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Low-carbon options for the French power sector: What role for renewables, nuclear energy and carbon capture and storage?

Behrang SHIRIZADEH 1,2*, Philippe QUIRION 1

Abstract

In the wake of the Paris agreement, France has set a zero net greenhouse gas emission target by 2050. This target can only be achieved by rapidly decreasing the share of fossil fuels and accelerating the deployment of low-carbon technologies. We develop a detailed model of the power sector to investigate the role of different low emission and negative emission technologies in the French electricity mix and we identify the impact of the relative cost of these technologies for various values of the social cost of carbon (SCC).

We show that for a wide range of SCC values (from 0 to $500 \notin tCO_2$), the optimal power mix consists of roughly 75% of renewable power. For a SCC value of $100 \notin tCO_2$, the power sector becomes nearly carbon neutral while for $200 \notin tCO_2$ and more, it provides negative emissions. The availability of negative emission technologies can decrease the system cost by up to 18% and can create up to $20MtCO_2$ /year of negative emissions, while the availability of new nuclear is much less important. This study demonstrates the importance of an effective SCC value (as a tax for positive emissions and remuneration for negative emissions) to reach carbon neutrality for moderate costs. Negative emissions may represent an important carbon market which can attract investments if supported by public policies.

Keywords: Power system modelling; Variable renewables; Negative emissions; Social cost of carbon; Nuclear energy.

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1. Introduction¹

The 2015 Paris agreement aims at keeping the global average temperature increase well below 2°C and reaching a net balance between anthropogenic emissions by sources and removals by sinks of greenhouse gases by the second half of this century (UNFCCC 2015). Decarbonization of the power sector is particularly highlighted in the literature, since it is easier to decarbonize this sector than industry, transport and agriculture (Edenhofer et al 2015). To reach the goal of keeping global average temperature increase below 2°C, CO₂ emissions from the power sector must fall to zero or even below zero (Sanchez et al. 2016, Rogelj et al. 2015).

Several studies have shown that nuclear power, variable renewable energy (VRE) sources and carbon capture and storage (CCS) technologies are useful CO₂ mitigation options (Brouwer et al. 2016), and according to Rogelj et al. (2018), renewable energy sources (RES) will be the cornerstone of decarbonization, making, with CO₂ capture and storage, a greater contribution than nuclear energy and fossil fuels. Similarly, according to Waisman et al (2019), a drastic increase in renewable energy share in electricity (from 70% to 85% of electricity mix) is necessary in the power generation sector.

The official target presented in the energy-climate law by the French government is to reach zero net GHG emission by 2050 (MTES, 2019). While the French electricity sector is relatively decarbonized, the relative shares of renewable energy resources and nuclear power is a highly debated topic. With 63GW of installed capacity by the end of 2019, nuclear power dominates the electricity mix of France with a 70.6% of net electricity production in 2018 (CGDD, 2019). France is at the crossroads of the decision towards retrofitting the existing power plants and investing in new nuclear power plants, or slowly decreasing the share of nuclear power in favor of a renewable dominated power mix (DNTE, 2013).

There exists a wide range of prospective studies conducted by public authorities, companies and associations for France. Among the scenarios by associations and public authorities, we can highlight "100% renewable electricity mix" (ADEME, 2015) and "Electricity mix evolution trajectories for 2020-2060" (ADEME, 2018) by ADEME (French environment and development agency), "négaWatt scenario 2017-2050" (RTE 2017), "French national low carbon strategy" (SNBC, 2019) and "Projected adequacy report" by RTE (French transmission network operator) presenting four electricity mix scenarios for France (RTE, 2019).

¹ We thank the anonymous referee from the FAERE Working papers series for his/her very useful comments, which have significantly improved the paper.

Similarly, a very wide range of academic studies evaluate the optimal electricity mix of France by 2050. Krakowski et al. (2016) argue that increasing the RES share from 40% to 100% would lead to a twice more expensive power system (more than 60bn€/year vs. 30bn€/year), and similarly Villavicencio (2017) shows even a higher cost for a 100% RES power system (180bn€/year). These two latter studies' costs are equivalent to respectively 3 times and 9 times the current electricity price in France. On the other hand, both ADEME reports (ADEME, 2015 and ADEME, 2018) show that investing in new nuclear power plants is not an optimal choice and that in an optimal scenario, renewables will represent 85% and 95% of the electricity mix in 2050 and 2060 respectively. This highly renewable electricity is expected to cost less than the current electricity price (90€/MWh vs. 100€/MWh excluding the taxes).

The controversial findings for the existing literature for France raise the question of the impact of cost scenarios for the respective share of nuclear power and VRE technologies in the optimal power mix. Moreover, carbon capture and storage (CCS) and negative emission technologies such as bioenergy with carbon capture and storage (BECCS) are not included in any of the existing literature for France, while these technologies show promising potential of decarbonizing electricity sector. The special 1.5°C global warming report published by Intergovernmental Panel on Climate Change (IPCC, 2018) argues that "Significant near-term emissions reductions and measures to lower energy and land demand" is necessary to limit the carbon dioxide removal (CDR) technologies to a few hundred GtCO₂ without reliance on BECCS. Daggash et al. (2019) conclude that it is significantly cheaper to decarbonize the power sector using BECCS and DACCS (direct air carbon capturing and storage) than considering only VRE technologies with storage options (37% to 48% cheaper).

This paper aims to evaluate the relative role of renewable energy technologies, nuclear power and carbon capture and storage technologies, the impact of different cost scenarios in the optimal electricity mix and the integration of social cost of carbon (SCC) into these evaluations. To investigate these issues, we develop the EOLES_elec model, from the EOLES (Energy Optimization for Low Emission Systems) family of models, which considers only the power sector. The EOLES family of models optimizes simultaneously the dispatch (assuring an hourly supply-demand balance) and the investment in production and storage capacities, in order to minimize the total cost. The sensitivity of the optimal power mix to a wide range of SCC scenarios (from 0 to $500 \notin/tCO_2$) and to the future cost development of new nuclear power plants (from $3000 \notin/kW$ to $4500 \notin/kW$ of capital expenditures) and VREs (three main scenarios; low, central and high cost for wind and solar power) is studied.

The remainder of this paper is organized as follows. Section 2 consists of presentation of the methods; the EOLES_elec model with respect to its previous version and used input parameters. Results and discussion are presented in sections 3 and 4 while section 5 concludes the article.

2. Methods

2.1. EOLES_elec model

The EOLES family of models optimizes the investment and operation of an energy system in order to minimize the total cost while satisfying energy demand. EOLES_elec is the electricity version of this family of models. It minimizes the annualized power generation and storage costs, including the cost of connection to the grid. It includes eight power generation technologies: offshore and onshore wind power, solar photovoltaics (PV), run-of-river and lake-generated hydro-electricity, nuclear power (EPR, i.e. third generation European pressurized water reactors), open-cycle gas turbines and combined-cycle gas turbines equipped with post-combustion carbon capture and storage. The latter two generation technologies burn methane which can come from three sources: fossil natural gas, biogas from anaerobic digestion and renewable gas from power-to-gas technology (methanation). EOLES_elec also includes four energy storage technologies: pumped-hydro storage (PHS), Li-Ion batteries and two types of methanation. These technologies are shown in Figure 1.

