How sensitive are optimal fully renewable power systems to technology cost uncertainty?

Behrang SHIRIZADEH [a,b] *, Quentin PERRIER [c] and Philippe QUIRION [a]

Abstract

Many studies have demonstrated the feasibility of fully renewable power systems in various countries and regions. Yet the future costs of key technologies are highly uncertain and little is known about the robustness of a renewable power system to these uncertainties. We build 315 long-term cost scenarios on the basis of recent prospective studies, varying the costs of key technologies. We model the optimal renewable power system for France over 18 meteorological years, simultaneously optimizing investment and dispatch.

Our results show that the optimal energy mix is highly sensitive to cost assumptions: the installed capacity in PV, onshore wind and power-to-gas varies by a factor of 5, batteries and offshore wind even more. Nevertheless, we have a robust result showing that the cost of a 100% renewable power system will not be higher than today. Finally, we show that the cost of not installing the absolutely 'optimal' mix is limited. Contrary to current estimates of increasing integration costs, this indicates that renewable technologies will become by and large substitutable.

Keywords: Power system modelling; Variable renewables; Electricity storage; Robust decision making.

[a] CIRED-CNRS, 45 bis avenue de La Belle Gabrielle, 94736 Nogent sur Marne Cedex, France
[b] TOTAL, Renewables division, R&D group, 2 place Jean Millier, 92078 Paris la Défense Cedex, France.
[c] I4CE, 24 Avenue Marceau, Paris, France.
* Corresponding author: shirizadeh@centre-cired.fr, +33 (0)1 43 94 74 78

1. Introduction

According to Article 4 of the Paris Agreement, the Parties shall endeavor to rapidly reduce greenhouse gas emissions in order to achieve a balance between anthropogenic emissions by sources and removals by sinks in the second half of this century. From this point of view, the electricity sector will have a key role to play, as decarbonation is considered to be easier in this sector than in transport, buildings or agriculture. Renewable energy will be the cornerstone of decarbonation, making, with a greater contribution than nuclear energy and fossil fuels combined to CO_2 capture and storage (Rogelj et al., 2018).

Following Joskow (2011) and Hirth (2015), many articles have focused on the optimal proportion of renewable energies in the electricity mix. This literature has highlighted the existence of systemic integration costs related to the deployment of variable renewable energies. In particular, a "self-cannibalization" phenomenon was highlighted, linked to the fact that all the solar panels in a given farm produce their electricity at the same time, just like wind turbines. In the absence of affordable storage, these integration costs have two consequences: (i) deployment of renewable energies leads to a significant additional cost, rapidly increasing with the deployment rate; (ii) the right balance must be struck between the different production technologies to minimize this additional cost.

However, two main factors encourage us to review these results. The first is the rapid decline in production and storage costs. Between 2010 and 2018, the cost of photovoltaic energy has decreased by 84%, while batteries now seem to be following a similar pattern (Henze, 2019). Moreover, recent wind turbines benefit from a flatter production profile than older models (Hirth and Müller, 2016). Finally, methanation, which offers an alternative for seasonal storage, is also making significant progress. These developments will probably still be significant by 2050, the political horizon used today in the design of public policies. While the feasibility of a 100% renewable mix has already been highlighted by many studies (Brown et al, 2018, and references therein), the question is now that of competitiveness: do these reductions in production and storage costs call into question the previous conclusions about the announced high additional systemic cost of renewable energy?

The second factor is the awareness that cost uncertainties should be taken into account when designing an optimal electricity mix, because the ex-ante optimal mix is not necessarily the most robust to cost uncertainty (Nahmmacher et al., 2016; Perrier 2018). Most studies which have analyzed the cost of a 100% renewable mix include little uncertainty analysis. One exception is Schlachtberger et al. (2018) who study the influence of technology costs on power capacity and system costs, but they vary each component separately, keeping the remaining parameters fixed. Since technologies are not independent of one another, a more complete uncertainty analysis is worthwhile.

These uncertainties generate a trade-off between visibility and flexibility. On the one hand, investors want visibility for the development of economic sectors, with the example of quantified targets in terms of installed renewable capacity. On the other hand, the progressive arrival of information about technology costs argues for a flexible approach, allowing trajectories to be readjusted along the way – which hinders investor visibility.

One way to shed some light onto this issue is to calculate the cost of error, i.e. the cost difference between the ex-post-optimal energy mix (based on actual costs) and the ex-ante-optimal energy mix (based on cost forecasts). If a “robust” energy mix, i.e. one which generally entails a low cost of error, can be identified, then committing to a visible trajectory is not too detrimental, in that the extra cost will not be too high if the ex-post costs turn out to differ from the ex-ante costs.

Against this background, the objective of this article is twofold. First, we assess the sensitivity of the optimal (i.e. cost-minimizing) renewable power system to technology costs. Second, we calculate the cost of error and look for a robust energy mix.

To achieve this objective, we build a new open-source model called EOLES (Energy Optimization for Low Emission Systems) and apply it to continental France. EOLES minimizes the total system cost while satisfying power demand each hour for a period of up to 18 years. It includes six power generation technologies (offshore and onshore wind, solar, two types of hydro and biogas) and three storage technologies (batteries, pumped hydro and power-to-gas). Based on recent prospective studies for the year 2050, especially from a JRC study (Tsiropoulos et al., 2017), we build 315 cost scenarios for 2050, varying key technology costs (inshore and offshore wind by +/- 25%; photovoltaics (PV), batteries and power-to-gas by +/-50%).

In a preliminary step, we first show that optimizing the energy mix for a randomly chosen meteorological year (henceforth “weather-year”) may yield a very different mix than that which results from optimizing over the 18 weather-years simultaneously, especially regarding the proportion of offshore vs. onshore wind and the role of storage technologies (batteries and power-to-gas). Then we select the weather-year that is most representative of the whole period (2006) and perform a sensitivity analysis with the above-mentioned 315 cost scenarios.

We then show that the optimal energy mix varies a lot across cost scenarios: the installed capacity in PV, onshore wind and power-to-gas varies by a factor of 5, batteries and offshore wind even more. However, we have a robust result showing that the system cost (including electricity production and storage) is not higher than the cost prevailing today: it reaches €50/MWh on average and €65/MWh in the worst-case scenario. The energy mix optimized for the central cost scenario turns out to be the most robust and the cost of error generally low: about €2/MWh on average, i.e. 4% of the system cost.

The remainder of this paper is organized as follows. In Section 2 we present the EOLES model and the input parameters. Results are presented in Section 3 while Section 4 provides a discussion and Section 5 concludes. Three Appendices provide additional results and methodological details.

2. Materials and methods

2.1 Model description

EOLES is a dispatch and investment model that carries out linear optimization with respect to total cost. It is written in GAMS and solved using the CPLEX solver. The code and data are available on Github[1]. We minimize the annualized power generation and storage costs, including the cost of connection to the grid. The costs related to the transmission and distribution grid are not taken into account because of

[1] https://github.com/BehrangShirizadeh/EOLES_elecRES.

lack of empirical data for a 100% renewable power system. We address this issue in the discussion in Section 4.

The EOLES model (Figure 1) includes six power generation technologies: offshore and onshore windpower, solar photovoltaics (PV), run-of-river and lake-generated hydro-electricity, and biogas combined with open-cycle gas turbines. It includes three energy storage technologies: pump-hydro storage (PHS), batteries and methanation combined with open-cycle gas turbines.

It considers continental France as a single node. PV and onshore wind are simulated for the 95 of French *départements* (an administrative entity corresponding to the European NUTS 3 level). The proportion of the installed capacity in each *département* remains the same in all simulations, at the level observed in 2017. EOLES builds on the FLORE (French Linear Optimization for Renewable Expansion) model developed by Perrier (2018) but includes more technologies and a different method to produce generation profiles.

