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# NUCLEAR FLEET FLEXIBILITY: MODELING AND IMPACTS ON POWER SYSTEMS WITH RENEWABLE ENERGY

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## ABSTRACT

This paper identifies the underlying physical mechanisms that frame the flexibility and operation of nuclear technologies, with analysis focused on the effects of two structural characteristics of nuclear fleets, i.e. nuclear schedule optimization and minimal power variations, on simplified French power system simulations. We develop a method to simulate nuclear schedule optimization to reflect how plant managers maximize plant availability during peak-demand periods. Using this schedule optimization, we compute each plant's minimum power level and its variation over time to evaluate the flexibility potential. Three nuclear flexibility hypotheses are considered: one where fleet schedule is considered constant, which is standard practice in the energy systems modeling literature, one with an optimized fleet schedule with constant minimum power, and one with an optimized fleet schedule with physics-induced minimum power variations. Sensitivity analysis highlights the links between the fleet's schedule optimization, minimal power variations, relative share of nuclear and renewables in the capacity mix, and results of simulation models. We find that the nuclear fleet's optimization and associated realistic minimum power variations gain in importance with increasing relative share of nuclear in the capacity mix. The schedule's importance holds as renewables' installed capacities heighten as the residual demand level decreases. This paper highlights the potential benefits of modeling nuclear schedule optimizations and the resulting minimum power evolutions. Both aspects are crucial for evaluating nuclear flexibility characteristics in simplified low-carbon electric systems that use a significant share of renewable energy.

## Keywords

Nuclear energy; Flexible power operation; Nuclear schedule; Renewable energy integration; Unit commitment; Economic dispatch; Mixed-integer linear programming

## Nomenclature

### Abbreviations

EDF: Electricité de France – French utility

EFPD: Effective Full Power Day

MILP: Mixed-Integer Linear Programming

PCI: Pellet-Cladding Interaction

PWR: Pressurized Water Reactor

RTE: Réseau de Transport d'Electricité (French Transmission System Operator)

UC: Unit-Commitment

VRE: Variable Renewable Energy

## Notations

Ba: Barium

Cs: Caesium

I: Iodine

Xe: Xenon

$\beta^-$ : Beta decay

## Indices

$t$ : index of time, week.

$i$ : index for nuclear units.

$\bar{t}$ : index of peak demand of the year

## Variables

$U_{i,t}$ : binary state variable for nuclear availability and outages, for nuclear unit  $i$  at time  $t$ .

## Constants

$D_t$ : electricity demand (MWh), time  $t$ .

$Q_i$ : maximum power output (MW) for nuclear unit  $i$

$\underline{C}_i$ : minimum irradiation cycle duration (weeks) for nuclear unit  $i$

$\bar{C}_i$ : maximum irradiation cycle duration (weeks) for nuclear unit  $i$

$\underline{S}_i$ : minimum outages duration (weeks) for nuclear unit  $i$

$\underline{\delta}$ : minimum number of nuclear units that have to stay online simultaneously

$\delta_{outages}$ : maximum number of nuclear units that can start their outage phase at the same time

$N$ : number of nuclear reactors

$T$ : number of timesteps

# 1. Introduction

To address rising concern around climate change, most countries have committed to steadily reduce the carbon emissions of their electricity mix, notably by expanding variable renewable technologies like onshore and offshore wind, solar photovoltaic and concentrated solar power (e.g. 42% variable renewable energy (VRE) by 2050 in the United States<sup>1</sup> 40% by 2030 in the European Union<sup>2</sup>) [1]. This transition brings a significant change in the supply-side of electric systems. VRE technologies are characterized by high capital with negligible variable costs and by prime position in the economic ‘merit order’<sup>3</sup> dispatch to meet electricity demand [2]. The added fact that VRE generation is highly dependent on weather conditions makes it optimal to prioritize them to meet demand. The outcome of developing high shares of variable renewables in the generation mix is to progressively replace technologies such as coal, lignite, and even nuclear as the primary means of electricity generation [3], [4]. To remain valuable to the grid system, these technologies will need to operate flexibly to adapt to the inherent variability of renewable energies [5]. In the context of deep decarbonization of the electric capacity mix, nuclear emerges as one of the ‘baseload’ technologies that may play a role in future systems, alongside other components such as VRE, hydropower, storage facilities, demand-response, or low-carbon hydrogen.

Nuclear power plants (NPP) typically operate in ‘baseload’ mode, meaning that most of the time they produce at their nominal power level. Nuclear has high fixed costs and low variable costs, making it economically optimal to use this operation mode. However, countries with a higher share of nuclear capacity may be forced to maneuver their NPP output to balance electricity demand and supply. The French electric system is a case in point: NPP represent 46.6% of France’s installed capacity and 70.6% of its electricity generation (2019 figures) [6], so NPPs frequently maneuver to participate in flexibility operations, either by load-following (power variations usually higher than 10% of a reactor’s nominal power to adapt to residual demand variations), primary frequency control (short-term adjustment to stabilize production and power-system demand in the timeframe of seconds) or secondary frequency control (several seconds to several minutes of automatic power adjustment aiming to restore frequency following frequency deviations) [7]–[9]. The nuclear fleet then covers a significant share of the current French flexibility requirements. Broadly speaking, part of the installed nuclear fleet was either initially designed to operate flexibly [8] or can be adapted to this regime through re-design work [9]. There is a dense literature on nuclear flexibility, its ability to load-follow, and the additional costs generated, i.e. wear of components, cost of retrofit and re-design, fuel, and staff costs [9]–[18].

Nonetheless, as noted by [17], most of the electric power systems modeling literature (e.g. [19]) still represents nuclear power as an inflexible technology. Studies that partially encompass nuclear flexibility typically represent nuclear generation using assumptions such as ramping constraints or minimal stable power levels similar to other thermal technologies [18], [20]–[24]. Such modeling practices do not accurately represent the specificities of NPP flexibility driven by neutronic constraints, primary circuit dynamics, or refueling strategies. Reactor designs across the world differ in their underlying technologies (Pressurized-Water Reactors, Boiling-Water Reactors, CANada Deuterium Uranium, Fast-Neutron Reactor...), but most of them are capable of flexible maneuvers [9]. This paper focuses solely

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<sup>1</sup> Annual Energy Outlook 2021: Narrative, [https://www.eia.gov/outlooks/aeo/pdf/AEO\\_Narrative\\_2021.pdf](https://www.eia.gov/outlooks/aeo/pdf/AEO_Narrative_2021.pdf)

<sup>2</sup> Proposal for a DIRECTIVE OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL amending Directive (EU) 2018/2001 of the European Parliament and of the Council, Regulation (EU) 2018/1999 of the European Parliament and of the Council and Directive 98/70/EC of the European Parliament and of the Council as regards the promotion of energy from renewable sources, and repealing Council Directive (EU) 2015/652. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021PC0557>

<sup>3</sup> We refer here to the ranking of available generating units of an electric system based on ascending order of marginal costs, with the aim of minimizing the overall generation costs of the system. Low-marginal-cost technologies then take priority over high-marginal-cost technologies in responding to the corresponding electricity demand.

on Pressurized-Water Reactors (PWRs), currently the dominant nuclear design (304 PWRs out of 439 nuclear reactors in operation<sup>4</sup> and 44 PWRs out of 52 under construction, as of 1<sup>st</sup> February, 2022).

This paper is in line with recent works ([16], [17]) that highlight the impact of physics-induced plant flexibility modeling on the evaluation of future electric systems with renewable energy. Although we address the main constraints framing nuclear flexibility, our objective is to focus on the impact of two nuclear flexibility characteristics on modeling results: fleet schedule optimization and minimal power variations. The paper first highlights the benefits of nuclear schedule optimization to integrate VRE production in simplified electric systems. Another finding is the importance of representing minimal power variations to evaluate nuclear–renewable energy interactions. Our main contribution is to propose a novel Mixed-Integer Linear Programming model based on realistic refueling constraints of PWRs to simulate fleet schedule optimization, which enables the computation of each plant’s minimum power variations. Another contribution is the case studies based on representative French electric-system data, where we evaluate the benefits of using nuclear flexibility characteristics to integrate renewable energy in a nuclear-based capacity mix.

Our findings nevertheless come with limits. The numerical results are case-specific, and so caution is warranted when comparing against real-life power systems, as assumptions such as gas prices heavily influence these numerical results. The represented power systems are simplistic, with only one country represented, and thus they do not factor in the physical network constraints that may influence energy curtailments levels. Most of the levers of flexibility are also excluded, i.e. interconnections with neighboring electric systems, storage facilities, hydroelectricity, and demand-side response, all of which would likely decrease the value of nuclear flexibility. Results reported in this paper should therefore be extrapolated with care. Nonetheless, we argue that nuclear flexibility should yield similar benefits in power systems with significant nuclear and VRE capacity, where the seasonality of nuclear availability would participate in VRE integration, reducing costs, environmental impacts, and energy curtailment. Future work will focus on measuring the impact of nuclear flexibility in broader power systems with larger balancing areas, a larger number of generating technologies, and more advanced modeling of flexibility levers.

The goal here is not to have a precise calculation for a specific country but to demonstrate, through an academic approach, that a precise calculation taking into account nuclear flexibility needs to include aspects related to nuclear fleet fuel management and its effects on the available power range of the fleet.

The paper is structured as follows. Section 2 summarizes the technical constraints governing flexible operation of nuclear PWRs. Section 3 presents a novel mathematical model to represent the nuclear fleet’s schedule optimization, the resulting minimum power variations of the plants, and the ‘Antares-RTE’ unit commitment and economic dispatch model used in this paper. Section 4 resumes the different case studies and the model’s results related to fleet schedule optimization and minimum power variations. Section 5 concludes with the main findings and discusses future work.

## 2. Flexibility limits of nuclear power plants

This section summarizes the potential flexibility constraints that apply to PWRs. We determine the underlying phenomena framing essential flexibility constraints, i.e. pellet-cladding interaction, Xenon transients, and outaging constraints. The objective is to determine the relevance of modeling these constraints and guide practice to reflect nuclear flexibility in electric systems simulations.

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<sup>4</sup> IAEA PRIS Database, <https://pris.iaea.org/PRIS/WorldStatistics/OperationalReactorsByType.aspx>, consulted January 2022.

## 2.1 Pellet-cladding interaction and ramping constraints

Nuclear PWRs can modify their output level by changing their primary circuit's boric acid concentration, a neutron absorber, or by changing neutron-absorbing control rod insertion levels. The underlying principle is to manage the fuel's chain reaction and the thermal energy level it produces by modulating the fission reaction rate in the core<sup>5</sup>. Typically, increasing boron concentration in the primary circuit or increasing the insertion level of control rods in the fuel assemblies will decrease the fission reaction rate, thus lowering the thermal power produced, the steam production rate, and the electrical output of the power plant. [12], [17], [25], [26] note that as control rods movement allows for faster and more precise power management, plant managers favor it over boric acid regulation<sup>6</sup> to operate flexibly. However, such power variations do not come without thermal and mechanical consequences.

The movement of control rods in the core creates thermal variations that influence the volume of fuel pellets and their surrounding claddings. When control rods are inserted, the temperature drops locally in the core, and part of the fuel's pellets and claddings contract. Conversely, when control rods are withdrawn, the temperature rises locally, and part of the fuel's pellets and claddings dilate. Because the fuel pellets have a higher temperature (especially in the center) and a higher thermal expansion coefficient than their claddings<sup>7</sup>, their volume evolves more consequentially to power variations [29], [30]. These power variations may bring pellets into contact with the claddings [31], [32], creating mechanical stress that endangers the integrity of the claddings, which is a breach of the first containment barrier of PWRs. This Pellet-Cladding Interaction (PCI) phenomenon does not bring production to a standstill, but it is common practice to not carry out flexible maneuvers following breaches in the cladding [12]. Other corrosion effects due to corrosive fission products may increase the occurrence of such breaches.

The overall effect of PCI on the flexibility capabilities of PWRs is that the maximum power ramping rate has to be limited to avoid creating excessive mechanic stress and keep the number of breaches within the design tolerance of the fuel assemblies. This ramp level is highly dependent on the type of reactor, its irradiation cycle advancement, its operating mode, and the amplitude of the power variation [17], [33], [34]. Although most power variations historically do not exceed 0.5% of the plant's nominal power ( $P_{nom}$ ) per minute [8], the theoretical ramping rate limits of PWRs range from 2%  $P_{nom}$  per minute to 5%  $P_{nom}$  per minute, and even 10%  $P_{nom}$  per minute for German PWRs [35]. Thus, even though a majority of the power simulation models literature does implement hourly ramping constraints to represent historical nuclear power variations (e.g. 25%  $P_{nom}$  per hour [17], [36]), PWRs actually have higher ramping capacities that do not limit their flexibility at an hourly time-step.