The main simplification assumptions in the EOLES_elec model are as following; it considers continental France as a single node, demand is inelastic, and the optimization is based on full information about the weather and electricity demand. This model uses only linear optimization: non-linear constraints might improve accuracy, especially when studying unit commitment, however they entail significant increase in computation time. Palmintier (2014) has shown that linear programming provides an interesting trade-off, with little impacts on cost, CO2 emissions and investment estimations, but a speed-up by up to x1500. The model is written in GAMS and solved using the CPLEX solver. The code and data are available on Github.¹

¹ <u>https://github.com/BehrangShirizadeh/EOLES_elec</u>



Figure 1 Graphical description of the EOLES_elec model

2.1.1. Objective function

The objective function, shown in Equation (1), is the sum of all costs over the chosen period, including the annualized investment costs as well as the fixed and variable O&M costs. For some storage options, two CAPEX-related costs are accounted for: one proportional to the charging capacity in \notin/kW_e $(capex_{str}^{ch})$, the second proportional to the energy capacity in $\notin/kWh_e(annuity_{str}^{en})$.

$$COST = \left(\sum_{tec} [(Q_{tec} - q_{tec}^{ex}) \times annuity_{tec}] + \sum_{str} (VOLUME_{str} \times annuity_{str}^{en}) + \sum_{tec} (Q_{tec} \times fO\&M_{tec}) + \sum_{str} (S_{str} \times (capex_{str}^{ch} + fO\&M_{str}^{ch})) + \sum_{tec} \sum_{h} (G_{tec,h} \times (vO\&M_{tec} + e_{tec}SCC_{CO_2})))/$$

$$1000 \quad (1)$$

where Q_{tec} represents the production capacities, q_{tec}^{ex} represents the existing capacity (notably for hydro-electricity technologies with high lifetime), $VOLUME_{str}$ is the energy storage capacity in GWh, S_{str} is the storage capacity in GW, *annuity* is the annualized investment cost, fO&M and vO&Mrespectively represents fixed and variable operation and maintenance costs, $G_{tec,h}$ is the hourly generation of each technology, $capex_{str}^{ch}$ is the charging annualized investment cost and $fO\&M_{str}^{ch}$ is the charging fixed operation and maintenance cost of the storage technology str, e_{tec} is the specific emission of each technology in tCO2/GWh of power production and SCC_{CO_2} is the social cost of carbon in ℓ tCO2.

2.1.2. Adequacy equation

Electricity demand must be met for each hour. If power production exceeds electricity demand, the excess electricity can be either sent to storage units or curtailed (equation 3).

$$\sum_{tec} G_{tec,h} \ge demand_h + \sum_{str} STORAGE_{str,h}$$
(3)

Where $G_{tec,h}$ is the power produced by technology *tec* at hour *h* and $STORAGE_{str,h}$ is the energy entering the storage technology *str* at hour *h*.

2.1.3. Variable renewable power production

For each variable renewable energy (VRE) technology, for each hour, the hourly power production is given by the hourly capacity factor profile multiplied by the installed capacity available (equation 4).

$$G_{vre,h} = Q_{vre} \times cf_{vre,h} \tag{4}$$

Where $G_{vre,h}$ is the electricity produced by each VRE resource at hour *h*, Q_{vre} is the installed capacity and $cf_{vre,h}$ is the hourly capacity factor.

2.1.4. Energy storage

Energy stored by storage option *str* at hour h+1 is equal to the energy stored at hour h plus the difference between the energy entering and leaving the storage option at hour h, accounting for charging and discharging efficiencies (equation 5):

$$STORED_{str,h+1} = STORED_{str,h} + (STORAGE_{str,h} \times \eta_{str}^{in}) - \left(\frac{G_{str,h}}{\eta_{str}^{out}}\right)$$
(5)

Where $STORED_{str,h}$ is the energy in storage option str at hour h, while $\eta_{str}^{in} \in [0,1]$ and $\eta_{str}^{out} \in [0,1]$ are the charging and discharging efficiencies.

2.1.5. Secondary reserve requirements

Three types of operating reserves are defined by ENTSO-E (2013), depending on their activation speed. The fastest reserves are Frequency Containment Reserves (FCRs), which must be able to be on-line within 30 seconds. The second group is made up of Frequency Restoration Reserves (FRRs), in turn divided into two categories: a fast, automatic component (aFRRs), also called 'secondary reserves', with an activation time of no more than 7.5 min; and a slow manual component (mFRRs), or 'tertiary reserves', with an activation time of no more than 15 min. Finally, reserves with a startup-time beyond 15 minutes are classified as Replacement Reserves (RRs).

Each category meets specific system needs. The fast FCRs are useful in the event of a sudden break, like a line fall, to avoid system collapse. FRRs are useful for variations over several minutes, such as a decrease in wind or PV output. Finally, the slow RRs act as a back-up, slowly replacing FCRs or FRRs when the system imbalance lasts more than 15 minutes.

In the model we only consider FRRs, since they are the most impacted by VRE integration. FRRs can be defined either upwards or downwards, but since the electricity output of VREs can be curtailed, we consider only upward reserves.

The quantity of FRRs required to meet ENTSO-E's guidelines is given by equation (6). These FRR requirements vary with the variation observed in the production of renewable energies. They also depend on the observed variability in demand and on forecast errors:

$$\sum_{frr} RSV_{frr,h} = \sum_{vre} (\varepsilon_{vre} \times Q_{vre}) + demand_h \times (1 + \delta_{variation}^{load}) \times \delta_{uncertainty}^{load}$$
(6)

Where $RSV_{frr,h}$ is the required hourly reserve capacity from each of the reserve-providing technologies (dispatchable technologies) indicated by the subscript *frr*; ε_{vre} is the additional FRR requirement for VRE because of forecast errors, $\delta_{variation}^{load}$ is the load variation factor and $\delta_{uncertainty}^{load}$ is the uncertainty factor in the load because of hourly demand forecast errors. The method for calculating these various coefficients according to ENSTO-E guidelines is detailed by Van Stiphout et al. (2017).

2.1.6. Power production related constraints

The relationship between hourly-generated electricity and installed capacity can be calculated using equation (7). Since the chosen time slice for the optimization is one hour, the capacity enters the equation directly instead of being multiplied by the time slice value.

$$G_{tec,h} \le Q_{tec}$$
 (7)

The installed capacity of all the dispatchable technologies should be more than the electricity generation required of those technologies to meet demand; it should also satisfy the secondary reserve requirements Installed capacity for dispatchable technologies can therefore be expressed by equation (8).

$$Q_{frr} \ge G_{frr,h} + RSV_{frr,h} \tag{8}$$

Monthly available energy for the hydroelectricity generated by lakes and reservoirs is defined using monthly lake inflows (equation 9). This means that energy stored can be used within the month but not across months. This is a parsimonious way of representing the non-energy operating constraints faced by dam operators, as in Perrier (2018). The French transmission system operator RTE (ref) uses the same assumption.

$$lake_m \geq \sum_{h \in m} G_{lake,h}$$
 (9)

Where $G_{lake,h}$ is the hourly power production by lakes and reservoir, and $lake_m$ is the maximum electricity that can be produced from this energy resource during one month.

Run-of-river power plants represent another source of hydro-electricity power. River flow is also strongly dependent on meteorological conditions and it can be considered as a variable renewable energy resource. We define the hourly capacity factor profile of this energy resource as $river_h$ in equation (10);

$$G_{river,h} = Q_{river} \times river_h$$
 (10)

As shown in Figure 1, in addition to natural gas, two renewable gas technologies are considered; biogas and methanation. They can be sent either to the OCGT power plants with high operational flexibility, with no emissions for renewable gas, or to the CCGT power plants equipped with post-combustion CCS where renewable gas technologies have negative emissions and the natural gas residual positive emissions. Equations (11) and (12) show these two power plants' operation with each of three gas production technologies;

$$G_{ocgt,h} = G_{biogas1,h} + G_{methanation1,h} + G_{ngas1,h}$$
(11)

Where $G_{biogas1,h}$ and $G_{methanation1,h}$ are the power production from each of two combustible renewable gas resources by OCGT, $G_{ngas1,h}$ is the power production from natural gas in OCGT, and $G_{ocgt,h}$ is the power production from the OCGT power plant which uses these three resources as fuel. The efficiency of this combustion process is taken into account for power production from biogas, natural gas and the discharge efficiency of the methanation process, so capacities and production are expressed in electrical MW (MW_e) and TWh (TWh_e).

$$G_{ccgt-ccs,h} = G_{biogas2,h} + G_{methanation2,h} + G_{ngas2,h}$$
(12)

Where $G_{biogas2,h}$ and $G_{methanation2,h}$ are the power production from each of two combustible renewable gas resources, $G_{ngas2,h}$ is the power production from natural gas and $G_{ccgt-ccs,h}$ is the power production from the CCGT power plant combined with post-combustion CCS which uses these three fuels.

The OCGT power plants are chosen because of their high ramping rates, and consequently their higher load following capability. Since in the study used for cost assumptions (JRC 2017) the only postcombustion CCS technology for gas power plant was the combination of CCGT and CCS, CCGT power plants are considered to be the gas plants equipped with post-combustion CCS technology.