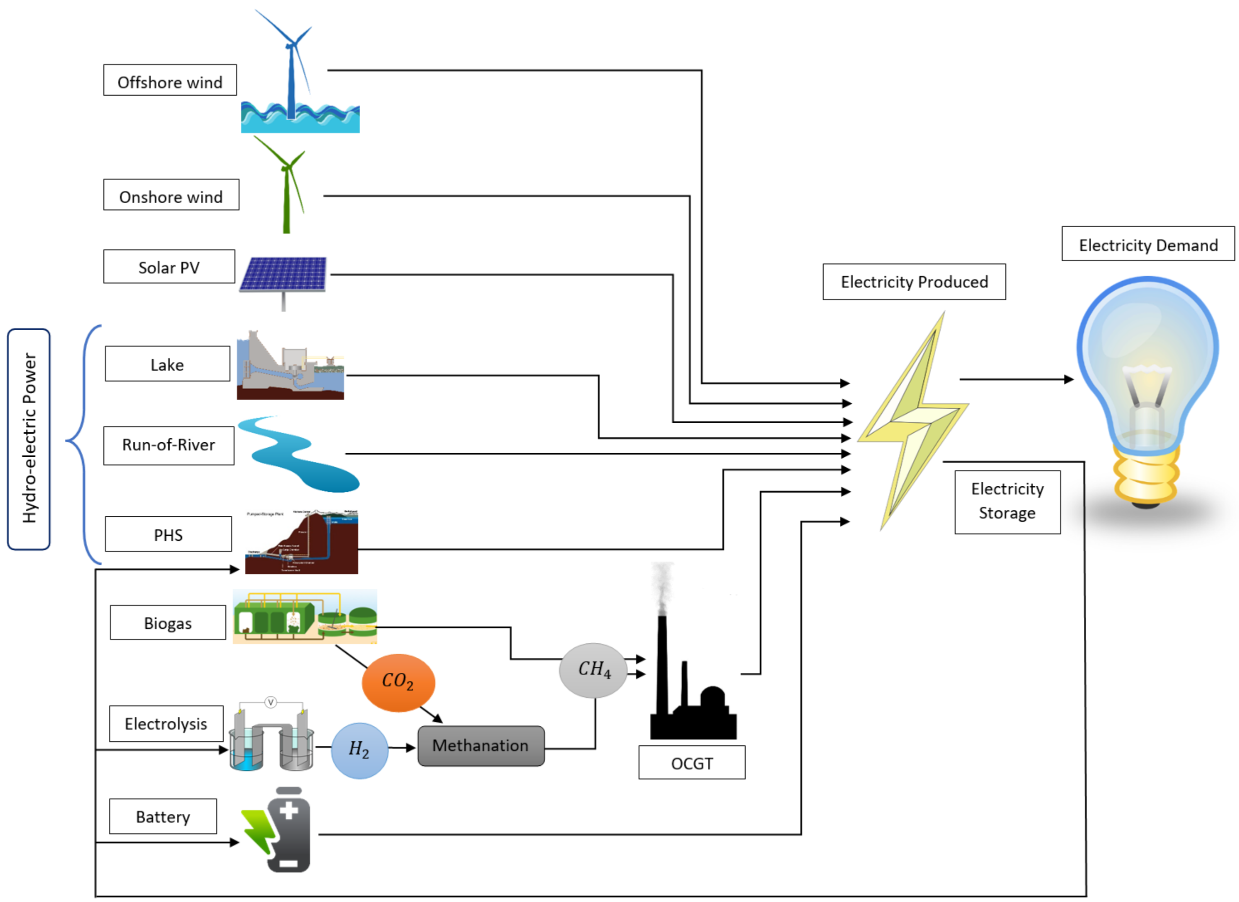

Figure 1. Graphical description of the EOLES model

2.1.1. Sets and parameters

Table 1 presents the sets and indices of the EOLES model, Table 2 the parameters. Throughout the paper, every energy unit (e.g. MWh) or power unit (e.g. MW) is expressed in electricity-equivalent. For instance, some energy is stored in the form of methane, to be transformed later into electricity using open-cycle natural gas plants with 45% efficiency. In this case, when we indicate that 45 MWh_e is stored in the natural gas network, it means that 100 MWh of methane is stored, which will allow 45 MWh_e of electricity to be generated.

Table 1. Sets and indices of the EOLES model

Index	*Set*	*Description*
h	∈ H	Hours
m	∈ M	Months
tec	∈ TEC	Electricity generation and energy storage technologies
gen	∈ GEN ⊆ TEC	Electricity generation technologies
vre	∈ VRE ⊆ TEC	Variable renewable electricity generation technologies
str	∈ STR ⊆ TEC	Energy storage technologies
$ncomb$	∈ NCOMB ⊆ TEC	Non-combustible generation technologies
$comb$	∈ COMB ⊆ TEC	Combustible generation technologies
frr	∈ FRR ⊆ TEC	Dispatchable technologies for secondary reserves

Table 2. Parameters of the EOLES model

Parameter	*Unit*	*Value*[1]	*Description*
$month_h$	*[-]*		A parameter to show which month each hour is in
$cf_{vre,h}$	*[-]*		Hourly production profiles of variable renewable energies
$demand_h$	*[GW_e]*		Hourly electricity demand profile
$lake_m$	*[GWh_e]*		Monthly extractable energy from lakes
$river_h$	*[-]*		Hourly run-of-river capacity factor profile
ε_{vre}	*[-]*		Additional frequency restoration requirement for renewables because of forecast errors
q_{tec}^{ex}	*[GW_e]*		Existing capacity by technology
$annuity_{tec}$	*[M€/GW_e/year]*		Annualized capital cost of each technology

[1] For vectors and matrices, no value is displayed in the Table but the information is available at https://github.com/BehrangShirizadeh/EOLES_elecRES.

$annuity_{str}^{en}$	*[M€/GWh/year]*		Annualized capital cost of energy volume for storage technologies
$capex_{str}^{ch}$	*[M€/GW /year]*		Annualized capital cost of storage technology charging power
$fO\&M_{str}^{ch}$	*[M€/GW /year]*		Fixed operation and maintenance cost of storage technology charging power
$fO\&M_{tec}$	*[M€/GW$_e$ /year]*		Annualized fixed operation and maintenance cost
$vO\&M_{tec}$	*[M€/GWh$_e$]*		Variable operation and maintenance cost of each technology
η_{str}^{in}	*[-]*		Charging efficiency of storage technologies
η_{str}^{out}	*[-]*		Discharging efficiency of storage technologies
q^{pump}	GW_e	*9.3*	Pumping capacity for Pumped hydro storage
e_{PHS}^{max}	GWh_e	*180*	Maximum energy volume that can be stored in PHS reservoirs
e_{biogas}^{max}	TWh_e	*15*	Maximum yearly energy that can be generated from biogas
$\delta_{uncertainty}^{load}$	*[-]*	*0.01*	Uncertainty coefficient for hourly electricity demand
$\delta_{variation}^{load}$	*[-]*	*0.1*	Load variation factor

2.1.2. Variables

The main variables resulting from the optimization are presented in Table 3.

Table 3. Variables of the EOLES model

variable	*Unit*	*description*
$G_{tec,h}$	GWh_e	Hourly electricity generation by technology
Q_{tec}	GW_e	Installed capacity by technology
$STORAGE_{str,h}$	GWh	Hourly electricity entering each storage technology
$STORED_{str,h}$	GWh_e	Hourly energy stored in each technology
S_{str}	*GW*	Installed charging capacity by storage technology
$VOLUME_{str}$	GWh	Energy capacity by storage technology
$RSV_{frr,h}$	GW_e	Hourly upward frequency restoration requirement
$COST$	*b€*	Overall final investment cost, annualized

2.1.3 Equations

2.1.3.1. Objective Function

In EOLES, dispatch and investment are determined simultaneously by linear optimization. CAPEX (capital expenditure) and OPEX (operational expenditure) are considered annually. For some storage options, two categories of CAPEX are introduced: one per kW_e of charging capacity, the other per kWh_e of energy-related capacity.

Equation (1) is the objective function, which minimizes the objective variable (annualized total cost) over the chosen period using hourly time slices.

$$COST = \left(\sum_{tec}[(Q_{tec} - q_{tec}^{ex}) \times annutiy_{tec}] + \sum_{str}(VOLUME_{str} \times annuity_{str}^{en}) + \sum_{tec}(Q_{tec} \times fO\&M_{tec}) + \sum_{str}(S_{str} \times \left(capex_{str}^{ch} + fO\&M_{str}^{ch}\right)) \ \sum_{tec}\sum_{h}(G_{tec,h} \times \ vO\&M_{tec})\right)/1000 \quad (1)$$

The different components of the cost for a power plant are *CAPEX*, fixed operation and maintenance costs (*fO&M*) and variable operation and maintenance costs (*vO&M*). *fO&M* is the yearly maintenance costs of a power plant and *vO&M* is the fuel cost. *Annuity* in equation (1) is the annualized form of the overall *CAPEX* of the power plant calculated as in equation (2).

$$annuity_{tec} = \frac{DR \times CAPEX_{tec}}{1-(1+DR)^{-lt}} \qquad (2)$$

Where *DR* is the discount rate; here *DR*=4.5% i.e. the discount rate recommended by the French government for use in public socio-economic analyses (Quinet 2014). *lt* is the lifetime of the investment.

2.1.3.2. 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).

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

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.*

2.1.3.3. Renewable power production

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

$$G_{vre,h} = Q_{vre} \times cf_{vre,h} \qquad (4)$$

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.

2.1.3.4. 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):

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

Where $STORED_{str,h}$ is the energy in storage option *str* at hour *h*, while η_{str}^{in} and η_{str}^{out} are the charging and discharging efficiencies.

2.1.3.5. Secondary reserve requirement

Three types of operating reserves are defined by ENTSO-E (2013), according to 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:

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

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 (2017).

2.1.3.6. 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.

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

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).

$$Q_{frr} \geq G_{frr,h} + RSV_{frr,h} \qquad (8)$$

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).

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

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. 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 RTE[1] (the French transmission network operator).

The energy that can be produced by biogas is limited, since the main resources of this energy are methanization (anaerobic digestion) and pyro-gasification of solid biomass. Both processes are limited by several constraints and according to the ADEME "visions 2030-2050" report (2013) electricity from biogas produced by these two processes can be projected as 15 TWh per year from 2030 on (e_{biogas}^{max}), which is presented in equation 10.

[1] https://www.rte-france.com/fr/eco2mix/eco2mix-telechargement

$$\sum_{h=0}^{8759} G_{biogas,h} \leq e_{biogas}^{max} \qquad (10)$$

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. 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, $river_h$ in equation (11);

$$G_{river,h} = Q_{river} \times river_h \qquad (11)$$

As shown in Figure 1, two renewable gas technologies are considered; biogas and methanation. Both of them produce renewable methane, which can be used in gas power plants. In the model, the latter is considered to be an open cycle gas turbine (OCGT) due to its high operational flexibility and equation (12) shows the relationship of the power production from these two methane resources;

$$G_{gas,h} = \sum_{comb} G_{comb,h} \qquad (12)$$

Where $G_{comb,h}$ is the power production from each renewable gas resource, and $G_{gas,h}$ is the power production from the OCGT power plant which uses these two resources as fuel. It is worth mentioning that the efficiency of this combustion process is taken into account in both the $15\ TWh_e$ of yearly electricity production from biogas, and the discharge efficiency of the methanation process as defined in equation (5).

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 (13) where q_{tec}^{max} is this capacity limit, taken from the development trajectories for the French electricity mix for the period 2020-2060 (ADEME, 2018):

$$Q_{tec} \leq q_{tec}^{max} \qquad (13)$$

2.1.3.7. 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 14):

$$STORED_{str,h=0} \leq STORED_{str,h=8759} \qquad (14)$$

While equations (5) and (14) 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 15):

$$STORED_{str,h} \leq VOLUME_{str} \qquad (15)$$

Equation (16) limits the energy entry to the storage units to the charging capacity of each storage unit, which means that the charging capacity cannot exceed the discharging capacity.

$$STORED_{str,h} \leq S_{str} \leq Q_{str} \qquad (16)$$

2.2 Input data

The main input data can be placed in three main classes: cost data, VRE profiles and electricity demand profiles.

