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The second French nuclear bet

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Abstract

Following the first oil crisis, France launched the worlds largest ever nuclear energy program, commissioning 58 new reactors. These reactors are now reaching 40 years of age, the end of their technological lifetime. This places France at an energy policy crossroads: should the reactors be retrofitted or should they be decommissioned? The cost-optimal decision depends on several factors going forward, in particular the expected costs of nuclear energy production, electricity demand levels and carbon prices, all of which are subject to significant uncertainty.

To deal with these uncertainties, we apply the Robust Decision Making framework to determine which reactors should be retrofitted. We build an investment and dispatch optimization model, calibrated for France. Then we use it to study 27 retrofit strategies for all combinations of uncertain parameters, with nearly 8,000 runs.

Our analysis indicates that robust strategies involve the early closure of 10 to 20 reactors, while extending the life of all other reactors. These strategies provide a hedge against the risks of unexpected increases in retrofit costs, low demand and low carbon prices.

Our work also highlights the vulnerabilities of the official French government scenarios, and complements them by suggesting new robust strategies. These results provide a timely contribution to the current debate on the lifetime extension of nuclear plants in France.

Keywords: Power system; Uncertainty; Nuclear costs; Robust Decision Making; Investment

JEL Classification: C6; D8; Q4

Highlights

- We estimate how many nuclear reactors should be retrofitted in France
- We identify key uncertainties and apply the framework of robust decision making
- Robust strategies imply closing 10 to 20 reactors and retrofit the others
- These results suggest a new strategy compared to the official French scenarios

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The opinions expressed in this paper are those of the author alone and might not represent the views of ENGIE.

1. Introduction

The first oil shock provoked the engagement of France in an unprecedented nuclear program, which would make it up to now the country with the highest share of nuclear in its power mix. The first Contract Program was launched in 1969. A batch of six reactors of 900 MWe was ordered (the CP0 batch) and their construction started in 1971. But the 1973 oil embargo triggered a more ambitious nuclear program. In early 1974, 18 identical reactors of 900 MWe were ordered (CP1 batch). They were followed in late 1975 by 18 new reactors: 10 reactors of 900 MWe (CP2 batch) and 8 of 1300 MWe (CP4 batch). 12 additional reactors of 1300 MWe were ordered in 1980 (P'4 batch). Finally, in 1984, 4 reactors of 1450 to 1500 MWe (N4 batch) concluded this nuclear policy (Boccard, 2014). These massive orders have shaped power production in France ever since. In 2015, these nuclear plants produced 78% of the country's electricity. Along with a 12% of hydropower production, it leaves only around 10% for all other sources of power (RTE, 2014).

But these power plants are now reaching the end of their lifetime. The reactors were initially designed to last for 32 years at nominal power and 40 years at 80% of their nominal power (Charpin et al., 2000, p. 31). In practice, the 40-year threshold is used by the national authority on nuclear safety, the ASN, through a system of ten-year licences. The fourth decennial inspections, which decide whether the technical lifetime can be extended beyond 40 years, are coming soon: in 2019 at Tricastin, and 2020 for Fessenheim and Bugey (Autorité de Sûreté du Nucléaire, 2014).¹

The lifetime of these nuclear plants can be extended if retrofit works are undertaken. A report by the French 'Cour des Comptes'² (Cour des Comptes, 2016) revealed that EDF estimates at 100 billion euros the cost of retrofitting the plants up to 2030. Should all plants be retrofitted? And more generally, what is the future of nuclear energy in France? These questions are now at the heart of public debate. The diversity of opinions on this matter was highlighted by the French National Debate on Energy Transition in 2012. The views on the future of nuclear generation in France ranged from a fully maintained nuclear share, to partial retrofit strategies, to a full and early phase-out (Arditi et al., 2013).

France is now at a crossroads. The economics of this decision crucially depend on the cost of nuclear, both new and retrofitted; but these are subject to significant uncertainty. A combination of recent setbacks in the nuclear industry has raised some doubt about the future cost and safety of this technology, for both the construction new nuclear reactors and the retrofitting of existing plants.

Other uncertainties must also be accounted for, in particular those concerning the level of demand and CO₂ price. The level of demand can be affected by economic growth or downturn, by energy efficiency and the development of new uses like electric cars. CO₂ price can impact the relative competitiveness of gas and coal, but also renewable energies backed up by gas. This CO₂ price depends on political will, which is difficult to anticipate.

Given these uncertainties, what are the policy options available, and what are their risks and benefits? As suggested by the current debates, there is clearly no silver bullet, no single optimum

¹In practice, due to a drift in decennial inspections, the fourth decennial inspections are sometimes planned after 40 years. This drift varies among reactors and goes up to 4 years for Bugey 3. This explains why Fessenheim, although being the oldest plant, comes after Tricastin for the fourth decennial inspection.

² The Court of Auditors (in French Cour des Comptes) is a quasi-judicial body of the French government charged with conducting financial and legislative audits of most public institutions

40 strategy for all plausible values. If retrofit proves to be cheap while CO₂ price and renewable costs are relatively high, then a continuation of the nuclear policy might be the cost-minimizing strategy. If nuclear is more expensive than expected and CO₂ price is low, then gas turbines might be an interesting source of energy. Finally, if the cost of renewable energies keeps dropping while nuclear proves to be expensive then, with a rising CO₂ price, renewable energies might become a
45 cost-effective alternative. Thus, we aim to find a robust strategy, i.e. a strategy that “performs relatively well –compared to alternatives– across a wide range of plausible futures” (Lempert et al., 2006).

From a policy point of view, it is important to define now a strategy for the medium-term and even long-term, because investment in retrofitting must be made months or years in advance. It can
50 even be ten years in advance, as the decennial stop related to the mandatory safety check is a good opportunity to start a retrofit. This implies that the future of the oldest nuclear plants must be decided soon. Proposing long-term robust strategies would contribute to the current public debate in France about the decommissioning of this plant, and about the amount of compensations to EDF if the plant were to be closed by a public decision. In the future, as new information becomes
55 available regarding costs, demand, CO₂ price or any other important parameter, the analysis should be re-run in an iterative and flexible process.

Many studies have analysed a low-carbon transition in the power sector, at a national level (Henning and Palzer, 2015) or a European level (Jägemann et al., 2013; European Commission, 2012). Focusing more specifically on nuclear, Bauer et al. (2012) study the cost of early nuclear
60 retirement at world level, and show that the additional cost of enforcing a nuclear phase-out is an order of magnitude lower than the total cost of a climate policy. But this result might not hold true for France as the share of nuclear is much higher than the world average.

Linares and Conchado (2013) analyse the break-even overnight cost of nuclear, using an optimization model of the Spanish power sector. They come up with a medium estimate of 2,609
65 €/kW, and conclude that the cost-competitiveness of this technology is questionable given the cost estimates of new projects.

In France, the French Energy Agency, ADEME, produced a study of renewable penetration in 2050 (ADEME, 2015). However, they do not study the path between today and 2050: the power mix was built ex nihilo (greenfield optimization) in 2050 as an optimization with 2050 projected
70 costs. Petit et al. (2016) study wind penetration in France, but without modelling the potential of hydro optimization to smooth wind penetration, and consider only cases in which nuclear is cheaper than wind - a debatable assumption, as we will show. Cany et al. (2016) examined the impact of renewable penetration on the load factor and economics of French nuclear reactors, using load duration curve. They conclude on the importance of improving nuclear flexibility and on the
75 necessity of incentives such as a carbon price for nuclear to be competitive with CCGT-gas back-up. However, their approach without an optimization model does not fully capture the challenges raised by intermittent renewables, in particular regarding daily and seasonal variations.

The uncertainties of power system planning have recently been emphasized by Nahmmacher et al. (2016), using the Robust Decision Making (RDM) methodology - the same methodology that
80 we use in this paper. To our knowledge, this study by Nahmmacher et al. (2016) was the first - and the only one up to this article - in which the RDM methodology is applied to the power mix. However, their focus is different from ours: they study the resiliency of the power system to unexpected shocks, such as a transmission break-down or a heat wave. They do not deal with cost or demand uncertainty, nor with strategies of nuclear fleet management.

85 In this paper, we combine the cost-minimizing optimization model of the French power sec-

tor FLORE with the framework of Robust Decision Making (Lempert et al., 2006). This RDM framework combines scenario-based planning with statistical analysis, in order to identify robust strategies, vulnerabilities and trade-offs. We apply it to the results of nearly 8,000 runs made with the FLORE model. Our paper aims to provide insight for the current debate in France concerning the retrofit of existing nuclear plants. More generally, it also explores the importance of uncertainties related to nuclear energy in power system planning, and could thus contribute to the debates in other European countries, in particular Germany and Switzerland.

Our paper contributes to the literature in several points. The first and main one is to use a methodology of robust decision making to deal explicitly with the high uncertainty about nuclear costs. The literature as a whole shows a wide uncertainty over nuclear costs. Rather than using specific – and controversial – values, we propose a methodology to include this uncertainty in the decision-making process. This is an improvement compared to the pure cost-minimization, thresholds-based or sensitivity analyses. In addition, we provide new estimates on the cost of nuclear retrofit based on a novel report by the French government, and include a retrofit option in our analysis, rather than focusing on new plants. We also provide a model to study nuclear and renewables with around 12% hydro and optimized pumped storage, while the literature has focused mainly on thermal power systems, and seldom on power system with a high share of hydro (Hirth, 2016a; Linares and Conchado, 2013). Finally, we provide trajectories of nuclear for France, which is often difficult to represent properly in models covering a larger region because of its large nuclear fleet.

The remaining of this paper is as follow. In section 2, we review the literature to get the ranges of uncertainty. These ranges will be used for the parameters of our model FLORE, which is introduced in section 3. We present the RDM framework in section 4 and apply it in section 5 to identify robust strategies. Finally, we compare our results to the French official scenarios in section 6. Section 7 outlines the conclusions.

2. Literature review on uncertainty ranges

2.1. Overview

Various uncertainties stretch the range of plausible future costs for both retrofitted and new nuclear.

On one hand, the recent literature and events about nuclear costs presents arguments supporting the idea of increasing costs in the future:

Increased regulatory pressure on safety. Increased regulatory pressure can increase costs (Cooper, 2011). In particular, the Fukushima accident has led the French nuclear regulator, the ASN, to impose new safety measures.

Unexpected cost surges. The EPR technology in Flamanville (France) has been delayed several times, and its cost tripled. For new nuclear reactors, the most famous example is the significant cost overrun of the EPR at Flamanville (France). The project was initially estimated at 3 billion euros, but this estimate has increased progressively up to 10.5 billion euros in 2015 (Garric and Bezat, 2015), and there are still concerns about the safety of its vessel (Le Hir, 2015). The EPR in Olkiluoto (Finland) is also facing several difficulties. In the UK, EDF signed a contract at 92.5 £/MWh (127 €/MWh at 2015 exchange rate of

Eurostat³) and indexed on inflation, which means the nominal price will be higher when the plant starts to produce. The exact costs of the French EPR are difficult to assess as they are not publicly displayed. This market price is thus an important clue as to the cost of this technology. All these manifestations of uncertainty raise doubts about the ability of EDF to build competitive EPR power plants.