Equation (13) limits the yearly power production from biogas (with and without CCS), where e_{biogas}^{max} is the maximal yearly power that can be produced from biogas;

$$\sum_{h=0}^{8759} G_{biogas1,h} + \sum_{h=0}^{8759} G_{biogas2,h} \le e_{biogas}^{max}$$
(13)

For open-cycle and combined-cycle gas turbines, there are some safety- and maintenance-related breaks. Equations (14) and (15) limit the yearly power production for each of these plants to their maximum yearly capacity factors;

$$\sum_{h} G_{ocgt,h} \leq Q_{ocgt} \times cf_{ocgt} \times 8760 \quad (14)$$
$$\sum_{h} G_{ccgt-ccs,h} \leq Q_{ccgt-ccs} \times cf_{ccgt} \times 8760 \quad (15)$$

Where cf_{ocgt} and cf_{ccgt} are the capacity factors of OCGT and CCGT power plants.

The maximum installed capacity of each technology depends on land-use-related constraints, social acceptance, the maximum available natural resources and other technical constraints; therefore, a technological constraint on maximum installed capacity is defined in equation (16) where q_{tec}^{max} is this capacity limit;

$$Q_{tec} \leq q_{tec}^{max}$$
 (16)

2.1.7. Nuclear power related constraints

Addition of nuclear power plants to the model brings three main constraint type equations: ramping up and ramping down rates (because we allow these plants to be used in load-following mode, Loisel et al., 2018) and the yearly maximal capacity factor.

Nuclear power plants have limited flexibility, so definitions of hourly ramp-up and ramp-down rates are essential for accurate modelling of nuclear power plants. Equations (17) and (18) limit the power production of nuclear power plants with these ramping constraints;

$$G_{nuc,h+1} + RSV_{nuc,h+1} \le G_{nuc,h} + r_{nuc}^{up} \times Q_{nuc}$$
(17)
$$G_{nuc,h+1} \ge G_{nuc,h}(1 - r_{nuc}^{down})$$
(18)

Where $G_{nuc,h+1}$ is the nuclear power production at hour h + 1, $G_{nuc,h}$ is the nuclear power production at hour h, $RSV_{nuc,h+1}$ is the reserve capacity provided by nuclear power plants at hour h + 1 and r_{nuc}^{up} and r_{nuc}^{down} are the ramp-up and ramp-down rates for the nuclear power production.

Nuclear power plants' capacity factor also should be limited with the safety and maintenance constraints. Equation (19) quantifies this limitation;

$$\sum_{h} G_{nuc,h} \le Q_{nuc} \times cf_{nuc} \times 8760$$
(19)

Where cf_{nuc} is the maximum yearly capacity factor of nuclear power plants.

2.1.8. Storage related constraints

To prevent optimization leading to a very high amount of stored energy in the first hour represented and a low one in the last hour, we add a constraint to ensure the replacement of the consumed stored electricity in every storage option (equation 20):

$$STORED_{str,0} = STORED_{str,8759} + (STORAGE_{str,8759} \times \eta_{str}^{in}) - (\frac{G_{str,8759}}{\eta_{str}^{out}})$$
(20)

While equations (5) and (20) define the storage mechanism and constraint in terms of power, we also limit the available volume of energy that can be stored by each storage option (equation 21):

$$STORED_{str,h} \leq VOLUME_{str}$$
 (21)

Equation (22) limits the energy entry to the storage units to the charging capacity of each storage unit. Similarly, we consider a charging capacity lower than or equal to discharging capacity (mainly to limit the charging capacity of batteries) which means that the charging capacity cannot exceed the discharging capacity.

$$STORED_{str,h} \leq S_{str} \leq Q_{str}$$
 (22)

2.2. Input parameters

2.2.1. VRE profiles

Variable renewable energies' (offshore and onshore wind and solar PV) hourly capacity factors have been prepared using the renewables.ninja website¹, which provides the hourly capacity factor profiles of solar and wind power from 2000 to 2018 at the geographical scale of French counties (*départements*), following the methods elaborated by Pfenninger and Staffell (2016) and Staffell and Pfenninger (2016). These renewables.ninja factors reconstructed from weather data provide a good approximation of observed data: Moraes et al. (2018) finds a correlation of 0.98 for wind and 0.97 for solar power with the observed annual duration curves (in which the capacity factors are ranked in descending order of magnitude) provided by the French transmission system operator (RTE).

To prepare hourly capacity factor profiles for offshore wind power, we first identified all the existing offshore projects around France using the "4C offshore" website², and using their locations, we extracted the hourly capacity factor profiles of both floating and grounded offshore wind farms. The Siemens SWT 4.0 130 has been chosen as the offshore wind turbine technology because of recent increase in the market share of this model and its high performance. The hub height of this turbine is set to 120 meters.

Appendix 1 provides more information about the methodology used in the preparation of hourly capacity factor profiles of wind and solar power resources.

2.2.2. Electricity demand profile

Hourly electricity demand is ADEME's (2015) central demand scenario for 2050. This demand profile falls in the middle of the four proposed demand scenarios for 2050 in France during the national debates on the French energy transition (DNTE, 2013). It amounts to $422 TWh_e$ /year, 12% less than the average power consumption in the last 10 years. It takes into account foreseeable change in the demand profile up to 2050, including a reduced demand for lighting and heating and an increased demand for air conditioning and electric vehicles.

2.2.3. Limiting capacity and power production constraints

Similar to the 100% version of EOLES model, we use the maximal capacities of VRE technologies from ADEME (2018), the maximal and existing hydro-electricity capacities from ADEME (2015), and the run-

¹ <u>https://www.renewables.ninja/</u>

² <u>https://www.4coffshore.com/</u>

of-river and lake-generated hydro-electricity profiles from RTE's (the French transmission network operator) online portal for year 2016¹.

2.2.4. Economic parameters

Table 1 summarizes the economic parameters (and their sources) used as input data in EOLES model;

Technology	Overnight	Lifetime	Annuity	Fixed O&M	Variable	Construction	Efficiency	Source
	costs	(years)	(€/kWe/year)	(€/kW _e /year)	0&M	time (years)	(%)	
	(€/kWe)				(€/MWh _e)			
Offshore wind	2330	30	150.9	47	0	1	-	JRC (2017)
farm*								
Onshore wind	1130	25	81.2	34.5	0	1	-	JRC (2017)
farm*								
Solar PV*	423	25	30.7	9.2	0	0.5	-	JRC (2017)
Hydroelectricity –	2275	60	115.2	11.4	0	1	-	JRC (2017)
lake and reservoir								
Hydroelectricity –	2970	60	150.4	14.9	0	1	-	JRC (2017)
run-of-river								
Biogas	2510	25	141.6	83.9	3.1	1	-	JRC (2017)
(Anaerobic								
digestion)								
Natural gas	-	-	-	-	50/61**	-	-	IEA (2018)
Nuclear power	3750	60	262.6	97.5	9.5***	10	38%	JRC (2014)
CCGT with CCS	1280	30	82.1	32	18****	1	55%	JRC (2017)
OCGT	550	30	35.3	16.5	-	1	45%	JRC (2014)

Table 1 Economic parameters of power production technologies

*For offshore wind power on monopiles at 30km to 60km from the shore, for onshore wind power, turbines with medium specific capacity (0.3kW/m²) and medium hub height (100m) and for solar power, an average of the costs of utility scale, commercial scale and residential scale systems without tracking are taken into account. In this cost allocation, we consider solar power as a simple average of ground-mounted, rooftop residential and rooftop commercial technologies. For lake and reservoir hydro we take the mean value of low-cost and high-cost power plants.

**50€/MWh-e for CCGT power plants with 55% efficiency, and 61€/MWh for OCGT power plants with 45% efficiency (accounting for 9\$/MBtu, projected for Europe for the year 2040 by IEA in the World Energy Outlook 2018).

***This variable cost accounts for 2.5€/MWh-e of fuel cost and 7€/MWh of other variable costs, excluding the waste management and insurance costs.

****this variable cost accounts for a 500km CO₂ transport pipeline and offshore storage costs estimated by Rubin et al. (2015).

¹ <u>https://www.rte-france.com/fr/eco2mix/eco2mix-telechargement</u>

Construction time accounts for the date the first expenditures are spent on public works, until the last day of construction and tests, when the plant starts operation; therefore, the local authorities' admission process and the preliminary business studies are not considered in this period.

The economic parameters are exogenous. This assumption is debatable especially for technology costs, which, in the real world, depend on the installed capacity (learning-by-doing effect). Since these costs depend on the capacity installed worldwide rather than in France only, we do not model this effect.