2.2.1. Cost data

The economic parameters for the power production technologies are taken from the European Commission Joint Research Center (2017) study of scenario-based cost trajectories to 2050, while energy technology reference indicator projections for 2010-2050 (JRC,(2014) have been used for OCGT gas power plants. Values attributed to the economic parameters of power production technologies for 2050 are summarized in Table 4. It is worth mentioning that the grid entry cost of €25.9/kW for each power plant mandated by RTE (2018) has been added to the capital expenditure values of each VRE technology, and the annuities (annualized CAPEX) are the results of these calculations. More information about the cost scenarios and the cost estimation methodology used in the JRC's 2017 study can be found in Appendix 1.

Table 4. Economic parameters of power production technologies

Technology	**CAPEX (€/kW$_e$)**	**Lifetime (years)**	**Annuity (€/kW$_e$/year)**	**Fixed O&M (€/kW$_e$/year)**	**Variable O&M (€/MWh$_e$)**	**Source**
Offshore wind farm*	2330	30	144.3677	47.0318	0	JRC (2017)
Onshore wind farm*	1130	25	77.6621	34.5477	0	JRC (2017)
Solar PV*	425	25	30.0052	9.2262	0	JRC (2017)
Hydroelectricity – lake and reservoir	2275	60	110.2334	11.375	0	JRC (2017)
Hydroelectricity – run-of-river	2970	60	143.9091	14.85	0	JRC (2017)
Biogas (Anaerobic digestion)	2510	25	135.5066	83.9	3.1	JRC (2017)
OCGT	550	30	33.7653	16.5	0	JRC (2014)

*For offshore wind power on monopiles at 30km to 60km from the shore, for onshore wind power, turbines with medium specific capacity (0.3kW/m^2) 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.

For the storage technologies, the "Commercialization of Energy Storage in Europe" report prepared by FCH-JU (2015) and a very recent article by Schmidt (2019) about long-term cost projections of storage technologies have been used respectively for pumped hydro storage and Li-Ion battery storage options. "The potential of Power-to-Gas" study by De Bucy (2016) has been used for methanation storage. Using these three studies the 2050 cost projection of storage technologies are presented in Table 5. The cost of methanation is made up of the cost of electrolysis units and the Sabatier reaction[1].

Table 5. Economic parameters of storage technologies

Technology	CAPEX (€/kW$_e$)	CAPEX (€/kWh$_e$)	Lifetime (years)	Annuity (€/kW$_e$/year)	Fixed O&M (€/kW$_e$/year)	Variable O&M (€/MWh$_e$)	Storage annuity (€/kWh$_e$/year)	Source
Pumped hydro storage (PHS)	500	5	55	24.6938	7.5	0	0.2261	FCH-JU (2015)
Battery storage (Li-Ion)	140	100	12.5	14.8876	1.96	2	10.3247	Schmidt (2019)
Methanation	1150	0	20/25*	117.9262	75.75	3	0	ENEA (2016)

*The lifetime of electrolysis units is 20 years, while the lifetime of methanation units is 25 years.

The carbon dioxide required for methanation is assumed to come from capturing and transporting the excess carbon dioxide resulting from the methanization process (for the production of biogas). About 30% of the product of bio-methane production from methanization by anaerobic digestion is gas phase carbon dioxide (Ericsson, 2017). According to ZEP (2011) on CO_2 transport, the cost of transporting carbon dioxide along a 200km onshore pipeline is $€4/tCO_2$, 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):

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

Considering a 100km long onshore pipeline (considering maximum 100km of distance between the methanation units and the biogas production units), the CO_2 transport cost for the methanation storage is €1/MWh, to be added to the gas storage cost which is €2/MWh (according to CRE (2018) - French energy regulation commission), the variable cost of the methanation storage is $€3/MWh_e$.

2.2.2. VRE profiles

Variable renewable energies' (offshore and onshore wind and solar PV) hourly capacity factors have been prepared using the renewables.ninja website[2], which provides the hourly capacity factor profiles of solar and wind power from 2000 to 2017 at the geographical scale of French *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 in-situ observations 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" website[3], and using their locations, we extracted the hourly capacity factor profiles of both floating and grounded offshore wind farms. We then averaged the most remarkable projects for each offshore wind foundation technology (floating and

[1] The reaction that produces methane from hydrogen and carbon dioxide – $CO_2 + 4H_2 \rightarrow CH_4 + 2H_2O$ – is called the Sabatier reaction.
[2] https://www.renewables.ninja/
[3] https://www.4coffshore.com/

grounded) for each year from 2000 to 2017. 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 2 provides more information about the methodology used in the preparation of hourly capacity factor profiles of wind and solar power resources.

2.2.3. Electricity demand profile

Hourly electricity demand is ADEME (2015)'s central demand scenario for 2050. This demand profile falls in the middle of the four proposed demand scenarios for 2050 in France by Arditi et al. (2013) during the national debates on the French energy transition (DNTE). It amounts to 422 TWh_e/year, 12% less than the average power consumption in the last 10 years.

3. Results

In this section, we first present the optimization results for each year from 2000 to 2017 and the optimization over the whole 18-year period. Then we select a representative year in order to perform a sensitivity analysis.

3.1. Optimization results

3.1.1. Yearly and 18-year optimization results

First, we ran the model for each year from 2000 to 2017 (henceforth "weather-years"). Thus, we can test how the optimal mix of variable renewables varies for different weather-years.

Our results show that the optimal power mix varies significantly from one year to another, both in terms of electricity production, installed capacity, storage volume and storage capacity (Figure 2b and Table A.1 in Appendix 2). The largest variations (taking the ratio of the highest-to-lowest value) are associated with the proportion of onshore and offshore windpower. In particular, offshore capacity ranges from zero to 20 GW which is the maximum value allowed[1]. High values for offshore wind are reached either for weather-years with a high capacity factor for offshore wind (as in 2015) or for weather-years with a low capacity factor for onshore wind (as in 2016), cf. Tables A.1 and A.2 in Appendix 2.

In comparison, installed solar capacity is more stable (between 100.5GW and 122.2GW), due to a less volatile capacity factor (Figure 2c and Table A.2). Biogas always reaches the maximum allowed power generation and hydro the maximum allowed capacity.

As far as storage capacity is concerned, pumped-hydro storage (PHS) also always reaches its maximum value while batteries and methanation vary a lot across weather-years (Figures 2d1 and 2d2). In comparison, the system LCOE and average power price (the dual variable of the adequacy constraint, i.e. equation 3), as well as the sum of VRE curtailment and storage losses are much more stable (Figures 2e and 2f).

[1] Maximum values are not binding for solar PV and onshore wind.

These results show that if the aim is to find an optimal energy mix, running a model on a randomly-chosen weather-year can be very misleading. The optimal mix of renewables is highly sensitive to the chosen weather-year. This conclusion is consistent with those of Collins et al. (2018) and Zeyringer et al. (2018). As the weather of future years cannot be predicted, the best approach would be to run the model over several weather-years, as in our 18-year simulation. However, the drawback is a much longer optimization time, which prevents us from doing this for the 315 cost scenarios used in our sensitivity analysis. Hence it is necessary to select a representative year for this stage in the work.

3.1.2. Representative year selection

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 18-year optimal 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 18-year optimal mix, we compute the sum of absolute difference[1] of the three VREs. Using this approach, 2006 is the closest year to the overall 18-year period, with a sum of absolute error values of 1.5% (Table A.4). 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 17 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.

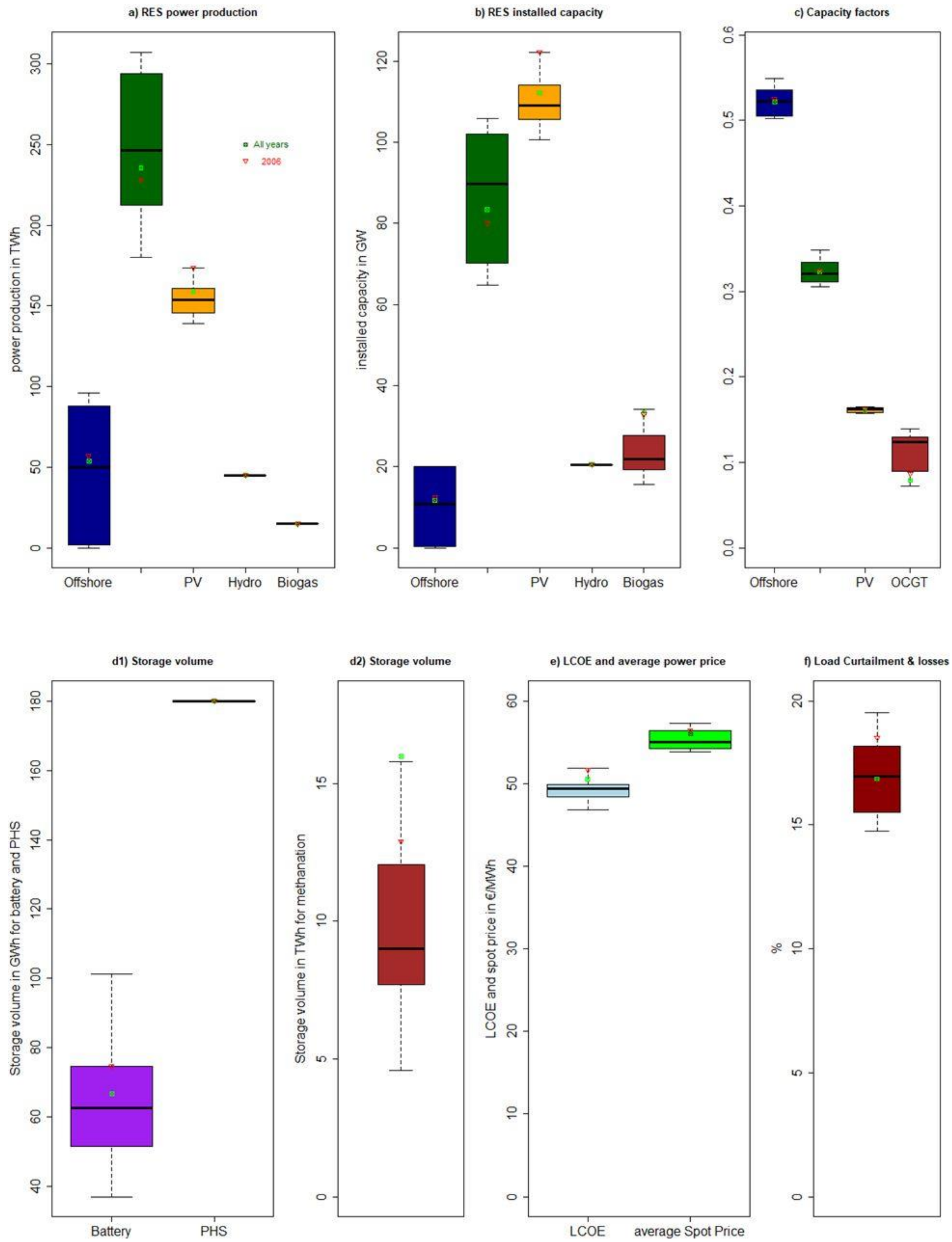

Figure 2. Optimization results for each weather-year from 2000 to 2017 and for the whole 18-year period. (a) power production; (b) installed capacity; (c) average capacity factor of each VRE and the gas power plant for biogas produced by anaerobic digestion and methane produced by methanation; (d) storage volume in GWh_e for batteries and pumped hydro storage (d1) and in TWh_e for methanation (d2); (e) system LCOE and average power price of electricity; (f) load curtailment and storage losses.

