'}}[V_{w'}^\pi(x', \phi)]$ is the expected cost-to-go function at stage w, which corresponds to the expected cost of solving the optimization problems of subsequent stages. It quantifies the anticipated future costs associated with the decision-making process. At a given stage w, control variables take their values according to a decision rule u, which balances out the trade-off between the minimization of the subproblem at stage w and the related impact on future costs, that is, the impact on $\mathbb{E}_{w' \in w^+, \phi \in \Omega_{w'}}[V_{w'}(x', \phi)]$:

$$u = \pi_w(x, \omega) \in U_w(x, \omega), \tag{7}$$

with $U_w(x, \omega)$ a non-empty, bounded convex set with respect to x. Decisions made at stage w have an impact on children stages $w' \in w^+$, and information is conveyed by a transition function that maps the incoming state, control, and random variables to their outgoing values x' as follows:

$$x' = T_w(x, u, \omega). \tag{8}$$

Once an optimal policy $\pi_w(x, \omega)$ has been determined for each stage of the problem, multiple simulations are conducted to evaluate its performance under various scenarios of random variable realizations.

4.2. General assumptions

We propose modeling the system as a stylized multistage stochastic linear programming problem. Electricity generation is dispatched hourly from the various technologies of power plants involved. The year is divided into 52 stages (weeks) of 168 hours each. As we analytically showed in the previous section, the linear relaxation of the problem closely approximates the real unit commitment decisions that are made at the reactor scale. Hence, we consider NPPs to be a unique technological cluster. The electric transportation network is disregarded. No investment decisions are considered in the analysis, and the variable costs associated with each generating technology are determined based on commodity prices and carbon costs. The technologies considered are gas and oil thermal plants (CCGT, OCGT, OCOT), NPPs, and renewables, including solar panels, wind turbines, biomass, and hydropower composed of Run-of-River (RoR), hydro reservoir, and Pumped Hydro Storage facilities (PHS).

Figure 3 provides a concise illustration of the approach applied to model uncertainty. The uncertainty related to VRE generation and power load is addressed weekly, where each stage represents a full week of the year. At the start of each week, the values of the random variables are revealed, and the corresponding subproblem of cost minimization is solved. The random variables are assumed to be time-independent within the SDDP framework, as modeling time correlation would require significant computational resources.[2] The SDDP framework also requires the discretization of the distribution function for the random variables. In this study, the random variables are sampled from three different sets: Ω_w^{pv}, Ω_w^{wind}, and Ω_w^{dem}, with each set representing five potential realizations of the associated variable for each stage w based on historical data. For example, in the first stage, VRE generation and power load time series for the week are selected from five past occurrences of that specific week, ensuring the incorporation of seasonal characteristics and possible correlations between PV, wind, and demand.

4.3. Subproblem formulation

Appendix C presents the sets, parameters, and variables of the model. We use four state variables: the level of nuclear generation, the reservoir of nuclear flexibility available for cycling operations, PHS reservoirs levels, and hydropower reservoir levels. The daily and weekly constraints on nuclear power modulation do not require a separate state variable as it is captured within the time span of a stage in the problem and can be managed using decision variables alone. For each stage, the subproblem at stake is to solve:

[2]For the sake of tractability, the approximation of time independence is preferred over the use of Auto-Regressive models, which would increase the number of state variables. We refer to Papavasiliou et al. (2018) for an example of an SDDP AR-1 model.

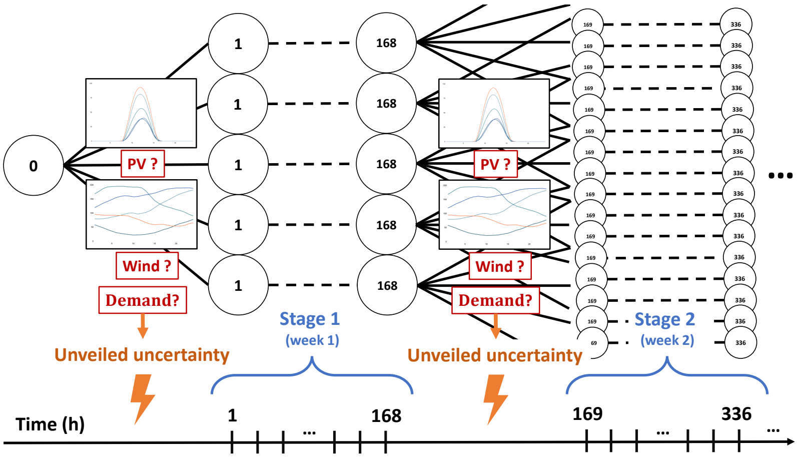

Figure 3: Illustration of the probabilistic tree and randomness generation process for two stages.

