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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. 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. To analyze it, we build 315 cost scenarios by varying the costs of key technologies and we model the optimal renewable power system for France, simultaneously optimizing investment and dispatch. We add to the literature by studying a consecutive 18-years weather period; by testing all combinations of technology costs rather than changing them one-at-a-time; and by calculating the regret from optimizing the energy mix on the basis of cost assumptions that do not materialize.

Our results indicate that the cost of a 100% system is not that sensitive to uncertainty. Admittedly, the optimal energy mix is highly sensitive to cost assumptions: across our 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, in every scenario the total production and storage cost is similar to, or lower than the current cost. This indicates that renewable technologies will become by and large substitutable. Moreover, even if the energy mix is optimized based on cost assumptions which turn out to be wrong, the extra cost is low: 4% in average and less than 9% in 95% of the scenarios.

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

JEL classification: C21; O21; Q21; Q47; Q48.

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1 Introduction¹

According to Article 4.1 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. The electricity sector will have a key role to play, as decarbonisation is easier in this sector than in transport, buildings or agriculture. Renewable energy will be the cornerstone of decarbonisation, making a greater contribution than nuclear energy and fossil fuels with CO₂ capture and storage (Rogelj et al., 2018).

While the feasibility of a 100% renewable electricity system has already been highlighted by many studies (Brown et al, 2018, and references therein), the cost of such a system is heavily debated. Following Joskow (2011), Hirth (2015) and Hirth et al. (2016), 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 or wind turbines in a given location produce their electricity at the same time. 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, these results of increasing costs and right balance might not hold much longer, due to the rapid decline in storage costs and the fact that recent wind turbines benefit from a flatter production profile than older models (Hirth and Müller, 2016).

If this phenomenon of increasing costs does not hold any more, it means that the relationship between renewable energy sources is changing from being complements to being substitutes. It would be then possible to identify one or several “robust” energy mixes, in the sense that their overall cost does not vary much, even if the cost of the different technologies finally differs from the initial forecast.

To shed light on these questions, 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 energy demand at 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

¹ We thank four anonymous referees from *The Energy Journal* and an anonymous referee from the FAERE Working papers series for their very useful comments, which have significantly improved the paper.

and biogas) and three storage technologies (batteries, pumped hydro and power-to-gas).

Using this model, we study the sensitivity of the power mix in 2050, through 315 cost scenarios for 2050, varying all key technology costs: onshore and offshore wind by +/- 25%; PV, batteries and power-to-gas by +/-50%. Most existing studies are based on a single weather-year or on a few ones, and when a sensitivity analysis on technology costs is performed, it generally varies these costs one-at-a-time. We add to this literature by studying a consecutive 18-years weather period and carefully choosing a representative year for the sensitivity analysis; by testing all combinations of technology costs rather than changing them one-at-a-time; and by calculating the regret from optimizing the energy mix on the basis of cost assumptions that do not materialize.

The remainder of this paper is organized as follows. In Section 2 we present the EOLES_elecRES model, the 100% renewable electricity sector version of EOLES family of models. Results are presented in Section 3 while Section 4 provides a discussion and concludes.

2 Materials and methods

2.1 Model description

EOLES_elecRES is a dispatch and investment model that minimizes the annualized power generation and storage costs, including the cost of connection to the grid. It includes six power generation technologies: offshore and onshore wind power, solar photovoltaics (PV), run-of-river and lake-generated hydro-electricity, and biogas combined with open-cycle gas turbines. It also includes three energy storage technologies: pump-hydro storage (PHS), batteries and methanation combined with open-cycle gas turbines. These technologies are shown in Figure 1.

The model considers continental France as a single node. PV and onshore wind are simulated for the 95 counties (*départements*, an administrative entity corresponding to the European NUTS 3 level). The proportion of the installed capacity in each department remains the same in all simulations, at the level observed in 2017. We consider that this is the best simple method to represent the possible future repartition of these capacities, because it takes into account the local resource (e.g. more PV in the South, more wind in the North), land availability and social acceptability (e.g. little possibility to install wind farms in densely populated areas, in the mountains or in very touristic locations). As detailed in subsection 2.3 below, this scale-up method applies neither to hydro, which is capped by assumption due to the very limited availability of new production sites, nor to offshore wind, for which the repartition of capacities follows the existing offshore projects around France, identified through the “4C offshore” website.