The green dot shows the results of the optimization over the 18-year period and the red dot the results for weather-year 2006. The box plots show the first and third quartiles and the median for each scenario.

There is a very close match between the percentage of each energy source for the overall 18-year long optimization and the representative year, i.e. 2006 (Figure 3). Onshore wind power is clearly dominant with solar power and offshore windpower as the second- and third- biggest sources of energy respectively.

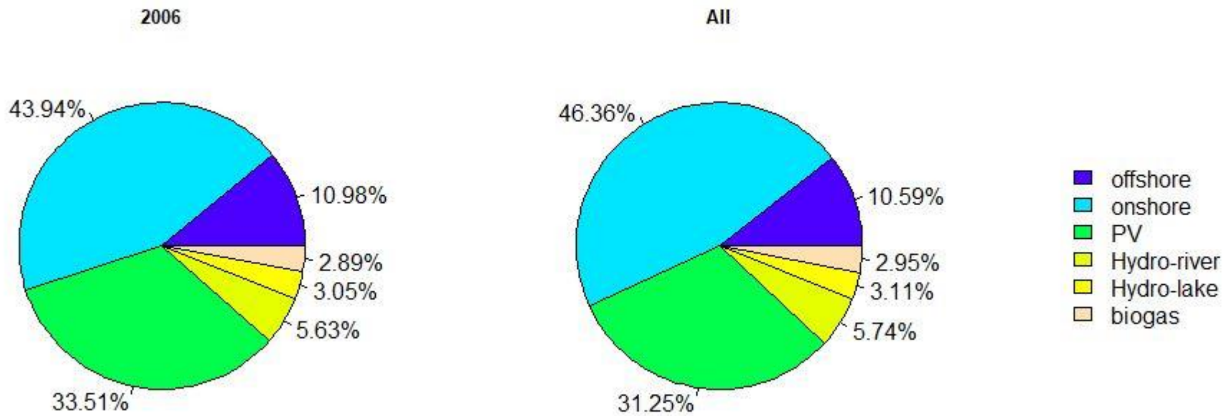

Figure 3. Energy mix for the chosen representative weather-year (2006, left) and for the 18-year optimization (right)

Figure 4 also shows the dual-variable value of the supply-demand equilibrium constraint (equation 3) which can be interpreted as the power price in an energy-only competitive market. When demand exceeds production by non-dispatchable technologies, OCGTs are used and the power price often reaches €140.2/MWh_e. On the contrary, when production by non-dispatchable technologies exceeds demand, the price often drops to €36.44/MWh_e which corresponds to the value of storing energy by methanation for future use. Sometimes it even drops to zero, corresponding to load curtailment. These price ranges are similar to those observed today on the spot market in France, and to those calculated by Abrell et al. (2019) for Germany, assuming a storage capacity similar to that of France.

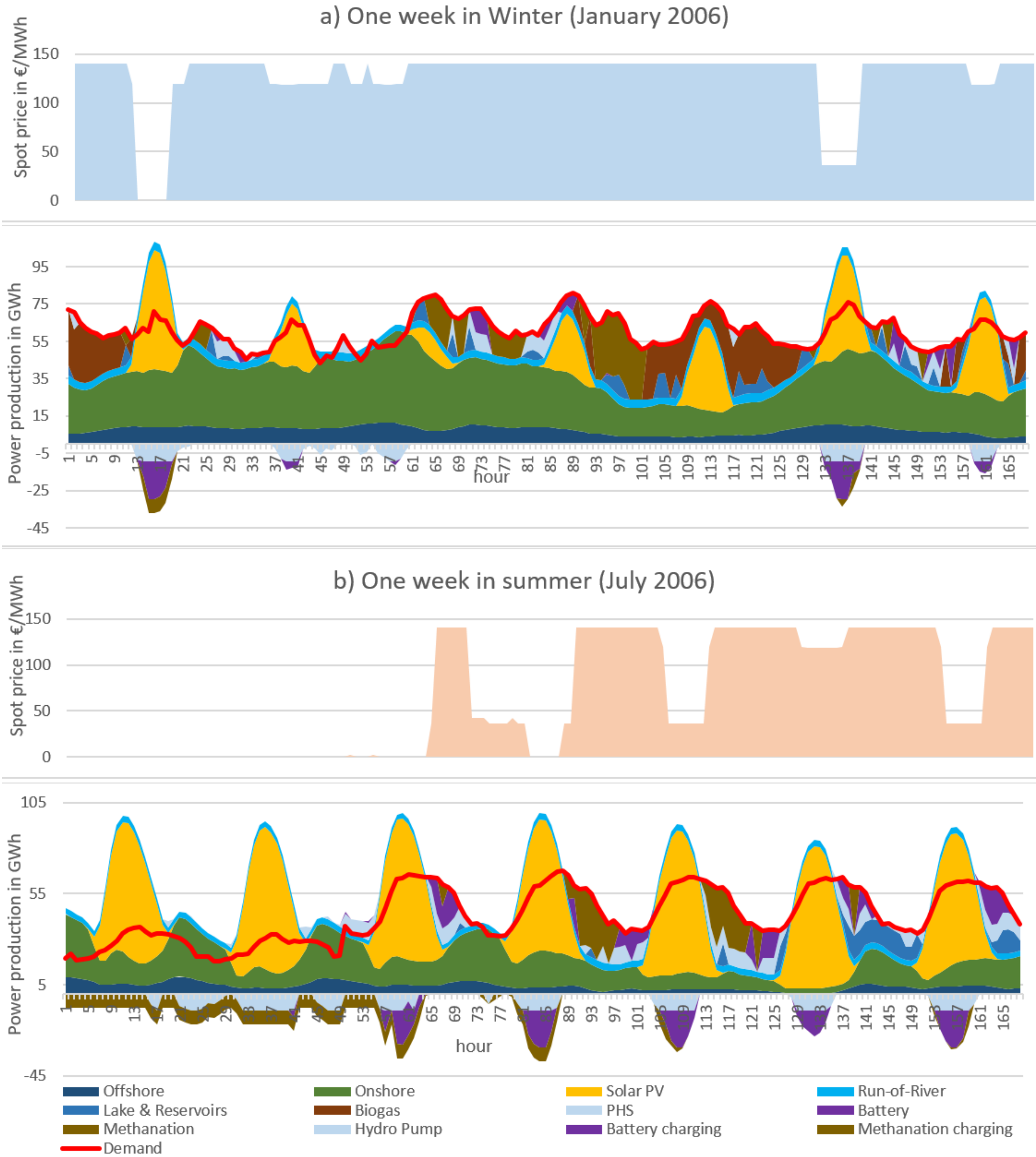

Figure 4. Hourly power generation, electricity demand, storage charge and discharge profiles and power prices for (a) the third week of January (Winter) and (b) the third week of July (Summer) 2006

In Table 6 we summarize the yearly power production LCOE (the levelized cost of electricity produced from each power plant without considering any future load curtailment or other losses) and average selling price for each generation technology and LCOS (levelized cost of storage; cf. Jülch et al., 2015) and the average selling price of each storage technology for weather-year 2006.

Table 6. LCOE/LCOS and average price of electricity sold and bought and unit profit for each technology, for weather-year 2006

Prices ($€/MWh_e$)	Offshore	Onshore	PV	Lake	River	Biogas	Battery	PHS	Methanation
LCOE/LCOS	41.58	39.45	27.60	100.00	40.80	82.00	83.65	16.80	109.36
Average price of energy sold	41.68	39.60	28.00	136.90	55.10	140.24*	98.00	89.10	140.24*
Average price paid for energy	-	-	-	-	-	-	21.53	23.76	27.90
Unit profit	0.10	0.15	0.40	36.90	14.30	58.24	-7.18	48.54	2.98

* Price of gas sold, converted into electricity-equivalent by dividing the gas price by the energy efficiency of OCGTs.

For all power production technologies, the average market selling price is higher than the LCOE, the difference being very low for the VRE resources (offshore wind ~€0.10/MWh_e, onshore wind ~€0.15/MWh_e and solar PV ~€0.40/MWh_e) while for the other technologies this difference is much greater, especially for biogas (€44.40/MWh_e). The profitability of hydro is due to the capacity constraint, while for biogas it is due to the production constraint, since these constraints generate a scarcity rent.

While the profitability analysis is straightforward for all the power production technologies, it is more complicated for the storage technologies since they buy electricity from the market, and there are losses related to charging and discharging inefficiencies. Equation (17) shows the profitability criteria for the storage technologies in the calculation of unit profit:

$$profit_{str}^{unit} = \left[\sum_h (G_{str,h} \times p_h^{market}) - \sum_h (STORAGE_{str,h} \times p_h^{market}) - (Q_{str} \times (Capex_{str} + fO\&M_{str}) + (VOLUME_{str} \times Capex_{str}^{en}) + \sum_h \left(G_{str,h} \times vO\&M_{str}\right))\right] / \sum_h G_{str,h} \quad (17)$$

Where p_h^{market} is the market price of electricity at hour h and $profit_{str}^{unit}$ is the net profit of the unit of electricity bought by the storage units, charged and sold on the electricity market (accounting for storage-related inefficiencies), which can be considered as the net present value of each storage technology per unit of power sold.