## 2.2 Xenon transients and boron concentration

During the fuel fission reaction that produces heat, two fission fragments are emitted and later considered fission products. These are often unstable atoms that will give birth to other radioactive decay

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<sup>5</sup> The core is the place in a nuclear reactor where fission reactions take place and the heat is generated. In a PWR, this core is composed of multiple meters-long fuel rods that are grouped together to form fuel assemblies. Fuel-rod claddings are made with zirconium alloy, which is used for its resistance to corrosion and its permeability to neutrons. Inside each fuel rod are stacked fuel pellets, most commonly composed of Uranium Oxide ( $UO_2$ ). The heat generated from the fission reactions originating from the fuel pellets is transferred to the water of the reactor's primary circuit that flows through the core. Inside the core are also control rods, which are composed of neutron-absorbent materials, and the depth that these control rods are inserted regulates the chain reaction.

<sup>6</sup> The main advantage of using boric acid concentration over control-rod movements is that boron is uniformly distributed in the nuclear core and does not affect its power distribution [12], [17], [26]. However, the long delay (roughly 15 minutes) between injection into the system and the effect in the core, the generation of effluent due to injection/dilution of the primary coolant, and the slow reactivity modification achievable with boron concentration variation (it takes around 5 hours to half the boron concentration at the end of the fuel cycle) make it less effective for fast power variations [12].

<sup>7</sup> At a temperature of 293 K, the mean thermal coefficient of the fuel pellets ( $UO_2$ ) is  $9.99 \times 10^{-6} \text{ K}^{-1}$  (relative volume change per K variation), and  $5.660 \times 10^{-6} \text{ K}^{-1}$  for their surrounding Zircaloy claddings [27], [28].

fission products. Some fission products are neutron poisons, meaning that they are undesired neutron absorbers that decrease the fuel’s fission reaction rate. Three different neutron poisons significantly impact core reactivity: xenon-135, samarium-149, and gadolinium-157. As xenon-135 has the biggest impact, notably due to its large cross-section<sup>8</sup>, and affects the reactor’s short-term flexibility, we chose not to consider samarium-149 (poisoning effect that takes approximately three weeks [37]) or gadolinium-157 (which has a significantly smaller cross-section than xenon-135<sup>9</sup>).

As seen in Fig. 1, xenon is a fission product that mainly originates from the decay of iodine-135, a fission product with a 6.53h half-life whose production rate is proportional to the fission reaction rate. Xenon-135 production in the core thus evolves accordingly with the iodine concentration in the core and then ‘disappears’, either by neutron capture or decay, giving a 9.17h half-life.

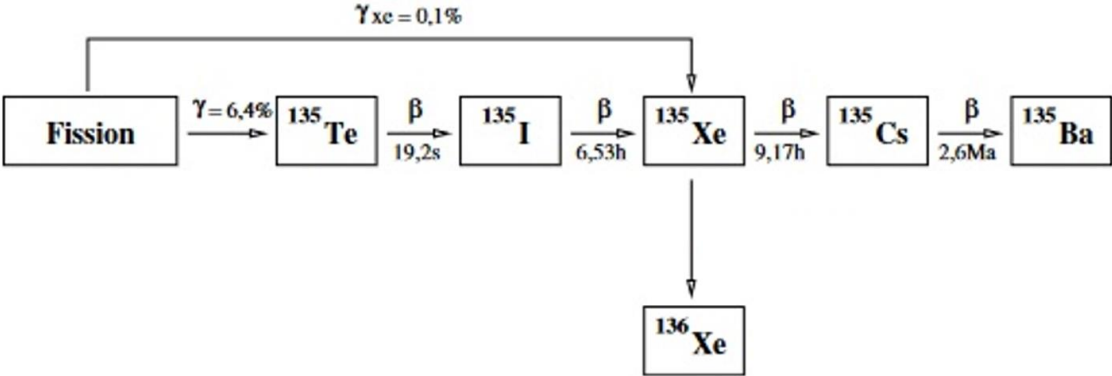


Fig. 1: Xenon-135 evolution chain, yields, and half-lives reproduced from [38]

The fact that xenon-135 originates mainly from iodine-135 decay creates a temporal lag between the fission reaction rate variations and xenon-135 concentration, resulting in a flexibility challenge that has to be managed [39]. As reactor power increases, I-135 concentration also rises until the reactor’s new equilibrium state is reached. Xe-135 concentration decreases due to increased neutron flux, reaching a minimum a few hours after the start of maneuvers, then returns to an equilibrium state due to the I-135 accumulated in the core. Conversely, as reactor power decreases, I-135 production rate decreases but Xe-135 concentration rises as it is still generated from the accumulated I-135. As Xe-135 is a strong neutron absorber, managing such transients is a big challenge to maneuverability, especially after large power variations. The reactivity variations induced by the xenon transients can nonetheless be overcome during most of the fuel’s irradiation cycle, according to [16]. With a sufficient reactivity margin after refueling, it is possible to compensate for the xenon reactivity defects through boric acid concentration adjustments or control rod position changes. [17] notes that plant managers who stabilize their plant’s output after maneuvering for several hours[8] do it to simplify operations, not to address technical limitations. However, at the end of the irradiation cycle, the core’s reactivity decreases, and the reactivity margin becomes insufficient to compensate for xenon transient effects without losing criticality [10], [24]. Indeed, the boric acid concentration in the primary circuit changes following the reactivity decrease due to progressive fuel ‘burn-up’, resulting in a decreasing margin for boric acid adjustments in the plant’s primary circuit to control the fission reaction rate. Plants would then need to stabilize their output for multiple hours after maneuvering before ramping back to their initial level. According to [16], xenon transients start to limit flexibility during the last part of the plant’s irradiation

<sup>8</sup> A nuclear cross section of a nucleus, measured in barns ( $1b = 10^{-28} m^2$ ), is used to describe the probability that a specific nuclear reaction will occur. A larger cross-section results in a larger probability of interaction.

<sup>9</sup> Xenon 135, Samarium 149, and Gadolinium 157 have respectively cross-sections for thermal neutrons of  $2.6 \times 10^6$  barns,  $4.1 \times 10^4$  barns, and  $2.5 \times 10^5$  barns [37]. Thus, Xenon 135 is the strongest neutron absorber in a thermal reactor.

cycle. Xenon transient reactivity defects also explain why reactors need to remain closed for several hours after shutting down while in their irradiation cycle.

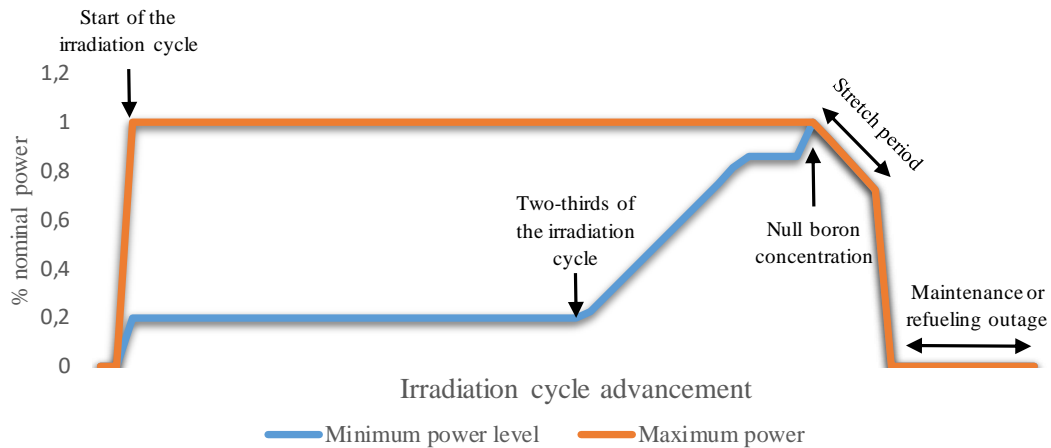


Fig. 2. Evolution of minimum power through the pressurized water reactor (PWR) irradiation cycle

The achievable minimal stable power of PWRs thus evolves according to the plants' advancement in their irradiation cycle [9], [41]. During the first two-thirds of the irradiation cycle, plants can operate flexibly up to 20% of their nominal power, as the boric acid margins are sufficient to compensate for the negative reactivity effects driven by xenon transients. The potential of PWRs to meet flexibility requirements is then maximal, and they can handle load-following services as well as frequency regulation. Then, due to the decreasing boric acid concentration, the achievable scope for 'load-following' scope diminishes, and the plant's minimal power starts to increase linearly until the boric acid concentration reaches zero at the end of the fuel's irradiation cycle (as illustrated in Fig. 2). The reactor can then only ensure primary and secondary frequency regulation. Afterward, the PWR enters a 'stretch-out' phase where flexible maneuvers are no longer possible, and the achievable maximal production capacity slowly decreases once the fuel has depleted.

### 2.3 Refueling strategies and NPP availability

Each NPP alternates between successive phases of generation and planned outage. Planned outages have to be scheduled to 1) recharge fuel assemblies once the fuel has depleted, 2) run maintenance on components, and 3) conduct safety inspections to ensure that the reactor can operate safely. These three elements are crucial factors that govern plant-level available flexibility capacity throughout the year.

The duration of the generation phase depends on reactor type, fuel cycle, and utilities strategy. The irradiation cycle length that frames the duration of the generation phase is defined as the Effective Full Power Day (EFPD), which specifies how long reactors can operate at full power before their fuel gets depleted. EFPD depends on fuel enrichment, and ranges from 280 EFPD for older reactor designs such as CP0 reactors in France [42] to 500 EFPD (as in the case of the EPR [43]) and even 640 EFPD (AP1000 [44] in the case of long operational cycles). These irradiation cycle lengths correspond to generation phase durations ranging from 12 months to 24 months, depending on the NPP's load factor. Similar to irradiation cycles, the lengths of outage phases also depend on reactor type, fuel cycle, and utilities strategy, but can broadly be classified into two categories: shorter refueling outages, or longer refueling and maintenance outages. Additional regulatory outages may be needed to check that the NPP meets safety requirements (i.e. decennial audit in France). Based on operational feedback, the outage phases



represent approximately one-fifth of the irradiation cycle length [45]. This alternation between availability and unavailability is optimized beforehand to maximize the available nuclear generation through peak demand and the plants' load factor. By maximizing their availability to produce electricity during peak demand periods, plant managers profit from higher prices as electric load increases [46], [47]. Thus, outages are typically scheduled during low-demand periods in order to maximize nuclear output and the system's security of supply. The resulting schedule influences flexibility at two levels: the plant, and the overall nuclear fleet. At plant level, there are some periods where generation and participation in flexibility requirements are impossible due to outages or fuel burn-up. At the fleet level, the addition of each reactor's availability and flexibility capacities define the fleet's overall generation capacity and maneuverability. Nuclear generation and flexibility availability vary throughout the year, as illustrated in Fig.2 below for nuclear availability.

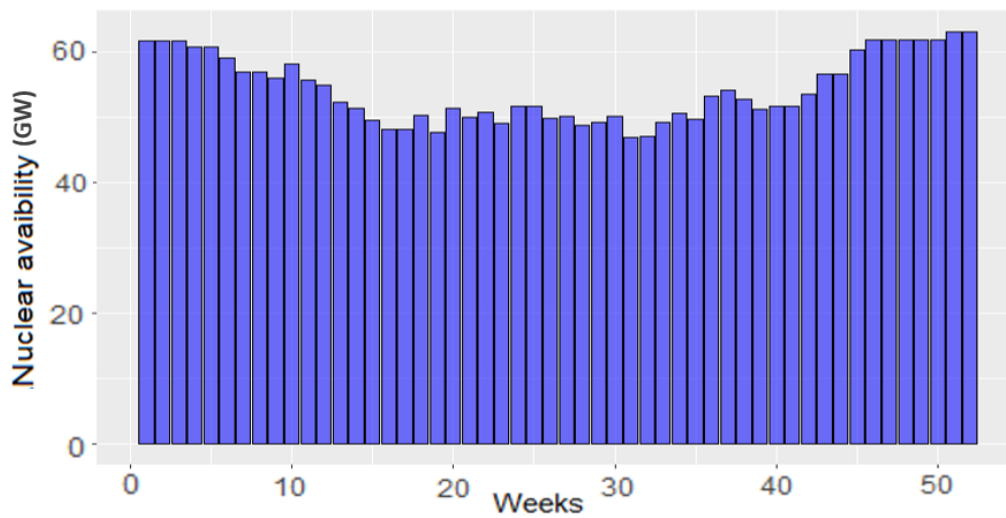


Fig. 3: Average weekly nuclear availability, Years 2015-2019, France

Second, plant managers typically do not shut down every reactor simultaneously, as they have to accommodate human-resource and utility requirements constraints and because simultaneous shutdown could endanger the power system's security of supply in countries with a high share of nuclear capacity. Consequently, optimizing human resources for refueling and maintenance tasks while maintaining the electric-system's generation margins is a crucial factor when planning the fleet's outage schedule [48]. For example, in the US, a maximum of 22.5 GWe<sup>10</sup> of its 97.2 GWe<sup>11</sup> fleet went offline simultaneously over the 2016–2020 period. In France, which has a large nuclear fleet, a maximum number of 27 of its 58 reactors fleet went offline simultaneously over the 2010–2019 period<sup>12</sup>. Even though there are no physical constraints preventing reactors from shutting down simultaneously, it is crucial to ensure that a minimum fleet share is online to ensure that the optimized schedule is realistic.