For retrofitted nuclear, the estimation may also be optimistic, as unexpected delays often occur in such megaprojects. For example, the first retrofit, in the plant of Paluel, has led to an incident⁴ which may cause delays and significant cost increases (Autorité de Sûreté du Nucléaire, 2016);

Lower availability of retrofitted plants. The discovery of anomalies has led to reinforced controls. As a consequence, in October 2016, 12 reactors out of 58 were stopped to check the resistance of their steam generators (De Monicault, 2016). This led to concerns about the security of supply and the future load factor of these plants, which is a key parameter of their value (International Energy Agency and Nuclear Energy Agency, 2015).

Risks and insurance costs. The Fukushima accident prompted a renewed interest on the question of insurance costs from the French court of audit (Cour des Comptes, 2012). This insurance should match the criticality of nuclear, i.e. the probability of an accident multiplied by severity of the consequences. Up to now, the French nuclear operator EDF has benefited from a limited liability. But both probability and damage costs are difficult to estimate. To give an idea of these uncertainties, Boccard (2014) estimates this insurance cost at 9.6 €/MWh, while Lévêque (2015) provides an expected cost below 1 €/MWh.

Decommissioning and waste management. No decommissioning has been finished yet, so the total cost is difficult to estimate. The first nuclear installation to be decommissioned in France, Brennilis, saw its cost multiplied by twenty compared to initial estimates. And in a novel report, a commission of the French Parliament reckons that the cost of dismantling might be underestimated in France (Aubert and Romagnan, 2017). As to waste management, a project called Cigeo is planned to store highly radioactive long-lived wastes. Its cost was estimated at between 15,9 and 55 billion euros in 2002 by the national radioactive waste management agency, ANDRA (Cour des Comptes, 2012, p. 142).

On the other hand, constructing several reactors of the same type can lead to learning-by-doing in the construction process. Standardization reduces lead times and thus reduces the cost of this technology. The size of reactors is also positively correlated with cost (Escobar Rangel and Lévêque, 2015), so a standardized approach with smaller reactors could thus stop the observed cost increase and even decrease the future costs of nuclear. A worldwide comparison of cost shows that cost trends vary significantly among countries, with the US experiencing strong cost escalation, while, on the other extreme, the late adopter South Korea saw a reversed trend (Lovering et al., 2016), although these results have been challenged (Gilbert et al., 2017; Koomey et al., 2017).

These elements should encourage carefulness when assessing the future costs of nuclear. They entail that a wide range of costs can be considered as *plausible*, in the sense that they cannot be

³<http://ec.europa.eu/eurostat/web/exchange-rates/data/main-tables>

⁴ on March 31, 2016, a steam generator of 465 tonnes and 22m high fell during its replacement operation

immediately dismissed since some elements support them. In the next sections, we examine what could be the future cost of retrofitted and new nuclear, based on the current literature.

2.2. Production cost of retrofitted nuclear plants

2.2.1. Historical costs

170 The cost of the French nuclear reactors has been the focus of a few papers. The first official report on the historic French nuclear program was made by Charpin et al. (2000). It was later analysed by Grubler (2010), who evidenced cost escalation in time, which he coined as “negative learning-by-doing”. This cost increase was then confirmed by Berthélemy and Escobar Rangel (2015). After the Fukushima accident, the French court of audits undertook a comprehensive
175 analysis of the costs and safety of French nuclear reactors. Based on this report, Boccard (2014) revealed larger than expected operation costs for French reactors: 188 €/kW/year, or 28.5 €/MWh with the historical load factor. This value is a key determinant of the cost of retrofitted nuclear, since fixed capital costs are already amortized to a large extent. And this estimate is much higher than the value suggested by International Energy Agency and Nuclear Energy Agency (2015) at
180 13,3 €/MWh. Using the same report, Escobar Rangel and Lévêque (2015) also noticed a cost escalation, but revealed a learning curve within technologies of the same type and size.

2.2.2. Costs of retrofitting

These old reactors now reach the end of their planned lifetime, initially intended to be 40 years⁵. These lifetimes can be extended, but only if some upgrade work is performed. A new report
185 published by the French court of audit (Cour des Comptes, 2016) provides the costs estimated by EDF⁶ to retrofit its nuclear fleet and bring safety up to post-Fukushima standards. According to EDF, an investment of 100 billion euros is required by 2030: 74.73 billion euros in CAPEX and 25.16 billion euros in OPEX (Cour des Comptes, 2016). Between 2014 and 2030, 53.2 GW will reach 40 years, so the 74.73 billion euros in CAPEX yield an average additional cost of 1,404
190 €/kW.

In addition to these overnight capacity costs, the cost per unit of energy produced is influenced by capital cost, load factor and lifetime.

Financial costs are highly dependent on the rate at which capital is borrowed. In France, Quinet (2013) recommends to use a rate of 4.5% for public investments. The IEA uses a rate of
195 5%, which we use for our best-case scenario, to account for financial costs. We use a rate of 10% for our worst-case scenario, following Boccard (2014).

For the load factor, we use a best case based on the estimates by Cour des Comptes (2016, p. 116), which shows that the availability of French nuclear plants has been up to 83.5% since 2005. In 2012, the load factor was down to 73% in 2012, but considering the recent difficulties faced by
200 French reactors, we use a load factor of 70% as a worst case.

As to lifetime, we suppose that the investment of 100 billion euros will enable the plant to run for 20 more years. This is currently the implicit assumption of EDF (Aubert and Romagnan, 2017, p. 13), but there is significant uncertainty around this hypothesis. In France, nuclear plants are given license by periods of ten years. The French Authority of Nuclear Safety seems willing

⁵ French reactors were initially designed for a lifetime of forty years, with a count start at their first nuclear reaction. In the US, lifetime is counted from the first layer of concrete.

⁶Electricité de France, the main operator of the nuclear fleet in France.

205 to provide licenses for a ten-year extension; but there is no certainty that it will give a second approval, ten years later, to go beyond fifty years of operation. It may decide to close some plants, or ask for additional investment at that time. However, the magnitude of the investment indicates that EDF is confident it will be able to run for twenty more years without incurring in large additional costs. Thus, this is our best-case hypothesis. We consider a worst case in which lifetime
210 extension will be granted for ten years only.

2.2.3. Cost of a nuclear accident

The Fukushima accident has prompted a renewed interest on the question of insurance costs. The insurance cost should match the criticality of nuclear, i.e. the probability of an accident multiplied by severity of the consequences. However, both the probability of an accident and
215 damage costs are difficult to estimate.

Damage costs depend on several assumptions about indirect effects, as well as on monetizing nature and human lives (Gadrey and Lalucq, 2016). Thus, an irreducible uncertainty remains. To give an order of magnitude, the Institute for Radiological Protection and Nuclear Safety (IRSN) estimated the cost of a “controlled” release of radioactive material between 70 and 600 billion
220 euros (Cour des Comptes, 2012), and Munich Re (2013) evaluates the damages of the Fukushima accident at 160 billion euros.

To assess the probability of a nuclear accident, two approaches coexist. The first one is the Probabilistic Risk Assessment (PRA). It consists in a technical bottom-up approach, which compounds the probabilities of failures which could lead to a core meltdown. In France, the probability
225 of an accident which would release a significant amount of radioactivity in the atmosphere is estimated at 10^{-6} per reactor per annum for current plants, and at 10^{-8} per reactor per annum for EPR reactors (Cour des Comptes, 2012, 241).

However, a wide discrepancy is observed at first glance between the expected number given by PRA estimates and the much higher number of observed nuclear accidents worldwide. This
230 discrepancy has motivated another approach, based on the statistical analysis of past historical accidents, in particular since Fukushima. For example, Ha-Duong and Journé (2014) estimate that the historical probability of an accident was closer to 10^{-4} per reactor and per year - a difference of a factor 100 with PRA estimates.

However, this second approach suffers from two short-comings. The first one is the low number
235 of occurrences. Only two events are classified in the category of major accident, i.e. a level 7 on the INES scale.⁷ Such a small sample hinders robust statistical analysis. Most studies thus estimate the probability of a larger pool of events by including events lower on the INES scale, but the gain in estimation accuracy comes at the cost of a change in the meaning of the results (Escobar Rangel and Lévêque, 2014). What is measured is not only the probability of major accidents occurring,
240 but it also includes the probability of less dramatic events.

The second shortcoming comes from the use of past, historical data. This does not enable to account for the potentially increased risks due to ageing power plants, nor for the tense political situation with fears of terrorist attacks. This uncertainty can drastically change the cost of insurance. If we estimate the cost of insurance should match the criticality of nuclear, and if we assume
245 the cost of a major nuclear accident to be 100 billion euros, as recommended by Cour des Comptes

⁷The INES scale, introduced by the International Nuclear Energy Agency, ranges nuclear events from 1 (anomaly) to 7 (major accident).

Table 1: Estimated nuclear insurance costs for a damage cost of 100 billion euros and a load factor of 0.8

Estimated probability of an accident (per reactor per annum)	Insurance cost (euro/MWh)
10^{-8}	1.4×10^{-4}
10^{-6}	1.4×10^{-2}
10^{-4}	1.4
10^{-3}	14

(2012), then a probability of accident between 10^{-6} and 10^{-3} per reactor per annum makes the insurance cost vary from 1.4×10^{-2} €/MWh to 14 €/MWh, as shown in table 1. According to Bocard (2014), based on reports from the French ‘Cour des Comptes’ and the French Senate, the cost of insurance should be around 8.5 €/MWh.

250 The point behind these figures is that the cost of insurance cannot be dismissed once and for all. Expectations of security improvements can explain an almost negligible value for nuclear insurance, while a more conservative view can lead to significantly higher estimates.

2.2.4. Decommissioning and waste management costs

A novel report by the French Parliament provides several clues as to the uncertainty surrounding decommissioning costs (Aubert and Romagnan, 2017). Let us quote three. The first is related to Brennilis. This experimental reactor built in 1962, marks the first decommissioning of a nuclear power station in France. Although not achieved yet, the cost of decommissioning is currently estimated to be 482 million euros, around twenty times its initial estimate. This evolution leads to be cautious with the current cost assessments of other nuclear installations. Second, even the technical feasibility of decommissioning is not granted yet. This is illustrated by the decision of EDF to postpone to 2100 the decommissioning of several experimental nuclear installations, in order to develop new decommissioning technologies. Finally, there is a large divergence between the estimates of European operators. The accounting provision is generally between 900 and 1.3 billion euros per reactor, while EDF’s provision is only 350 million euros per reactor. Due to the significant difference with other European operators, we also consider a worst-case scenario in which a doubling of current costs and provisions cannot be excluded.