PHS is highly profitable because its capacity is limited, which generates a scarcity rent. Conversely, the profitability of batteries is negative because the FRR requirement leads to a higher battery capacity (by a factor of approximately two).

3.2. Sensitivity analysis

We take into account the uncertainty in the cost of the technologies indicated in Table 7. No variation in the cost of hydro and biogas is accounted for, the former because it is a mature technology with low uncertainty and the latter because in the model the amount of biogas used is determined by the availability constraint, not by its cost.

For power generation technologies, uncertainty applies to the fixed costs, defined as capital costs and fixed operation and maintenance costs. For storage technologies, it applies to the main cost component of each of them; fixed costs for methanation (similar to power generation technologies) and energy-related CAPEX for batteries. For wind technologies, the choice of a +/- 25% uncertainty range rather than +/- 50% comes from the expert elicitation survey by Wiser et al. (2016).

Table 7. Variations in the costs of key technologies accounted for in the sensitivity analysis

Technology	Solar PV	Offshore wind	Onshore wind	Batteries	Methanation
Uncertainty range	-50%; -25%; 0%; +25%; +50%	-25%; 0%; +25%;	-25%; 0%; +25%;	-50%; 0%; +50%	-50%; 0%; +50%

All the combinations of variations presented in Table 7 would give 405 different cost scenarios ($5^1 \times 3^4$), but only 315 of them are included in the sensitivity analysis. Indeed, a future in which offshore wind would be more expensive than expected and onshore wind cheaper than expected (or vice-versa) is not realistic so the costs of these technologies can only differ by 25% at most. This leads to seven different offshore and onshore wind power cost scenario combinations. Multiplying by five solar power cost scenarios and three cost scenarios for each storage technology ($7 \times 5^1 \times 3^2$) we obtain 315 future cost scenarios.

The optimal energy mix is highly sensitive to cost uncertainty (Figure 5). Offshore often reaches either zero installed capacity or the maximum allowed value, while the range of onshore and PV capacities is approximately five-fold across the cost scenarios. Storage technologies also demonstrate such high sensitivity, with the exception of PHS whose capacity is always fixed by the maximum allowed value. Battery capacity ranges from 7.6 to more than 279 GWh_e (nearly four times the capacity in the reference cost scenario) and methanation from 7 to 33.5 TWh (more than twice the capacity in the reference cost scenario).

However, the results for the whole system are much more robust: the sum of load curtailment and storage losses is generally in the range of 15%-20%, the system LCOE is scattered around €50/MWh_e and the average power price around €55/MWh_e. The LCOE ranges from €36.5 to €65.5/MWh_e for the most extreme cases, and the average LCOE is €2/MWh_e (i.e. 4%) less than in the reference cost scenario. The explanation is that in every scenario the energy mix is optimized, taking into account information about technology costs. This result shows that uncertainty about future technology costs is not necessarily a problem: it also provides opportunities to optimize the energy mix, reducing the expected system cost – provided that information on costs arrives soon enough to be accounted for when designing the power system. In the next subsection we will analyze the case of information arriving after the design of the power system.

Colored arrows besides the whisker plots in Figure 5 show the impact of uncertainty on a single technology (combining offshore and onshore wind technologies). Obviously, each option is particularly influenced by its own cost, but less obvious relationships appear. In particular, a higher cost of methanation entails much more offshore wind and vice-versa. Indeed, electricity from offshore wind suffers from a higher LCOE than the other VREs (Table 6) but is more stable, generating less need for storage. Conversely a higher cost of batteries reduces solar capacity: batteries are especially interesting when energy must be stored for a few hours, so they complement solar technology. Finally, the system LCOE and the average power price are much more influenced by the cost of generation technologies than by that of storage technologies[1].

[1] Schlachtberger et al. (2018) find nearly no effect of storage cost variation on the final cost of the electricity system, which is in accordance with our conclusions.

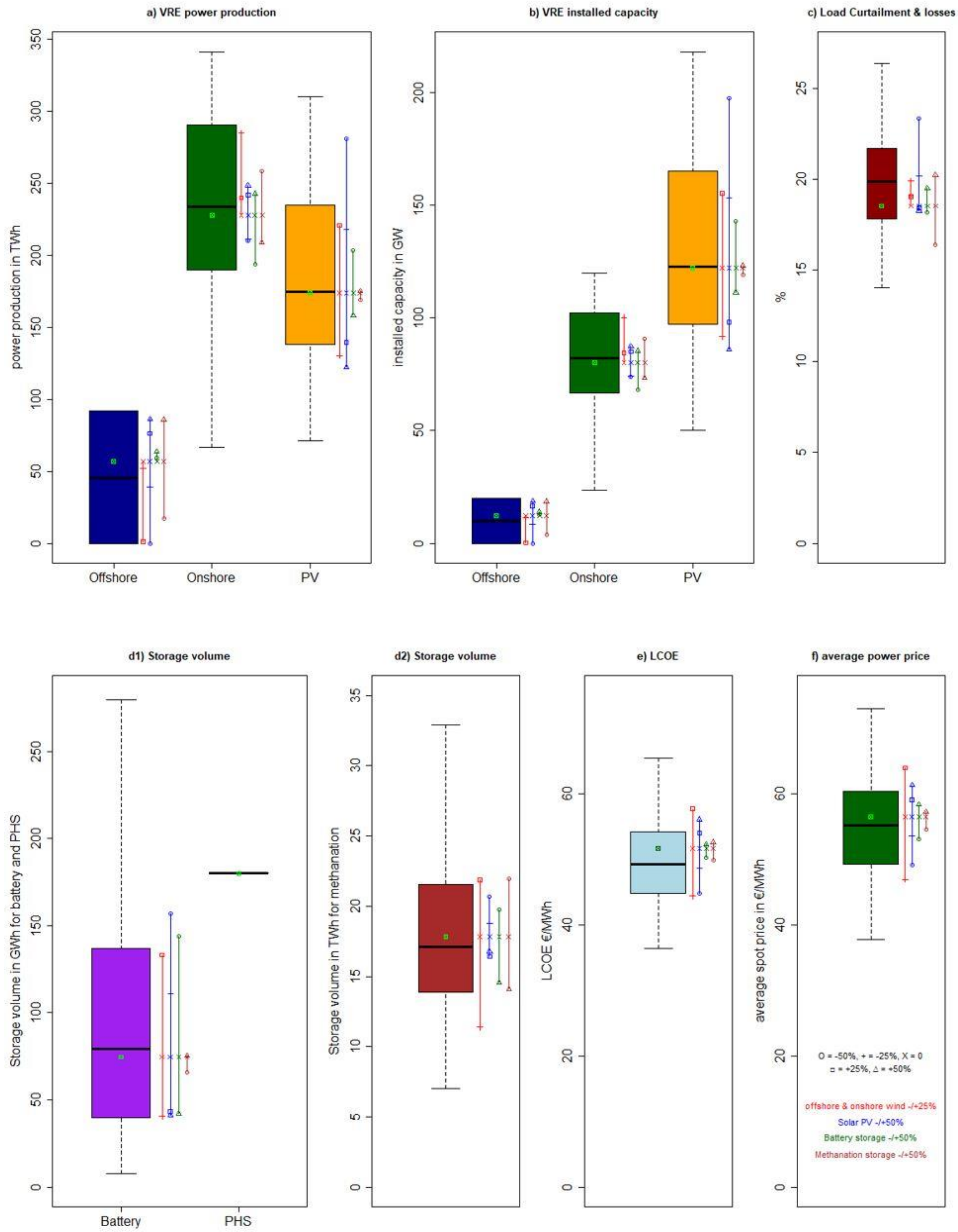

Figure 5. Optimization results over the 315 future cost projection scenarios. (a) power production and (b) installed capacity of each VRE resource; (c) load curtailment and storage losses; (d) required storage volume in GWh_e for batteries and pumped hydro storage (d1) and in TWh_e for methanation (2); (e) system LCOE in €/MWh_e; (f) average power price in €/MWh_e. The green point

shows the reference cost scenario, the box plots show the first and third quartiles and the median for each scenario. The colored lines beside the whisker plots show the impact of varying the cost of one technology separately, keeping all other technologies at their reference cost.

3.3. The cost of optimizing the power system on erroneous cost assumptions

In the results presented so far we have assumed that the power system is optimized on the true set of technology costs. In reality, information about these costs will arrive gradually and part of the investment will have to be made before it has arrived. Being static, our model cannot represent this gradual arrival of information but it can represent the worst case, in which all the investment has to be made before the information arrives.

The first step consists of selecting the power system which is the most robust to cost uncertainty. Calculating the robustness of each possible power system is not possible, but due to the linear nature of the model and to the symmetrical probability laws used to represent cost uncertainty, we might suspect that the most robust power system is that which minimizes the system LCOE in the reference cost scenario. To verify that this is the case, we have selected a subset of 10 out of our 315 cost scenarios, generating energy mixes that are contrasting and representative of those resulting from cost-optimization in the 315 scenarios (Table 8).

Table 8. Chosen scenarios and the future states in which these scenarios are optimal

Scenario	Offshore wind cost variation	Onshore wind cost variation	Solar PV cost variation	Battery storage cost variation	Methanation storage cost variation	Optimal VRE mix % (offshore; onshore; PV)
37	-25%	-25%	+50%	-50%	-50%	20; 60; 20
48	0	-25%	-50%	-50%	+50%	0; 50; 50
52	0	-25%	-50%	+50%	-50%	0; 60; 40
69	0	-25%	0	0	+50%	0; 70; 30
106	-25%	0	-25%	+50%	-50%	20; 40; 40
115	-25%	0	0	+50%	-50%	20; 45; 35
124	-25%	0	+25%	+50%	-50%	20; 50; 30
158	0	0	0	0	0	10; 50; 40
231	0	+25%	-50%	0	+50%	20; 20; 60
277	+25%	+25%	-50%	+50%	-50%	0; 40; 60

The regret value of each combination is calculated as the difference in total cost for each combination in each future state and the optimal mix in each future state. The percentage of regret is calculated by dividing these values into the total cost of the chosen scenario in the studied future state. Figure 6 shows these regret values as percentages for each scenario in all 315 future states.