### 3. Methods

Given the above PWR flexibility constraints, our analysis focuses on two key parameters: nuclear schedule optimization, and minimum power level permitted by xenon transients management and boron

<sup>10</sup> STATUS OF U.S. NUCLEAR OUTAGES, EIA 2021, "<https://www.eia.gov/nuclear/outages/>"

<sup>11</sup> World Nuclear Performance Report 2020. Produced by: World Nuclear Association. Published: August 2020. Report No. 2020/008

<sup>12</sup> Computation by the authors, based on ASN data, <https://www.asn.fr/Controler/Actualites-du-controle/Arret-de-reacteurs-de-centrales-nucleaires>

concentration. The objective is to replicate nuclear schedule optimization and the advancement of each simulated reactor in its respective irradiation cycle in order to evaluate the flexibility potential of a nuclear fleet. As ramping constraints do not limit nuclear flexibility at an hourly level, we excluded it from this analysis. The following section details the modeling practices and assumptions used to represent nuclear flexibility and electric-system operations.

### 3.1 Mixed-Integer Linear Programming (MILP) schedule optimization model and representation of minimum power evolution

As a plant's irradiation cycle typically lasts several months, we need to adopt an inter-annual approach to simulate the nuclear schedule optimization. Using a benevolent system manager approach for simplicity, we built a MILP model that maximizes nuclear availability when it benefits the electric system over several years. We consider this benefit equivalent to maximizing nuclear availability during peak electric demand periods. A higher nuclear availability during peak electric demand decreases peaking-plant use and tends to drive prices down. The following model aims to represent the dynamics of the nuclear schedule:

$$\text{Maximize } \sum_{t=1}^T \sum_{i=1}^N D_t * Q_i * U_{it} \quad (1)$$

With constraints:  $\forall i, t$ :

$$\forall x \in [0: \underline{C}_i] : U_{i,t+x} \geq U_{i,t} - U_{i,t-1} \quad (2)$$

$$\sum_{y=0}^{y_i=\bar{C}_i} U_{i,t+y} \leq \bar{C}_i \quad (3)$$

$$\forall z \in [0: \underline{S}_i] : U_{i,t+z} \leq 1 + U_{i,t} - U_{i,t-1} \quad (4)$$

$$\sum_{i=1}^N U_{i,t} \geq \underline{\delta} * N \quad (5)$$

$$\sum_{i=1}^N U_{i,\bar{t}} = N \quad (6)$$

$$\sum_{i=1}^N U_{i,t-1} - U_{i,t} \leq \delta_{outages} * N \quad (7)$$

Eq. (1) is the model's objective function that maximizes the sum of the  $N$  reactors  $i$  times their nominal power  $Q_i$  over a determined period  $T$ .  $U_{it}$  is a binary variable equal to 1 if reactor  $i$  is available at time  $t$ , else 0.  $D_t$  captures the demand variability across the studied period. Eqs. (2) and (3) frame the length of each plant's irradiation cycle, ensuring that each reactor is available during the entirety of its minimum irradiation cycle length  $\underline{C}_i$  and preventing potential overrun of its maximal cycle length  $\bar{C}_i$ . Eq. (4) frames the length of outages. It ensures that each reactor is unavailable for  $\underline{S}_i$  timesteps after shutting down for refueling or maintenance. Eq (5) limits the share  $\underline{\delta}$  of nuclear units that can operate maintenance and refueling outages simultaneously, and Eq (6) ensures that all reactors are online during the peak demand of the year  $\bar{t}$ . Finally, Eq (7) limits the share of nuclear units  $\delta_{outages}$  that can start their outage phases at the same time in order to prevent all reactors from stopping simultaneously.

Table 1: Hypotheses used for irradiation-cycle and outage lengths

Unit	Nominal power (MW) - $Q_i$	Equivalent Full Power Days	Average availability factor	Minimum outage duration (weeks) - $\underline{S}_i$	Minimum irradiation cycle duration (weeks) - $\underline{C}_i$	Maximum irradiation cycle duration (weeks) - $\overline{C}_i$	Minimum share of online reactors - $\underline{\delta}$	Maximum share of simultaneous outage-phase starts - $\delta_{outages}$
Value	1000	280	79.1%	6	38	48	50% <sup>13</sup>	10% <sup>14</sup>

This paper considers simplified reactors, all similar, with a 1000 MW nominal power, 12-month irradiation cycle length, and 79.1% availability factor, which is equal to the availability factor of French PWRs since they were commissioned to industrial service [49] (see Table 1). We chose to build our model at a weekly timestep to limit computational time. We hypothesized that each reactor shuts down or starts its irradiation cycle at the beginning of a week. The schedule optimization timeframe chosen throughout the paper is 18 years, spanning the 2001–2019 period. Note that the proposed nuclear schedule optimization model is a simplified formulation of a complex process to determine when NPPs begin their irradiation cycle or outage phase (standardized reactors, foreseeable future across 19 years, and so on). The durations of maintenance and refueling operations are considered deterministic, which is a simplification of real-life outages whose duration may randomly increase as operational difficulties arise. The inclusion of stochastic elements into the nuclear schedule model would increase the model’s soundness, but we do not include such considerations here. Each schedule optimization MILP problem is solved using the CPLEX® solver with a 5% relative optimality gap. The problem resolution ran on a computer with a 20-core Intel® Xeon® Gold 6230 CPU clocked at 2.30 GHz using 125 GB of RAM, running CentOS Linux version 7.

Using this MILP model, it is possible to determine the start and end of each reactor’s irradiation cycle as well as its advancement at each point in time. Following [3] and [26], we compute each reactor’s minimum power level based on this advancement, which is linked to the decreases in reactivity margin and boron concentration and the burn-up of the fuel, as represented in Figure 2 (see Section 2.2).

Each reactor’s minimum power variation follows a curve where the first phase consists of significant capability to maneuver reactor production level until 20% of nominal power during the first two-thirds of the irradiation cycle. Minimum power level then rises linearly until the boron concentration becomes null, which is the period where PWR flexibility is the lowest. The reactor then enters a ‘stretch’ phase, where its maximum power and minimum power are equal and do not allow any production level changes apart from starting up/shutting down. The fleet’s overall minimum power level equals the sum of each reactor’s minimum power level variations, computed from the optimized schedule resulting from our MILP model. Given that start and end date of each reactor’s irradiation cycle need to be known in order to evaluate the potential benefit of this aspect of nuclear flexibility, this further justifies the need to adopt a MILP approach to simulate nuclear schedule optimization.

### 3.2 MILP/UC electric system model

The economic dispatch model used here is the open-source ANTARES<sup>15</sup> power system simulator developed by RTE, the French Transmission Systems Operator, that simulates the electric demand–supply equilibrium. A broad summary of the model can be found in [50]. The model consists of a unit-commitment (UC) program that determines the optimal economic dispatch of all the generating units in

<sup>13</sup> Based on computation by the authors derived from ASN data, <https://www.asn.fr/Controler/Actualites-du-controler/Arret-de-reacteurs-de-centrales-nucleaires>

<sup>14</sup> Operational feedback on the French nuclear fleet, <https://www.asn.fr/Controler/Actualites-du-controler/Arret-de-reacteurs-de-centrales-nucleaires>

<sup>15</sup> RTE, <https://antares-simulator.org/>

the system at an hourly timestep over one calendar year. The objective function minimizes the operational costs (variable, fixed, start-up, and unsupplied energy costs) to meet the exogenous hourly demand. Thus, the underlying discriminatory criterion between generators is the merit-order approach that ranks generators based on ascending order of short-term marginal costs. Apart from VRE sources, for which generation is considered exogenous to the model, each generating unit's behavior is subject to UC constraints related to its maximum/minimum production capacity and maximum/minimum up/downtime. The ANTARES simulator includes each unit's availability schedule, allowing modelers to finely adjust for seasonal plant outage. A custom ANTARES solver solves the MILP problem, finding the optimal generation profile for each unit given its constraints, and computes the resulting market prices, CO<sub>2</sub> emissions, spilled energy, and unsupplied energy of the modeled electric system.

The model represents frequency regulation management by integrating spinning reserves for thermal power plant technologies. Aside from coal, gas, and fuel oil technologies, NPP react to automatic generation control signals sent by system operators to ensure frequency regulations and contribute to operating reserves<sup>16</sup>. As existing reactors reserve 5%–10% of their nominal capacity to ensure primary and secondary frequency adjustments and spinning reserves, we consider that thermal plants reserve 10% of their nominal capacity.

This paper uses version 7.0.1 in Accurate-Economy mode, for which the mathematical formulation can be found in [51]. Contrary to version 8.0, version 7.0.1 does not optimize the system's capacity mix, meaning that this paper will focus on specific case studies for which installed capacities were determined exogenously. We consider a deterministic environment, with no uncertainties on future VRE production, demand level, thermal plant availabilities, and reserve requirements.

## 4. Case study and results

### 4.1 Assumptions

The case studies in this paper are based on a simplified French electric system. We chose this system due to its high share of installed nuclear power, meaningful feedback on nuclear fuel-cycle management, and available data on renewables and electric demand. The electric demand data used to optimize the nuclear schedule range (2001–2019) is historical French demand from RTE. We consider that NPP managers optimize their schedule based on their electricity demand expectations. The demand profile used to compute the optimized schedule is thus the average profile across those years. We excluded 2020 due to the decrease in demand due to economic slowdown caused by the Covid-19 pandemic. The paper builds VRE production profiles using actual capacity factor data from the renewables.ninja website, which is widely used in the electric simulation literature. Using capacity factors instead of actual generation profiles allows us to test out multiple case studies at different VRE integration levels.

Although our model creates an inter-annual schedule for a specified fleet, we limit our electric system simulation to only a representative year. As noted by [52], the choice of a representative year can be made under several criteria. Here we chose the year with the renewable capacity factor closest to the French capacity factor profiles over the 2000–2019 period. The year 2006 was determined to be the most representative for France, with a sum of absolute error values of 1.5% for onshore wind, offshore wind and solar photovoltaic capacity factors compared to the capacity factors of the whole period. We note that other factors that impact our simulations' numerical results, such as electric demand variations, could have been included in the representative year selection process. Selecting a different year would indeed impact our numerical results, notably energy curtailment levels, market prices, and technology

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<sup>16</sup> Especially spinning reserves, which are extra generating capacity made available by increasing the power output of generators that are already connected to the power system. Generators already connected to the power system do not generally produce at full nominal power, as a strategy to cover spinning reserves.

revenues, but we argue that the effect of additional fleet flexibility would yield similar results with different selected years. Moreover, [52] thoroughly confirmed that selecting 2006 as a representative year did not impact the operational adequacy of the simulated power system, notably when testing years with different VRE capacity factors. Thus, electric demand, VRE capacity factors, and the reactors' operation and outage phases resulting from our nuclear schedule model, which the Antares Simulator uses to simulate electric system operations, are all year-2006 data.

Furthermore, this paper focuses only on the isolated electric system of one country, meaning that the following case studies do not account for potential levers of flexibility such as interconnections or sector-coupling mechanisms (EV charging, hydrogen production, and so on). We address only a limited set of installed technologies, i.e. onshore wind, offshore wind, solar photovoltaic, nuclear, and natural gas. Installed capacities of nuclear and VRE are case-specific and fixed exogenously, whereas natural gas capacity is an output of each simulation, where gas capacity is scaled to cover peak residual demand and no load loss. Gas capacity is thus oversized in our cases, but because the paper focuses solely on variable costs, the over-capacity of natural gas does not impact the model's economic results aside from gas being the last marginal unit that fixes the marginal prices. The natural gas technology considered here is open-cycle gas turbine (OCGT) plants with 38% electrical efficiency due to their high flexibility. Variable costs such as fuel are fixed over one year, and sourced from the Nuclear Energy Agency (NEA) report *The Costs of Decarbonisation: System Effects with High Shares of Nuclear and Renewables* [18].