It is worth mentioning that the annuity includes the interest during construction (IDC) respective to the construction time, and the decommissioning cost for nuclear power plants. The construction time for nuclear power plants can take as little as 7 years, while the three projects of Olkiluoto in Finland, Hinkley Point C in the UK and Flamanville 3 in France show much longer construction times. According to NEA (2018), an average construction time of 10 years can be considered for new nuclear power plants. The same report provides a labor during construction profile, and assuming expenditures proportional to labor for each year, the yearly expenditure on the construction has been calculated. Using the formula provided by GEN IV international forum (2007), the interest during construction can be calculated using equation (23);

$$IDC = \sum_{j=1}^{ct} C_j [(1+r)^{t_{op}-j} - 1]$$
(23)

Where *IDC* is the interest during construction, C_j is the money spent on year j of construction, ct is the construction time and t_{op} is the year the power plant starts operating. Solving this equation leads to IDC=1078€/kW. According to the same GEN IV study, decommissioning of a nuclear power plant accounts for 10% of the overnight costs. Including these interest during construction and decommissioning costs, the final investment cost is found to be 5311€/kW, which is the value used to calculate the annuity.

Table 2 shows the economic parameters of power storage technologies.

Technology	Overnigh	CAPEX	Lifetime	Annuity	Fixed	Variable	Storage	Construc	Efficiency	Source
	t costs	(€/kWh _e)	(years)	(€/kW _e /	O&M	0&M	annuity	tion time	(input /	
	(€/kWe)			year)	(€/kW _e /year)	(€/MWh _e)	(€/kWh _e /year)	(years)	output)	
Pumped										FCH-IU
hydro	500	5	55	25.8050	7.5	0	0.2469	1	95%/90%	(2015)
storage (PHS)										(2013)

Table 2 Economic parameters of storage technologies

Battery										Schmidt
storage	140	100	12.5	15.2225	1.96	0	10.6340	0.5	90%/95%	(2010)
(Li-Ion)										(2019)
Mothanation	1150	0	20/25*	97 0/91	50.25	5 11	0	1	50%/15%	ENEA
Wethanation	1150	0	20725	87.5481	55.25	5.44	0	T	55/0/45/0	(2016)

It is worth mentioning that OCGT and CCGT with CCS power plants are technologies using natural gas, biogas and renewable methane (from power-to-gas) as fuel; therefore, the full cost of electricity generated through these technologies is the sum of the combustion technology cost and the used fuel cost. The cost of CO₂ transportation is presented in Appendix 2.

2.2.5. Model parametrization

Equations (14), (15), (17), (18) and (19) need technology-related input parameters. These parameters such as ramp rate, yearly maximal capacity factor (availability limits due to maintenance) and efficiencies of different processes need to be identified to the model. Similarly, equation (6) as the reserve requirement definition consists of several input parameters relating the needed secondary reserves with respect to installed capacities of VRE technologies and hourly demand profiles. Natural gas with CCS is not a zero-emission technology and according to JRC (2014), it captures only 86% of the carbon dioxide produced by the combustion, therefore, there are residual emissions. The values of these input parameters, as well as their resources are presented in table 3.

parameter	definition	value	Resource
cf_{ocgt}	Yearly maximal capacity factor of OCGT	90%	JRC (2014)
cf_{ccgt}	Yearly maximal capacity factor of OCGT	85%	JRC (2014)
cf _{nuc}	Yearly maximal capacity factor of nuclear plants	90%	JRC (2017)
r_{nuc}^{up}	Hourly ramping up rate of nuclear plants	25%	NEA (2011)
r_{nuc}^{down}	Hourly ramping down rate of nuclear plants	25%	NEA (2011)
E offshore	Additional FRR requirement for offshore wind	0.027	Perrier (2018)
$\boldsymbol{\varepsilon}_{onshore}$	Additional FRR requirement for onshore wind	0.027	Perrier (2018)
\mathcal{E}_{PV}	Additional FRR requirement for solar PV	0.038	Perrier (2018)
$\delta^{load}_{variation}$	Load variation factor	0.1	Van Stiphout et al (2017)
$\delta_{uncertainty}^{load}$	Load uncertainty because of demand forecast error	0.01	Van Stiphout et al (2017)

Table 3 technical parameters of the model

Equations (9), (10), (13) and (16) also have some input parameters with respect to the chosen country. These parameters are the maximal available energy from the constrained technologies, maximum available capacities and hourly and monthly profiles of hydro-electricity technologies. In this paper we study the French power sector, therefore we use the values provided for France. Table 4 summarizes these values and their resources.

Table 4 country specific limiting input parameters of model

parameter	definition	value	Resource
lake _m *	Monthly maximum electricity from dams & reservoirs	See GitHub ¹	RTE (2016)
river _h **	Hourly maximal power production from run-of-river	See GitHub ²	RTE (2016)
e_{biogas}^{max}	Yearly maximal power production from Biogas	15TWh	ADEME (2013)
q_{tec}^{max}	Maximum installable capacity limit for each technology	See GitHub ³	ADEME (2018)

* This parameter is calculated by summing hourly power production from this hydroelectric energy resource over each month of the year to capture the meteorological variation of hydroelectricity, using the online portal of RTE⁴ (the French transmission network operator).

** Hourly run-of-river power production data from the RTE online portal has been used to prepare the hourly capacity factor profile of this energy resource.

2.2.6. Choice of the discount rate

The discount rate recommended by the French government for use in public socio-economic analyses is 4.5% (Quinet, 2014). This discount rate is used to calculate the annuity in the objective function, using the following equation:

$$annuity_{tec} = \frac{DR \times CAPEX_{tec}((DR \times ct_{tec})+1)}{1 - (1 + DR)^{-lt_{tec}}}$$
(24)

Where *DR* is the discount rate, ct_{tec} is the construction time, lt_{tec} is the technical lifetime and annuity_{tec} is the annualized investment of the technology *tec*. Appendix 6 provides a sensitivity analysis, varying this rate from 2% to 7%.

¹ <u>https://github.com/BehrangShirizadeh/EOLES_elec/blob/master/lake_inflows.csv</u>

² <u>https://github.com/BehrangShirizadeh/EOLES_elec/blob/master/run_of_river.csv</u>

³ <u>https://github.com/BehrangShirizadeh/EOLES_elec/blob/master/max_capas.csv</u>

⁴ <u>https://www.rte-france.com/fr/eco2mix/eco2mix-telechargement</u>

2.3. Studied scenarios

Previously we showed the importance of the choice of the weather year data, and that 2006 is the most representative of the period 2000-2017 (Shirizadeh et al. 2019). Therefore, 2006 has been used as the weather year for the VRE technologies' hourly capacity factor profiles. More information about the choice of the weather year can be found in appendix 3.

The model has been run for 126 cost scenarios: 6 social cost of carbon scenarios, from 0 to $500 \notin /tCO_2$ with $100 \notin /tCO_2$ variation slices, 7 nuclear power cost scenarios and 3 VRE cost scenarios. For nuclear power, the central scenario is $3750 \notin /kW$, ranging from $3000 \notin /kW$ to $4500 \notin /kW$ with $250 \notin /kW$ variation slices. VRE cost scenarios are labeled low cost (offshore wind: $1747.5 \notin /kW$, onshore wind: $847.5 \notin /kW$ and solar PV: $318 \notin /kW$), central cost (offshore wind: $2330 \notin /kW$, onshore wind: $1130 \notin /kW$ and solar PV: $423.3 \notin /kW$) and high cost (offshore wind: $2912.5 \notin /kW$, onshore wind: $1412.5 \notin /kW$ and solar PV: $530 \notin /kW$), where the variation from the central cost scenario is 25%.

The choice of central scenarios has been made from the cost resources (tables 1 and 2), while the 25% variation for VRE resources is taken from the expert elicitation survey by Wiser et al. (2016). The cost variation boundaries for nuclear power plants has been chosen based on simulations, where the highest cost scenario for this technology is chosen as the scenario where the optimization for central VRE cost scenario and any SCC scenario leads to zero installed capacity of this technology. To keep the symmetry, the same relative variation is applied for the lowest cost scenario for nuclear power. The variation slice (6.66%) is chosen because of the high sensitivity of the optimal mix to the cost variation of this technology. The SCC values are based on the official 'value for climate action' social cost of carbon introduced by Quinet et al. (2019) for France for 2050, (between $600 \notin /tCO_2$ and $900 \notin /tCO_2$), but the results presented are for a maximum $500 \notin /tCO_2$ SCC, since for higher values, no particular change has been observed.