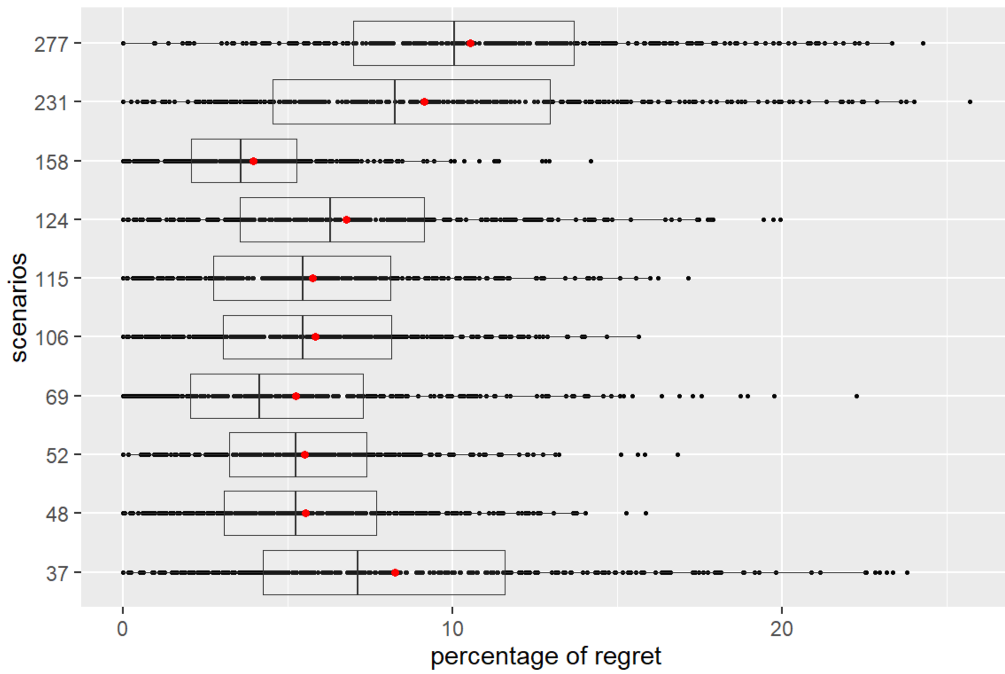

Figure 6. Regret percentage of each chosen combination in each future state; the box plots show the first and third quartiles and the median for each scenario, and red points show the mean value for each scenario

As suspected, the power system resulting from optimization in the reference cost scenario (scenario 158) brings the lowest mean regret, the lowest median regret, the lowest maximum regret and the lowest third quartile[1]. In other words, the certainty equivalence property applies.

Hence we calculate the distribution of LCOE across our 315 cost scenarios, for a power system consisting of the installed capacities of generation and storage technologies optimized for the reference cost scenario (Figure 7). The average system LCOE is only 4% (less than €2/MWh_e) more than when investment takes place after the arrival of information about costs; it equals the system LCOE under the reference cost scenario, positive and negative cost shocks cancelling out on average.

[1] Lempert (2006), Nahmmacher (2016) and Perrier (2018) have all used this third quartile to identify the most robust scenario.

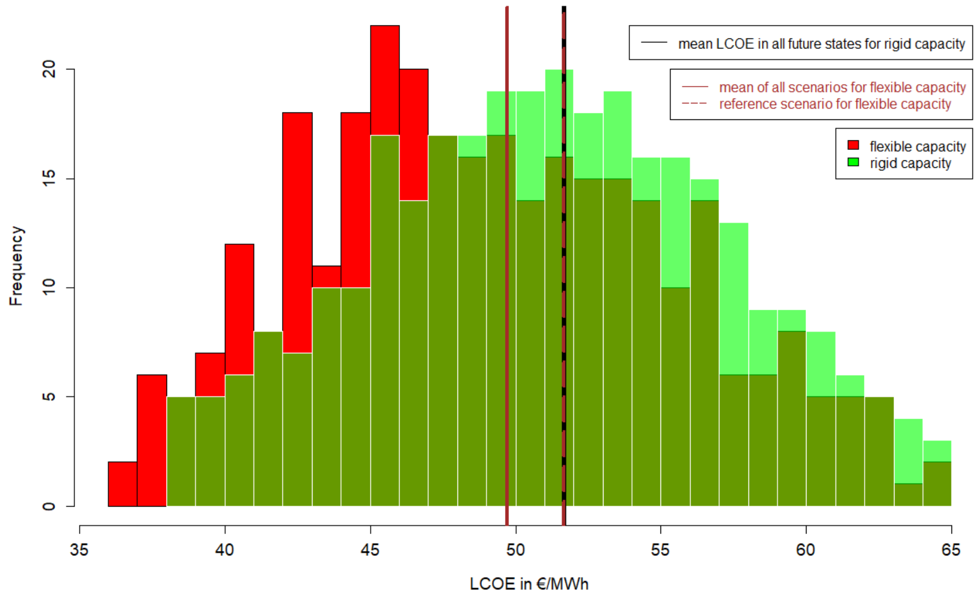

Figure 7. Comparison of LCOE in a flexible installed capacity mix and a rigid installed capacity mix

4. Discussion

4.1. Comparison with existing studies

Some authors have argued that the storage facilities required for a fully renewable power system would massively increase the power system cost (e.g. Sinn, 2017, whose conclusions have been challenged by Zerrahn et al., 2018). In our reference cost scenario, storage (batteries, PHS and methanation) accounts for only 14.5% of the system cost, vs. 85.5% for electricity generation (Figure A.2 in Appendix 3). Moreover, we have seen that the system LCOE is much more robust to the cost of the storage technologies than to that of PV and wind. Hence the importance of the storage cost should not be overemphasized.

The system LCOE for power generation and storage ranges from €36 to €65/MWh_e, depending on technology costs, with an expected value between €50 and €52/MWh_e, depending on whether the power system is optimized before or after the arrival of information about technology costs. According to the latest quarterly report from the French energy regulator (CRE, 2018), 35% of a typical electricity bill represents electricity production, hence from a bill varying between €160 and €170/MWh_e, €56-€60/MWh_e represents production. Hence the cost of a 100% renewable electricity system for France in 2050 would be lower than or similar to that of the current power system.

These results contrast with those of Krakowski et al. (2016) who find an annualized cost of more than €60 bn/yr. in their scenario 100RES2050 (cf. their Fig. 23) vs. €21 bn/yr. in ours. The explanation does not stem from their investment cost assumptions, which are similar to ours (cf. their Table 1). One explanation might be that they take a higher discount rate, but they do not disclose it so we cannot verify this hypothesis. Partial explanations are (i) a slightly higher power demand (cf. their Fig. 7: about

460 TWh_e/yr. vs. 422); (ii) a slightly lower capacity factor for onshore wind (28%) and offshore wind (50%); (iii) the fact that they assume a perfect correlation between onshore and offshore wind production, which artificially limits the complementarity between these technologies. Moreover, they base their wind production profiles on observed power generation in 2012, which neglects the fact that advanced turbines generate electricity more constantly than those installed in the past (Hirth and Müller, 2016).

Villavicencio (2017), who does not specify the time horizon considered, finds even higher annualized cost: more than €180 bn/yr. for 100% renewables, i.e. more than 8 times our result. Several factors may explain this huge difference. First, he takes a real discount rate of 7%/yr. This is much higher than ours, which corresponds to the rate recommended for socio-economic analysis in France (4.5%). Second, his investment cost for PV is much higher than ours: €3.6/W_e, while the current investment cost at utility scale is around \$1/W_e (Lazard, 2018)[1]. This explains why PV does not appear in his reference scenario (F1) with 100% renewables. Third, total demand is higher than ours (512 TWh_e vs. 422TWh_e).

To sum up, while our results point to a much lower system cost than the two above-mentioned studies modeling a 100% renewable system for France, there are good reasons to conclude that the system cost for 2050 will be lower than that estimated by these studies. In the remainder of this subsection, we address several factors in turn which could push our estimates up or down.

4.2. Factors which could push costs up

4.2.1. Cost of the transmission and distribution network

Our system LCOE includes storage and connection of power generation to the grid, but not the cost of the transmission and distribution network. Currently this cost accounts for 27% of the typical electricity bill, i.e. about €45/MWh_e. Calculating this cost for the various power systems considered in the present study would exceed the scope of the present article, but several recent studies indicate that the cost differential across scenarios featuring greater or lesser percentage of renewables would be limited.

- According to the RTE systems and network perspectives study (2018), for a 71% renewable electricity mix (the so-called Watt scenario for 2035) in France, the extra network costs would be in the order of €1 bn/yr., less than 5% of the total production cost. However, the relationship is not linear and it cannot be easily extrapolated for higher proportions of renewables.
- According to two studies by ADEME (2015, 2018), the cost of renovating the French network, which is planned to take place before 2030, will be at least one order of magnitude more than the cost required to strengthen the grid for a fully renewable power network.
- According to EirGrid[2] (the Irish electricity network operator), for an electricity mix with nearly 90% of renewables, the reinforcement required to integrate VREs will cost no more than €1/MWh_e.

[1] A more recent article by the same author features a much lower investment cost parameter for PV: €0.71/W but does not provide simulations with 100% renewable energy (Villavicencio and Finon, 2019).
[2] http://www.eirgridgroup.com/newsroom/record-renewable-energy-o/index.xml

4.2.2. Acceptability of wind power

Our optimal scenario corresponding to the reference technology costs includes about 80 GW of onshore wind, 12 GW of offshore wind and 110 GW of PV. The availability of land for PV does not appear to be problematical since the amount of suitable land is much higher than required (Cerema, 2017). For offshore wind, WindEurope's "high" scenario for 2030 forecasts 11 GW, roughly equivalent to our optimal scenario corresponding to the reference technology costs. Here again, reaching this capacity does not seem problematical.