$$\min_{g^k_{w,t}} \sum_{k\in\mathbb{K}} \sum_{t\in(1,\ldots,168)} C^k \cdot g^k_{w,t} + \mathbb{E}(V(g^{nuc}_w, l^{nuc}_w, l^{phs}_w, l^{hydro}_w)) \tag{9}$$

Constraints concerning the maximum output power of the different technologies, as well as the minimum power threshold for nuclear, are depicted in equations (10) and (11). Equation (12) ensures production to equal consumption for every hour, and the associated dual variable λ_t defines the market price for electricity for each hour. All equations are set for every timestep t considered in the model when relevant, and all variables are non-negative.

$$0 \leq g^k_{w,t} \leq A^k_{w,t} \cdot \overline{P}_k, \quad \forall k \in \mathbb{K} \tag{10}$$

$$g^{nuc}_{w,t} \geq \underline{P}^{nuc}_{w,t} \tag{11}$$

$$\sum_{k\in\mathbb{K}} g^k_{w,t} + g^{phs,+}_{w,t} - g^{phs,-}_{w,t} = \xi^{dem}_{w,t} - \xi^{pv}_{w,t} - \xi^{wind}_{w,t} \qquad (\lambda_{w,t}) \tag{12}$$

Equations binding the evolution of PHS, hydro, and nuclear-considered stocks are displayed below and account for energy conservation within the system.

$$l^{phs}_{w,t+1} - l^{phs}_{w,t} = g^{phs,-}_{w,t} - \rho \cdot g^{phs,+}_{w,t} \tag{13}$$

$$l^{hydro}_{w,t+1} - l^{hydro}_{w,t} = W - g^{hydro}_{w,t} \tag{14}$$

$$\sum_{t \in d} \left|(g^{nuc}_{w,t+1} - g^{nuc}_{w,t})\right| \leq L^{nuc}_{day} \quad \forall d, w \tag{15}$$

$$\sum_{t \in w} \left|(g^{nuc}_{w,t+1} - g^{nuc}_{w,t})\right| \leq L^{nuc}_{week} \quad \forall w \tag{16}$$

$$l^{nuc}_{w+1} - l^{nuc}_{w} = \sum_{t} |g^{nuc}_{w,t+1} - g^{nuc}_{w,t}| \quad \forall w \tag{17}$$

$$l_{0,0} = L^{nuc}_{year} \tag{18}$$

As shown in equations (15)-(18), nuclear power variations are discounted iteratively. NPP load-following operations are subject to three distinct constraints, each corresponding to a specific timescale. These constraints impose limitations on the frequency of load-following operations on a daily, weekly, and yearly basis. As we show in Section 3, the value of nuclear flexibility for a given week μ_w can be expressed as the partial derivative of the Bellman term to the variable l^{nuc}_{w}, i.e., the stock of cycles nuclear is allowed to undergo during the year:

$$\frac{\partial \mathbb{E}(V(g^{nuc}_{w}, l^{nuc}_{w}, l^{phs}_{w}, l^{hydro}_{w}))}{\partial l^{nuc}_{w}} = \mu_w. \tag{19}$$

5. Application to the French case

We now detail an application of our methodology and consider the future French power system in 2035 as a case study. Our focus on France is motivated by the country's historical endowment in nuclear generation. At the 2035 horizon, the projected deployment of VREs will likely necessitate an increased use of nuclear-based load-following operations. In recent years, the cycling operations conducted at French reactors have experienced rapid growth. Between 2012 and 2015, the percentage of reactors engaged in such operations climbed from 20 to 40%, while the electricity production from renewable sources increased by more than 55% (Cany et al., 2018). That percentage is projected to increase to accommodate an increasingly VRE-dominated system. Given France's strong political commitment to the combined development of VREs and NPPs, examining the future economics of flexible nuclear generation in this country is particularly relevant.[3]

[3] Recall that the country is endowed with a large fleet of nuclear power plants which, in 2023, contributed to around 65% of electric generation.