3. Results

3.1. Central cost scenario

3.1.1. Power mix

Figure 2 shows the yearly power production of each technology for central VRE and nuclear power cost scenarios. Whatever the SCC scenario is, approximately 75% of the electricity generated consists of renewable energy resources. The remaining 25% is shared among nuclear power and natural gas, with or without carbon capture and storage technologies. For low SCC scenarios, nuclear power holds only

10% of the yearly electricity production share, while for high social cost of carbon, the whole remaining 25% is produced by nuclear power.



Figure 2 Optimal power mix for central VRE and nuclear power cost scenarios with respect to different SCC scenarios

Figure 3 shows the yearly power production from storage options for each social cost of carbon scenario. As we saw from figure 2, Natural gas without CCS exists only for the zero SCC scenario, and once the social cost of carbon is 100€/tCO₂ or more natural gas without CCS is abandoned and replaced by natural gas with CCS and by bio-energies. Because of residual emissions, for high SCCs (400€/tCO₂ and more), natural gas with CCS is also eliminated. We observe from figure 3 that natural gas with CCS is also abandoned and replaced by the supply chain decarbonized electricity-methanation-CCGT with CCS from a social cost of carbon of 400€/tCO₂ on.



Figure 3 yearly power production by storage technologies for the central VRE and nuclear power cost scenario

The installed capacities of each technology and a summary of the main model outputs (such as overall cost and load curtailment) for different SCC scenarios are presented in appendix 4 (tables A.2, A.3 and A.4). In appendix 5 we show that the wind and solar installed capacities stay well below the potentials identified for France.

3.1.2. Emissions

The relationship between the social cost of carbon and the overall CO_2 emissions of the system is presented in figure 4. Power system becomes nearly carbon neutral for $100 \notin tCO_2$ and for at least $200 \notin tCO_2$, emissions fall below zero. These negative emissions increase with the SCC, and at $500 \notin tCO_2$ the power system captures $12MtCO_2/year$.



Figure 4 Yearly positive, negative and net (net = positive – negative) CO₂ emissions and CO₂ captured by CCS technologies in MtCO₂/year for different SCC scenarios, for central VRE and nuclear power cost scenarios

One of the main hurdles to the deployment of CCS is the availability of enough safe storage sites. Hence Figure 4 presents the amount of captured CO_2 (from both fossil fuels and biomass), which gives a useful insight about the needed CO_2 storage for each year.

3.1.3. Cost and revenues

We define two different system cost definitions: the technical cost (eq. (1) except the last part) and the cost including the social cost of carbon, which accounts for the whole eq. (1). In a decentralized equilibrium, the gap between these two costs would include the remuneration earned by negative CO_2 emitting plant operators and the tax paid by CO_2 emitting plant operators. Figure 5 shows these two costs for different SCC scenarios, for the central nuclear power and VRE cost scenarios. At $200 \notin tCO_2$ of SCC and more, these costs diverge significantly, and for $500 \notin tCO_2$, this gap reaches around $6bn \notin year$ i.e. around 20% of the technical cost.



Figure 5 Yearly technical cost and cost with social cost of carbon for central VRE and nuclear power cost scenarios, split by technology, for different SCC scenarios

Since we consider that positive and negative emissions are valued at the same price, in case of positive CO_2 emissions the cost with SCC is higher than the technical cost of the system, and vice-versa in case of negative emissions.

This large difference between the technical cost and the cost with the social cost of carbon raises another question: what is the share of CO_2 related revenues of CCS technologies in the overall revenues of the operators of technologies which include CCS? To answer to this question, we have calculated, first, the yearly revenues from the electricity 'market' for each CCS technology and, second, the revenues (or expenditures) coming from negative (or positive) emissions. Figure 6 shows the revenues for each technology with CCS, from each of these two 'markets'.



Figure 6 Share of revenues from electricity market and CO₂ emissions market for each technology with CCS, for central nuclear power and VRE cost scenarios

The electricity 'market' price is calculated from the dual of adequacy equation (eq. 3). This hourly dual can be interpreted as the wholesale electricity price at each hour. The overall market revenues for each technology can be calculated by using this dual and the amount of electricity sold at each hour. For the storage technologies, money spent on buying electricity when the storage technologies are in the charging phase are deducted from the revenues. For the fuel technologies (biogas, natural gas and methanation), the revenues come from the gas market, whose price can be found using the dual of the combustion equations (equations (11) and (12)).

Since biogas and methanation with CCS are not used for SCCs of less than respectively $200 \notin /tCO_2$ and $300 \notin /tCO_2$, and similarly since the natural gas with CCS is only used for SCC of $200 \notin /tCO_2$ to $400 \notin /tCO_2$, the graphs are limited to these values. We can observe that while biogas with CCS has a balanced revenue share from two markets, for methanation with CCS above $400 \notin /tCO_2$ actually the balance between expenditures and earnings in the power market is negative. Hence for a high carbon price, the development of the biogas+CCGT+CCS supply chain and even more that of the methanation+CCGT+CCS supply chain would occur thanks to the remuneration of negative emissions rather than thanks to the electricity market.

3.1.4. How important is the availability of nuclear power and CCS technologies?

In this section, the importance of the nuclear power and the carbon capture and storage technologies has been studied, by removing each of them one at a time, and both. This part of the study has been done only for the central VRE and nuclear power cost scenarios. Figure 7 shows the system-wide Levelized Cost Of Electricity (LCOE), i.e. the average system cost per unit power production, for each SCC scenario and for 4 different technology availability cases: a) with all technologies, b) without nuclear



power, c) without CCS and d) with neither nuclear power nor CCS. The cost considered here includes the social cost of carbon.

Figure 7 System-wide LCOE of the system for different technology availability scenarios, for central VRE and nuclear power cost scenario and different SCC scenarios

Since the negative emission remunerations come from CCS technologies combined with carbon neutral combustion technologies, the condition to decrease the system cost by increasing SCC is the availability of CCS technology. Availability of nuclear power leads to an average cost reduction of $2.5 \notin /MWh_e$ for SCC scenarios of $200 \notin /tCO_2$ and more. The cost reduction from the availability of CCS is much higher, up to nearly $7 \notin /MWh_e$, and both together can lead to a cost reduction from $2 \notin /MWh_e$ for a SCC of $100 \notin /tCO_2$ up to $8 \notin /MWh_e$ for a social cost of carbon of $500 \notin /tCO_2$.



Figure 8 Yearly CO₂ emission of power system for central VRE and nuclear power cost scenario, and different availability and SCC scenarios

The sensitivity of CO₂ emissions to the availability of technologies is presented in figure 8. As shown previously, a nearly carbon neutral power system can be reached for a SCC of $100 \notin /tCO_2$, but this happens only if CCS is available. If CCS is available, a SCC of $200 \notin /tCO_2$ will result in negative emissions, while for the same SCC, the system with none of the technologies discussed above will not even reach carbon neutrality. To sum up, the system cost and emissions are more sensitive to the availability of CCS than to that of nuclear.

3.2. Sensitivity to the relative cost of nuclear power and VRE technologies

Figure 9 shows the power production share of each technology. The shares of renewables and nuclear are inversely related to their relative cost. Even for the most expensive VRE and cheapest nuclear scenario, nuclear power does not exceed 75% of the power mix. Conversely, for the low cost VRE, it provides less than 15% of power production, and for most of the nuclear power cost scenarios (including the central one), nuclear power does not even enter the optimal power mix. On the other hand, the RES share in power production almost never drops below 25%, while it can reach 100%.



Figure 9 Yearly power production share of each technology for different VRE and nuclear power cost and SCC scenarios

While increasing the SCC leads to lower and even negative emissions, if decentralized in the form of public subsidies for negative emissions it also leads to a significant public budget cost. Figure 10 shows the annualized technical cost and the cost with social cost of carbon. As we observed in figure 5, for high SCC scenarios the gap between these two costs is large. The implied transfer can go up to $10.5bn \notin/year$ for the low VRE cost and high SCC ($500 \notin/tCO_2$) scenario, which also leads to higher negative emissions (approximately -22MtCO₂/year).