For onshore wind, WindEurope's (2017) "high" scenario forecasts 41 GW in 2030, vs. 14 in 2018, i.e. an increase of 2.2 GW/yr. on average. Reaching 80 GW in 2050 means an increase of 2 GW/yr. on average, from 2018 onwards, a bit less than WindEurope's "high" scenario, but almost twice the current rate of increase. Sustaining such a high rate of increase requires a high degree of political determination, given the current opposition faced by many wind projects in France.

4.2.3. Discount rate

Some studies use higher discount rates than ours, e.g. 7% in Villavicencio (2017), as mentioned above. This would increase the annualized LCOE, and especially the cost of capital-intensive technologies. While higher rates may well be used by private companies, 4.5% is already much higher than both the rate-free real interest rate available on financial markets, and expected GDP growth over the next few decades. Using a higher rate in a socioeconomic analysis means than future generations would be penalized when compared to current ones, which can hardly be defended on ethical grounds.

4.2.4. Perfect weather forecasts

Our optimization has been conducted on the assumption that the weather is known for the whole period. With imperfect weather forecasts, the cost would be higher, but such an optimization for a country-scale system would be computationally challenging. Gowrisankaran et al. (2016) have performed such an optimization just for solar energy, on a limited geographical scale, and have found that "intermittency overall is quantitatively much more important than unforecastable intermittency." However, whether this conclusion would hold for a complex, multi-energy system is an open question.

4.3. Factors which could bring costs down

4.3.1. Demand-side management

Our model does not feature price-elastic electricity demand or flexibility in the power consumption profile, because this would have required debatable assumptions. Moreover, the demand profile, taken from ADEME (2015), is already flatter than the current one. Including these features would reduce the need for storage and the related energy losses.

4.3.2. Interconnection with neighboring countries

Many studies have shown that interconnections with neighboring countries can significantly reduce the cost of a fully renewable system. For instance, Annan-Phan and Roques (2018) have shown that power price volatility can be reduced by cross-border exchanges with neighboring countries. Indeed this leads to benefits from the differences both in climatic and weather conditions between the countries concerned.

4.3.3. Spatial optimization of renewable energy capacities

As mentioned above, we do not optimize the quantity of renewables at every location but only the aggregate capacity, which is thus scaled up compared to the value observed in 2017. A lower system cost would be obtained by optimizing their location, which would presumably lead to greater capacity in windier or sunnier locations, although this effect would be mitigated by the need to obtain a flatter aggregate generation profile. Yet this would make the model computationally intractable and might lead to unrealistic concentrations of onshore wind in some locations.

4.3.4. Neither vehicle-to-grid nor second-hand batteries

We have not taken into account vehicle-to-grid i.e. the possibility that electric vehicle batteries could be used to provide flexibility in the electricity system. Yet the storage capacity of electric vehicles may be huge by 2050: The French TSO RTE (2018) estimates it at 900 TWh_e, about ten times the battery capacities in our reference cost scenario. Mobilizing even a small part of this capacity for power storage would bring down the system LCOE, but we have preferred not to include this option because the impact on battery lifetime is still being debated. Another possibility is to recycle used car batteries as stationary batteries, but again, we believe that modeling this option would require precise assumptions on battery degradation.

5. Conclusion

We have developed EOLES, a model optimizing investment and dispatch in the power sector, and applied it to the study of fully renewable power systems in France. We have shown that the energy mix depends strongly on the chosen weather-year, so this year should be chosen carefully considering a longer period of weather data. Having selected a representative year, we built 315 cost scenarios by combining assumptions about the long-term cost of the key power generation and storage technologies.

We find that the system levelized cost of electricity, including generation and storage, ranges from €36.5 to €65.5/MWh_e, depending on the cost scenario, with an average value of €50/MWh_e. This average value is based on the assumption that the energy mix is optimized after the arrival of information on technology costs; if instead we assume that all investment must take place before knowing the true cost scenario, the average system LCOE is only 4% (€2/MWh_e) higher.

The main takeout message from this uncertainty analysis is thus that even though the technologies involved in a fully renewable power system are very different, they are by and large substitutable. For instance, if batteries are 50% more expensive than expected, the optimal energy mix includes fewer batteries and less PV, but this is compensated for by additional windpower, with a very limited impact on the system LCOE. On the contrary, if windpower is 25% more expensive than expected, the optimal mix obviously includes less of this technology, but this is compensated for by more PV and storage.

In addition, our analysis shows that the optimal power mix is highly sensitive to the chosen weather-year and to the cost assumptions. In the literature, many analyses of the power mix are still based on a unique weather-year, chosen for data availability rather than representativeness. Our result thus calls for caution over such conclusions on the optimal power mix, when they are based on a limited number of weather-years or cost scenarios.

Finally, the cost of storage should not be overestimated: in our reference cost scenario, storage (batteries, PHS and methanation) accounts for only 14.5% of the system cost, vs. 85.5% for electricity generation. Were our model to include demand-side management, interconnections with neighboring countries, vehicle-to-grid or second-hand batteries, the cost of storage would be even lower.

This work could be extended in many directions, for example including the other power generation technologies that entail low direct CO_2 emissions: CO_2 capture and storage and nuclear power. Their cost and the possibility of storing massive quantities of CO_2 being very uncertain in the French context, we decided not to include them in the present study, but they could be considered in future work.

Appendix 1. Additional information on the JRC 2017 study

In this JRC report, historic installed capacity of each technology for 2015, learning rate related to each technology and the capital investment cost of each technology in 2015 has been taken as input values, and using three different future installed capacity scenarios, three different future cost trajectories are proposed. Equation (A1) shows the main methodology used in the cost projection using the learning rate method:

$$Cost_t = Cost_0 \cdot \left(\frac{C_t}{C_0}\right)^{\delta} \qquad \text{(A1)}$$

This log-linear relation relates the future cost ($Cost_t$) of a technology to the existing cost ($Cost_0$), existing installed capacity (C_0) and the future projected installed capacity (C_t) of it using the experience parameter δ. The learning rate *LR* is related to the experience parameter as it is described in equation (A2);

$$LR = 1 - 2^{\delta} \qquad \text{(A2)}$$

The JRC report uses three different scenarios to project the future installed capacity of each technology, and finally to find the $\frac{C_t}{C_0}$ ratio for the equation (16). These three scenarios are described in Table A-1;

Table A-1 the chosen scenarios by JRC for the 2050 cost projections of low carbon power production technologies

Scenario	
Baseline	This scenario is used to cover the lower end of RES-E deployment. It is based on the "6DS" scenario of the Energy Technology Perspectives published by the International Energy Agency in 2016. It represents a "business as usual" world in which no additional efforts are taken on stabilizing the atmospheric concentration of greenhouse gases. By 2050, primary energy consumption reaches about 940 EJ, renewable energy supplies about 30 % of global electricity demand and emissions climb to 55 GtCO2.
Diversified	The "Diversified" portfolio scenario is taken from the "B2DS" scenario of the International Energy Agency's 2017 Energy Technology Perspectives and is used as representative for the mid-range deployment of RES-E found in literature. To achieve rapid decarbonization in line with international policy goals, all known supply, efficiency and mitigation options are available and pushed to their practical limits. Fossil fuels and nuclear energy participate in the technology mix, and CCS is a key option to realize emission reduction goals. Primary energy consumption is comparable to 2015 levels (about 580 EJ), the share of renewable electricity in the global supply mix is 74 % while emissions decline to about 4.7 GtCO2 by 2050.
ProRES	The "ProRES" scenario results are the most ambitious in terms of capacity additions of RES-E technologies. In this scenario the world moves towards decarbonization by significantly reducing fossil fuel use, however, in parallel with rapid phase out of nuclear power. CCS does not become commercial and is not an available mitigation option. Deep emission reduction is achieved with high deployment of RES, electrification of transport and heat, and high efficiency gains. It is based on the 2015 "Energy Revolution" scenario of Greenpeace. Primary energy consumption is about 430 EJ, renewables supply 93 % of electricity demand and global CO2 emissions are about 4.5 GtCO2 in 2050.

The used economical parameters for the power production technologies are taken from the 2050 projections of this study for the diversified scenario as an average and more realistic scenario.

Appendix 2. 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 3. Additional results

The results for each weather-year can be seen in Tables A.1, A.2, A.3 and Figure A.1;

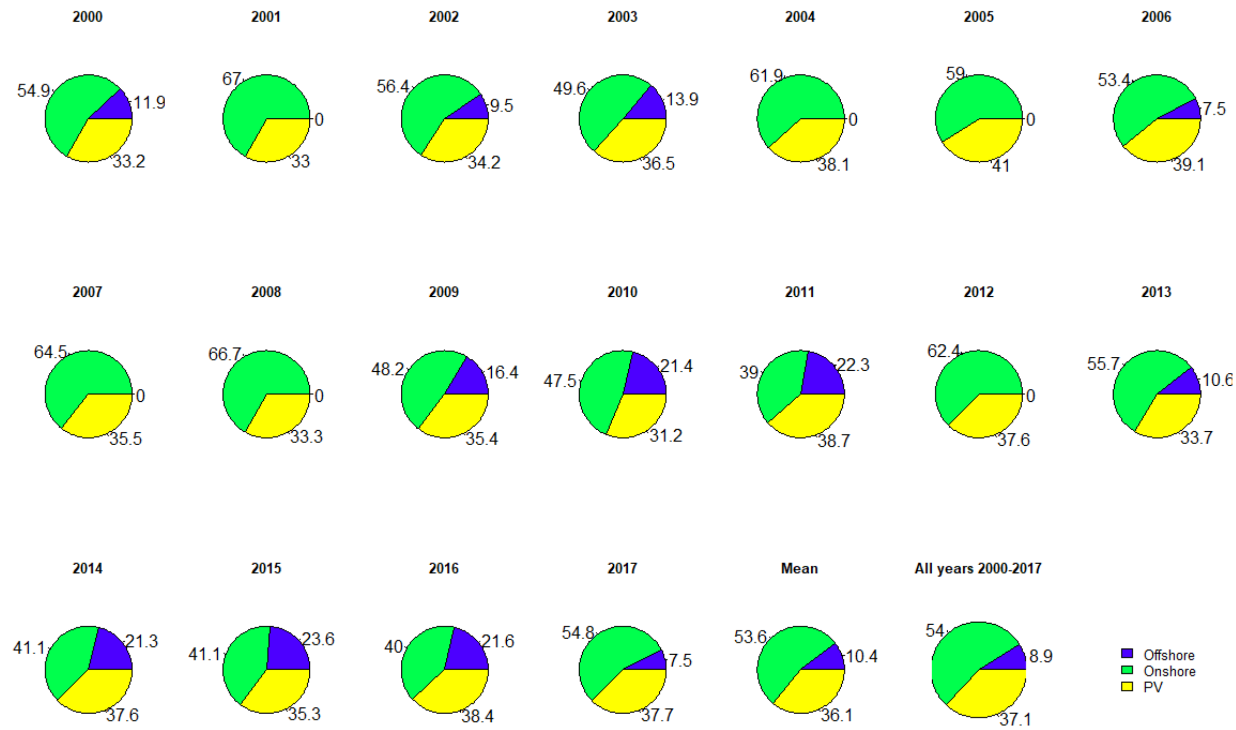

Figure A.1 VRE generation mix for each weather-year in single-year optimization and over the whole 18-year long period