As to waste management, a facility called Cigeo is planned to be built to serve as a repository for highly radioactive long-lived wastes. The cost of this project was estimated at between 15,9 and 55 billion euros in 2002 by the national radioactive waste management agency, ANDRA (Cour des Comptes, 2012, p. 142). Since these costs will be incurred in a distant future, valuing this nuclear liability depends on the choice of a discount rate. And this rate is subject to market fluctuations, which impacts the amount of accounting provisions and thus the cost of nuclear.⁸

⁸ In France, the discount rate is currently fixed by the application decree 2007-243 of 23 February 2007 relative to ensuring the financing of nuclear accounting charges (“décret 2007-243 du 23 février 2007 relatif à la sécurisation du financement des charges nucléaires”). The nominal rate must be lower than a four-year moving average of government bonds of constant maturity at 30 years, plus a hundred base points (Cour des Comptes, 2014, p. 110). But this calculation method for the discount rate is itself debatable. For example, Taylor (2008) estimates a risk-free rate should be used.

Given the uncertainty over costs and discounted rate, we consider another doubling of cost as our worst-case scenario.

275 In conclusion, decommissioning and waste management costs add another layer of uncertainty to generation costs. However, their overall impact, without being negligible, is mitigated by the discounting effects.

2.2.5. *Summing up*

280 Overall, there are at least eight sources of uncertainty for retrofitted reactors, as represented in figure 1: the overnight capital cost of retrofitting, the cost of borrowing, the future OPEX, the length of lifetime extension (10 or 20 years), the future availability of nuclear plants and the costs of waste, decommissioning and insurance. Using the most recent data available, detailed in table 5 and table 6, we compute that, in the best case, the cost of retrofitted nuclear would be 44 €/MWh. But based on conservative assumptions detailed in table 7 in appendix, various sources of uncertainty could amount to an additional 51.5 €/MWh. Plausible values for this technology thus range from 44 €/MWh to 95.5 €/MWh.

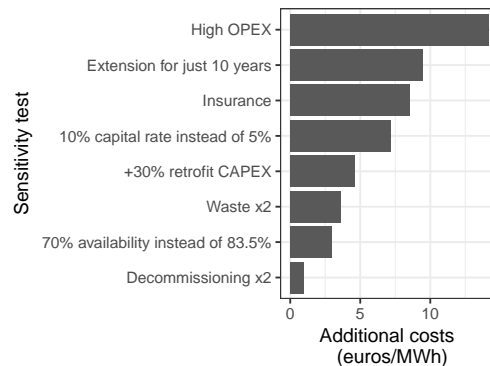


Figure 1: Plausible additional costs for retrofitted nuclear compared to a best case of 44 €/MWh. The assumptions for this sensitivity analysis are detailed in table 7 in appendix.

2.3. *Cost of new nuclear plants*

290 In parallel to retrofitting its existing reactors, EDF has developed a new technology: the European Pressurized Reactor (EPR). However, this model has also faced serious setbacks. The yet unfinished reactor developed in France saw its cost rising from 3 billion euros to 10.5 billion euros. In Finland, the construction work for an EPR reactor started in 2005 with a connection initially scheduled in 2009, but has so far been delayed until 2018. In the UK, the EPR has been negotiated at 92.5 £/MWh – approximately 127 €/MWh at the exchange rate of 2015 given by Eurostat.

295 As to the future of the EPR cost, a tentative cost is estimated by Bocard (2014) between 76 and 117 €/MWh, for a total cost of 8.5 billion euros (before its upwards adjustment to 10.5 billion euros) when including back-end and insurance costs (he estimates insurance costs at around 9.6 €/MWh). The high end is in line with the contract price of the Hinkley point C reactor. A wide spread is found in the literature, from 76 €/MWh to 120 €/MWh. In addition, the cost of nuclear

300 has been shown to depend on safety pressure. For example, Cooper (2011) showed that the Three Mile Island accident had a significant impact on cost escalation. Consequently, any new incident could increase these current estimates. This creates additional uncertainty over future nuclear costs. These significant uncertainties about future costs led some to qualify the nuclear option as a “bet” (Lévêque, 2013).

305 This wide range of nuclear cost is critical, as it encompasses the current levels of feed-in tariffs for wind in France and its LCOE⁹ expected in 2050. In France, in 2014, onshore tariff was set between 55 and 82 €/MWh for a lifetime of 20 years (82 €/MWh for the first ten years, and between 28 and 82 €/MWh afterwards, depending on wind conditions)¹⁰. Wind tariffs in neighbouring Germany were set at 59 €/MWh in 2015: 89 €/MWh during 5 years and 49.5 €/MWh afterwards
310 (Bundestag, 2014).

Finally, it is important to note that new nuclear is expected to be costlier than retrofitted plants. The general idea is that a brown field project (a retrofitted plant) requires less investment than a greenfield project. Thus, we will focus on the cases in which new nuclear is costlier than retrofitted nuclear.

315 *2.4. Demand, CO₂ price and renewable costs*

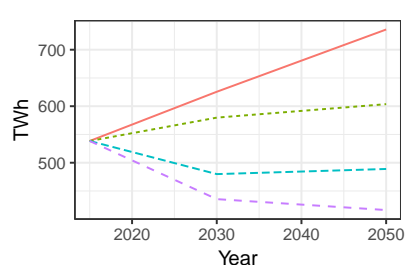
Uncertainty in electricity demand was highlighted during the National Debate on Energy Transition (DNTE) in France, which led to four contrasted demand scenarios: SOB, EFF, DIV and DEC, in order of increasing demand. These scenarios are represented in fig. 2a. The only change we made was to halve the demand increase in the DEC scenario, because its former rate did not
320 seem not quite plausible.

These contrasted scenarios reflect the numerous uncertainties in the underlying drivers of demand. On the one hand, energy efficiency might keep improving, lowering demand (Boogen, 2017; Boogen et al., 2017). On the other hand, the increase in the number of electric vehicles or in the use of hydrogen (Cany et al., 2017) could be drivers of power demand growth. The evolution of
325 GDP might drive demand up in case of economic expansion, or down in case of a new economic downturn. Climate change might also impact electricity demand, with higher cooling demand during summer and lower heat demand during winter (Auffhammer et al., 2017; De Cian et al., 2016). Although we do not take these evolutions explicitly into account, our contrasted demand scenarios implicitly refer to such uncertainties.

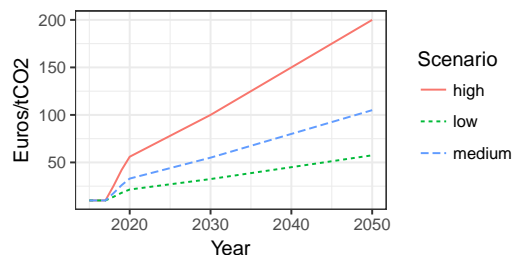
330 For CO₂, we use the official price used in French public investments as defined in Quinet (2009). In the central scenario, this price goes up to 100 euros in 2030 to 200 euros in 2050 (see figure 2b). In the short term, these prices are significantly higher than the price of emission allowances on the EU ETS market (which has stayed below 10 €/tCO₂ on the EEX market in the past year) and there is no reason to think that the EU ETS price might be higher, even with the proposition
335 of back-loading some allowances in the future (Lecuyer and Quirion, 2016). We also consider a variant with medium CO₂ price trajectory, in which we divide the official price by a factor of 2; and a low CO₂ price trajectory, in which we halve the price again. These prices could represent the evolution of the EU ETS, or the price floor for CO₂ currently discussed in France.

⁹ The Levelized Cost of Electricity, or LCOE, is an economic assessment of the average cost of one unit of energy produced by a power-generated asset. It is equal to total discounted costs divided by total discounted generation over the lifetime of the asset.

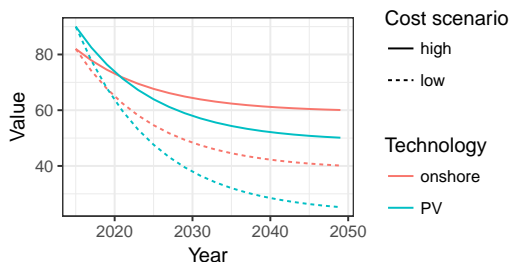
¹⁰ Note that the wind developer must pay for connection to and upgrade of the distribution network to access this FIT.



(a) Load scenarios taken from Grandjean et al. (2014).



(b) CO₂ price scenarios. The high end is in line with the national carbon reference price defined in Quinet (2009).



(c) Renewable energies cost scenarios. Current prices and high cost scenarios are taken from ADEME (2015). Low cost scenarios are based on recent world benchmark auction prices listed in IRENA (2017).

Figure 2: Scenarios on demand, CO₂ price and renewable energies costs

340 All these uncertainties thus raise the question of the optimal mix. However, cost alone cannot
 answer that question: a model of the power mix is required. The LCOE metric does not account
 for the “integration costs” of variable renewable energies (VRE) (Ueckerdt et al., 2013), nor for
 the dispatchable nature of nuclear energy. Because PV and solar are variable, their value decreases
 as their penetration rate increases, although the magnitude of this decrease is specific to the
 power system (Hirth, 2016a) and to the renewable technology characteristics (Hirth and Müller,
 345 2016). This phenomenon of value drop is sometimes called “self-cannibalization effect”. Using
 an optimization model of the entire power system enables us to capture these integration costs.
 Indeed, since the model finds the power system that satisfies demand at the least cost to society,
 wind or solar would only be installed if they are competitive.

3. Model description

350 The French power model FLORE (*French Linear Optimization for Renewable Expansion*) is an
 optimization model of investment and dispatch. It is based on representative technologies, with
 a particular focus on nuclear and hydropower modelling to reflect the specificities of the French
 power mix. All technologies are endogenous for both investment and dispatch, except for hydro

capacities for which investment is exogenous. Existing nuclear plants may be retrofitted for 20
355 years when they reach 40 years old, or they are decommissioned. Demand is represented by six
representative weeks of 24 hours each. Hydro resources from dams and pumping stations are
dispatched optimally within the representative week - but there is no annual optimization between
representative weeks. In addition, all capacities are jointly optimized over the horizon, in order
to provide a consistent trajectory of investments. France is represented as a single node. Hourly
360 demand, net exports and CO₂ prices are exogenous. The model is calibrated for the year 2015,
thus using the last generation data available from the network operator, RTE.¹¹

All the equations of the model are available on GitHub at [https://github.com/QuentinPerrier/
Flore](https://github.com/QuentinPerrier/Flore). In addition, an interactive online version of the model can be found at [http://flore.
shinyapps.io/OnlineApp](http://flore.shinyapps.io/OnlineApp). This open access should ensure transparency and reproducibility, as
365 advocated by Pfenninger et al. (2017).