Figure 10 Annualized technical cost and cost with social cost of carbon (including SCC) for different VRE and nuclear power cost and SCC scenarios

As argued in section 3.1.2, the overall CO_2 emission gives helpful insights about the overall CO_2 balance, and the real carbon impact of the power system, but the needed storage volume depends on the overall captured CO_2 . Figure 11 shows the yearly CO_2 emissions and yearly captured CO_2 by CCS options for different VRE and nuclear power cost scenarios and different SCCs.



Figure 11 Overall a) yearly net CO2 emissions and b) yearly captured CO2 by CCS options for different VRE and nuclear power cost and SCC scenarios

Varying these cost scenarios can make a big difference in the captured CO₂ amount. While for high and central VRE cost scenarios, the needed storage does not exceed $18MtCO_2/year$, low VRE cost scenario leads to more than $20MtCO_2/year$ storage capacity for $500 \notin /tCO_2$ of SCC. The reason for this surge in negative emissions is the increased share of VRE technologies in the final electricity mix, which leads to an increased use of methanation. Similarly, high cost VRE leads to a high share of power production from nuclear power technology (60 to 75% of power production), which entails much less need for dispatchable options such as combustible technologies, which eventually capture more CO₂ for high SCC scenarios.

3.3. Importance of reduction in electricity demand

We use ADEME's central electricity demand hourly profile for 2050 (ADEME, 2015). This demand accounts for 422TWh_e/year, which is equivalent of the EFF (efficiency) scenario of the four main demand scenarios proposed in the French national energy transition debate (DNTE, 2013). The other scenarios are DIV (divergence – 534TWh_e/year), SOB (sobriety – 280TWh_e/year) and DEC (decarbonisation – 651TWh_e/year). To study the importance of reducing the electricity consumption, we ran the EOLES_elec model for two alternative demand scenarios: SOB (low demand) and DIV (high demand). Figure 12 shows the emission and system-wide LCOE of the power system for different SCC values and different demand levels.



Figure 12 Impact of the electricity demand scenario on a) net CO_2 emissions and b) the system-wide levelized cost of electricity (including the social cost of carbon)

A low electricity demand leads to negative emissions for low SCC values (even 100€/tCO₂), but for a very high SCC, the amount of negative emissions decreases with electricity demand. Similarly, demand reduction does not only lower the total system cost (which is obvious) but also the system-wide LCOE, i.e. the cost per MWh consumed. The latter result stems mostly from the capacity and production constraints to hydro and biogas, which become less stringent (in percentage of electricity demand) under a lower electricity demand. The electricity mix for different demand scenarios is presented in appendix 7.

4. Discussion

4.1. Comparison with existing studies for France

According to our findings, for moderate SCCs ($200 \notin tCO_2$ and less), the system-wide LCOE will be between $46 \notin MWh_e$ and $50 \notin MWh_e$, depending on the availability of nuclear power and CCS technologies. If none is available, even for a very high social cost of carbon, this value will be less than $53 \notin MWh_e$. According to the latest quarterly report from the French energy regulator (CRE, 2019), 35% of a typical electricity bill (varying between 170 \notin and $200 \notin MWh_e$ depending on the tariff chosen and consumption profile) represents electricity production, which costs between $59 \notin -70 \notin MWh_e$.

Therefore, even for high SCC scenarios, the power production side (including storage, grid connection and secondary reserve requirements) is estimated to cost less than today.

Figure 2 shows a steep increase in the installed capacity and annual production by nuclear power for high SCC values (for $400 \notin tCO_2$ and $500 \notin tCO_2$). The reason can be traced in figure 3, where we observe a steep increase in the power production by methanation coupled with CCGT power plants equipped with CCS. Figure 6 shows that the main incentive for methanation with CCGT-CCS storage option is not participation in the electricity market, but participation in the carbon market. Therefore, a continuous electricity production technology such as nuclear power helps the methanation with CCGT-CCS plants provide constant negative emissions during the year. The reason of the steep increase in the nuclear power for high SCC values is thus related to the carbon revenues.

These results contrast with those of Krakowski et al. (2016), where the least costly scenario for France is presented as the business as usual one, and increasing the share of RES increases gradually the annualized cost of power system by approximately 20% for 80% RES share in electricity mix (40bn€/year). The main reasons for this difference in the results (20.5 to 22.3bn€/year depending on the availability and SCC scenario) are (i) lower VRE capacity potentials (70GW for wind and 65GW for solar power vs. 140GW for wind and 218GW for solar power in current study) which results in very high power importation costs, (ii) very low storage availability, which is only short-term storage with very low efficiency and (iii) the assumption of perfect correlation between offshore and onshore wind power, which leads to a lower complementarity between these technologies.

Schlachtberger et al. (2018), in a European study, finds a very close annualized system cost to our findings (20bn€ to 25bn€ depending on the wind availability scenario) for France, and similar to our previous findings (Shirizadeh et al. 2019) they observe a considerable robustness of total system cost to the weather data and cost assumptions, but they find a higher share of power production by onshore wind. This difference in the installed capacity comes from small differences in the relative cost of technologies (the relative cost of onshore wind to offshore wind and solar PV is lower in Schlachtberger's study) and their exclusion of nuclear power and negative emissions technologies.

According to another European continent-scale study (Brouwer et al. 2016), increasing the renewable share in the final electricity mix from 40% to 80% raises the total system cost, even in the existence of demand response. The average system cost (average LCOE) is approximately $91 \notin MWh_e$ for 80% RES case. This big difference in the results can be explained by (i) the difference in the chosen future cost

projections, where they use IEA's world energy investment outlook study (IEA, 2014), realized in 2012, and projected for 2035, while since 2012 a very big cost decrease in solar PV and storage technologies has been witnessed, (ii) the non-negligible higher yearly power demand (547TWh/year vs. 423TWh/year), (iii) a low calculated capacity factor for wind power (25% vs. 32.5%) which is also weakly correlated with the historical data (86% correlation), (iv) the choice of 2013 as the weather data year without studying the importance of this choice (in the current article the chosen representative weather year is 2006, which results from a correlation study with a 19-year weather data simulation), and finally (v) the methodological difference in the calculation, where they use a two-stage procedure, optimizing first the installed capacity, and later the dispatch, while EOLES_elec model optimizes dispatch and investment simultaneously.

Petitet et al. (2016) in their study of the French power sector, find an LCOE of $90 \notin MWh_e$ for wind power, and show that for a carbon price of less than $65 \notin /tCO_2$ wind power is competitive with neither coal nor CCGT power plants. They also show that in the case of considering the existing nuclear power plants of France, for carbon prices below $150 \notin /tCO_2$, wind power does not become economically competitive enough to enter the energy mix, while in the current article, we observe a very high RES share, as shown in the section 3.2. This big difference with our results comes from (i) not considering any storage option, (ii) using very different cost projection data (IEA and NEA's 2010 cost projection for electricity generation), (iii) no negative emission technology option availability and (iv) considering onshore wind power as the only renewable source, moreover with very low capacity factor (21.6% vs. 32.5%), based on the observation of the wind turbines installed at this time, which are much less efficient than state-of-the-art turbines (Hirth et al., 2016).

Several studies by ADEME focus on power mix planning for France. Among them, "100% renewable power mix" study (ADEME, 2015), and "electricity mix evolution trajectories 2020-2060" (ADEME, 2018) optimize explicitly the power system, and study the role of renewables in the French energy transition. Our results in the previous fully renewable power mix study were very close to those of these two studies. But other options, especially CCS may play an important role in cost reduction and reaching zero/negative emissions. Comparing our findings with ADEME's results, we highlight the importance of negative emission technologies.

To sum up, the main drivers of the different results from different studies are the assumptions about the cost components, availability of different technologies and the limiting constraints. More recent studies with up-to-date cost projections conclude to higher VRE shares in the final optimal electricity mix.

Similarly, introduction of more precise weather data, as well as flexibility options and simultaneous optimization of dispatch and investment (which takes into account variable costs in the total cost minimization objective) can overcome the underestimation of VRE share in power mix.

4.2. CO₂ emissions and storage capacity

For a social cost of carbon of $100 \notin tCO_2$ and more, the CO₂ emissions are expected to be either zero or negative. Without any SCC, the CO₂ emission is approximately $20MtCO_2/year$, which can be translated as $50kgCO_2/MWh_e$. This figure is even higher for the expensive VRE and nuclear power cost scenarios. According to RTE's online portal (eco2mix)¹ the average emission rate of power production in France in 2018 was $60kgCO_2/MWh_e$. Thus, without integration of a SCC, the carbon dioxide emission from the power sector would not decrease.