The model is written in GAMS and solved using the CPLEX solver. The code and data are available on GitHub.¹ EOLES uses only linear optimization. Non-linear constraints might improve accuracy, in particular when studying unit commitment, but 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.

Figure 2 provides an illustrative output of the model, i.e. the optimal dispatch for a week in winter and for a week in summer, for each hour of the week.

The remainder of this section presents the main equations (2.2) and the input data (2.3). A detailed description of all sets, parameters and variables of the model is available in Appendix 4.

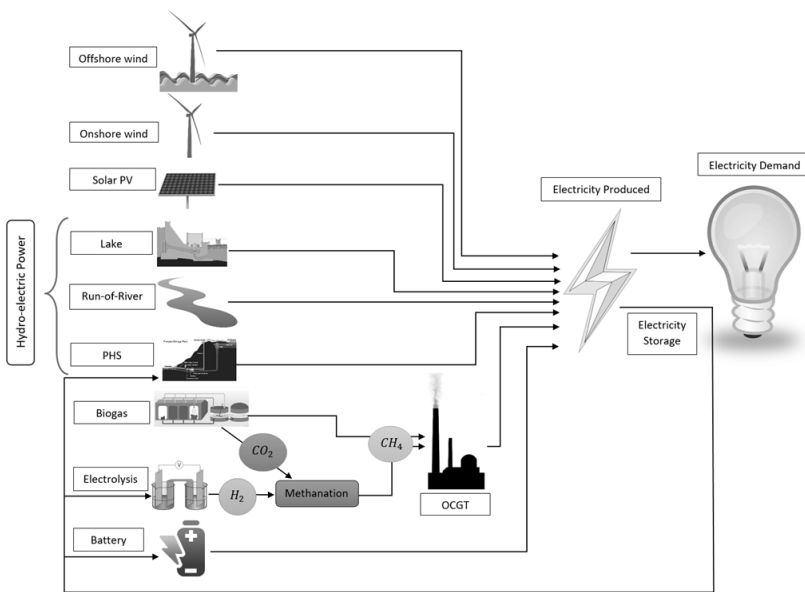


Figure 1 Graphical description of the EOLES_elecRES model

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

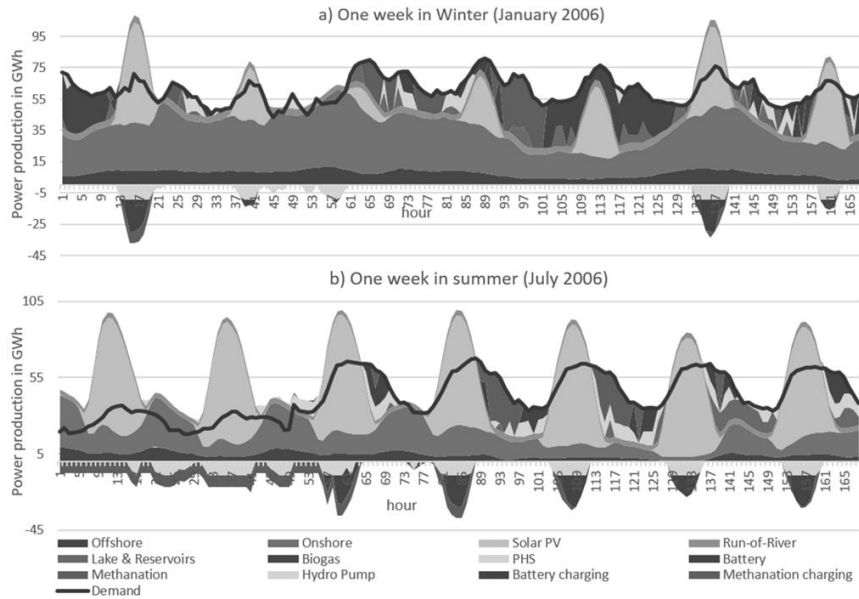


Figure 2 Hourly power generation, electricity demand, storage charge and discharge profiles for (a) the third week of January (Winter) and (b) the third week of July (Summer) 2006

2.2 Model equations

Objective Function

In EOLES, dispatch and investment are determined simultaneously by linear optimization. CAPEX (capital expenditure) and OPEX (operational expenditure).