5.1. Model calibration

5.1.1. Non-nuclear related data

We consider the projected generation mix retained in the national energy plans as reported in the studies by RTE, the French Transmission System Operator (TSO) (RTE, 2022). Table C.4 in Appendix C reports the posited generation capacities for 2035. VRE electricity generation time series and load patterns from 2015-2019 have been scaled up to the projected evolution of both VRE installed capacity and demand trends in the coming decade.[4] We impose hydropower reservoir levels to be half-filled at the beginning and the end of the modeled year, in line with real data from RTE. Our model omits export price setting, so any excess energy produced beyond domestic consumption is curtailed rather than exported, simplifying the model by not simulating the entire European energy market.

5.1.2. Nuclear-specific considerations

All the 57 reactors of the French nuclear fleet are aggregated into one unique nuclear cluster. To assess the number of cycles allowed at fleet scale for the French nuclear fleet, we calculate the effective historical nuclear flexibility based on EDF data from 2017 to 2023. During that period, French reactors performed an average of 26 cycling operations per year. In the sequel, we use this as a baseline value. The value of $20\%\overline{P}$ for the lower generation bound is drawn from Cany et al. (2018). It represents the usual value retained for the flexible operation of French reactors. The availability of the fleet is historically higher in winter than in summer in France since maintenance and refueling outages are strategically scheduled to minimize their impact on the system. To account for this effect, we set the fleet's availability equal to the average availability of the French reactors between 2017 and 2023. Similarly, the lower bound restricting nuclear generation is extracted from historical data. The fleet's total minimal power is the sum of each reactor's minimal power, reflecting variations in their irradiation cycles and operational schedules. Figure 4 shows the average operational schedule for the French nuclear fleet in the years 2015-2023 and its minimal power evolution based on the duration of each reactor's irradiation cycle. To estimate the minimum power output of the fleet, we assume that fuel burn-up is proportionate to the progress of each reactor's irradiation cycle.[5] The resulting feasible range of nuclear generation is presented in Figure 4.

[4]Source: ENTSO-e transparency platform (European Network of Transmission System Operators for Electricity).

[5]Sources: ENTSO-e and ASN (Autorité de sûreté nucléaire, the French Nuclear Safety Authority).

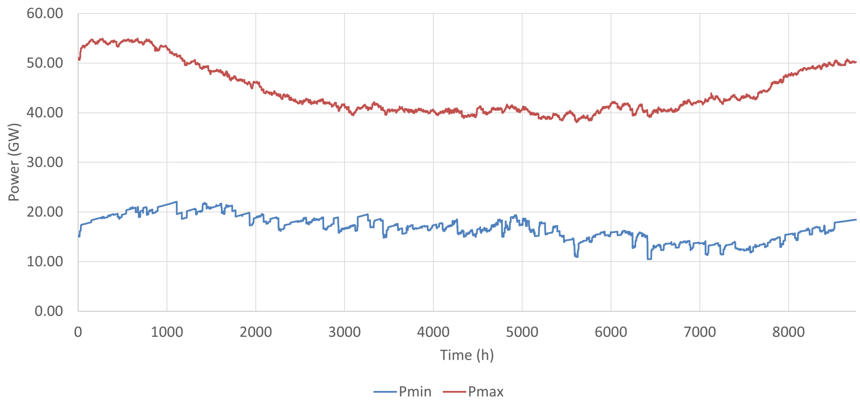

Figure 4: Retained minimal and maximal output power for nuclear power, based on 2015-2023 data.

5.2. Implementation

We investigate the effects of nuclear flexibility through a series of five case studies, each corresponding to different levels of nuclear flexibility. The constraint on the maximum number of cycling operations that a nuclear reactor can perform per year is set to 1, 26 (the baseline case, corresponding to the current flexibility of the French fleet), 50, 75, and 100, respectively. For each of these five cases, we solve the system cost minimization problem, which is implemented as an instance of a multistage stochastic dynamic programming problem solved with the SDDP algorithm. We determine an optimal policy—i.e., an approximation of the Bellman term across all stages—for each flexibility case in the algorithm's training phase. We then run simulations to assess its performance across 100 possible years. We use the Julia implementation proposed by Dowson and Kapelevich (2021) and the CPLEX solver. The model is trained over 1000 iterations, yielding 1000 Bender's cuts at each of the 52 stages considered. At each stage, the generating patterns of PV and wind plants, as well as the level of electricity demand, are extracted from 5 possible realizations. This results in a probabilistic space of more than 2.2×10^{36} possible scenarios.