Table 2. Overview of costs, flexibility and environmental impacts of electric utility technologies [18]

Technology	Nominal capacity (M)	Variable costs <sup>17</sup> (\$ <sup>18</sup> /MWh)	Minimum stable power (%)	Minimum uptime (hours)	Minimum downtime (hours)	Start-up costs (\$/MW/start)	Reserve requirements (%)	Environmental impacts (gCO <sub>2</sub> eq/kWh) – IPCC (2014)
Wind	-	0	-	-	-	-	-	11
Solar PV	-	0	-	-	-	-	-	41
Nuclear	1000	11.5	50%	8	24	500	10%	12
Natural Gas	300	96.11	25%	1	1	50	10%	490

The paper constrains the flexible behavior of each thermal technology modeled. As mentioned beforehand, we do not account for ramping constraints as they do not limit nuclear or OCGT flexibility at an hourly timestep. Thus, apart from the PWR characteristics discussed earlier, we limit flexibility constraints to minimum uptime and downtime constraints only. We chose a simplified representation of the minimal power evolution in the constant schedule case and the optimized schedule case with constant minimum power variations. Given that part of the nuclear fleet is at the beginning of its irradiation cycle—i.e. with high load-following capabilities—while other reactors are at the end of their irradiation cycle—i.e. with limited load-following capabilities—, we consider in these two cases that each reactor's minimum power is 50% of its capacity, and so all-fleet minimum power is at 50% of its availability, in line with [18]. This assumption allows us to isolate the respective impacts of nuclear schedule optimization and physics-induced minimum power variations. The other flexibility characteristics in Table 2 correspond to plants commissioned in 2020 [18].

<sup>17</sup> Over the long-term, marginal cost, i.e. cost linked to the production of one additional MWh, equalizes the first derivative of the linear cost function of generating technologies, and therefore variable cost per unit of production. Consequently, the variable costs presented here are used to compute the 'merit order' in the following simulations.

<sup>18</sup> USD<sub>2018</sub>: this assumption, derived from [18], is used throughout the entire study

## 4.2 Cases

We simulate three main nuclear flexibility assumptions. Table 3 recaps the underlying hypotheses.

Table 3. Nuclear flexibility assumptions of the cases

Name	Schedule assumption	Minimum power assumption
<i>A</i>	Constant	50% <sup>19</sup>
<i>B</i>	Optimized	50%
<i>C</i>	Optimized	Variable throughout each reactor's irradiation cycle

Assumption *A* assumes that nuclear availability and the fleet's minimum power are constant throughout the simulated year. This constant availability is equal to the average availability of the nuclear fleet in *B* and *C* that use our schedule optimization model described in 3.1. The first objective is to compare simulation results between *A* and *B* to evaluate the impact of nuclear schedule optimization on modeled results. The second objective is to analyze the potential additional impact of *C* to determine the stakes surrounding minimum power variations.

We include several sensitivity cases for all assumptions depending on number of reactors installed and VRE penetration, which are key factors for NPP flexibility requirements. Each reactor-fleet sensitivity case represents various reactor scenarios, ranging from 20 to 60 reactors, and each VRE penetration case represents various VRE scenarios, ranging from 0 to 80% of total load (no curtailment).

We consider that the production ratio of onshore and offshore wind to solar capacities remains constant for each test case. We assume that this production ratio is equal to its current value for the currently-installed French VRE capacities [53]. Table 4 details the corresponding installed capacities for each VRE penetration scenario and nuclear capacity case.

Table 4. Installed VRE and nuclear capacities for each simulated case

VRE penetration scenario	Solar PV (GW)	Wind – onshore and offshore - (GW)	Nuclear capacity (GW)		
			20 reactors scenario	40 reactors scenario	60 reactors scenario
0% VRE	0	0	20	40	60
20% VRE	19.96	33.86			
40% VRE	39.93	67.72			
60% VRE	59.89	101.58			
80% VRE	79.85	135.44			

The five VRE penetration scenarios, three fleet sizes, and three nuclear flexibility constraint assumptions gave us a simulated total of 45 different cases.

## 4.3 Results

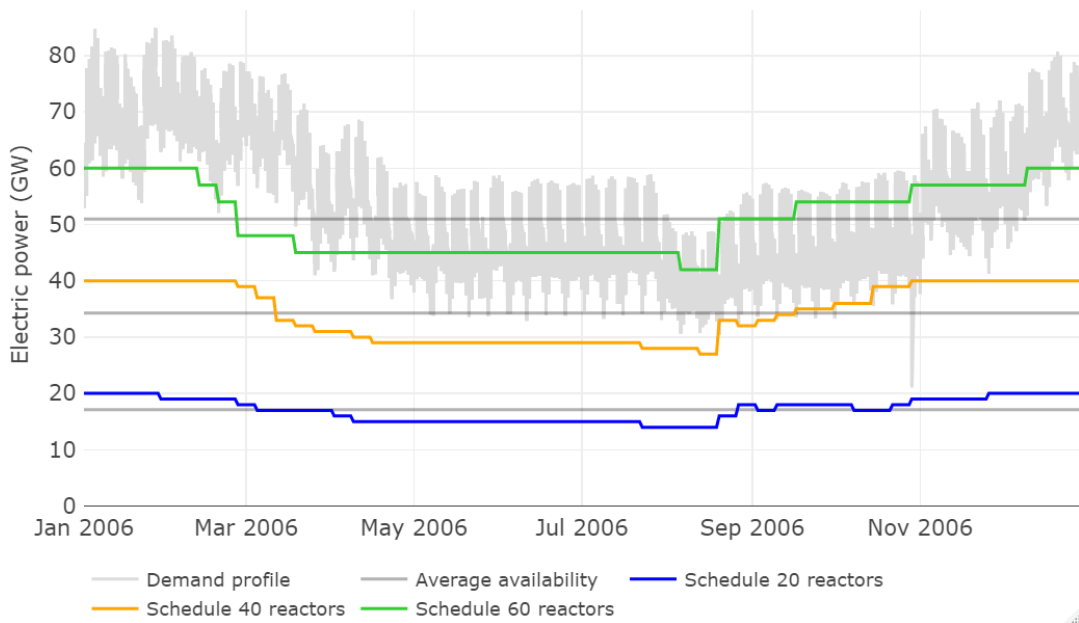
This section presents the key results for each of our nuclear flexibility assumptions. The paper's first findings are linked to the impact of nuclear schedule optimization on nuclear availability profile. We go on to discuss the effect of a physics-induced minimum power variations approach on available nuclear

<sup>19</sup> Refers to minimum power assumption found in the literature: 40% in [9], 50% in [12], [23], [36], 55% in [24]

flexibility. Finally, analysis of the simulation results and sensitivity cases highlights the stakes surrounding flexibility modeling practices as the share of VRE penetration and nuclear capacity increases, i.e. when the flexibility required for NPP increases.

#### 4.3.1 Schedule optimization and resulting minimum power variations

We computed the reactor operating schedule for each nuclear fleet scenario case, i.e. 20 reactors, 40 reactors, and 60 reactors (see Fig. 4.). The schedule allows for greater nuclear availability during peak-demand periods and lower availability during low-demand periods in each nuclear fleet scenario. Indeed, each schedule scenario is positively correlated to the electric demand profile. Our model thus replicates usual nuclear availability dynamics (see Fig. 3.). Compared to the constant availability assumption, each schedule is better correlated to the demand profile. Second, we find that the impact of the schedule optimization varies according to size of the fleet. The profile gap between the constant availability assumption and the optimized schedule gets more significant as nuclear installed capacity increases.



*Fig. 4. Nuclear availability for each nuclear fleet size scenario, resulting from the schedule optimization model.*

Our computed nuclear schedule results in a minimum nuclear availability during the period of lowest electric demand (i.e. in August) for all reactor fleet scenario cases. As the number of reactors that can stop simultaneously is constrained, not all reactors can stop during the minimal demand period, even though stopping may be economically optimal for the plant managers. Thus, a share of the reactors effectuate their outages before August, during the second-lowest electric demand period. As all outages occur during low-demand periods, the reactors are potentially available during high-demand periods (i.e. from November to April), thus minimizing the level of unsupplied energy of the electric system.

Based on these schedules, we computed the fleet's minimum power and load-following potential for each nuclear fleet scenario. We find that a physics-induced minimum power level results in an overall greater flexibility potential than the assumptions widely used in the electric simulation literature. Indeed, as seen in Fig. 5. in the 40 reactors case, the physics-induced minimum power level is lower than the 50% minimum power assumption for all nuclear fleet scenarios based on constant nuclear availability. This highlights that using a physics-induced approach results in higher flexibility capability, which could

be a lever for VRE integration. If we compare the physics-induced approach to the 50% minimum power assumption based on the optimized nuclear schedule, we find that the physics-induced approach broadly results in greater nuclear flexibility potential. However, these results do not hold for some months (around April–June), as nuclear flexibility may be higher in cases A and B than in case C (see Fig. 6.). This period is when most reactors are in the last phase in the irradiation cycle and so have minimal ability to maneuver. We conclude that a constant minimum power assumption tends to underestimate the overall nuclear flexibility potential and may overestimate it in some cases. The misestimation is greater as a constant nuclear schedule is considered. The difference between the physics-induced nuclear flexibility approach and the other assumptions underlines how the assessment of nuclear capability to accommodate renewable energy variability may differ depending on the chosen minimum power hypothesis.

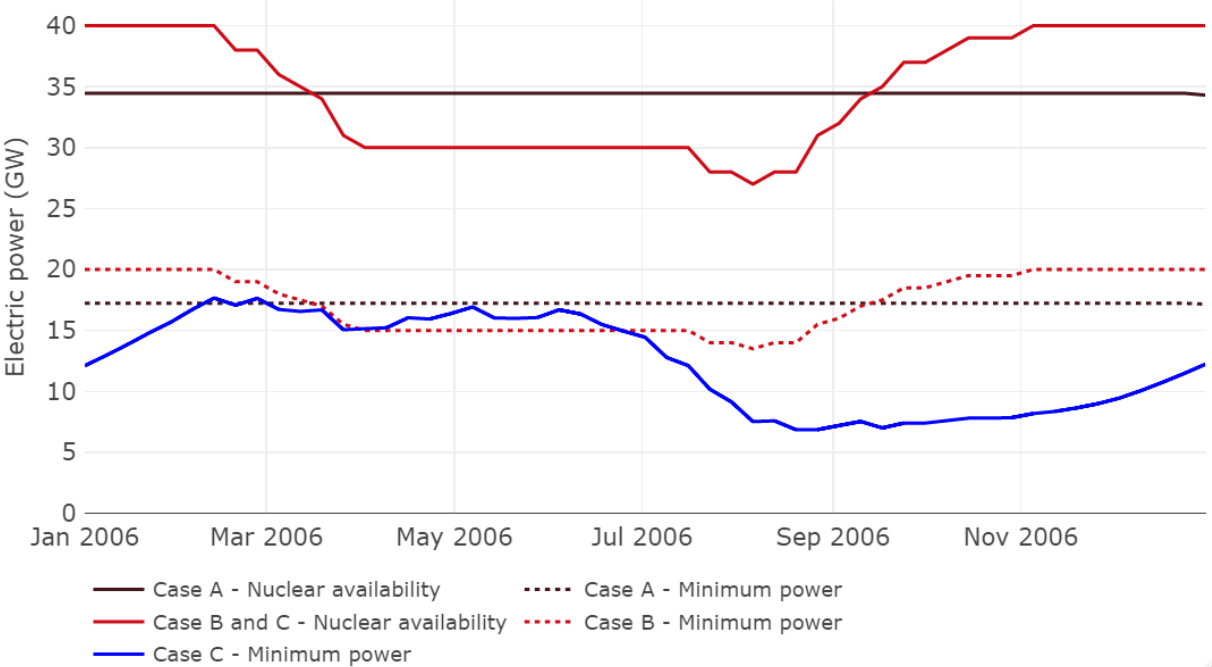


Fig. 5. Comparison of nuclear availability and minimum power assumptions in the 40-reactors case.