Table A.1 installed capacity of each power production technology in GWe and energy storage capacity of each storage technology during each optimization period

Weather-year	Offshore Wind	Onshore Wind	Solar PV	Run-of-river	Lake & reservoir	Biogas	Battery (GWh)	PHS (GWh)	Methanation (TWh)
2000	11.46	84.14	105.74	7.50	13.00	18.24	60.17	180	5.52
2001	0.38	104.62	101.16	7.50	13.00	28.61	41.91	180	8.45
2002	17.12	69.66	105.55	7.50	13.00	19.16	74.70	180	4.60
2003	10.21	90.15	106.83	7.50	13.00	25.70	62.78	180	5.52
2004	0.00	105.29	113.38	7.50	13.00	21.88	70.32	180	15.30
2005	0.00	105.89	110.38	7.50	13.00	25.22	60.27	180	9.37
2006	12.36	80.08	122.17	7.50	13.00	32.89	74.62	180	12.90
2007	0.00	98.40	118.33	7.50	13.00	27.61	65.73	180	12.05
2008	0.78	101.95	105.20	7.50	13.00	21.76	52.03	180	12.05
2009	11.61	89.32	107.79	7.50	13.00	18.83	51.47	180	6.92
2010	20.00	83.64	100.50	7.50	13.00	22.88	40.53	180	15.81
2011	20.00	65.81	114.17	7.50	13.00	28.32	101.33	180	8.54
2012	0.00	103.38	114.49	7.50	13.00	20.36	62.43	180	11.32
2013	10.32	92.30	100.82	7.50	13.00	21.54	37.06	180	10.59

2014	20.00	70.23	111.40	7.50	13.00	18.57	80.03	180	7.69
2015	20.00	64.77	103.78	7.50	13.00	34.09	63.19	180	8.22
2016	20.00	69.77	114.07	7.50	13.00	23.96	81.68	180	8.66
2017	5.29	100.72	111.62	7.50	13.00	19.30	50.05	180	11.77
Mean	9.97	87.78	109.30	7.50	13.00	23.83	62.79	180	7.74
All	11.77	83.30	112.21	7.50	13.00	33.25	66.71	180	16

Table A.2 Yearly power production of each production technology (in TWh) and capacity factor of VRE resources

Weat her-year	**Offshore Wind**	**Onshore Wind**	**Solar PV**	**Run-of-river**	**Lake & reservoir**	**Biogas**	**Offshore Wind**	**Onshore Wind**	**Solar PV**	**OCGT plant**
2000	54.08	246.41	146.58	29.19	15.82	15	0.538	0.334	0.158	0.139
2001	1.77	307.32	143.64	29.19	15.82	15	0.537	0.335	0.162	0.089
2002	82.05	121.44	145.52	29.19	15.82	15	0.547	0.348	0.157	0.127
2003	44.99	245.26	153.46	29.19	15.82	15	0.503	0.311	0.164	0.088
2004	0.00	296.53	159.65	29.19	15.82	15	0.509	0.322	0.161	0.130
2005	0.00	290.19	159.98	29.19	15.82	15	0.507	0.312	0.165	0.102
2006	56.90	227.80	173.72	29.19	15.82	15	0.525	0.324	0.162	0.087
2007	0.00	294.71	170.24	29.19	15.82	15	0.532	0.341	0.164	0.100
2008	3.67	296.22	145.50	29.19	15.82	15	0.536	0.331	0.158	0.120
2009	51.41	246.86	153.65	29.19	15.82	15	0.504	0.315	0.162	0.130
2010	88.51	226.65	140.74	29.19	15.82	15	0.505	0.308	0.160	0.130
2011	91.47	179.83	165.84	29.19	15.82	15	0.522	0.311	0.165	0.085
2012	0.00	294.01	164.07	29.19	15.82	15	0.523	0.326	0.163	0.130
2013	48.17	259.67	138.87	29.19	15.82	15	0.533	0.320	0.157	0.128
2014	89.18	193.92	153.49	29.19	15.82	15	0.509	0.314	0.157	0.133
2015	96.26	190.85	148.57	29.19	15.82	15	0.549	0.335	0.163	0.072
2016	88.09	187.04	160.28	29.19	15.82	15	0.502	0.302	0.160	0.101
2017	23.35	272.47	160.58	29.19	15.82	15	0.504	0.309	0.164	0.135
Mean	45.55	248.23	154.69	29.19	15.82	15	0.522	0.323	0.161	0.113
All	53.79	235.53	158.75	29.19	15.82	15	0.522	0.323	0.161	0.079

Table A.3 shows the total cost, marginal cost and the system LCOE[1] for each yearly optimization and for the whole 18-year long optimization.

Table A.3 Total cost, average marginal cost (average spot price), levelized cost of electricity, load curtailment and storage related losses of each year

Weat her-year	**Total Cost (b€)**	**System LCOE (€/MWh)**	**Market price (€/MWh)**	**Load Curtailment**	**Storage losses**	**Curtailment + loss**
2000	20.23	47.89	53.83	11.64	5.06	16.70
2001	20.44	48.40	54.20	12.76	4.87	17.63
2002	19.77	46.82	54.60	10.90	4.62	15.12
2003	20.83	49.31	54.21	12.38	3.76	16.14
2004	21.33	50.51	56.91	11.75	6.43	18.18
2005	21.04	49.81	54.18	11.94	5.26	17.20
2006	21.82	51.65	56.46	11.99	6.53	18.52

[1] System LCOE (levelized cost of electricity) is an economic assessment of the average total cost to build and operate an electricity system over its lifetime divided by total electricity consumption over that lifetime.

2007	20.87	49.40	55.59	13.40	6.14	19.54
2008	20.19	47.81	55.23	11.27	5.16	16.43
2009	20.71	49.02	54.72	13.02	4.47	17.49
2010	21.91	51.87	57.29	11.83	6.30	18.13
2011	21.06	49.85	54.43	10.30	4.74	15.04
2012	20.87	49.41	54.81	12.67	5.80	18.47
2013	20.82	49.28	55.47	10.63	6.01	16.64
2014	20.68	48.95	56.90	10.10	4.84	14.94
2015	20.29	48.04	54.18	10.12	4.66	14.78
2016	21.00	49.72	56.46	10.07	4.67	14.74
2017	21.13	50.03	55.43	12.95	5.26	18.21
Mean	20.83	49.32	55.27	11.65	5.25	16.90
All	21.33	50.50	56.01	11.52	5.34	16.86

Figure A.2 shows the share of each technology in overall cost of power system (except distribution and transmission costs);

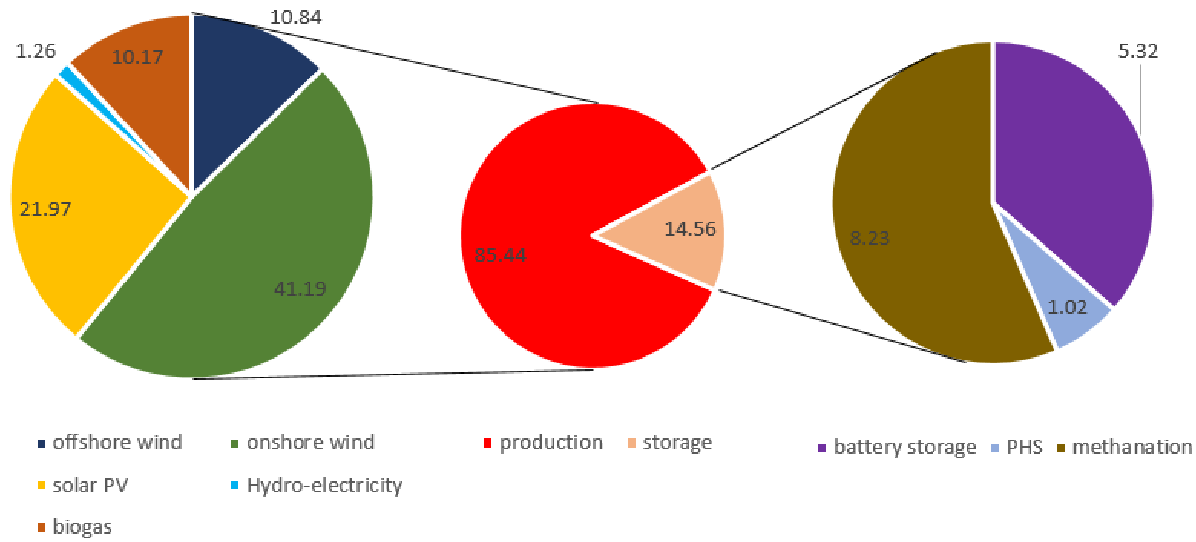

Figure A.2. Overall decomposition of the system cost in the reference cost scenario

Table A.4 shows the ranking of each weather-year in correlation with overall 18-year period.

Table A.4 Closest years to the overall 18-year period regarding to the capacity factor of VRE resources

	Closest year	**Second closest year**	**Third 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)	0.0150	0.0236	0.0280

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