The training phase of the algorithm takes between 5 and 10 hours per case study on an Intel Xeon Gold 6230 with 20 cores @ 2.1 GHz (Cascade Lake) and 10GB of dedicated RAM. Following Shapiro (2011), we ensure that the upper bound of the system's expected total cost (estimated via policy simulations) aligns with the lower bound (determined by the Benders' cuts) within a fixed tolerance of $\varepsilon = 2\%$. To confirm proper convergence, we track the evolution of this gap between the bounds across iterations, ensuring no significant change occurs in the variance of the interval when stopping the algorithm.

6. Results

6.1. System costs

For each scenario, we evaluate the performance of the optimal policy using 100 random simulations. The average system cost is calculated as the arithmetic mean of the total annual cost from the simulations. Table 1 presents the ratio of this estimate to the baseline case for each scenario. As expected, the mean cost decreases with higher nuclear flexibility, reflecting improved resource utilization and lower operational costs.

Nuclear flexibility (# allowed cycles)	Mean objective value (% of baseline case)
1	1.08
26	1
50	0.98
75	0.97
100	0.96

Table 1: Mean cost of the system across varying levels of nuclear flexibility.

With a flexible nuclear fleet, VRE integration improves, reducing curtailment levels, as shown in Figure 5. While there are diminishing returns from increased nuclear flexibility, the reduction in curtailment remains significant at first. However, after 75 cycles per year, further flexibility yields negligible improvements in curtailment, suggesting that the system is nearing the unconstrained optimum for nuclear flexibility.

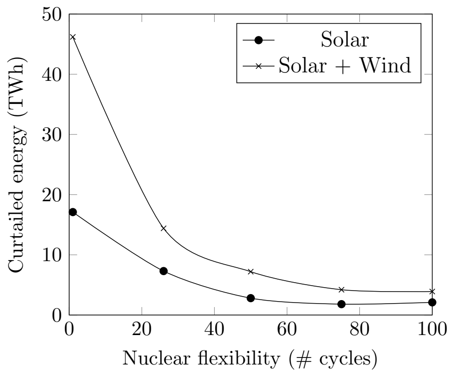

Figure 5: Total amount of curtailed energy from VRE across varying levels of nuclear flexibility.

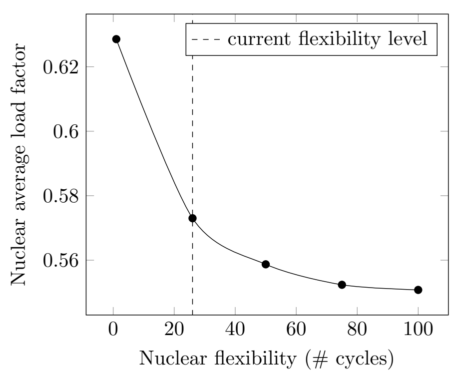

Figure 6: Mean load factor of NPPs across varying levels of nuclear flexibility.

NPP capacity factors decrease from 63% in the least flexible scenario to 55% at the highest flexibility level, as shown in Figure 6. For comparison, the average load factor for French NPPs from 2010 to 2019 was around 72%. These results highlight a significant reduction in nuclear output, even at flexibility levels similar to historical norms, driven by competition between nuclear and renewable generation.

6.2. The value of nuclear flexibility

The value of nuclear flexibility is derived from the shadow price of the flexibility constraint, representing the marginal cost reduction of the system when the constraint is slightly relaxed. This corresponds to the derivative of the Bellman function with respect to the flexibility constraint, capturing the system's sensitivity to the flexibility constraint and reflecting how much the overall system cost decreases as nuclear flexibility is incrementally increased.

Figure 7 illustrates the relationship between nuclear flexibility, measured in cycles per year, and its corresponding value in EUR/MW. The graph highlights that nuclear flexibility holds the highest value when scarce, particularly when the fleet's flexibility is limited to only one cycle per year (with flexibility value exceeding EUR 2000/MW). In this scenario, flexibility is crucial because it can only be used sparingly, and its application in critical moments significantly reduces system costs. As the nuclear fleet's flexibility increases, the marginal value of additional flexibility diminishes, down to EUR 5/MW in the 100-cycle case. This is because the most valuable opportunities to deploy flexibility are already utilized as flexibility increases, leaving fewer situations where additional flexibility would significantly impact system costs.