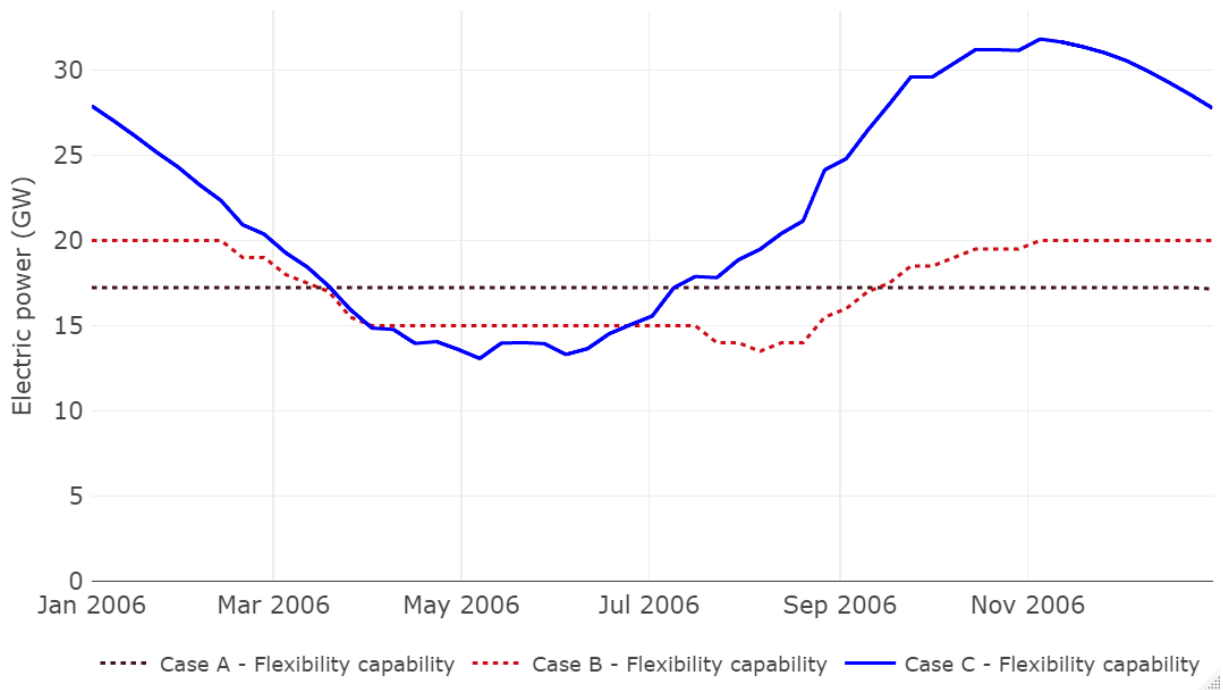


Fig. 6. Load-following potential in the 40-reactors case.

#### 4.3.2 Simulation results

Using the three flexibility assumptions (A, B, and C), we simulated power system operation with several VRE penetration levels (0%, 20%, 40%, 60%, 80%) and nuclear capacity levels (20, 40, 60 reactors). We then compared the simulation results to evaluate the impact of nuclear flexibility on electric system operation with renewable energy. We evaluated the impact of nuclear flexibility on six different metrics: thermal commitment dispatch, energy curtailment level, operational costs, direct CO<sub>2</sub> emissions, markets prices, and revenues per technology. The aim was to use these metrics to evaluate the technical, economic, and environmental aspects of a nuclear–renewable-based electric system.

##### Thermal commitment dispatch

As gross VRE production level is weather-dependent, its level is not sensitive to nuclear schedule optimization. For the sake of brevity, we do not detail gross VRE production level in this section, and instead focus on the thermal commitment dispatch. Thermal commitment dispatch evolves with each case’s installed capacities, with nuclear production increasing with an increasing number of reactors in the mix. Conjointly, gas production level decreases, as it is the marginal technology of the ‘merit order’.

Table 5: Annual thermal energy dispatch: illustration in *B* cases. See Appendix 1 – Table A1.

	0% VRE	20% VRE	40% VRE	60% VRE	80% VRE
20 reactors					
40 reactors					
60 reactors					

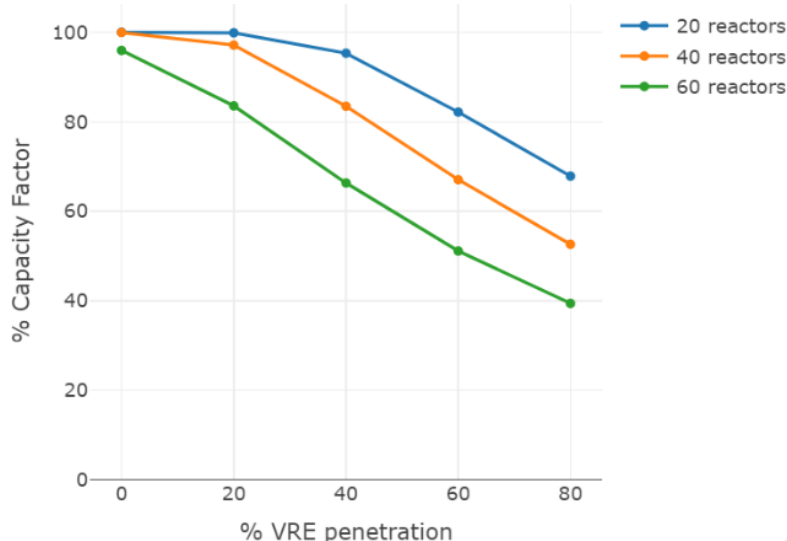


Fig. 7. Annual nuclear capacity factor in *B*

The impact of nuclear flexibility assumptions on optimal thermal commitment dispatch—measured by comparing the results of simulations for *A*, *B*, and *C*—varies depending on VRE penetration level and nuclear fleet size. In capacity cases with low VRE penetration and limited nuclear capacity, the optimal thermal dispatch does not diverge significantly between the nuclear flexibility assumptions. This may indicate that nuclear flexibility modeling is not a crucial concern when considering electric systems where NPPs profit from a load factor near 100% (reported in Figure 7).

In cases with higher VRE penetration and fleet capacity, NPP are expected to maneuver more due to the decreasing level of residual demand. The resulting nuclear capacity factor then evolves negatively to VRE penetration and fleet size (Fig. 7.). In such capacity mixes, schedule optimization, i.e. *B*, increases nuclear production and decreases gas production compared to *A* (Table 6.). The changes in nuclear and gas output become more significant as nuclear fleet size increases. Regarding the impact of minimum power variation, the comparison between *B* and *C* (Table 7.) shows that it only marginally increases nuclear production—by up to 0.04%—with increasing share of VRE and nuclear reactors installed in the capacity mix. The effect becomes more substantial when we consider gas production, with up to a 10.61% decrease in the high VRE and nuclear capacity mixes in *C* compared to *B*.

We thus conclude that nuclear flexibility increases nuclear production and decreases the use of gas in capacity mixes that require nuclear to be flexible. The impact is more substantial in *C* that better represents nuclear flexibility potential. These results underline that enhanced nuclear flexibility decreases the need for peaking plants to meet the demand–supply equilibrium of the electric system while increasing nuclear availability for production during peak-demand periods.

Table 6: Annual thermal energy dispatch change in Assumption *B* vs. *A*

Technology	0% VRE		20% VRE		40% VRE		60% VRE		80% VRE	
	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas
20 reactors	-0.03%	0.01%	0.00%	0.00%	0.76%	-0.71%	1.49%	-1.75%	2.31%	-3.18%
40 reactors	-0.04%	0.07%	1.07%	-3.27%	2.25%	-10.95%	2.86%	-18.92%	2.64%	-22.38%
60 reactors	1.84%	-12.69%	2.96%	-46.09%	2.19%	-65.90%	1.56%	-73.25%	1.23%	-75.52%

Table 7: Annual thermal energy dispatch change in Assumption *C* vs. *B*

Technology	0% VRE		20% VRE		40% VRE		60% VRE		80% VRE	
	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas
20 reactors	0.00%	0.00%	0.00%	0.00%	-0.01%	0.01%	0.02%	-0.02%	0.02%	-0.04%
40 reactors	0.00%	0.00%	0.00%	0.01%	0.00%	-0.02%	0.03%	-0.23%	0.03%	-0.29%
60 reactors	0.00%	-0.01%	0.00%	-0.07%	0.01%	-0.62%	0.02%	-3.07%	0.04%	-10.61%

### Energy curtailment

The curtailed energy level of our simulated cases ranged from 0% of total electricity production (e.g. 0% VRE penetration – 20 reactors – all Assumptions) to 18.41% (i.e. 80% VRE penetration – 60 reactors – Assumption *A*). Curtailment occurs when electric output exceeds the corresponding electric load due to excess VRE production or a lack of flexibility in thermal plants that, at some point, cannot adjust their output. Whatever the nuclear flexibility assumptions, curtailed energy level positively correlates with VRE penetration levels, which increase the need for balancing to ensure supply–demand

equilibrium. Another finding is that the curtailed energy level of our cases positively correlates to the installed nuclear fleet capacity, with share of curtailed energy increasing with increasing number of reactors in the simulated mixes. This negative effect of fleet size on energy curtailment level is due to the replacement of flexible gas production by limited-flexibility nuclear technology.

Comparing *B* to *A* first finds that nuclear schedule optimization decreases the share of wasted energy due to curtailment for all capacity mixes. This decreasing trend is more pronounced in *C*. Curtailment levels are the lowest in *C* compared to other nuclear flexibility assumptions, with a maximum curtailment share level of 11.93% (80% VRE penetration – 60 reactors). Like for thermal commitment dispatch, these impacts are less significant in low VRE and nuclear capacity cases, as the substantial gas production meets most of the flexibility requirements, resulting in marginal energy curtailment levels, and near-null benefits of additional nuclear flexibility. These benefits become substantial as soon as VRE covers a 40% share of electric demand.



Fig. 8. Curtailed energy share for each VRE, nuclear, and nuclear flexibility assumption case (see Appendix 2 – Table A2.3).

### System costs and direct CO<sub>2</sub> emissions

In all simulated capacity cases except scenarios with 0% VRE penetration and 20 or 40 reactors, the power system costs decrease in cases *B* and *C* compared to case *A*, as seen in Fig. 9 and Fig. 10. The cost decrease gets greater as the share of variable renewables and nuclear in the capacity mix increases. Thus, the overall effect of nuclear flexibility is that it decreases the operational costs of the electricity system in cases with a significant share of VRE penetration and high nuclear capacity. The first driver is the increasing share of the demand covered by VRE technologies—whose have zero variable costs—due to lower curtailment levels. Replacing gas production by nuclear production further reduces these system costs. The additional cost decrease of case *C* compared to case *B* (Fig. 10) as soon as VRE penetration reaches 40% underlines the impact of modeling the minimum power variations of the reactors in cases where nuclear operates flexibly. Indeed, the cost benefits derived from *C* compared to *A* can reach a 27.19% cost decrease (see Fig. 10 and Appendix. 2 – Table A2.1) for the case with 80% VRE penetration and 60 GW nuclear capacity (vs. 18.84% in *B*). Conversely, as the impact is null in low-VRE-penetration cases (Fig. 10), we conclude that minimum power variation of the reactors is not

an essential factor for evaluating operational costs in such power systems. Overall, the cost comparison between fleet flexibility cases highlights the economic benefits of nuclear flexibility, as we consider electric systems with substantial shares of renewables and nuclear.