The objective function, shown in Equation (1), is the sum of all costs over the chosen period, including fixed investment costs, fixed O&M costs (which are both annualized) and variable costs. For some storage options, in addition to the CAPEX related to charging capacity per kW_e , another type of CAPEX is introduced: a capex related to energy capacity, per kWh_e

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

where Q_{tec} represents the installed capacities of production, $VOLUME_{str}$ is the volume of energy storage in MWh, S_{str} is the capacity of storage in MW, $annuity$ is the annualized investment cost, $fO\&M$ and $vO\&M$ respectively

represents fixed and variable operation and maintenance costs and $G_{tec,h}$ is the hourly generation of each technology.

To calculate the annualized capex ($annuity_{tec}$ in the objective function), we use the following equation:

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

Where DR is the discount rate.

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).

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

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 .

Renewable power production

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

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

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.

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):

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

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.

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:

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

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).

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.

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

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).

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

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).

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

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 RTE¹ (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 ADEME (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.

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

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);

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

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

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

turbine (OCGT) due to its high operational flexibility and equation (12) shows the relationship of the power production from these two methane resources;

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

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 considered in both the 15 TWh_e of annual 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):

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

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):

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

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):

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

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.

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

2.3 Input data

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

Cost data

The economic parameters for generation technologies are taken from JRC (2014, 2017) and summarized in Table 1. It is worth mentioning that the grid upgrading cost of €24.6/kW for new renewable power plants mandated by the transport system operator RTE and by the distribution system operator ENEDIS (RTE, 2018b) has been added to the capital expenditure values of each VRE technology. The annuities (annualized CAPEX) are the results of these calculations. More information about the cost scenarios and the estimation methodology used in JRC (2017) can be found in Appendix 1.

Table 1 Economic parameters of power production technologies

<i>Technology</i>	CAPEX (€/kW_e)	Lifetime (years)	Annuity (€/kW_e/year)	Fixed O&M (€/kW_e/year)	Variable O&M (€/MWh_e)	Source
<i>Offshore wind farm*</i>	2330	30	144.3677	47.0318	0	JRC (2017)
<i>Onshore wind farm*</i>	1130	25	77.6621	34.5477	0	JRC (2017)
<i>Solar PV*</i>	425	25	30.0052	9.2262	0	JRC (2017)
<i>Hydroelectricity – lake and reservoir</i>	2275	60	110.2334	11.375	0	JRC (2017)
<i>Hydroelectricity – run-of-river</i>	2970	60	143.9091	14.85	0	JRC (2017)
<i>Biogas (Anaerobic digestion)</i>	2510	25	135.5066	83.9	3.1	JRC (2017)
<i>OCCGT</i>	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/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.

For the storage technologies, the “Commercialization of Energy Storage in Europe” report prepared by FCH-JU (2015) and a recent article by Schmidt et al. (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 ENEA consulting (2016) has been used for methanation storage. Using these three studies the 2050 cost projection of

storage technologies are presented in Table 2. The cost of methanation is made up of the cost of electrolysis units and the Sabatier reaction¹.

Table 2 Economic parameters of storage technologies

Technology	Overnight costs (€/kW _e)	CAPEX (€/kWh _e)	Lifetime (years)	Annuit. (€/kW _e /year)	Fixed O&M (€/kW _e /year)	Variable O&M (€/MWh _e)	Storage annuity (€/kWh _e /year)	Efficiency (input/output)	Source
Pumped hydro storage (PHS)	500	5	55	25.8050	7.5	0	0.2469	95%/90%	FCH-JU (2015)
Battery storage (Lithion)	140	100	12.5	15.2225	1.96	0	10.6340	90%/95%	Schmidt (2019)
Methanation	1150	0	20/25*	87.9481	59.25	5.44	0	59%/45%	ENE A (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), the cost of transporting carbon dioxide along a 200km onshore pipeline is €4/tCO₂.

Considering a 100km long onshore pipeline (considering maximum 100km of distance between the methanation units and the biogas production units), the CO₂ transport cost for the methanation storage is €1/MWh (See appendix 5), to be added to the gas storage cost which is €2/MWh (according to the French energy regulation commission (CRE, 2018), the variable cost of the methanation storage is €3/MWh_e.

VRE profiles

Variable renewable energies' (offshore and onshore wind and solar PV) hourly capacity factors have been prepared using the renewables.ninja website², which provides the hourly capacity factor profiles of solar and wind power from 2000

¹ The reaction that produces methane from hydrogen and carbon dioxide is called the Sabatier reaction.

² <https://www.renewables.ninja/>

to 2017 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 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” website¹, 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 2 provides more information about the methodology used in the preparation of hourly capacity factor profiles of wind and solar power resources.