The link between the value of flexibility and electricity prices is tied to price extrema, not the average price level. During high-price periods, upward flexibility (i.e., the ability to increase nuclear output) is valuable because it allows the system to avoid using more expensive peaking plants or to shed load. Conversely, during periods of negative prices, downward flexibility (i.e., the ability to decrease nuclear output) becomes valuable, as it prevents the need to sell electricity at a loss. Figure 8 displays the evolution of prices and shows the mean value stays roughly idle depending on the scenario, whereas price volatility highly diminishes.

6.3. Impact on profitability

Simulation results indicate that nuclear flexibility has little impact on NPPs' profits. Interestingly, the maximum profit occurs at 26 cycles per year, that is,

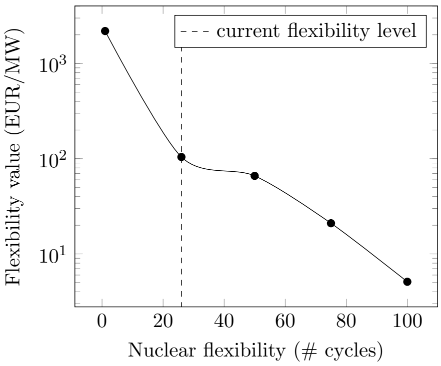

Figure 7: Marginal value of nuclear flexibility across varying levels of nuclear flexibility.

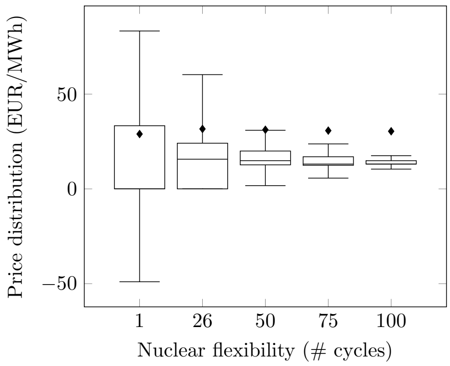

Figure 8: Price distribution across varying levels of nuclear flexibility. Diamonds indicate mean values.

the current practice. The differences in profit across flexibility levels are minimal, as shown in Figure 10. A Wilcoxon test was conducted to assess whether the profit distributions differ significantly. While comparisons between the 1 and 26-cycle cases, as well as between the 26 and 100-cycle cases, produced p-values low enough to reject the null hypothesis, most other tests yielded high p-values, indicating that samples cannot be clearly distinguished among themselves in the majority of cases. This suggests that nuclear profits depend only weakly on flexibility. Indeed, the largest profit difference —between 1 and 26 cycles—is about 7%. Since nuclear plants already operate with around 26 cycles per year, a more relevant comparison is between 26 and 100 cycles to see the impact of increasing the nuclear fleet flexibility in the future. Results indicate a drop of approximately 5% in profits. This indicates a nuclear operator would have little incentive to pursue such high flexibility.

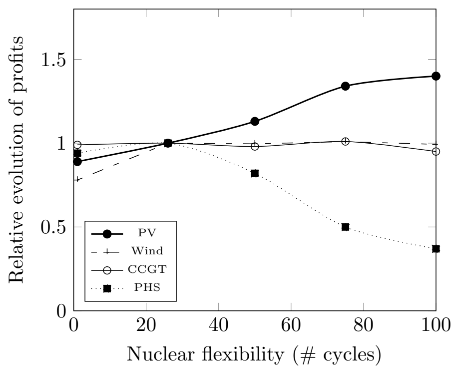

Figure 9: Impact of nuclear flexibility on average profit levels by technology.

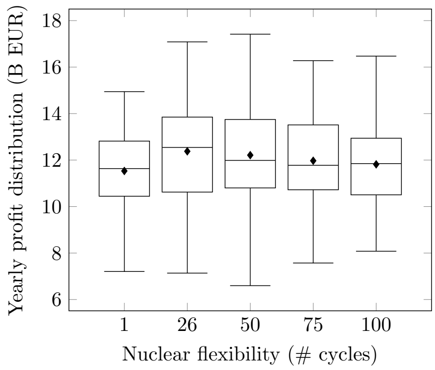

Figure 10: Distribution of profits for French NPPs across varying levels of nuclear flexibility.

Flexibility levels compared (# cycles)	p-value
1 / 26	0.004
26 / 50	0.54
50 / 75	0.38
75 / 100	0.75
26 / 100	0.04

Table 2: Wilcoxon test results for profit distribution across nuclear flexibility levels

This counterintuitive result stems from two counteracting dynamics. As the nuclear fleet becomes more flexible, NPPs can better align production with system needs and thus increase the market value of their production. In sharp terms, NPPs begin to produce less when prices are low and can better adjust for any price rise, potentially increasing profits. However, the nuclear generating pattern also impacts the price formation, which aligns more closely with the short-term marginal cost of the technology and lowers potential revenues. Also, given the reduction in load factor, NPPs produce less at higher flexibility levels, which hinders profits.