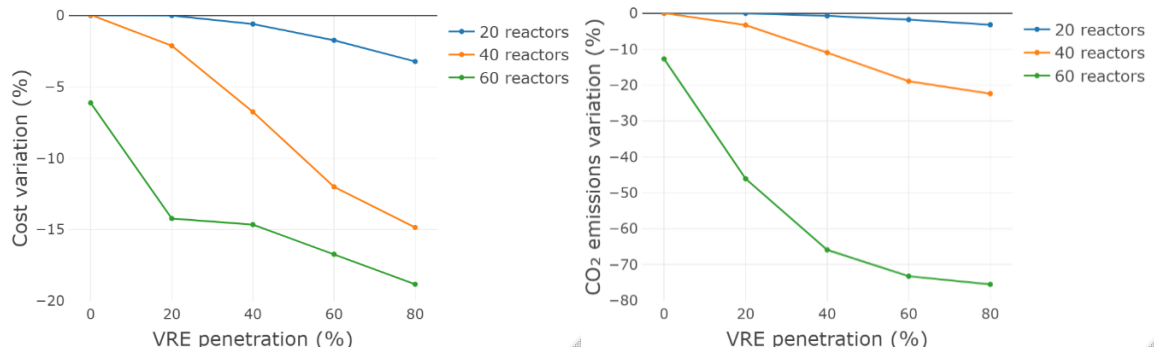


Fig. 9. Changes in costs (left) and direct CO<sub>2</sub> emissions (right) with optimized schedule cases (B) versus constant schedule cases (A)

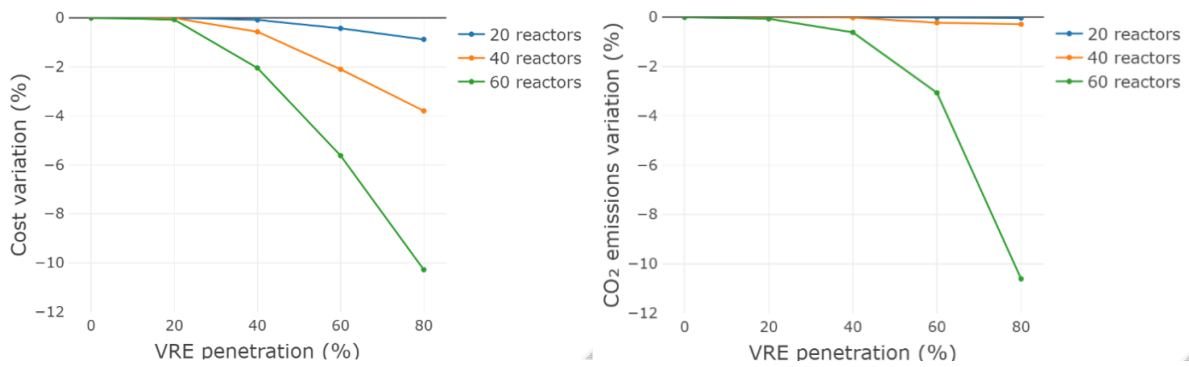


Fig. 10. Changes in costs (left) and direct CO<sub>2</sub> emissions (right) with physics-induced minimum power cases (C) versus optimized schedule cases (B)

Like system costs, nuclear schedule optimization decreases the direct CO<sub>2</sub> emissions of generating electricity (measured in CO<sub>2</sub> g/kWh generated). The relative decrease can reach up to 75.52% in the 80% VRE penetration – 60 GW nuclear capacity case in case B vs. case A (see Figure 9 and Appendix. 2 –Table A2.2). Nonetheless, we find that direct CO<sub>2</sub> emissions evolve only marginally (less than 3% decreases) in cases with 20 or 40 reactors and less than 40% VRE penetration. Assumption C also marginally reduces the system’s environmental footprint compared to case B, except in cases with 60 reactors only (Fig.10). Thus, nuclear fleet flexibility does not strongly influence the electric system’s environmental footprint if fleet capacity is low.

The conjoint evaluation of the considered electric system’s costs and CO<sub>2</sub> emissions highlights that nuclear flexibility gains potential benefit with increasing NPP flexibility requirements. In cases where nuclear plants operate in ‘baseload’ generation mode with low nuclear capacity and load factors close to 100%, the consideration of schedule optimization and minimum power variations does not appear a crucial factor for evaluating both system costs and environmental impacts.

## Market prices

The market price level formed by the merit order evolves as a function of the economic dispatch of each case, with higher market prices in cases with higher gas production (which links to Tables 2 and 4.). Thus, market prices decrease in cases with a higher nuclear and VRE capacity, as seen in Table 8. Although the cost assumptions described in Table 2 influence our numerical results for prices, we argue that they would not change the merit order ranking of the technologies, with gas plants still the marginal technology.

Table 8. Average market price (\$/MWh) for all capacity cases – Case A

Case A	0% VRE	20% VRE	40% VRE	60% VRE	80% VRE
<b>20 reactors</b>	96.11	95.62	84.07	64.29	48.00
<b>40 reactors</b>	95.49	80.63	52.88	35.99	23.35
<b>60 reactors</b>	68.89	40.51	24.07	13.69	8.83

The impact of nuclear flexibility on market prices varies with VRE penetration level and nuclear capacity installed. Cases *B* and *C* increase the total market price level in cases with low VRE penetration and nuclear capacity (see Appendix 3 – Table A.3). However, as relative VRE and nuclear capacity in the electric mix increases, this impact becomes negative, with decreasing market prices (e.g. cases with 60% and 80% VRE penetration – 40 reactors, and 20%, 40%, 60% and 80% VRE penetration – 60 reactors). This makes it hard to confidently rule on the impact of nuclear flexibility based on market price alone. To further evaluate this impact, we focus on negative and peaking price occurrences, which gives better insight into the relationship between nuclear flexibility and prices.

We find that in all capacity mix cases except low VRE penetration scenarios, cases *B* and *C* both decrease the occurrence of negative and null price hours (Table 9.). In periods of high VRE production and when thermal production cannot adjust production level to the residual demand variations, negative prices can occur, reflecting the willingness of thermal plant managers to avoid shutting down. Enhanced nuclear flexibility leads to lower energy curtailment levels in *B* and *C*, thus reducing the number of hours where price is negative or null, as noted in Table 9. We can thus conclude that the primary impact on market prices is a decrease in number of negative or null price hours for all capacity mix cases.

Table 9. Variations in occurrences of negative prices for all VRE penetration, nuclear capacity, and nuclear flexibility scenario cases

	Case comparison	0% VRE	20% VRE	40% VRE	60% VRE	80% VRE
<b>20 reactors</b>	$\frac{B - A}{A}$	0.00%	0.00%	-10.31%	-8.20%	-6.57%
	$\frac{C - A}{A}$	0.00%	0.00%	-33.70%	-22.48%	-17.32%
<b>40 reactors</b>	$\frac{B - A}{A}$	0.00%	-28.36%	-30.07%	-22.21%	-16.11%
	$\frac{C - A}{A}$	0.00%	-85.07%	-59.26%	-41.76%	-31.00%
<b>60 reactors</b>	$\frac{B - A}{A}$	0.00%	-60.28%	-37.78%	-27.17%	-18.83%

	$\frac{C - A}{A}$	-100.00%	-96.26%	-74.34%	-56.25%	-42.08%
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Conjointly to a decreasing number of hours with negative or null prices, nuclear flexibility also affects the occurrence of peaking prices in simulation results, as seen in Table 10. In cases with high VRE penetration and nuclear capacity, the number of hours with peaking prices decreases (i.e. cases with 80% VRE penetration and 40 reactors, or 40%, 60% and 80% VRE penetration and 60 reactors in Table 10). This evolution is linked to the decreasing gas output needed to balance electric demand and supply. As gas production is the primary driver of high market prices, the decrease in gas production directly impacts the occurrence of peaking prices. The average market price of the electric system therefore decreases, even though the number of negative price hours also decreases (Table 9).

Table 10. Variations in occurrences of peaking prices for all VRE penetration, nuclear capacity, and nuclear flexibility scenario cases

Nuclear scenario	VRE penetration	0%	20%	40%	60%	80%
20 reactors	$\frac{B - A}{A}$	0.00%	0.13%	1.10%	2.10%	2.26%
	$\frac{C - A}{A}$	0.00%	0.13%	1.07%	1.74%	1.88%
40 reactors	$\frac{B - A}{A}$	0.51%	5.54%	9.34%	0.79%	-3.06%
	$\frac{C - A}{A}$	0.51%	5.54%	9.16%	-0.04%	-4.40%
60 reactors	$\frac{B - A}{A}$	12.83%	1.92%	-34.66%	-42.95%	-49.73%
	$\frac{C - A}{A}$	12.83%	1.92%	-36.06%	-48.03%	-64.29%

In cases with lower VRE penetration (e.g. the 20% VRE penetration – 60 reactors case, Table 11), we find the opposite impact, with an increasing number of hours with peak prices even though overall gas production also decreased. This is directly linked to the schedule optimization process, as it reduces nuclear availability during low-demand periods. In cases with low VRE and nuclear capacity where gas is necessary to re-balance electric demand and supply, lower nuclear availability in low-demand periods results in a growing number of hours where gas is marginal, and thus where prices are peaking.

As peaking prices are more likely to occur during low-demand periods, the weighted average market prices per MWh produced may still decrease. Fig. 11 and Table 11 illustrate this situation in the 20% VRE penetration – 60 reactors case, where *B* increases the number of peak price hours relative to *A* by 1.92%, but the weighted average market price decreases. We argue that this is due to the simplicity of the simulated electric system, as gas production is the adjustment variable in cases where VRE and nuclear capacities may be undersized for the electric demand.

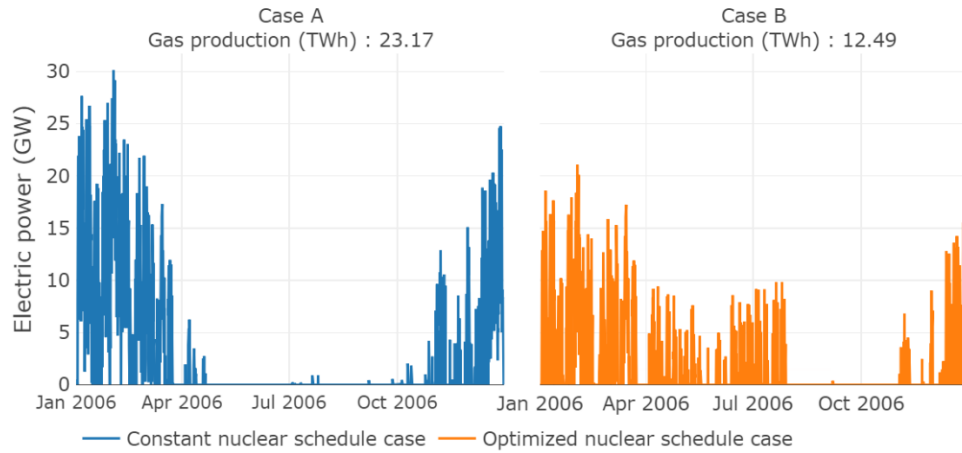


Fig. 11: Comparison of gas production between the constant schedule (A) and optimized schedule (B) assumptions – 20% VRE penetration and 60 reactors scenario

Table 11. Market price data: ‘20% VRE penetration – 60 GW nuclear capacity’ case

Nuclear flexibility assumption	Weighted average market price, \$/MWh	Number of hours <0 \$/MWh	Load share sold <0 \$/MWh	Number of hours >50 \$/MWh	Load share sold >50 \$/MWh
<i>A</i>	40.51	214	1.88%	2390	34.56%
<i>B</i>	39.43	85	0.74%	2436	33.12%
$\frac{B - A}{A}$	-2.65%	-60.28%	-60.62%	1.92%	-4.16%

Overall, *B* and *C* have similar impacts on market prices, although *C* further reduces negative price hours, resulting in higher market prices.

### Revenues per technologies

To further the analysis, we investigated the composition of each technology revenue. We argue that, in the simplified case studies used in this paper, there are two main drivers of revenues: first, the share of each technology output sold at low prices, which drives revenues down, and second, the share sold at peaking prices, which drives revenues up. If these two shares conjointly increase or decrease, their effects on revenues may balance out.

Overall, as seen in Table 12, nuclear is the low-carbon technology that first benefits from higher prices due to its ability to adjust production in response to the market price signal. This holds true for all our simulated capacity cases. On the other hand, solar is the lowest-remunerated technology as its production is concentrated during sunny hours, which is when most negative prices periods occur (as illustrated in Figure 12). Indeed, the high solar irradiance around midday decreases market price, especially in cases with high VRE penetration. Wind technology benefits from higher revenues than solar technology, as its production is spreads out across the day, thus benefiting more frequently from peaking prices (Fig 12). We find that in all VRE penetration and nuclear capacity scenarios, nuclear flexibility decreases the output share of all simulated technologies sold at low market prices due to the



in negative price occurrences described in Table 8, especially in case C compared to case B (illustrated in Fig 12). Detailed numerical results can be found in Appendix 4.