3.1. Generation technologies

Eleven generation technologies are modelled: two variable renewable energies (onshore wind
and solar PV), three fossil-based thermal technologies (coal plants, combined cycle gas turbine,
open cycle gas turbine), three nuclear technologies (historical nuclear, retrofitted nuclear and new
370 nuclear) and three hydro systems (run-of-river, conventional dams for lakes and pumped storage).
Investment in each technology is a choice variable of the model, except for hydropower and historical
nuclear, which are exogenous. Generation of each dispatchable technology is a choice variable.
Run-of-river production is exogenous and based on historical data. Wind and solar productions are
modelled as run-of-river, based on historical production profiles, with the possibility of curtailment.
375 They also incur needs for reserves, as detailed in section 3.2.

The capacity of run-of-river and conventional dams is supposed to be constant, while the
pumped hydro capacity is supposed to grow by 3.2 GW by 2050, with a discharge time of 20
hours, as in ADEME (2013). Hydro storage and dispatch are optimized by the model, under water
reservoir constraints and pumping losses. Dams receive an amount of water to use optimally at
380 each period. Pumped hydro can pump water (although there are losses in the process), store it
into a reservoir and release the water through turbines later on.

A particularity of the model is to represent explicitly the cost of extending the lifetime of nuclear
power plants. Nuclear plants normally close after 40 years, but their lifetime can be extended to 60
years, if upgrade costs are paid for. For historical nuclear, we model a phase-out of the capacity of
385 each power plant reaching 40 years. The same year it reaches 40 years, this capacity of a historical
nuclear plant is endogenously either extended for 20 years, or phased-out. Thus, each year, total
investment in retrofitted plants is limited to the capacity of historical nuclear reaching forty years.

Hourly Variable Renewable Energy (VRE) generation is limited by specific generation profiles
based on historical data for the year 2015. These technologies are installed whenever they are
390 competitive, although the model starts with the installed capacities of 2015 (the calibration year),
which were supported by feed-in tariffs.

Dispatchable power plants produce whenever the price is above their variable costs, unless they
are limited by their ramping constraints. At the end its lifetime, each capacity is decommissioned.
Power generation required for heat generation was on average 2% of consumption, and never above
395 5% of consumption in France in 2014 (RTE, 2014), so we do not model it.

¹¹<http://www.rte-france.com/fr/eco2mix/eco2mix-telechargement>

3.2. Reserves requirements

One concern with the penetration of variable renewable energies is the ability to meet demand at any time. As the share of VRE grows, this question of adequacy becomes a central concern for power system planning. RES forecast errors compound with other imbalances, such as demand forecast errors, and increase the need for operational flexibility. In order to provide the flexibility needed to cope with these imbalances, capacities which can rapidly add or withdraw power from the grid must be reserved: these are the reserves requirements. Modelling these reserve requirements is essential to properly evaluate the need for and the value of flexible capacities (Villavicencio, 2017).

In ENTSO-E areas, reserves are categorized into three groups: the Frequency Containment Reserves (FCR), the Frequency Restoration Reserves (FRR) and the Restoration Reserves (RR). Each group correspond to a different ramping speed. FCR must be on-line in 30 seconds. FRR restores is divided into a fast automatic component (aFRR) which must starts in 7.5 minutes, and a slow manual component (mFRR) which must be able to start in 15 minutes. Finally, RR are used to gradually replace FRR (Stiphout et al., 2016).

Since there is always a trade-off between the accuracy of technical constraints and computation time, which reserves should be considered? The expansion of renewable will put a particular emphasis on the need for FRR upwards reserve requirements. The requirements for downward reserves might be less stringent, as VRE should be able to participate in that market (Stiphout et al., 2016; Hirth and Ziegenhagen, 2015). As to RR, ENTSO-E sets no requirement for RR (Stiphout et al., 2016) as it is not the main issue. Finally, FCR are determined by ENTSO-E for the area of Continental Europe, and this effort is then shared among the different countries. Thus, in our model, we choose to insert upwards FRR requirements and FCR. We ignore downwards FRR reserve requirements and RR. We do not model the reserves requirement for conventional power plants either.

ENTSO-E provides guidelines as to the sizing of reserve requirements for variable renewable energies. The method for sizing is well explained in Stiphout et al. (2016). It is based on a probabilistic approach of the error forecasts. The total FRR requirement is equal to the 99% quantile of the probability density function of the normalized forecast errors. It gives the required amount of capacity of FRR per unit of VRE installed capacity.

3.3. Model resolution

The model optimizes new capacities with a two-year time step from 2015 to 2050. The dispatch of generation capacities is computed to meet demand for six representative weeks at an hourly step. Each typical week represents the average demand of two months of real data, through 168 hours. For example, demand of Monday for week 1 represents the average demand, on an hourly basis, of all the Mondays in January and February. This is similar to having $24*7=168$ time slices in the TIMES model¹² or in the LIMES-EU model¹³. Demand is exogenous and assumed to be perfectly price inelastic at all times. Net export flows are given exogenously, based on historical data. The various demand scenarios we study represent the initial demand profile (domestic consumption plus exports) and change it homothetically, thus without altering the shape of peak or base demands.

The model covers France as a single region. Each typical week is associated with i) a water inflow for run-of-river and dams, ii) an availability factor for conventional generation technologies

¹²<http://iea-etsap.org/docs/TIMESDoc-Intro.pdf>

¹³<https://www.pik-potsdam.de/members/paulnah/limes-eu-documentation-2014.pdf>

for each representative week, to account for maintenance and iii) a production profile for renewable technologies (onshore wind and PV) based on historical production.

3.4. Objective function

440 The objective of the model is to minimize total system costs over the period 2015-2050. The cost of each technology is annualized, both for O&M and capital costs. Capital annuities represent the payment of the investment loan, assuming a steady amortization plan. Using annuities allows us to avoid a border effect in 2050: the investment costs are still well represented at the end of the time horizon. This is a convenient modelling assumption, which leaves the utilization rate of
445 the plant endogenous in the model. However, it does not allow for early or deferred repayment of borrowed capital as could occur in reality, in case the plant has a high or low utilization rate.

We use a 0% rate of pure time preference, in order to give the same weight to the different years and generation up to 2050. This assumption is also made in the EMMA model (Hirth, 2016b) used for example by Hirth and Müller (2016). Costs include investment costs, fixed O&M costs, variable
450 costs and costs due to ramping constraints. To account for financing cost, investment costs are annualized with an 8% interest rate (the sensitivity to this parameter is included in our analysis by the fact that we vary the annualized CAPEX in our scenarios). Variable costs are determined by fuel costs, CO₂ price, plant efficiency and total generation.

In section 2, we studied the range of plausible values for nuclear, highlighting eight sources of
455 uncertainty. Looking at these specific cost items was necessary to understand the range of plausible costs for retrofitted nuclear, but we will not detail each of these items in our model, as it would lead to too many possibilities (and possibly overlapping ones). Instead, we will keep the OPEX fixed and make the annualized CAPEX vary to cover the uncertainty range. This simplified approach allows a decision maker to use its own assumptions about each cost item.

460 All assumptions regarding investment costs (table 9), fixed O&M costs (table 10), CO₂ price (table 11), fuel prices (table 12) and net efficiencies (table 13) can be found in appendix E.

3.5. Scope and limitations

The objective function does not include grid costs explicitly. However, for wind farms and large
465 PV stations, the feed-in tariffs we use include grid connection costs, as renewable producers must pay for the civil engineering works required to connect the installation to distribution or transport networks (for any power exceeding 100 kVA).

For nuclear plants, they will be most likely built on sites with grids already built (however, the size of the new reactors is significantly higher: 1.6 GW against 0.9 GW for many French reactors. Some upgrade works on the network might be necessary.)

470 Demand is exogenous. In the long-term, it means there is no price-elasticity of demand. However, we model four demand scenarios to account for demand variability.

We do not model endogenous learning curves. As we model only France, it seems like a reasonable assumption that worldwide learning curve will not be significantly impacted. However, installing more renewable energies could lead to learning at the industrial level for the installation
475 phase.

Using representative technologies entails some limits, but there is a trade-off between accuracy and runtime. Palmintier (2014) shows that using representative technologies provides errors around 2% with ~1500x speedup compared to a fully detailed approach with Unit Commitment. Our choice implies that the investment in nuclear plants is continuous rather than constrained by steps

480 of about 1 GW. To get an estimation of the number of new plants, we divide the total amount of new capacity by the average capacity of a plant.

We use only one representative technology for all historical nuclear plants, based on the relative standardization of the current fleet. This does not enable us to capture the residual heterogeneity in risks or costs between reactors (Berthélemy and Escobar Rangel, 2015). This heterogeneity 485 should be kept in mind to decide which plants should be closed first, once a given amount of capacity to decommission has been estimated by the model.

As to geographical resolution, we represent a single node and use average values. Simoes et al. (2017) shows that using a single node has a smoothing effect on renewable production, while a more accurate spatial disaggregation leads to a lower system value for both wind and solar. 490 Representing more regions would be more accurate, but also more computationally intensive. Also, the power network in France does not experience congestion problems, which justifies our single node assumption, and allows for smoothing the VRE output.

Flexibility options which could keep improving up to 2050, like demand response or storage technologies, are not represented either. Renewable technologies stay similar to today's, while there 495 is potential for improvements in order to better integrate with the power system - e.g. with larger rotor for wind turbines (Hirth and Müller, 2016). Finally, we consider only one average profile for onshore wind and no offshore wind (but this technology is still costly and would probably not appear in an optimization model), which limits the potential benefit of spreading generation over large geographic areas. France has three different wind regimes, plus a large potential for offshore 500 wind, but our assumptions do not take fully into account that potential. This does not impact scenarios with low renewable penetration. For scenarios with high renewable penetration, including these options could help increase the value of renewables.

4. Method: Presentation of the RDM framework

Knight (1921) made an important distinction between risk and uncertainty. There is a risk 505 when change can happen, for example in the value of a parameter, but the probability of any particular occurrence is measurable and known. When these probabilities are not known, there is uncertainty.

In the case of nuclear, the future costs are not known, and their probability of occurrence cannot be measured. The same holds true for demand levels, CO₂ prices and renewable costs. 510 We are dealing with a situation of uncertainty in the sense of Knight. In such situations, the traditional approach of practitioners is to employ sensitivity analysis (Saltelli et al., 2000). An optimum strategy is determined for some estimated value of each parameter, and then tested against other parameter values. If the optimum strategy is insensitive to the variations of the uncertain parameters, then the strategy can be considered a robust optimum.

515 However, when no strategy is insensitive to parameter changes, it is not possible to conclude to a single optimum strategy or policy. On the contrary, several optimal strategies coexist, each being contingent to the model specifications. In other words, each optimum is linked to some specific future(s).