The impacts on profits for other technologies can be highlighted by three main results. First, solar panel profits benefit substantially from increased nuclear flexibility, as Figure 9 shows. In the most flexible scenario, solar panel payoffs increase by almost 50% compared to the baseline. This increase is due to reduced curtailment of solar energy and mitigation of the cannibalization effect during peak solar generation periods. Second, wind turbine profits show no significant change despite a substantial reduction in energy curtailment of 27TWh between the two most extreme flexibility cases (see Figure 5). The increased flexibility of NPPs leads to higher wind energy volumes sold in the market, which is offset by deflated price levels in moments of wind production, resulting in stable profits for wind turbines. Finally, PHS profits are adversely affected by increased nuclear flexibility. The flattening of the price distribution reduces opportunities for time arbitrage, leading to a 63% decrease in PHS profits between the most flexible NPP scenario and the baseline.

7. Conclusion

The massive deployment of variable renewable generation radically shifts the role of nuclear power plants from providing baseload generation to offering flexibility through load-following operations. To examine the system implications of that change, this paper introduces a new model for nuclear flexibility, conceptualizing it as a fixed stock of load-following operations optimally dispatched in an uncertain environment. Using a linearized approximation of the inherently non-convex problem, we extend this model from the reactor level to the fleet scale. We derive the marginal value of nuclear flexibility as the dual value of the binding constraint on flexibility, showing that this value is determined by the extremum of expected prices in subsequent periods.

As an application of that model, the paper analyzes the French power system in 2035, treating it as a multistage stochastic dynamic programming problem solved using the Stochastic Dual Dynamic Programming (SDDP) algorithm. At an empirical level, our results quantify the value of nuclear flexibility across different flexibility levels, and we demonstrate its effects on market prices and the profitability of various technologies. At the current flexibility level of the French nuclear fleet, we estimate a value of EUR 100/MW by 2035, underscoring the economic incentive to enhance nuclear flexibility in the future.

While increasing nuclear flexibility improves overall cost efficiency, our findings suggest a potential misalignment with the profit-maximizing goals of individual operators, especially in imperfect markets susceptible to price manipulation. Future research should further explore these dynamics, particularly the role of market power in systems with flexible nuclear assets. Moreover, incorporating time correlations in renewable generation and demand patterns—treated as independent in this study—could provide more precise insights. Lastly, recent technical failures in French NPPs, which have affected availability, highlight the need for further investigation into how such outages might influence the value of nuclear flexibility.

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Declaration of interest

Authors hereby declare that they have no conflicts of interest to disclose regarding the content presented in this paper.

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Appendix A. The value of nuclear flexibility

Proof. In electric markets, two types of flexibility are generally distinguished: downward flexibility (ability to manage supply exceeding demand) and upward flexibility (ability to manage demand exceeding supply). We differentiate these by examining two typical market scenarios where nuclear flexibility is valuable, subsequently deriving the respective downward and upward values of nuclear flexibility.

Downward flexibility

Consider a case where the price in $t = 1$ is high ($p_1 \gg c$), and at time $t = 2$, the expected price is below the marginal cost, $\mathbb{E}[p_2] < c$. Since the expected price is below marginal cost in time 2, $\frac{\partial \mathbb{E}[(p_2-c)q_2]}{\partial q_2} \leq 0$ and the NPP operator lowers output to maximize profit down to a point the flexibility constraint is binding. Hence, $\lambda_2 = 0$ and $\mu > 0$. The Karush-Kuhn-Tucker (KKT) conditions for stationarity yield:

$$\frac{\partial \mathcal{L}}{\partial q_1} = (p_1 - c) - \mu = 0 \tag{A.1}$$

$$\frac{\partial \mathcal{L}}{\partial q_2} = \frac{\partial \mathbb{E}_{p_2}(V_2(q_2, p_2))}{\partial q_2} + \mu = 0 \tag{A.2}$$

and we have:

$$\begin{aligned}\frac{\partial \mathbb{E}_{p_2}(V_2(q_2,p_2))}{\partial q_2} &= \int \frac{\partial}{\partial q_2}(f(p_2)V_2(q_2,p_2))dp_2 \\ &= \int f(p_2)\frac{\partial V_2(q_2,p_2)}{\partial q_2}dp_2 \\ &= \mathbb{E}\left[\frac{\partial V_2(q_2,p_2)}{\partial q_2}\right] \\ &= \mathbb{E}(p_2) - c.\end{aligned}$$