According to the IPCC (2005) special report on carbon capture and storage, the worldwide carbon dioxide storage capacity in saline formations is between 1000 GtCO_2 and 10000 GtCO_2 and the main onshore CO₂ storage option for France is considered to be these saline formations. Kearns et al. (2017) estimate 8000 to 55000 GtCO₂ of worldwide geological (onshore) CO₂ storage capacity. Fuss et al. (2018) find the global carbon storage potential between 320GtCO₂ and 50,000GtCO₂, where the global estimates for aquifers is estimated between 200GtCO₂ and 50,000GtCO₂. According to the "Feasibility study for Europe wide CO₂ infrastructure" by the European commission (EC Directorate-General Energy, 2010), France is one of the few European countries having abundant carbon storage capacity for its own domestic production (more than 50 years of potential storage), and its global CO_2 storage capacity is estimated between 6GtCO₂ and 26GtCO₂. Yet according to CCFN (Chambre de Commerce Franco-Norvégienne)² "(1) Onshore CO₂ storage in France, even if possible, could face strong social acceptance issues, (2) Up to 17-20 MtCO₂/year could be sent by ship from France (Le Havre and Dunkerque clusters mainly) to the North Sea for storage or CO_2 Enhanced Oil Recovery, (3) In the longer term, an additional 20 MtCO₂/year capacity pipeline could be laid parallel to the NorFra gas pipeline from a hub in Dunkerque". Hence, although the need for yearly CO₂ storage is lower than these upper limits, the French accessibility to the North Sea and the availability of internal onshore storage still remain open questions.

¹ <u>https://www.rte-france.com/fr/eco2mix/chiffres-cles#chcleco2</u>

² <u>https://www.ccfn.no/actualites/n/news/french-norwegian-collaboration-on-carbon-capture-and-storage.html</u>

4.3. Funding negative CO₂ emissions

In a decentralized equilibrium, the difference between the technical cost and the cost with SCC requires pricing CO₂ by this amount, which may take the form of price instruments (taxes and subsidies) or of a CO₂ market. This market would reach up to $6bn \notin$ /year for central nuclear power and VRE cost scenarios, and up to $10.5bn \notin$ /year for the highest SCC scenarios. Considering only the power system, negative emissions would need to be funded by the public budget, but since decarbonization of other CO₂ emitting sectors such as agriculture, industry and transport is more difficult, negative emission in the power sector could be funded by taxing (or selling auctioned emission allowances for) the positive emissions for these sectors. In the second French national low carbon strategy report, the residual emissions for France are evaluated to be more than $80MtCO_{2eq}$ /year, assuming out negative emissions (SNBC, 2018). Negative emissions from the electricity sector can be one compensation options to reach the net zero emissions by 2050.

4.4. Policy implications

For the vast majority of the studied scenarios, renewable technologies dominate the energy mix. The VRE share in the final electricity production varies from 60% to 70%, and it can go up to 90% for low VRE cost and high SCC scenarios. These findings are in line with the 70% to 85% of renewable share in the final electricity production found by Waisman et al (2019). Therefore, a fast development scheme for VRE technologies is of key importance to be in line with the Paris agreement ambitions in the most cost optimal conditions.

Carbon dioxide emissions become null or negative if a taxation/remuneration scheme is implemented in the electricity market at a rate equal to the SCC value. The importance of availability of CCS to reach to null and even negative emissions for low SCCs, and for lower costs, emphasizes the importance of this technology and its role in the future energy mix.

The level of electricity demand also matters: a lower demand decreases the total system cost (obviously) but also the cost per MWh consumed. Moreover, it allows decarbonizing the power system for lower SCC values. Therefore, electricity savings are important to enable energy transition for moderate costs.

The CO₂ storage capacity in the order of ~10Mt CO₂/year shows an emerging need for geological storage which might be achieved either by exploiting the French available saline formations or transporting the captured carbon dioxide to the North Sea. Since the literature about the available storage capacity in France is very blurry, further research is needed to quantify the existing internal carbon dioxide storage

capacity nationwide. If storage in onshore saline formations is too difficult, commercial and political agreements with neighboring countries of the North Sea are the key solution for the availability of carbon capture and storage technologies.

5. Conclusion

In this article, the cost-optimal low-CO₂ energy mix for the French electricity sector has been studied. To that end, the EOLES_elec model, an electricity model from the EOLES family, has been developed, including six renewable technologies, conventional power production technologies (natural gas and nuclear power), natural gas with carbon capture and storage, and negative emission technologies (biogas with CCS and methanation storage with CCS). 126 cost scenarios have been built to assess a wide range of future cost projections for VRE and nuclear power technologies, as well as a wide range of social cost of carbon scenarios.

Findings of this study highlight the important role of the renewable power generation technologies in the electricity mix, whose share is approximately 75% for central cost scenario for VRE and nuclear power, whatever the SCC is. Moreover, the relative share of nuclear power and renewable energy resources is very sensitive to the chosen cost scenario, but not to the SCC.

Setting a SCC of $100 \notin tCO_2$ leads to the effective exploitation of CCS technology, where for most of the cost scenarios, the power system becomes carbon neutral and a SCC of $200 \notin tCO_2$ can be enough for the power system to reach negative emissions by appearance of BECCS technology in the optimal mix. While increasing SCC leads to an increased need for carbon storage, this needed storage capacity does not surpass $20MtCO_2$ /year. Whether this amount of CO2 can be stored in the French context remains an open question.

Depending on the cost projection and SCC scenarios, a carbon neutral, and even negative carbon emission power system will cost between $45 \notin /MWh_e$ and $49 \notin /MWh_e$ excluding the grid related costs and deducing the social benefit from negative emissions. This value stays well below the current electricity production cost in France. Availability of CCS technology plays an important role in both reaching the carbon neutrality and the cost reduction of the production side (5% to 18% cost reduction depending on the SCC scenario), and without CCS and nuclear power system, the cost can go up to $53 \notin /MWh_e$ and even more for high VRE cost scenarios.

Finally, the gap between the cost with and without the social cost of carbon shows an emerging need to a public support scheme for the negative emission technologies. This gap also shows the importance of

carbon businesses which can take place for high SCC scenarios, where the main incentive for negative emission technologies can be only to generate negative emissions, but not so much to produce electricity.

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Appendices

Appendix 1. Wind and solar production profiles

The wind power hourly capacity factor profiles existing in the renewables.ninja website are prepared in four stages:

a) Raw data selection; using NASA's MERRA-2 data reanalysis with a spatial resolution of 60km×70km provided by Rienecker et al. (2011),

b) Downscaling the wind speeds to the wind farms; by interpolating the specific geographic coordinates of each wind farm using LOESS regression,

c) Calculation of hub height wind speed; by extrapolating the wind speed in available altitudes (2, 10 and 50 meters) to the hub height of the wind turbines using logarithm profile law,

d) Power conversion; using the primary data from Pierrot (2018), the power curves are built (with respect to the chosen wind turbine), and smoothed to represent a farm of several geographically dispersed turbines using Gaussian filter.

The solar power hourly capacity factor profiles in the renewables.ninja website are prepared in three stages:

a) Raw data calculation and treatment; using NASA's MERRA data with the spatial resolution of 50km×50km. The diffuse irradiance fraction estimated with Bayesian statistical analysis introduced by Lauret et al. (2013) and the global irradiation calculated in inclined plane. The temperature is given at 2m altitude by MERRA data set.

b) Downscaling of solar radiation to farm level; values are linearly interpolated from grid cells to the given coordinates.

c) Power conversion model; Power output of a panel is calculated using the relative PV performance model by Huld et al. (2010) which gives temperature dependent panel efficiency curves.