Having a multiplicity of optimal scenarios does not enable to choose one strategy. In such a 520 case, a decision-maker might be interested in a strategy that performs well over a large panel of futures, i.e. a robust strategy, even if it means departing from an optimal non-robust strategy. In the case of uncertainty, it means to determine a robust scenario without assuming a distribution of

probabilities. This concept of robustness for power systems planning in face of uncertainty is not new (Burke et al., 1988; Linares, 2002), but it has received a renewed interest with the increase of computational power, and with the issue of climate change (Hallegatte, 2009).

In this paper, we use the Robust Decision Making framework developed by Lempert et al. (2006) to study the future of nuclear in France under uncertainty. This methodology was originally developed in the context of climate change. It has recently been applied to power systems - for the first time to our knowledge - by Nahmmacher et al. (2016).

The RDM framework uses the notion of regret introduced by Savage (1950). The regret of a strategy is defined as the difference between the performance of that strategy in a future state of the world, compared to the performance of what would be the best strategy in that same future state of the world. To formalize it, the regret of a strategy $s \in \mathbb{S}$ in a future state of the world $f \in \mathbb{F}$, is defined as:

$$regret(s, f) = \max_{s'} \{Performance(s', f)\} - Performance(s, f)$$

where s' goes through all possible strategies \mathbb{S} and \mathbb{F} is the set of all plausible future states. Performance is measured through an indicator, cost-minimization in our case. The regret is then equivalent to the cost of error of a strategy, i.e. the additional cost of the *ex ante* chosen strategy compared to the cost of what would have been the best strategy. The regret indicator allows to measure and order various strategies in each state of future. In addition, regret has the property of preserving the ranking which would result from any probability distribution. We can thus use this indicator without inferring any probability of distribution *ex ante*, and apply different probability distribution *ex post*.

The RDM method proceeds in several steps:

Determine the set of all plausible future states \mathbb{F} . This step aims at defining all plausible model inputs or parameter specifications. By plausible, we mean any value that cannot be excluded *ex ante*. The idea is to have a large set, because a set too narrow could lead to define strategies which would end up being vulnerable to some future states that were initially dismissed.

Define a set of strategies \mathbb{S} . These strategies will we analyzed to find a robust strategy among them. In our case, it means to define different policies as to the retrofit of nuclear plants. For example, a strategy could be to refurbish the 58 reactors; another policy, to refurbish every other reactor, and so on.

Identify an initial candidate strategy $s_c \in \mathbb{S}$. In RDM, a commonly used indicator is the upper-quartile regret (Lempert et al., 2006; Nahmmacher et al., 2016). To get this upper-quartile regret, we compute the regret for each strategy and each future state of the world, i.e. for each tuple $(s, f) \in \mathbb{S} \times \mathbb{F}$. Then, we compute the upper-quartile regret of each strategy. In other words, for each strategy, 75% of plausible future states will be below the upper-quartile regret of that strategy. The candidate strategy is the one with the lowest upper-quartile regret.

Identify the vulnerabilities of this strategy. Here, we identify where the candidate strategy s_c does not perform well. To do so, we find the subset of future states of the world $\mathbb{F}_{vuln}(s_c) \in \mathbb{F}$ for which the regret is high, i.e. above some threshold value (Lempert et al., 2006). The

value of this threshold is often defined as the upper-quartile of the regrets when considering all future states of the world (Lempert et al., 2006; Nahmmacher et al., 2016). With this definition, the vulnerabilities correspond to the future states whose regret is within the top 25%. However, since this threshold value is somewhat arbitrary, it must be ensured that final results are not sensitive to the choice of this threshold. Thus, we will also consider the upper-quintile threshold to check that our results are robust. Using statistical methods (the PRIM algorithm), we then try to find what are the conditions associated with these high regret states (for example, a low demand and a high CO₂ price). Finding these conditions allows to highlight the vulnerabilities of a strategy. By elimination, we can also deduct the subset $\mathbb{F}_{rob}(s_c) = \mathbb{F} - \mathbb{F}_{vuln}(s_c)$ in which the candidate strategy is robust.

Characterize trade-offs among strategies. For the subset $\mathbb{F}_{vuln}(s_c)$ and $\mathbb{F}_{rob}(s_c)$, we rank all the strategies in terms of regret, and identify the best strategy in terms of regret. Some strategies will have low regret in one subset and a high regret in the other; others will have medium regrets. It is then possible to draw a low-regret frontier, highlight the few alternative strategies on that frontier and show their trade-offs.

5. Results

5.1. Optimal trajectories

First, we study the optimal trajectories of nuclear in a cost-minimization framework, to see if there is an optimum which proves stable to sensitivity analysis, for all plausible values of uncertain parameters. In this part, we let the model choose endogenously which plants should be retrofitted.

A sensitivity analysis indicates that there is no optimum which is insensitive to the choice of input parameters. Within the plausible range, the optimal share of retrofitted nuclear varies from 0% to 100% (see appendix B). The analysis shows that the optimal share increases with the level of demand, the cost of renewable energies and the CO₂ price, but decreases with the cost of retrofitted nuclear.

Hence, in this case, the framework of cost-minimization and sensitivity analysis does not allow to find a single optimum. Following our discussion in section 4, this motivates the use of the Robust Decision Making framework developed by Lempert et al. (2006). We now apply it to find robust strategies, and to highlight the potential trade-offs between various robust strategies.

5.2. Determine plausible future states

This step derives from the literature review in section 2. For retrofitted nuclear, we consider that plausible costs range from 40 €/MWh to 90 €/MWh, by step of 10 €/MWh. Again, the idea is to encompass a broad initial range in order not to miss any possible value, and the RDM analysis will later identify subsets of costs to draw conclusions. As to new nuclear costs, we consider two scenarios: 90 €/MWh and 110 €/MWh. We only take two scenarios because of the very low sensitivity to this parameter shown in the previous section 5.1.

For renewable energies, we consider two trajectories: one with a quick decrease of wind and PV costs, and one with a lower decrease.

For demand, we consider four trajectories drawn from the French national debate on energy transition: a low, a decreasing, an increasing and a high trajectory. They corresponding respectively to the SOB, EFF, DIV and DEC scenario, as shown in fig. 9.

Finally, we examine three CO₂ price trajectories: a high trajectory using the official price trajectory from Quinet (2009), and a medium trajectory in which this price is divided by two, and a low trajectory in which we halve the price again.

Overall, this combination of scenarios for costs, demand and CO₂ price leads to the 288 plausible futures. Multiplied by the 27 strategies, we reach the 7,776 simulations.

5.3. Define a set of strategies

The next step is to define strategies of nuclear retrofit. Here, we define a *strategy* as the choice of which reactors to retrofit. The 58 existing reactors offer $2^{58}=2.9*10^{17}$ possibilities. As we aim to test each strategy against multiple values of uncertain parameters, testing all these possibilities would be too computationally intensive. Thus, we choose to work with a sample of strategies. This sample should represent a variability in the number (or share) of retrofitted reactors, and a variability in the time-dimension as it might be more interesting to retrofit at the beginning of the period (e.g. due higher renewable costs) or at the end (e.g. due to higher CO₂ price).

To account for the time-dimension, we split the reactors into three groups: the 20 oldest reactors, the 19 medium ones, and 19 the newest ones. These groups are obtained based on chronologically-ordered cumulative capacity, divided into three thirds. This split enables to explore whether an early retrofit (or phase-out) should be preferred over a late retrofit (or phase-out).

To account for the variability in the share of retrofitted reactors, we consider three possibilities for each group: i) all reactors are retrofitted; ii) half of the reactors are retrofitted, refurbishing every other reactor from oldest to newest in the group and iii) no reactor is retrofitted.

Combining the time dimension and the retrofit share, we end up with $3^3=27$ different strategies. Figure 3 illustrates how strategies were chosen. More information on these 27 strategies can be found in appendix C. Our aim is now to find which of these strategies are robust, performing well in a wide range of futures.

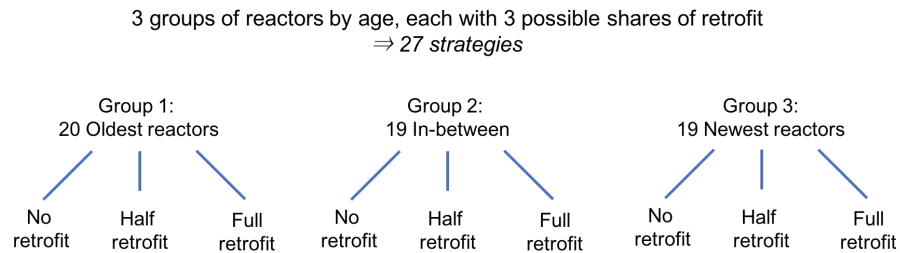


Figure 3: Defining 27 strategies

5.4. Identify candidate strategies

The following step is to choose a candidate strategy s_c that performs well across plausible futures. Our indicator of performance is the upper-quartile regret. This upper-quartile regret is also the indicator used by Lempert et al. (2006) and Nahmmacher et al. (2016) to pick a candidate strategy. The idea of this indicator is to select a strategy that is not too far from the optimum in 75% of the cases, i.e. that performs well in most cases – and we will explore remaining 25% later by analyzing the vulnerabilities of our candidate strategy.

635

Using the costs resulting from our model runs, we compute for each strategy $s \in \mathbb{S}$ its regret in each future state $f \in \mathbb{F}$. Then we compute the upper-quartile regret for each strategy s . The results are shown in fig. 4. Each dot in the figure shows the regret, in percent, for a strategy s indicated on the x-axis, and a future f . The upper-quartile regrets are represented by the larger dots.

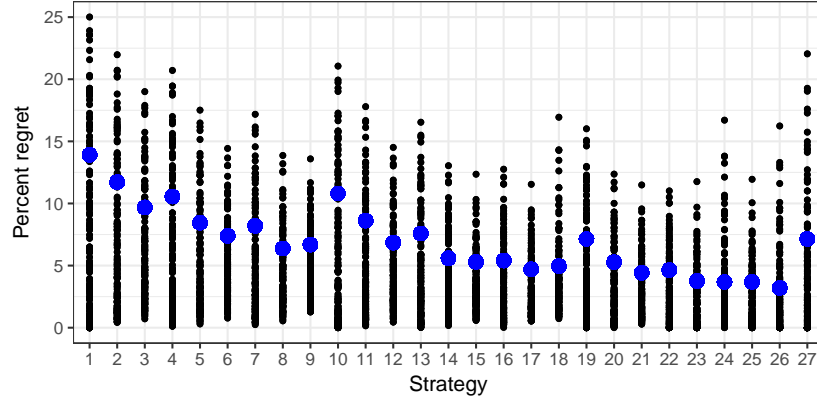


Figure 4: Each small black dot represents the regret of a strategy, indicated on the x-axis, for one of the 288 plausible states of future considered. Details of the 288 plausible states are given in section 5.2. The larger dots, in light blue, indicate the upper-quartile regrets for each strategy. See figure 3 and appendix C for a definition of the 27 strategies.

640

The strategy with the lowest upper-quartile regret is S26 (3.2%), and thus makes a good candidate strategy. With this strategy, ten reactors are closed, among the twenty oldest, and all the others are retrofitted.