Table 12. Technology revenues (\$/MWh) for all capacity cases – Case A

Case A	Nuclear				Wind				Solar			
	20% VRE	40% VRE	60% VRE	80% VRE	20% VRE	40% VRE	60% VRE	80% VRE	20% VRE	40% VRE	60% VRE	80% VRE
20 reactors	95.58	86.60	73.45	63.94	94.517	71.927	45.51	30.12	94.40	67.72	37.70	18.09
40 reactors	79.08	56.11	43.81	33.89	70.569	36.642	21.50	12.01	67.69	28.31	12.62	5.85
60 reactors	39.83	27.07	18.22	14.21	30.835	14.824	7.15	4.36	25.27	11.18	4.16	1.73

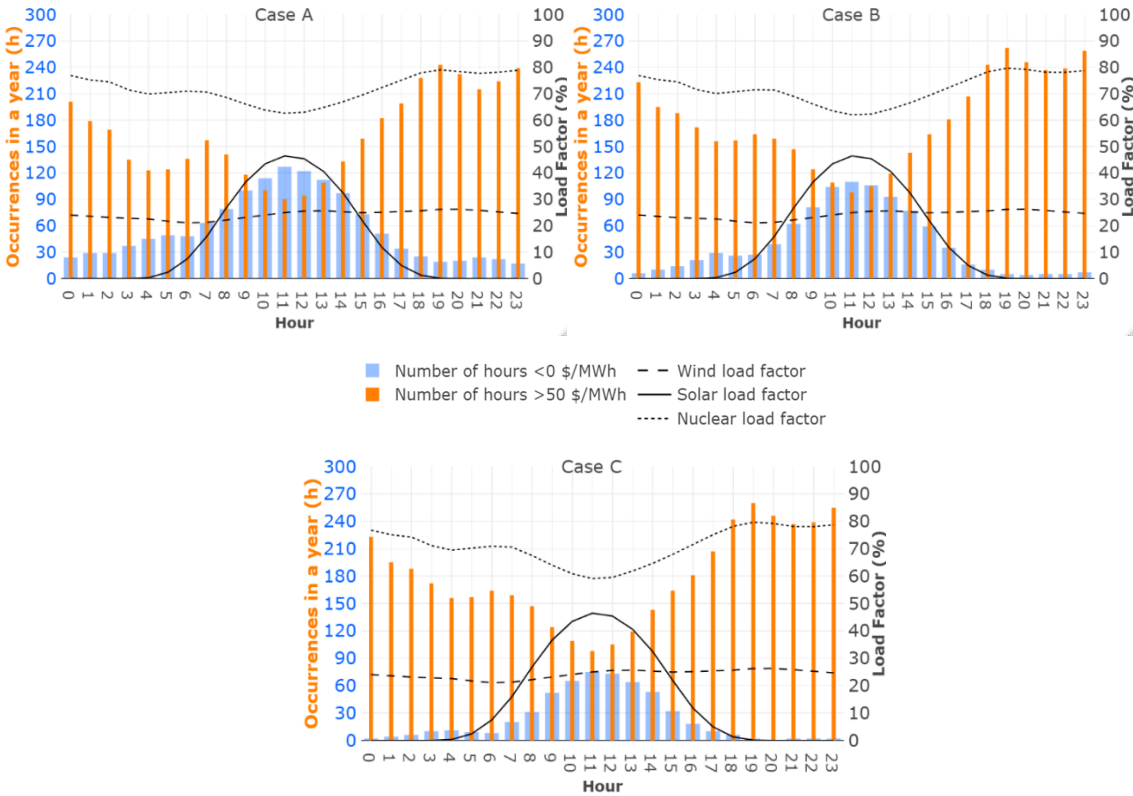


Fig 12. Average load factor for each technology and frequency of occurrences of negative and peaking prices, by hours: the ‘40% VRE penetration – 40 reactors’ case

Nuclear benefits more from flexibility, as it is the most dispatchable low-carbon technology in the electric system considered in this paper. Schedule optimization and physics-induced minimum power enhance the ability of nuclear to adjust production to market price signals. In most capacity cases (i.e. with 20 and 40 reactors; see Appendix 4.3), nuclear revenues per MWh increase thanks to a diminishing share of production sold at negative price hours and an increasing share sold at peak prices, as illustrated in Table 13 for the 40% VRE penetration – 40 reactors case. Note that case C further reduces the share of production sold at negative prices, resulting in even higher revenues for nuclear. This highlights the benefits of nuclear flexibility for nuclear revenues. In cases with high nuclear capacity (i.e. 20%, 40%,

60%, 80% VRE penetration and 60 reactors; see Appendix 4.3), nuclear revenues decrease as gas production firmly declines with additional nuclear flexibility, thus reducing the share of nuclear production sold at peak prices. Note, however, that *C* reduces this effect and results in higher nuclear revenues than *B* (e.g. Table 13).

Table 13. Average revenues level (\$/MWh) and profile: 40% VRE penetration – 40 GW nuclear capacity case

Nuclear flexibility assumption	Solar			Wind			Nuclear		
	Average revenues \$/MWh	Output share sold <0 \$/MWh	Output share sold >50 \$/MWh	Average revenues \$/MWh	Output share sold <0 \$/MWh	Output share sold >50 \$/MWh	Average revenues \$/MWh	Output share sold <0 \$/MWh	Output share sold >50 \$/MWh
<i>A</i>	28.31	31.70%	24.17%	36.64	27.20%	33.41%	56.11	9.25%	53.99%
<i>B</i>	34.39	26.50%	30.66%	37.60	19.63%	33.52%	61.74	4.86%	60.04%
<i>C</i>	35.40	17.75%	30.66%	38.32	12.31%	33.38%	62.75	1.76%	60.81%
$\frac{B-A}{A}$	21.48%	-16.41%	26.81%	2.61%	-27.85%	0.31%	10.03%	-47.46%	11.22%
$\frac{C-A}{A}$	25.04%	-44.00%	26.81%	4.59%	-54.73%	-0.11%	11.83%	-80.93%	12.65%

Solar technology also benefits from higher revenues due to enhanced nuclear flexibility (Table 14). Enhanced ability of nuclear to accommodate renewable production variability means that the share of solar production sold at negative prices decreases, especially in *C* (illustrated for the 40% VRE penetration – 40 reactors case in Table 13). The decreased energy curtailment drives up the average revenues per MWh of solar, which also benefits from an increased share of production sold at peak prices, as seen in Table 13. In some cases with higher VRE penetration and nuclear capacity (i.e. 80% VRE penetration and 40 reactors, or 40% VRE penetration and 60 reactors), this trend towards increasing revenues may be offset by a diminished number of peak price hours, thus decreasing solar revenues in *B*. However, the additional nuclear flexibility in *C* increases solar revenues for all VRE penetration and nuclear capacity scenarios (Table 14).

Table 14. Average revenues from solar (\$/MWh) in all capacity cases – Comparison of *A* vs. *C*.

Solar	Case	20% VRE	40% VRE	60% VRE	80% VRE
20 reactors	<i>A</i>	94.40	67.72	37.70	18.09
	<i>C</i>	94.84	70.23	40.63	19.39
	$\frac{C-A}{A}$	0.46%	3.71%	7.79%	7.17%
40 reactors	<i>A</i>	67.69	28.31	12.62	5.85
	<i>C</i>	74.49	35.40	13.88	6.37
	$\frac{C-A}{A}$	10.04%	25.04%	9.97%	9.01%
60 reactors	<i>A</i>	25.27	11.18	4.16	1.73
	<i>C</i>	32.66	11.59	6.65	3.72
	$\frac{C-A}{A}$	29.26%	3.74%	59.72%	114.99%

The overall impact of nuclear flexibility on wind revenues remains undetermined, as wind revenues slightly increase in cases with low VRE penetration and nuclear capacity and vary in cases with higher VRE penetration and nuclear capacity, with no definite trend emerging. Like for nuclear and solar technology, we find that nuclear flexibility decreases the share of wind production sold at negative prices in all capacity mix cases. On the other hand, as VRE and nuclear are higher than the 40% penetration and 40 GW (see Appendix 4.), the share of wind production sold at peaking prices decreases, thus having varying influence on the overall revenues level. Comparing simulation results for *B* and *C*'s, we learn that the average wind revenues per MWh increase with increasing nuclear flexibility.

Table 15. Average revenues from wind (\$/MWh) in all capacity cases – Comparison of *A* vs. *C*.

Wind	Case	20% VRE	40% VRE	60% VRE	80% VRE
20 reactors	<i>A</i>	94.517	71.927	45.51	30.12
	<i>C</i>	94.726	72.521	46.36	30.93
	$\frac{C-A}{A}$	0.22%	0.83%	1.88%	2.69%
40 reactors	<i>A</i>	70.569	36.642	21.50	12.01
	<i>C</i>	72.006	38.324	21.95	12.52
	$\frac{C-A}{A}$	2.04%	4.59%	2.11%	4.24%
60 reactors	<i>A</i>	30.835	14.824	7.15	4.36
	<i>C</i>	27.335	13.752	8.61	5.83
	$\frac{C-A}{A}$	-11.35%	-7.24%	20.47%	33.59%

Even though the impact of nuclear flexibility on revenues is ambiguous and differs depending on the technology and capacity mix case (see Table 13, Table 14, Table 15, and Appendix 4), we find that schedule optimization and minimum power variations have a strong influence on their revenue compositions. Indeed, nuclear flexibility limits the extreme negative price events that drive average revenue per MWh down. We thus find that it is essential to consider nuclear flexibility parameters when evaluating the economic viability of an electric system's technologies.

## 5. Conclusions

This paper explores the stakes surrounding nuclear flexibility modeling to evaluate decarbonized electric system operations with renewable energy. We present a novel formulation of the nuclear refueling and maintenance schedule that frames nuclear operations, including irradiation-cycle and outage lengths. Using the resulting schedule, we computed a physics-induced minimum power variation to accurately evaluate a fleet's flexibility potential. This work highlights that current schedule modeling assumptions rarely represent the seasonality factor of nuclear availability, which results in higher nuclear availability during peak-demand periods and schedules maintenance and refueling outages during low-demand periods. We find that nuclear schedule optimization reduces operational costs, energy curtailments, peaking-plant use, and environmental impacts linked to electricity generation. Another key finding is that nuclear schedule optimization becomes increasingly relevant with increasing relative share of VRE and nuclear capacity in the capacity mix: it shows little influence on simulation results in cases with few reactors and limited VRE penetration, but significant impacts in other cases. The overall impact of schedule optimization on market prices and revenues per technology remains undetermined, as the revenue benefits linked to the decrease of negative price occurrences may be offset by a decreasing number of peak prices. Nonetheless, we note that as nuclear is the low-carbon generating technology

modeled in this paper that is the most responsive to price signals, its revenues per MWh benefit the most from additional flexibility.

The paper also points out that a constant minimum power assumption misestimates the nuclear fleet's flexibility potential. A physics-induced minimum power approach based on an optimized nuclear schedule leads to higher flexibility margins, resulting in more efficient electric system operations with nuclear and renewable energy. Indeed, we find that a physics-induced approach enhances the benefits of the optimization schedule in terms of electric-system operational costs, VRE integration, peaking-plant use, and environmental impacts. Minimum power variations are therefore essential to assessing the operation of electric systems with high shares of nuclear and renewable energy.

Finally, our joint analysis of the stakes surrounding schedule optimization in tandem with minimum power variations modeling practices highlights the need to accurately represent flexibility constraints in order to evaluate electric system operations with renewables and nuclear. Although historically used as a 'baseload' technology, the use of nuclear as a flexible low-carbon technology to further integrate VRE capacities while ensuring security of supply could be favored if it proves cost-optimal. This work shows that enhanced nuclear flexibility modeling practices are essential to validly assess this potential cost-optimality.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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APPENDIX 1: Economic dispatch for all VRE–Nuclear scenarios

Table A1. Economic dispatch for all VRE–Nuclear cases – Optimized nuclear schedule assumption  
(B)

TWh	0% VRE		20% VRE		40% VRE		60% VRE		80% VRE	
Technology	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas	Nuclear	Gas
<b>20 reactors</b>	149.69	330.36	149.51	234.53	140.13	149.57	114.62	94.62	89.50	61.62
<b>40 reactors</b>	300.94	179.11	292.29	91.76	245.76	43.94	186.96	22.28	138.75	12.38
<b>60 reactors</b>	426.99	53.06	371.55	12.49	286.52	3.17	208.07	1.17	150.53	0.59

APPENDIX 2: Cost and CO<sub>2</sub> evolutions

Table A2.1 Relative change in operational costs of the electric system for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

		0% VRE	20% VRE	40% VRE	60% VRE	80% VRE
$\frac{B - A}{A}$	20 reactors	0.01%	0.00%	-0.59%	-1.73%	-3.22%
	40 reactors	0.05%	-2.12%	-6.75%	-12.01%	-14.86%
	60 reactors	-6.12%	-14.23%	-14.66%	-16.74%	-18.84%
$\frac{C - A}{A}$	20 reactors	0.01%	0.00%	-0.67%	-2.15%	-4.07%
	40 reactors	0.06%	-2.12%	-7.28%	-13.86%	-18.09%
	60 reactors	-6.12%	-14.29%	-16.40%	-21.42%	-27.19%

Table A2.2 Relative change in direct CO<sub>2</sub> emissions of the electric system for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

		0% VRE	20% VRE	40% VRE	60% VRE	80% VRE
$\frac{B - A}{A}$	20 reactors	0.01%	0.00%	-0.71%	-1.75%	-3.18%
	40 reactors	0.07%	-3.27%	-10.95%	-18.92%	-22.38%
	60 reactors	-12.69%	-46.09%	-65.90%	-73.25%	-75.52%
$\frac{C - A}{A}$	20 reactors	0.01%	0.00%	-0.70%	-1.77%	-3.22%
	40 reactors	0.08%	-3.26%	-10.96%	-19.11%	-22.60%
	60 reactors	-12.70%	-46.12%	-66.11%	-74.07%	-78.12%

Table A2.3 Share of curtailed electricity of the electric system for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