Thus we find:

$$-\mu = \mathbb{E}[p_2] - c. \tag{A.3}$$

Here, μ represents the shadow price associated with the flexibility constraint. It quantifies the cost of the reduced flexibility at time 2 due to a higher production level at time 1. This relationship highlights the trade-off the operator faces when setting the production level at 1. A lower production level at 1 increases the flexibility available at 2, increasing the expectancy of profit at time 2 by the value of:

$$\mu = c - \mathbb{E}[p_2] \geq 0. \tag{A.4}$$

Upward flexibility

Now consider the situation of a nuclear plant producing below nameplate capacity at time 1 (as the result of a former optimization as we just calculated, for instance) but facing a very high price at time 2. With no flexibility constraint, the optimal dispatch would result in producing at maximum capacity in time 2 to maximize profit, but as before, we consider the flexibility constraint to be binding. The NPP cannot reach nameplate capacity in time 2, and the KKT conditions of this problem lead to a value of flexibility of

$$\mu = \mathbb{E}[p_2'] - c, \tag{A.5}$$

with p_2' the peak price in 2. The value of flexibility—which is the marginal change in the value of the Lagrange function when the flexibility constraint is relaxed by an infinitesimal amount— is now equal to the expectancy of price in time 2, minus the variable cost of running the plant c.

Multistage framework

We showed that the value of nuclear flexibility is determined by the expected extremum of the price, adjusted for the variable cost. The variable cost is either added or subtracted, depending on whether the flexibility is upward or downward:

$$\mu = |\mathbb{E}(p_2) - c|. \tag{A.6}$$

This is true if the flexibility constraint on load-following cycles is binding. Since the value of flexibility is set by the Lagrange multiplier of the flexibility constraint, if the latter is not binding, the former equals zero, and adding more potential of flexibility to the NPP does not bring any economic gain for the system or the operator. In a multistage framework with more than two timeframes, the dual value of the flexibility constraint will be determined by the period when the constraint is most binding, i.e., when the dual value is at its maximum. Economically, this can be understood as follows. Initially, with limited flexibility, the nuclear plant utilizes its flexibility in the most valuable situations, typically involving extended periods of low prices followed by high prices, such as seasonal variations. As the plant's flexibility increases, it can address less critical, less valuable needs. Consequently, the marginal value of nuclear flexibility μ decreases, settling at the value of the next most valuable opportunity for additional flexibility. Thus, in a multistage case, the value of nuclear flexibility is determined by the highest-value opportunity for marginal flexibility that remains unused. The marginal value of nuclear flexibility thus writes:

$$\mu = \max_{t \in \mathcal{B}} \left(|\mathbb{E}[p_t] - c| \right), \tag{A.7}$$

where p_t represents the price at time t, c is the variable generation cost and $\mathcal{B}$ is the set of timeframes where the flexibility constraint is binding. $\square$

Appendix B. The problem of aggregation

Proof. Consider a fleet of N nuclear reactors, each subject to a non-convex flexibility constraint represented by a discrete variable n, which counts the number of reactors performing a load-following cycle. The proportion of reactors cycling is $\frac{n}{N}$. The system requires a certain amount of flexibility, δ, while the total flexibility the fleet can provide is Δ. Hence, the relative flexibility need is $\frac{\delta}{\Delta}$. Each reactor contributes a flexibility of $\frac{\Delta}{N}$ when performing a full load-following cycle. Any plant participating in a flexibility request without completing a full cycle underutilizes its flexibility potential, depleting its available cycling operations. Therefore, the optimal strategy to preserve the nuclear fleet's flexibility is to minimize the proportion of reactors engaged in load-following cycles, $\frac{n}{N}$, while still meeting system demand:

$$\min_{n} \quad \frac{n}{N} \quad \text{s.t.} \quad \frac{n}{N} \geq \frac{\delta}{\Delta}.$$

The solution to this is $n = \lceil \frac{\delta}{\Delta} \times N \rceil$, where $\lceil \cdot \rceil$ denotes the ceiling function to account for the fact that n must be an integer. The ceiling function introduces a small error, as $\frac{\delta}{\Delta} \times N$ may not be an integer. The error between the discrete solution $\frac{n}{N}$ and the continuous solution $\frac{\delta}{\Delta}$ can be written as:

$$\eta = \frac{\lceil \frac{\delta}{\Delta} \times N \rceil}{N} - \frac{\delta}{\Delta}. \tag{B.1}$$