645

In their paper, Lempert et al. (2006) go on with the RDM analysis considering just one candidate strategy, stating that the final results are not sensitive to the choice of the initial candidate strategy. However, we will test this assumption by performing the rest of the analysis using alternative candidate strategies. Figure 4 shows that the strategies S23, S24 and S25 are not far from S26 in terms of regret: their upper-quartile regret is 3.76%, 3.68% and 3.69% respectively. We thus choose to study also S23, S24 and S25 as alternative candidate strategies.

650

The definition of these top four candidate strategies, as well as their regret, is shown in table 2.

Strategy	20 oldest reactors	19 intermediate	19 newest reactors	Total number of early closures	Regret (%)
S26	half retrofit	full retrofit	full retrofit	10	3.20
S24	full retrofit	half retrofit	full retrofit	10	3.68
S25	no retrofit	full retrofit	full retrofit	20	3.69
S23	half retrofit	half retrofit	full retrofit	20	3.76

Table 2: Detail of the four strategies with lowest regret

5.5. Identify vulnerabilities

We keep following the RDM framework by applying the Patient Rule Induction Method (PRIM), in order to identify the vulnerabilities of our candidate strategies. This PRIM algorithm, originally been developed by Friedman and Fisher (1999), helps identify subsets of parameters in which our target indicator (regret) is above a defined threshold. Documentation on PRIM’s operation can be found in Bryant and Lempert (2010). We use a public version of the PRIM algorithm implemented in R in the package called “sdtoolkit”, available on CRAN.¹⁴

Vulnerabilities correspond to the set of parameters (or futures) in which regret are too high, i.e. exceed a defined threshold. The threshold used by Lempert et al. (2006) and Nahmmacher et al. (2016) is the upper-quartile regret. With this definition, the 25% futures with highest regret will be above that threshold and considered as vulnerabilities. Although this upper-quartile is often used in the RDM approach, it is somewhat arbitrary. Thus, we will test the sensitivity of our results to this threshold by using also the upper-quintile regret.

With the upper-quartile threshold, the set of parameters associated with high regret are shown in table 3. The PRIM algorithm indicates that, for our main candidate strategy S26, the most common pattern associated with a regret above the upper-quartile regret is when retrofit costs is equal to or greater than 65 €/MWh in conjunction with low CO₂ price. These conditions provide a cluster of states of future $\mathbb{F}_{vuln}(S26)$ to which S26 is vulnerable.

To test how these results change when selecting another candidate strategy, we apply PRIM to S23, S24 and S25. To our knowledge, this exploration of other candidate strategies has not been undertaken in other works. In our case, it appears that other clusters of vulnerabilities emerge, as indicated in table 3. These multiple clusters indicate that there are several ways to frame the debate on nuclear in France. Each of these clusters represent a possible fault line in the debate on the best strategy, where strongly diverging options exist. The debate could focus only on nuclear costs and CO₂ price (with S26 or S24), or mostly on CO₂ price (with S23 and S25). CO₂ price is a key parameter as it defines the competitiveness of coal and gas power plants compared to nuclear and renewable energies.

Table 3: Vulnerabilities of candidate strategies

Candidate strategy	Subset of vulnerable futures	Strategies on the low-regret frontier
S26	retrofit > 65 €/MWh low CO ₂ price	S1, S10, S19, S22, S23 and S26
S24	retrofit > 65 €/MWh low to medium CO ₂ price	S1, S10, S19, S22, S23 and S26
S25	low to medium CO ₂ price	S23 and S26
S23	low to medium CO ₂ price	S23 and S26

¹⁴<https://cran.r-project.org/web/packages/sdtoolkit/index.html>

5.6. Characterize trade-offs among strategies

Identifying vulnerabilities enables us to characterize trade-offs between different strategies. Figure 5 compares the upper-quartile regret values for each of the 27 strategies over the two subsets of future states yielded by the PRIM analysis of S26: $\mathbb{F}_{vuln}(S26)$ and $\mathbb{F}_{rob}(S26)$. By switching from one strategy to another, it is possible to lower the regret in one cluster of states, but at the expense of increasing the regret in the other cluster of states. For example, switching from S22 to S19 reduces the regret in the vulnerable states $\mathbb{F}_{vuln}(S26)$, but increases the regret in the other states.

Among the 27 strategies studied, some offer a better trade-off than others. In figure 5, from left to right, these are S1, S10, S19, S22, S23 and S26. These strategies are located on what can be called a Pareto-efficient or low-regret frontier. Evidencing this low-regret frontier is an important result, because it enables to select only six strategies as potential robust candidates out of the 27 initial strategies examined. This narrowed choice provides a simpler picture of our initial problem, showing only the strategies with interesting trade-offs.

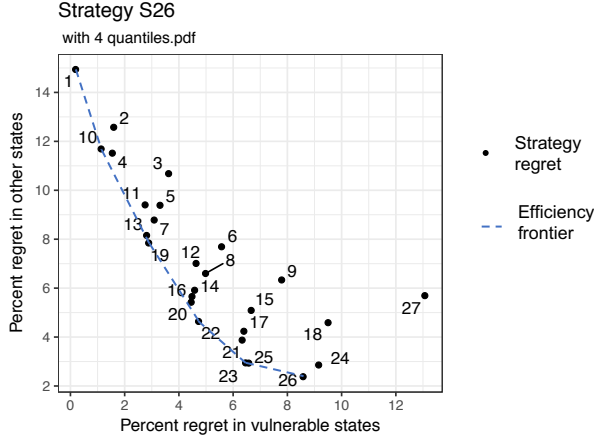


Figure 5: Regret for each strategy in $\mathbb{F}_{vuln}(S26)$ and $\mathbb{F}_{rob}(S26)$. The low-regret frontier is indicated by the blue dotted line.

We saw that using other candidate strategies, namely S23, S24 and S25, yields other subsets of vulnerable states. We can determine the low-regret frontier associated with these subsets. These figures are shown in fig. 7 in appendix F.1, and the strategies on these low-regret frontiers are indicated in table 3.

Among all of the 27 strategies, only two appear as Pareto-efficient in each of the clusters considered: S23 and S26. These two strategies represent the intersection of all the low-regret frontiers studied. For that reason, they can be considered as our robust strategies among the 27 strategies considered. S26 consists in closing 10 of the oldest reactors. S23 consists in closing 10 of the oldest reactors plus 10 intermediate reactors. In terms of cost, choosing S23 instead of S26 reduces regret by 2.1 percentage points in the vulnerable states of S26, $\mathbb{F}_{vuln}(S26)$, which represents about 30 billion euros; but it increases regret by 0.56 percentage points in the robust states of S26, $\mathbb{F}_{rob}(S26)$, which represents about 8 billion euros.

We test the sensitivity of our results to the threshold used - the upper-quartile regret - by doing
705 the same analysis with the upper-quintile instead. The results, shown in appendix F, are highly
similar to the ones with the upper-quartile threshold. The main difference is that strategy S25 now
also appears on the low-regret frontiers. This is not surprising, given how close S25 was to S23
in terms of regret with the upper-quartile threshold. These two strategies both imply the early
710 decommissioning of 20 reactors, the only difference is that these closures are split between old and
intermediate reactors in S23, while they are concentrated in old reactors in S25. In addition, the
vulnerabilities of S23 and S25 are the same, with both upper-quartile and upper-quintile regret
threshold (cf. table 14 in appendix). Thus, S25 can also be considered a robust strategy.

Closing between 10 and 20 reactors thus sketches a robust middle road, away from the two
extremes of full phase-out and full retrofit. However, this result keeps the debate open, as there
715 is still a significant range of 10 reactors. Our approach has shown that these strategies (S26, S23
and S25) are on the low-regret frontier, but it does not enable us to choose between these options.
The decision ultimately depends on the choice (or implicit probabilities) of the decision maker,
and which vulnerabilities he would rather face. S26 is vulnerable to a conjunction of retrofitted
nuclear above 65 €/MWh and low CO₂ price; S23 and S25 are vulnerable to low to medium CO₂
720 price .

In conclusion, we have evidenced that given the current estimates of cost, demand and CO₂
price, the most robust strategies - among the 27 strategies considered - imply an early phase-out of
at least 10 of the oldest reactors, and up to 20 reactors. The intuition behind these results comes
725 from a balance between risks and costs. On the one hand, retrofitting all plants is a strategy
vulnerable to lower demand or higher than expected costs of retrofit. On the other hand, a high
share of variable renewable energies can be costly - at least in the medium term, until batteries or
new renewable sources such as hydrogen become more cost-effective.

Our analysis has revealed robust strategies in-between these two extremes. Unless retrofit costs
get out of hand and carbon price remains so low that it allows for a return of coal and gas power
730 plants, retrofitting 38 to 48 reactors provides a competitive flexible source of generation. We
also highlighted the vulnerabilities of these robust strategies, their alternatives, and the potential
trade-offs with other strategies. Our approach keeps the debate open, as we highlight that other
strategies might be considered cost-optimal for assumptions less in line with the literature, but
still plausible given the current uncertainty.

735 **6. Comparison with French official scenarios**

6.1. Presentation of the official scenarios

From 2012 to 2015, France engaged in a National Debate on the Energy Transition (DNTE),
which finally led to a new “Law on the Energy Transition for a Green Growth”¹⁵. This discussion
on the future of the energy mix brought together various political stakeholders, as well as unions
740 and NGOs. During the debate, the power mix and the share of nuclear were a point of particular
focus, with a dedicated working group. Eleven energy transition scenarios were created by the
different parties to promote their own vision of France’s energy landscape, and these scenarios
were ultimately grouped into four representative scenarios.

¹⁵ Loi 2015-992 du 17 août 2015 relative à la transition énergétique pour la croissance verte.

Table 4: Description of the DNTE scenarios

Scenario name	Scenario description	Demand	Nuclear Share
Sobriety (SOB)	A strong energy efficiency and sobriety reduce power demand. Nuclear and fossil fuels are phased out.	Strong decrease	Full phase-out
Efficiency (EFF)	Ambitious energy efficiency targets and diversification of power sources	Slight decrease	Decrease to 50% in 2030 and 25% in 2040
Diversification (DIV)	Diversification of power sources	Slight increase	Decrease to 50% from 2030 onwards
Decarbonation (DEC)	High power demand due to increase electrification and high nuclear share	Strong increase	Full retrofit

745 These four scenarios represent the different views that existed in 2012, and they have been structuring the French debate on nuclear ever since. Quantitatively, each scenario can be defined by two criteria: demand level and nuclear share. The rationale of each representative scenario is summarized in table 4 and more information can be found in fig. 9 and in Arditi et al. (2013).