		0% VRE	20% VRE	40% VRE	60% VRE	80% VRE
A	20 reactors	0.00%	0.00%	0.96%	5.74%	13.16%
	40 reactors	0.00%	0.05%	2.48%	8.89%	16.40%
	60 reactors	0.00%	0.15%	4.07%	11.22%	18.41%
B	20 reactors	0.00%	0.00%	0.87%	5.06%	12.27%
	40 reactors	0.00%	0.03%	1.47%	6.27%	13.47%
	60 reactors	0.00%	0.06%	2.09%	7.08%	14.27%
C	20 reactors	0.00%	0.00%	0.63%	4.34%	11.42%
	40 reactors	0.00%	0.00%	0.77%	4.82%	11.93%
	60 reactors	0.00%	0.00%	0.79%	4.66%	11.41%

APPENDIX 3: Market prices for all simulation and nuclear flexibility cases

		0% VRE			20% VRE			40% VRE			60% VRE			80% VRE		
	C as e	Avg market price	Hours < 0\$/MWh	Hours > 50\$/MWh	Avg market price	Hours < 0\$/MWh	Hours > 50\$/MWh	Avg market price	Hours < 0\$/MWh	Hours > 50\$/MWh	Avg market price	Hours < 0\$/MWh	Hours > 50\$/MWh	Avg market price	Hours < 0\$/MWh	Hours > 50\$/MWh
20 reactors	A	96.11	0	8736	95.62	0	8669	84.07	543	7394	64.29	2086	5464	48.00	3563	3980
	B	96.11	0	8736	95.70	0	8680	84.60	487	7475	65.26	1915	5579	48.66	3329	4070
	C	96.11	0	8736	95.70	0	8680	84.74	360	7473	65.44	1617	5559	49.04	2946	4055
	$\frac{B-A}{A}$	0.00%	0.00%	0.00%	0.09%	0.00%	0.13%	0.62%	-10.31%	1.10%	1.51%	-8.20%	2.10%	1.38%	-6.57%	2.26%
	$\frac{C-A}{A}$	0.00%	0.00%	0.00%	0.09%	0.00%	0.13%	0.79%	-33.70%	1.07%	1.79%	-22.48%	1.74%	2.18%	-17.32%	1.88%
40 reactors	A	95.49	0	8630	80.63	67	6709	52.88	1360	3930	35.99	3233	2537	23.35	4619	1568
	B	95.72	0	8674	82.94	48	7081	55.73	951	4297	35.90	2515	2557	22.84	3875	1520
	C	95.72	0	8674	82.98	10	7081	56.17	554	4290	36.54	1883	2536	23.59	3187	1499
	$\frac{B-A}{A}$	0.24%	0.00%	0.51%	2.87%	-28.36%	5.54%	5.40%	-30.07%	9.34%	-0.24%	-22.21%	0.79%	-2.17%	-16.11%	-3.06%
	$\frac{C-A}{A}$	0.24%	0.00%	0.51%	2.92%	-85.07%	5.54%	6.22%	-59.26%	9.16%	1.53%	-41.76%	-0.04%	1.03%	-31.00%	-4.40%
60 reactors	A	68.89	1	5199	40.51	214	2390	24.07	2136	1209	13.69	4210	610	8.83	5401	364
	B	73.30	1	5866	39.43	85	2436	19.18	1329	790	11.55	3066	348	7.60	4384	183
	C	73.30	0	5866	39.52	8	2436	20.02	548	773	12.90	1842	317	8.82	3128	130
	$\frac{B-A}{A}$	6.40%	0.00%	12.83%	-2.65%	-60.28%	1.92%	-20.32%	37.78%	-34.66%	15.57%	27.17%	-42.95%	13.88%	18.83%	-49.73%
	$\frac{C-A}{A}$	6.40%	100.00%	12.83%	-2.44%	-96.26%	1.92%	-16.82%	74.34%	-36.06%	-5.77%	-56.25%	-48.03%	-0.06%	-42.08%	-64.29%

Table A3. Market price variations for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

APPENDIX 4: Revenues for each low-carbon technology

Table A4.1 Solar revenues for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

	Case	20% VRE penetration			40% VRE penetration			60% VRE penetration			80% VRE penetration		
		Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh
<b>20 reactors</b>	<b>A</b>	94.40	0.00%	97.98%	67.72	15.85%	68.60%	37.70	46.48%	37.28%	18.09	70.11%	17.32%
	<b>B</b>	94.84	0.00%	98.50%	69.87	13.98%	70.88%	40.05	45.20%	39.88%	18.82	68.63%	17.98%
	<b>C</b>	94.84	0.00%	98.50%	70.23	10.79%	70.88%	40.63	40.02%	39.87%	19.39	63.51%	17.96%
	$\frac{B-A}{A}$	0.46%	0.00%	0.53%	3.17%	-11.78%	3.33%	6.23%	-2.76%	6.98%	4.02%	-2.11%	3.80%
	$\frac{C-A}{A}$	0.46%	0.00%	0.53%	3.71%	-31.92%	3.33%	7.79%	-13.90%	6.95%	7.17%	-9.42%	3.67%
<b>40 reactors</b>	<b>A</b>	67.69	2.02%	66.69%	28.31	31.70%	24.17%	12.62	62.68%	9.84%	5.85	82.39%	4.52%
	<b>B</b>	74.37	1.31%	74.48%	34.39	26.50%	30.66%	12.70	57.48%	9.23%	5.38	79.10%	3.51%
	<b>C</b>	74.49	0.28%	74.48%	35.40	17.75%	30.66%	13.88	47.12%	9.21%	6.37	70.33%	3.50%
	$\frac{B-A}{A}$	9.86%	-35.02%	11.69%	21.48%	-16.41%	26.81%	0.65%	-8.31%	-6.21%	-8.05%	-3.99%	-22.23%
	$\frac{C-A}{A}$	10.04%	-86.12%	11.69%	25.04%	-44.00%	26.81%	9.97%	-24.84%	-6.39%	9.01%	-14.64%	-22.50%
<b>60 reactors</b>	<b>A</b>	25.27	5.77%	17.05%	11.18	45.23%	5.77%	4.16	76.39%	1.71%	1.73	88.76%	0.52%
	<b>B</b>	32.42	2.27%	25.03%	9.76	33.57%	2.51%	4.32	66.32%	0.53%	2.03	83.78%	0.19%
	<b>C</b>	32.66	0.20%	25.03%	11.59	17.61%	2.51%	6.65	45.99%	0.51%	3.72	68.67%	0.14%
	$\frac{B-A}{A}$	28.32%	-60.66%	46.80%	-12.68%	-25.79%	-56.54%	3.81%	-13.18%	-69.14%	16.94%	-5.61%	-63.54%
	$\frac{C-A}{A}$	29.26%	-96.56%	46.80%	3.74%	-61.06%	-56.54%	59.72%	-39.79%	-69.95%	114.99%	-22.64%	-72.69%



Table A4.2 Wind revenues for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

	Case	20% VRE penetration			40% VRE penetration			60% VRE penetration			80% VRE penetration		
		Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh
<b>20 reactors</b>	<b>A</b>	94.517	0.00%	98.12%	71.927	12.36%	73.10%	45.51	39.70%	45.59%	30.12	58.06%	29.90%
	<b>B</b>	94.726	0.00%	98.36%	72.264	11.63%	73.40%	46.24	36.81%	46.06%	30.60	55.24%	30.08%
	<b>C</b>	94.726	0.00%	98.36%	72.521	9.06%	73.35%	46.36	32.40%	45.61%	30.93	50.79%	29.87%
	$\frac{B-A}{A}$	0.22%	0.00%	0.25%	0.47%	-5.93%	0.41%	1.61%	-7.28%	1.04%	1.59%	-4.86%	0.61%
	$\frac{C-A}{A}$	0.22%	0.00%	0.25%	0.83%	-26.68%	0.35%	1.88%	-18.38%	0.04%	2.69%	-12.52%	-0.10%
<b>40 reactors</b>	<b>A</b>	70.569	1.88%	70.07%	36.642	27.20%	33.41%	21.50	53.76%	19.12%	12.01	68.02%	9.85%
	<b>B</b>	71.881	1.44%	71.56%	37.600	19.63%	33.52%	21.27	43.90%	17.51%	11.87	59.98%	8.59%
	<b>C</b>	72.006	0.35%	71.56%	38.324	12.31%	33.38%	21.95	35.62%	17.19%	12.52	52.51%	8.35%
	$\frac{B-A}{A}$	1.86%	-23.42%	2.13%	2.61%	-27.85%	0.31%	-1.06%	-18.34%	-8.41%	-1.18%	-11.82%	-12.78%
	$\frac{C-A}{A}$	2.04%	-81.15%	2.13%	4.59%	-54.73%	-0.11%	2.11%	-33.75%	-10.10%	4.24%	-22.80%	-15.28%
<b>60 reactors</b>	<b>A</b>	30.835	4.87%	23.51%	14.824	37.64%	9.05%	7.15	62.72%	3.38%	4.36	74.64%	1.71%
	<b>B</b>	27.100	2.34%	18.76%	12.338	25.51%	4.46%	7.15	49.49%	1.58%	4.65	64.79%	0.71%
	<b>C</b>	27.335	0.30%	18.76%	13.752	11.90%	4.28%	8.61	34.96%	1.34%	5.83	52.17%	0.39%
	$\frac{B-A}{A}$	-12.11%	-51.85%	-20.23%	-16.77%	-32.24%	-50.72%	-0.04%	-21.09%	-53.26%	6.63%	-13.19%	-58.35%
	$\frac{C-A}{A}$	-11.35%	-93.76%	-20.23%	-7.24%	-68.40%	-52.71%	20.47%	-44.26%	-60.42%	33.59%	-30.10%	-77.41%

Table A4.3 Nuclear revenues for all VRE penetration, nuclear capacity, and nuclear flexibility assumptions cases

	Case	20% VRE penetration			40% VRE penetration			60% VRE penetration			80% VRE penetration		
		Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh	Avg \$/MWh	%Hours < 0\$/MWh	%Hours > 50\$/MWh
<b>20 reactors</b>	<b>A</b>	95.58	0.00%	99.38%	86.60	3.28%	89.20%	73.45	12.54%	74.92%	63.94	21.00%	64.84%
	<b>B</b>	95.68	0.00%	99.49%	87.60	2.67%	90.31%	76.99	8.92%	78.62%	69.09	14.85%	70.08%
	<b>C</b>	95.68	0.00%	99.49%	88.40	1.25%	91.06%	79.46	4.60%	80.94%	73.00	8.01%	73.78%
	$\frac{B-A}{A}$	0.10%	0.00%	0.11%	1.16%	-18.60%	1.24%	4.82%	-28.86%	4.93%	8.04%	-29.28%	8.08%
	$\frac{C-A}{A}$	0.10%	#0.00%	0.11%	2.08%	-61.77%	2.08%	8.18%	-63.32%	8.04%	14.16%	-61.84%	13.79%
<b>40 reactors</b>	<b>A</b>	79.08	0.40%	79.93%	56.11	9.25%	53.99%	43.81	22.97%	41.31%	33.89	32.73%	30.91%
	<b>B</b>	82.20	0.26%	83.59%	61.74	4.86%	60.04%	48.19	12.10%	45.01%	38.24	18.06%	34.06%
	<b>C</b>	82.26	0.04%	83.63%	62.75	1.76%	60.81%	50.35	5.31%	46.64%	41.01	8.68%	36.05%
	$\frac{B-A}{A}$	3.94%	-34.02%	4.59%	10.03%	-47.46%	11.22%	9.99%	-47.30%	8.95%	12.83%	-44.83%	10.17%
	$\frac{C-A}{A}$	4.02%	-89.70%	4.63%	11.83%	-80.93%	12.65%	14.92%	-76.89%	12.89%	20.99%	-73.46%	16.62%
<b>60 reactors</b>	<b>A</b>	39.83	1.35%	33.67%	27.07	16.11%	20.59%	18.22	33.59%	12.51%	14.21	43.70%	9.14%
	<b>B</b>	40.34	0.43%	34.15%	22.78	7.32%	14.32%	16.45	16.50%	8.09%	13.08	23.55%	5.07%
	<b>C</b>	40.41	0.03%	34.17%	23.55	1.53%	14.45%	17.91	4.24%	8.16%	14.73	5.85%	4.61%
	$\frac{B-A}{A}$	1.28%	-67.91%	1.43%	-15.84%	-54.60%	-30.43%	-9.71%	-50.87%	-35.30%	-7.94%	-46.12%	-44.56%
	$\frac{C-A}{A}$	1.46%	-98.03%	1.51%	-13.00%	-90.48%	-29.82%	-1.67%	-87.37%	-34.77%	3.66%	-86.61%	-49.54%

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