Appendix 2. Transport cost of carbon dioxide for methanation

The cost of transporting carbon dioxide along a 200km onshore pipeline is $\notin 4/tCO_2$, for 100km ling pipeline, this transporting cost can be assumed around $\notin 2/tCO_2$. Given that each mole of carbon dioxide weighs 44 grams, and we can produce one mole of methane from one mole of CO_2 with an efficiency of 80% and each mole of methane can produce 802.3kJ of thermal energy, considering an OCGT combustion efficiency of 45% (JRC 2014):

 $\frac{1 t CO_2}{1000000 g CO_2} \times \frac{44 g CO_2}{1 mol CO_2} \times \frac{1 mol CO_2}{0.8 mol CH_4} \times \frac{1 mol CH_4}{802.3 kJ} \times \frac{1 kJ th}{0.00022277778 kWh th} \times \frac{1 kWh th}{0.45 kWh elec} \times \frac{1000 kWh elec}{1 MWh elec} = 0.5486 \frac{tCO_2}{MWh elec}$

Multiplying this transport cost by $\notin 2/tCO_2$, the CO_2 transport cost for methanation becomes $\notin 1.0972/MWh$.

Appendix 3. Choice of the representative year

The selection of a representative year could be made using several criteria. We chose to select the year with a capacity factor closest to our 19-year optimal 100% renewable power mix. We used the capacity factor because it is invariable with respect to technology costs, on which we perform the sensitivity analysis. To measure the distance to the 19-year optimal mix, we compute the sum of absolute difference¹ of the three VREs. Using this approach, 2006 is the closest year to the overall 19-year long period, with a sum of absolute error values of 1.5% (Table A.1). We launched the model with the optimal installed capacities found for 2006 over all other weather-years to test the adequacy of this installed capacity with respect to the other 18 weather-years, and we did not observe any operational inadequacy.

¹ Sum of normalized absolute differences $\sum_{i=1}^{3} \left| \frac{x_i - x^*_i}{x^*_i} \right|$ where x_i is the CF of each technology i in each year and x^*_i is the CF of that technology over 18 years.

Representative year selection	Closest year	2 nd closest year	3 rd closest year
Offshore Wind	2011	2012	2006
Onshore Wind	2006	2004	2012
Solar PV	2004	2006	2009
Overall year	2006	2012	2004
Overall error (absolute)	1.5%	2.4%	2.8%

table A. 1 choice of the representative year and it's compatibility with each VRE technology

Appendix 4. installed capacities for the central cost scenarios

table A. 2 installed capacity of each power production technology in GW for the central VRE and nuclear power cost scenarios

SCC (€/tCO2)	Offshore Wind	Onshore Wind	Solar PV	Run- of- river	Lake & reservoir	OCGT	CCGT w/ CCS	Nuclear power
0	0	58.5	91.8	7.5	12.9	33.4	0	5.3
100	5.4	48.9	80.3	7.5	12.9	20.1	9.9	10.3
200	5.5	48.3	75.2	7.5	12.9	13.8	15.7	12.1
300	6	46.3	75.7	7.5	12.9	10	17.5	14.3
400	0	57.1	85.5	7.5	12.9	7.9	15.6	16
500	0	58.9	89.7	7.5	12.9	8	13.1	19.7

table A. 3 installed capacity (and energy volume) of each storage technology in GW (and GWh/TWh) for the central VRE and nuclear power cost scenarios

SCC (€/tCO2)	Battery (GW)	PHS (GW)	Battery (GWh)	PHS (GWh)	Methanation (TWh)	Methanation w/CCS (TWh)
0	15.1	9.3	40.2	180	0	0
100	12.8	9.3	29.4	180	0	0
200	11.2	9.3	21.1	180	0	0
300	11.2	9.3	21.1	180	0	3.26
400	14.2	9.3	36.5	180	0	16.88
500	14.8	9.3	38.9	180	0	16.93

table A. 4 the main model outputs for the central VRE and nuclear power cost scenarios

SCC (€/tCO2)	Annualized cost with SCC (bn€/year)	Annualized technical cost (bn€/year)	System- wide LCOE (€/MWh)	Average 'market price' (€/MWh)	Load curtailment (%)	CO2 emissions (MtCO2/year)
0	19.6	19.6	46.41	49.37	4.27	20.92
100	20.61	20.49	48.8	49.39	2.9	1.28
200	20.59	21.01	48.75	49.47	2.51	-2.09
300	20.32	21.49	48.11	49.65	2.08	-3.9
400	19.7	22.6	46.65	49.92	1.75	-7.25
500	18.9	25.18	44.74	50.19	1.48	-12.56

Appendix 5. Renewable capacities compared to potentials

	Maximal	Current	Renewable potential					
	optimum in reference cost scenario	capacity, mid- 2019 (RTE, 2019)	ADEME (2018)	Enevoldsen et al. (2019)	FEE (2019)	Cerema (2017)		
Offshore wind	6GW	0GW	66GW	-	220GW	-		
Onshore wind	59GW	16GW	174GW	300GW	-	-		
Solar PV	92GW	9GW	459GW	-	-	776GW+ for south of France		

table A. 5 Renewable capacities in our study, capacities currently installed, capacities in other scenarios and available potential

For the reference cost scenario, the optimal mix features 0 to 6 GW of offshore wind (vs. 2 MW as of mid-2019), 46 to 59 GW of onshore wind (vs. 16 GW) and 75 to 92 GW of solar PV (vs. 9 GW). For each of the three technologies at stake, the capacity resulting from our optimization is much lower than those identified by the potential estimation studies (Table A.5). Hence there is no physical barrier to the implementation of these capacities.

Yet, many onshore wind projects suffer from local opposition, mostly related to landscape issues. These oppositions may constitute the main obstacle to the implementation of the optimum mix that we have identified for our reference cost scenario. Indeed, reaching 59 GW in 2050 means an increase of 1.3 GW/yr. on average, from 2018 onwards, less than WindEurope's (2017) "high" 2030 scenario, but a bit more than the current rate of increase. Sustaining such a rate of increase is feasible, but requires a high degree of political determination, given the current opposition faced by many wind projects in France. On the other hand, we have seen that renewable technologies are by and large substitutable, so our intuition is that a scenario with less onshore, more offshore and more PV would not be much costlier.

Appendix 6. Sensitivity to the discount rate

As explained in chapter 2, the discount rate chosen is the one proposed by Quinet (2014), for the public socio-economic analyses, 4.5%. Therefore, a sensitivity analysis has been carried out over the discount rate (DR), from 2% to 7%. Figures A.1, A.2 and A.3 show the installed capacities, yearly costs and yearly CO₂ emissions for each SCC and DR scenario.



Figure A. 1 installed capacity of each technology for different discount rate and social cost of carbon scenarios

Raising the discount rate increases the installed capacities of onshore wind and solar PV technologies, as well as gas turbines (both OCGT and CCGT with CCS); meanwhile, a higher discount rate reduces the share of nuclear and offshore wind because of their longer lifetime (60 and 30 years vs. 25 for onshore wind and PV). Besides, the discount rate increases the annualized cost (Figure A.2), and figure A.3 shows the linearity of this relationship.



Figure A. 2 Yearly total cost for each social cost of carbon and discount rate scenario



Figure A. 3 yearly cost with respect to different SCC and discount rate scenarios

What we can observe from figure A.3 is the fact that by increasing the SCC, the slope of this relationship increases, therefore the intensity of cost dependence to the discount rate also increases. This can be explained as follows; increasing the discount rate favors the technologies with negative or positive emissions (OCGT and CCGT with CCS power plants) because of the low importance of the capital expenditures in their total costs. Therefore, the sensitivity to the SCC (impacting the total cost even more) also goes higher in this case.



Figure A. 4 Yearly CO2 emission for each social cost of carbon and discount rate scenario

Figure A.4 shows the impact of the discount rate on the yearly CO_2 emissions. As the discount rate increases, the shares of zero-emission technologies (VRE technologies and nuclear power) decrease in comparison with both gas turbines, therefore, the impact of variable costs (where fuel costs and SCC values are applied) becomes less significant in comparison with the investment costs. Hence, emissions become higher; as an example, with a discount rate of 7%, even for $200 \notin /tCO_2$ of SCC value, the yearly CO_2 emissions are still positive, while for a discount rate of 2%, the lowest emissions are observed for each SCC scenario.

Appendix 7. Electricity mix for different demand scenarios

Figure A.5 shows the electricity mix for the central cost scenario, six SCC scenarios and three different electricity demand scenarios.

We observe a steep increase in the nuclear power share in the electricity mix by increasing electricity demand (DIV). On the opposite, for a low electricity demand (SOB), nuclear power does not contribute significantly to electricity production and the use of fossil natural gas is massively reduced. Therefore, under a low demand scenario, the electricity mix is massively renewable (>90%) whatever the SSC.



Figure A. 5 electricity mix for different demand and SCC scenarios