6.2. Robust vs official scenarios

750 Based on this information on demand levels and nuclear shares, we can find which strategy among the 27 studied in this paper would best represent each official scenario. The DEC scenario corresponds to a retrofit of all nuclear plants. The SOB scenario is a scenario of full phase-out. Thus, their equivalent strategies are S27 and S1 respectively. But a methodology is required to determine the equivalent strategy of the EFF and DIV scenarios. To that end, we combine the information on nuclear share and demand level in each scenario to deduct the annual nuclear 755 power generation in 2020, 2030 and 2040. Generation is used as a proxy to estimate the number of retrofitted plants. For each scenario of the DNTE, we compare the nuclear production with the nuclear production in each of the 27 strategies, using the demand level corresponding to the DNTE scenario. We compute the distance using three difference norms: Euclidean, Taxicab and Infinity, in order to find the best match.

760 With this methodology, the best matches SOB and DEC are S1 (no retrofit) and S27 (full retrofit) respectively, as expected. The best match for DIV is S25 for the three norms (closing the 20 oldest reactors). The best match for EFF is S7, S11 or S13 depending on the norm, which means closing 40 reactors in each case but with variation in the timing. The correspondence between DNTE scenarios and our 27 strategies is shown in figure 10 in appendix.

765 Now that we have identified which strategy matches each scenario of the DNTE, we can build on our previous analysis and conclude that two of the DNTE scenarios offer interesting trade-offs. In particular, DIV (S25) has been identified as a robust strategy by closing 20 reactors. EFF is not a robust strategy, but it offers interesting trade-offs as it is almost on the efficiency frontier shown in figure 5. On the contrary, the two other scenarios SOB and DEC seem less robust. They 770 may provide a good option in some futures, but also risk to incur large losses in other plausible

futures: the DEC scenario is vulnerable to a decreasing demand, and the SOB scenario bets on the high end of retrofitting cost (cf. appendix G).

In addition to evaluating the vulnerabilities of existing official scenarios, applying the RDM methodology has revealed a new option: closing about 10 of the oldest reactors. By exploring 27
775 initial strategies - instead of the 2 to 4 scenarios often considered in policy-making - we were able to highlight this new path, which is in-between the DIV and DEC scenarios.

The DNTE scenarios allowed an open debate with all policy options on the table, ranging from a full retrofit to an entire phase-out of all nuclear plants. Here, the search for robust strategies provides a narrower road for the years to come: closing 10 to 20 of the oldest reactors, and
780 retrofitting the rest of them. These results could contribute to the public debate in France, in particular with respect to the retrofit of the nuclear plants of Fessenheim, Bugey and Tricastin.

7. Conclusion

After the first oil shock, France launched the world's largest nuclear program, ordering 36 reactors within three years, and 58 reactors in total. These reactors are now reaching the end
785 of their technological lifetime. But extending these lifetimes requires an investment up to 100 billion euros by 2030. France is thus at a crossroads and must define a new nuclear policy. The economics of this decision crucially depend on several parameters, in particular the future costs of nuclear (including decommissioning, waste and insurance) and renewable energies, demand levels and carbon price, all of which are subject to significant uncertainty.

In face of all these uncertainties, we apply the framework of Robust Decision Making to find a robust strategy indicating which plants should be retrofitted. Based on nearly 8,000 runs and an analysis of 27 strategies, the RDM methodology revealed that the robust strategies imply the early phase-out of 10 to 20 reactors. We also assessed the vulnerabilities and alternatives of these strategies, as well as the potential trade-offs with other strategies. Our approach keeps
795 the debate open: we highlight that several options exist depending on the implicit probabilities of decision-makers. But considering the current estimates of cost, demand and carbon price, the aforementioned robust strategies seem to have the least regret.

Our work highlights the vulnerabilities of the official French government scenarios which stem from the national debate, and reveals new robust strategies. It provides a timely contribution to the
800 debate on nuclear in France and in other countries where the decision to retrofit or decommission nuclear power plants is discussed.

Our methodology focuses on the economic costs and could be enriched by complementary analyses to include other key elements. The final decision of which power plants to close should also include safety aspects (which plants have aged better), as well as distributional and political
805 consideration, such as the risks of financial losses for companies, public perception (Cardin et al., 2017) and employment impacts (Garrett-Peltier, 2017). Furthermore, we only tested 27 strategies out of the 2^{58} possible options. Our sample was chosen to be representative of the main paths, but studying more strategies might help refine our results, and may even bring up other robust strategies.

This framework could be used iteratively in the future. Each time the decision to retrofit a nuclear plant has to be made, the same analysis could be run. The advantage would be to benefit from the latest information on costs, the level of electricity demand or the social cost of carbon. Even then, any strategy of nuclear fleet management will involve trade-offs and risks. The
810

815 decision-maker and stakeholders should therefore pay particular attention to understanding them
and making them explicit, in order to minimize the inevitable vulnerabilities and contribute to
public debate.

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Appendix A Plausible costs of retrofitted plants

Table 5: Historical values of French nuclear plants in the literature, in the best case

Item	Value	Unit	Source
Historical OPEX	13.3	euro/MWh	Boccard, 2014
Fuel	5.7	euro/MWh	Cour des Comptes, 2014, p. 13
Waste	3.6		Cour des Comptes, 2014, p. 24
Decommissioning	1		Cour des Comptes, 2014, p. 24
Capital rate	5	%	
Lifetime extension	20	years	
availability	83.5	%	

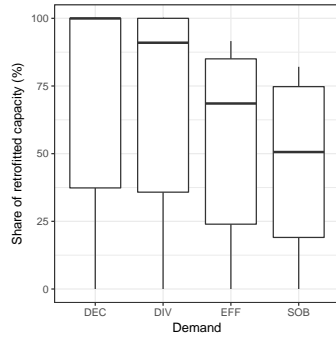
Table 6: Retrofit costs according to EDF

Item	Value	Unit
Additional CAPEX	74.73	billion euros
Additional OPEX	25.16	billion euros
Capacity concerned	53.2	GW

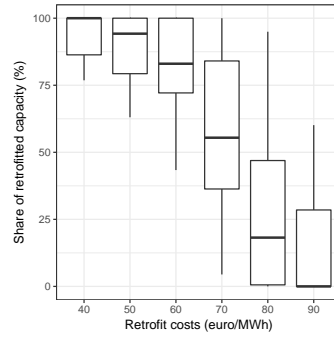
Table 7: Sensitivity tests: upper end used for nuclear costs. The variations are calculated compared to the baselines indicated in table 5.

Item	Value	Unit
CAPEX	30	%
Historical OPEX	27.5	euro/MWh
Capital rate	10	%
Lifetime extension	10	years
Availability	70	%
Waste	x2	
Decommissioning	x2	
Insurance	8.5	euro/MWh

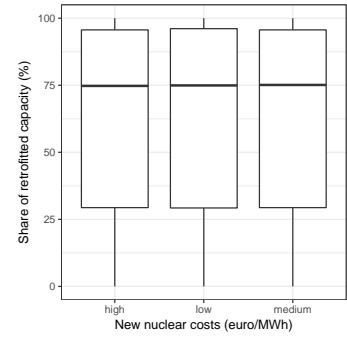
Appendix B Sensitivity analysis of runs with the FLORE model



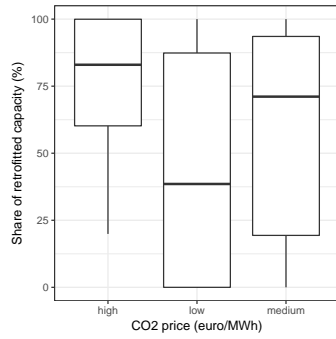
(a) Impact of demand



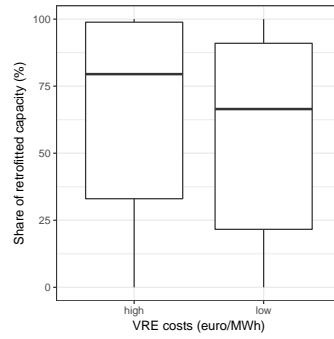
(b) Impact of retrofitting costs



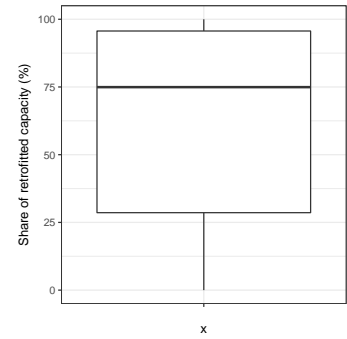
(c) Impact of new nuclear costs



(d) Impact of CO2 price



(e) Impact of VRE costs



(f) Variation across all scenarios

Figure 6: Variations of the optimal share of retrofitted nuclear capacity

Appendix C Strategies examined

Table 8: Detail of the 27 strategies

Strategy	Oldest reactors	Intermediate reactors	Newest reactors
S1	no retrofit	no retrofit	no retrofit
S2	half retrofit	no retrofit	no retrofit
S3	full retrofit	no retrofit	no retrofit
S4	no retrofit	half retrofit	no retrofit
S5	half retrofit	half retrofit	no retrofit
S6	full retrofit	half retrofit	no retrofit
S7	no retrofit	full retrofit	no retrofit
S8	half retrofit	full retrofit	no retrofit
S9	full retrofit	full retrofit	no retrofit
S10	no retrofit	no retrofit	half retrofit
S11	half retrofit	no retrofit	half retrofit
S12	full retrofit	no retrofit	half retrofit
S13	no retrofit	half retrofit	half retrofit
S14	half retrofit	half retrofit	half retrofit
S15	full retrofit	half retrofit	half retrofit
S16	no retrofit	full retrofit	half retrofit
S17	half retrofit	full retrofit	half retrofit
S18	full retrofit	full retrofit	half retrofit
S19	no retrofit	no retrofit	full retrofit
S20	half retrofit	no retrofit	full retrofit
S21	full retrofit	no retrofit	full retrofit
S22	no retrofit	half retrofit	full retrofit
S23	half retrofit	half retrofit	full retrofit
S24	full retrofit	half retrofit	full retrofit
S25	no retrofit	full retrofit	full retrofit
S26	half retrofit	full retrofit	full retrofit
S27	full retrofit	full retrofit	full retrofit

Appendix D Model documentation

1005 D.1 Overview

The French power model FLORE is a dispatch and investment model of the French power mix. It is a partial equilibrium model of the wholesale electricity market, which determines optimal investment and hourly generation.

1010 FLORE minimizes total cost with respect to investment and production under a set of constraints. The model is linear, deterministic, and solved in hourly time step for each year, from 2015 to 2050.

1015 Generation is modelled as twelve distinct technologies: three VRE with zero marginal costs - onshore wind, offshore wind and solar, three fossil-based thermal technologies - coal, combined cycle gas turbine (CCGT), open cycle gas turbine (OCGT), three nuclear technologies (historical nuclear, retrofitted nuclear and new nuclear), and three hydro systems - run-of-river, conventional dams (lakes) and pumped storage. Hourly VRE generation is limited by specific generation profiles. Dispatchable power plants produce whenever the price is above their variable costs, and unless they are limited by their ramping constraints. Hydro storage and dispatch are optimized by the model, under water reservoir constraints and pumping losses. At the end its lifetime, each capacity is decommissioned.