Recall that the set of rational numbers $\mathbb{Q}$ is dense in the set of real numbers $\mathbb{R}$. This implies that for any real number $\frac{\delta}{\Delta}$, and for any small positive ε, there exists a rational number $\frac{n}{N}$ such that:

$$\left| \frac{n}{N} - \frac{\delta}{\Delta} \right| \leq \varepsilon. \tag{B.2}$$

Thus, for any desired accuracy ε, we can always find a sufficiently large N such that the discrete ratio $\frac{n}{N}$ is arbitrarily close to the continuous value $\frac{\delta}{\Delta}$. We now quantify this error explicitly. The ceiling function introduces an error of at most 1:

$$\lceil \frac{\delta}{\Delta} \times N \rceil - \left(\frac{\delta}{\Delta} \times N \right) \leq 1,$$

dividing by N, we obtain:

$$\frac{\lceil \frac{\delta}{\Delta} \times N \rceil}{N} - \frac{\delta}{\Delta} \leq \frac{1}{N}.$$

Thus, $\frac{1}{N}$ is an upper-bound for the error η:

$$\eta \leq \frac{1}{N} \quad \forall N \in \mathbb{N}. \tag{B.3}$$

In conclusion, the discrete, non-convex constraint at the reactor level $\frac{n}{N}$ converges to the continuous, linearized constraint $\frac{\delta}{\Delta}$ at the fleet level as $N \to \infty$. The convergence error decreases at a rate bounded by $1/N$, ensuring that as the number of reactors increases, the fleet-level linearized model becomes an increasingly accurate approximation of the individual reactor-level non-convex model. $\square$

Appendix C. Nomenclature & Data

Table C.3: Notations

Abbreviation	Dimension	Description
Sets		
$k \in \mathbb{K}$		Generating technologies
$t \in (1, ..., 168)$		Hours of the week
$d \in (1, ..., 7)$		Days of the week
$w \in (1, ..., 52)$		Weeks of the year
Parameters		
C^k	EUR/MWh	Generation variable cost
$\overline{P_k}$	GW	Installed capacity of technology k
$\underline{P_{w,t}^{nuc}}$	GW	Minimum generating power of nuclear power plants
$A_{w,t}^k$		Availability factor of technology k at time t
ρ		Round trip efficiency of PHS
W	GW	Water inflow for hydro reservoirs (constant)
$VoLL$	EUR/MWh	Value of Lost Load
L_{day}^{nuc}	GW	Maximum amount of nuclear power variation allowed per day
L_{week}^{nuc}	GW	Maximum amount of nuclear power variation allowed per week
L_{year}^{nuc}	GW	Maximum amount of nuclear power variation allowed per year
Initial values		
$l_{0,0}^{nuc}$	GW	Initial stock of flexibility for NPPs
$l_{0,0}^{PHS}$	GWh	Initial stock of water for PHS
$l_{0,0}^{hydro}$	GWh	Initial stock of water for hydrothermal plants
Stochastic Variables		
$\xi_{w,t}^{pv}$	GW	Electricity production from solar
$\xi_{w,t}^{wind}$	GW	Electricity production from wind
$\xi_{w,t}^{dem}$	GW	Electricity demand
State Variables		
g_w^{nuc}	GWh	Nuclear generation level at the end of week w
l_w^{nuc}	GWh	Remaining nuclear flexibility at the end of week w
l_w^{phs}	GWh	Filling levels of PHS stocks at the end of week w
l_w^{hydro}	GWh	Filling levels of hydro reservoirs stocks at the end of week w
Control Variables		
$g_{w,t}^k$	GW	Generating power of technology k
$g_{w,t}^{phs,+/-}$	GW	Turbining (+) or pumping (-) from/into PHS reservoirs

[6]Sources: Villavicencio (2017) for efficiency rates, Pietzcker et al. (2021) for emission factors and input prices, and the posited carbon price, which is set at EUR 170 per ton.

Technology	Capacity (GW)	Derating factor	Variable cost (EUR/MWh)
Solar	50	Ø	0
Wind	50	Ø	0
RoR	2.2	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 C.4: Capacity and variable costs of considered technologies in France in 2035 [6]

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