1020 A particularity of the model is to represent explicitly the cost of extending the lifetime of nuclear power plants. Nuclear plants normally close after 40 years, but their lifetime can be extended to 60 years, if upgrade costs are paid for.

Demand is exogenous and assumed to be perfectly price inelastic at all times.

1025 FLORE is currently calibrated for France. Exports are given exogenously.

D.2 Total System Costs

The model minimizes total system costs C with respect to several constraints and decision variables. Total system costs are the sum of fixed costs (representing the sum of capital and fixed O&M costs), and variable costs, over all hours h , weeks w , years y and generation technologies tec .

Fixed costs are the product of the capacity installed $CAPA_{tec,y}$ for each technology in year y , by its annualized capacity cost c_{tec}^{inv} plus fixed O&M costs c_{tec}^{fix} . Variable generation costs are the product of $GENE_{tec,w,y,h}$, the generation from technology tec in year y , week w and hour h , by variable generation costs c_{tec}^{var} .

$$C = \sum_{tec,y} CAPA_{tec,y} \cdot (c_{tec}^{inv} + c_{tec}^{fix}) + \sum_{tec,y,w,h} GENE_{tec,y,w,h} \cdot c_{tec}^{var} \quad (1)$$

1030 Throughout this model description, capital letters denote choice variable for the model, while lowercase letters denote exogenous data.

D.3 Supply and demand

Power balance between supply and demand is the central constraint of the model. Demand is the sum of national load d , pumping for pumped-storage hydro $PUMP$ and exports flow $flows$. Supply is the sum of generation over all technologies.

$$\forall h, y \quad \sum_{tec} GENE(tec, h, y) \geq \sum_{tec} LOAD(h, y) + PUMP(h, y) + flow(h, y)$$

In this framework, demand is perfectly price-inelastic. Cost minimization is thus equivalent to welfare-maximization.

Generation is constrained by capacities installed and the load factor (also called availability), for all technologies except wind, PV and run-of-river hydro, which present a specific generation profile.

$$GENE(tec_noprof, y, w, h) \leq CAPA(tec_noprof, y) * loadfactor(tec_noprof)$$

For wind and PV, a generation profile is an additional constraint:

$$GENE(tec_res, y, w, h) \leq CAPA(tec_res, y) * res_profiles(h, tec_res)$$

For run-of-river hydro, generation is fixed exogenously for each week:

$$GENE("river", y, w, h) = river_flow(w)$$

Investment is exogenous for historical nuclear and the three hydro technologies. The capacity of historical nuclear technology is decreasing based on plant-level data, with each plant capacity being phased-out when it reaches 40 years old. For hydro, we assume constant capacities for run-of-river and lakes. Pumped-hydro potential is expected to grow by 3.2GW by 2050, starting from 5 GW in 2014, with a discharge time of 20 hours, as in ADEME (Visions ADEME 2030).

$$CAPA(tec_ex, y) = capa_exo(y, tec_ex)$$

The capacity of all other technologies is determined endogenously by the model. Capacity is installed when optimal, and then decommissioned when it reaches its lifetime. The initial capacity, already installed in 2015, is supposed to be decommissioned linearly from 2015 onwards in a period of 40 years.

$$\begin{aligned} CAPA(tec_end, y + 1) &= CAPA(tec_end, y) + INVE(tec_end, y) - DECO(tec_end, y) \\ DECO(tec_end, y) &= INVE(tec_end, y - lifetime(tec_end)) + \\ &\quad (tec_data(tec_end, 'initcap')/40) * (ord(y) <= 40) \end{aligned}$$

1035 D.4 Power System Inflexibilities

The model includes ramp-up and ramp-down constraints for nuclear and coal power plants, to represent the fact that generation cannot vary too quickly from one hour to the next. These constraints are modelled as a maximum variation rate: The ramp up constraint is:

$$\forall tec_ramp, y, w, h \quad GENE(tec_ramp, y, w, h + 1) \leq GENE(tec_ramp, y, w, h) * (1 + ramp_rate)$$

The ramp-down constraint is:

$$\forall tec_ramp, y, w, h \quad GENE(tec_ramp, y, w, h + 1) \geq GENE(tec_ramp, y, w, h) * (1 - ramp_rate)$$

We take the value of 0.08 for coal and 0.05 for nuclear - for both ramp-up and ramp-down, as in ADEME (2015).

D.5 Reserve requirements

We following ENTSO-E guidelines as to the sizing of reserve requirements. The method for
1040 sizing is well explained in Stiphout et al. (2016). It is based on a probabilistic approach of the
error forecasts. The total FRR requirement is equal to the 99% quantile of the probability density
function of the normalized forecast errors. It gives the required amount of capacity of FRR per
unit of VRE installed capacity.

$$\forall y, w, h \quad \sum_{tec_dispa} RES(tec_dispa, y, w, h) = \sum_{tec_vre} \epsilon(tec_vre) * CAPA(tec_vre, y)$$

Numerically, for the year 2015, we find the following values for ϵ : 0.027 for onshore, and 0.038
1045 for PV.

Appendix E Model Calibration

Table 9: Investment costs

euros/kW	onshore	PV	Coal	CCGT	TAC	river	lake	pump	nuc_hist	nuc_renov	nuc_new
2014	1650	1560	1500	800	400	3000	2000	2000	1320	1938	6000
2020	1572	1194	1500	800	400	3000	2000	2000	1320	1938	6000
2030	1443	869	1500	800	400	3000	2000	2000	1320	1938	6000
2040	1313	735	1500	800	400	3000	2000	2000	1320	1938	6000
2050	1184	600	1500	800	400	3000	2000	2000	1320	1938	6000

Table 10: Fixed O&M costs

euro/MWh	onshore	PV	Coal	CCGT	TAC	river	lake	pump	nuc_hist	nuc_renov	nuc_new
2014	35	25	30	20	15	60	60	20	188	188	100
2020	35	25	30	20	15	60	60	20	188	188	100
2030	35	25	30	20	15	60	60	20	188	188	100
2040	35	25	30	20	15	60	60	20	188	188	100
2050	35	25	30	20	15	60	60	20	188	188	100

Table 11: CO₂ price

Year	CO ₂ price		
	Central	Low	High
2014	21	10	42
2020	28	14	56
2030	50	25	100
2040	75	38	150
2050	100	50	200

Table 12: Fuel prices

euro/MWh	Coal	Gas	Uranium
2014	10,3	25,3	7,30

Table 13: Efficiencies

Coal	CCGT	TAC
0,43	0,61	0,410

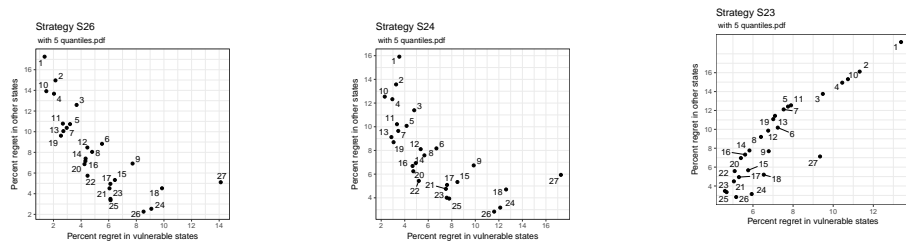
Appendix F Analysis with PRIM

F.1 Efficiency frontier



(a) With the cluster from S25 (b) With the cluster from S24 (c) With the cluster from S23 or S25

Figure 7: Trade-offs and efficiency frontier using the PRIM-generated clusters with upper-quartile regret



(a) With the cluster from S25 (b) With the cluster from S24 (c) With the cluster from S23 or S25

Figure 8: Trade-offs and efficiency frontier using the PRIM-generated clusters with upper-quintile regret

F.2 Sensitivity of the threshold

Table 14: Vulnerabilities of candidate strategies and threshold sensitivity. The italicized strategies are the strategies on the low-regret frontier

Candidate Strategy	Upper-quartile	Upper-quintile
S26	retrofit > 65 €/MWh low CO ₂ price <i>S1, S10, S19, S22, S23 and S26</i>	retrofit > 65 €/MWh low to medium CO ₂ price <i>S1, S10, S19, S22, S25 and S26</i>
S24	retrofit > 65 €/MWh low to medium CO ₂ price <i>S1, S10, S19, S22, S23 and S26</i>	retrofit > 65 €/MWh low demand (SOB) <i>S10, S13, S19, S22, S23, S25 and S26</i>
S23	low to medium CO ₂ price <i>S23 and S26</i>	low to medium CO ₂ price <i>S23, S25 and S26</i>
S25	low to medium CO ₂ price <i>S23 and S26</i>	low to medium CO ₂ price <i>S23, S25 and S26</i>

1050 **Appendix G Comparison with official scenarios: additional material**

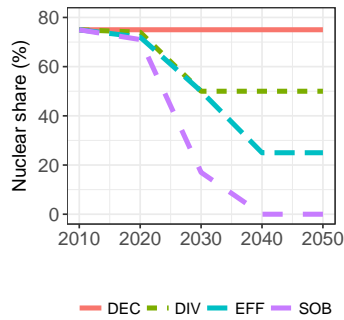


Figure 9: Nuclear share in the four official scenarios of the French national debate
Source: Arditi et al. (2013)

There are several norms which can be used to evaluate the deviation between our 27 strategies and the scenarios from the DNTE. Here, we consider three of them: the Euclidean norm, the taxicab norm and the infinity norm. The results are shown in table 15. The three norms give the same results, except for the "EFF" scenario. For this scenarios, the three norms indicates a strategy which implies to retrofit 20 reactors, but the timings vary.

1055

Dnte scneario	Euclidean	Taxicab	Infinity
DEC	S27	S27	S27
DIV	S25	S25	S25
EFF	S13	S7	S11
SOB	S1	S1	S1

Table 15: Closest match, according to three norms, between the DNTE scenarios and our strategies

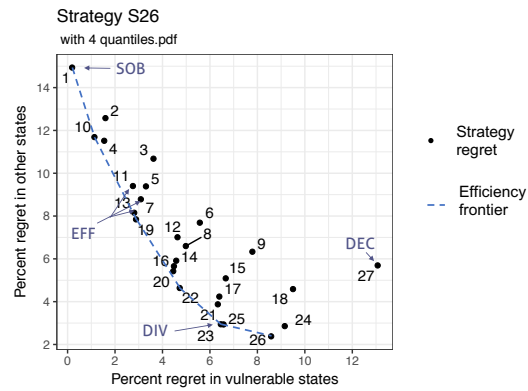


Figure 10: Correspondence between our 27 strategies and the Dnte scenarios



(a) Impact of retrofit cost on the SOB scenario

(b) Impact of demand on the DEC scenario

Figure 11: Vulnerabilities of DNTE scenarios