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. We include this demand profile rather than the one observed in recent years because by 2050, electricity demand will have been impacted by climate change, progress in energy efficiency and new uses of electricity.

Discount rate

We use a discount rate of 4.5% i.e. the value recommended by the French government for use in public socio-economic analyses (Quinet, 2014).

2.4 Cost scenarios

To test the sensitivity of the optimal power to the costs of various technologies, we consider the range of uncertainty indicated in Table 3. 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.

¹ <https://www.4coffshore.com/>

For solar PV, the +/- 50% uncertainty range is chosen to reflect the various scenarios in the JRC (2017) study. We chose the same +/- 50% uncertainty range for batteries, the lower bound being based on the prolongation of the assessment made by BNEF (2017) for 2030, and the upper bound being chosen to keep symmetry in the uncertainty ranges. For methanation, less information is available in the literature. We also chose a +/- 50% uncertainty range since we consider that it has reached a similar maturity stage as batteries. Moreover, the upper bound is close to the 2030 projection of ENEA consulting (2016). For wind technologies (a more mature technology), the choice of a +/- 25% uncertainty range comes from the expert elicitation survey by Wiser et al. (2016).

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.

Table 3 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 3 would give 405 different cost scenarios ($5^1 \times 3^4$). Out of all these options, we select 315 scenarios which provide higher internal consistency. 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 we select only the scenarios in which 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.

Optimizing the model for every 315 cost scenario over 18 years would have been impossible for computational reasons. Therefore, we first ran the annual model over each weather-year from 2000 to 2017, we chose a representative weather-year (2006), then we performed the sensitivity analysis over this representative weather-year.

3 Results

3.1 Weather-year selection

Testing sensitivity to the choice of a weather-year

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

Our results show that the optimal power mix varies significantly from one year to another, in terms of electricity production, installed capacity, storage volume and storage capacity (Figures 3 and 4 and Appendix 3). The largest variations between minimum and maximum installed capacity are associated with onshore and offshore wind power. In particular, offshore capacity ranges from zero to 20 GW, which is the maximum value allowed¹. 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). In comparison, installed solar capacity is more stable (between 100.5GW and 122.2GW), due to a less volatile capacity factor (Figure 4c). 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 4d1 and 4d2). In comparison, the system-wide 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 4e and 4f).

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

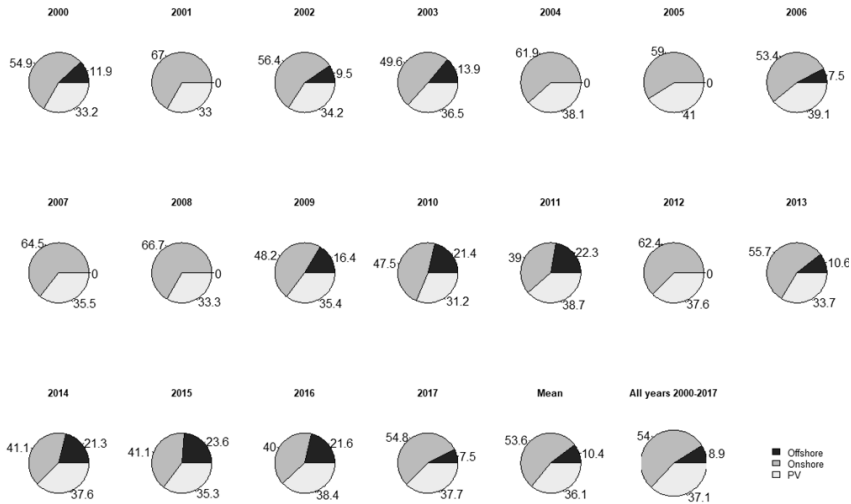


Figure 3 VRE generation mix for each weather-year in single-year optimization and over the whole 18-year long period

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). Therefore, 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, we have chosen another approach: selecting a representative year that gives the results closest to the results when optimizing over 18 years.

Selecting a representative weather-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 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 computed the sum of absolute difference¹ of the three VREs. We also calculated the mean squared error² which

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

² Sum of the squared differences $\frac{1}{3} \sum_{i=1}^3 (x_i - x_i^*)^2$ where x_i is the average capacity factor (CF) of each technology i in each year and x_i^* is the average CF of that technology over 18 years.

puts more weight on outliers. Using both approaches, 2006 is the closest year to the overall 18-year long period, with a sum of absolute error values of 1.5% (Table 4 in Appendix 3).

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.

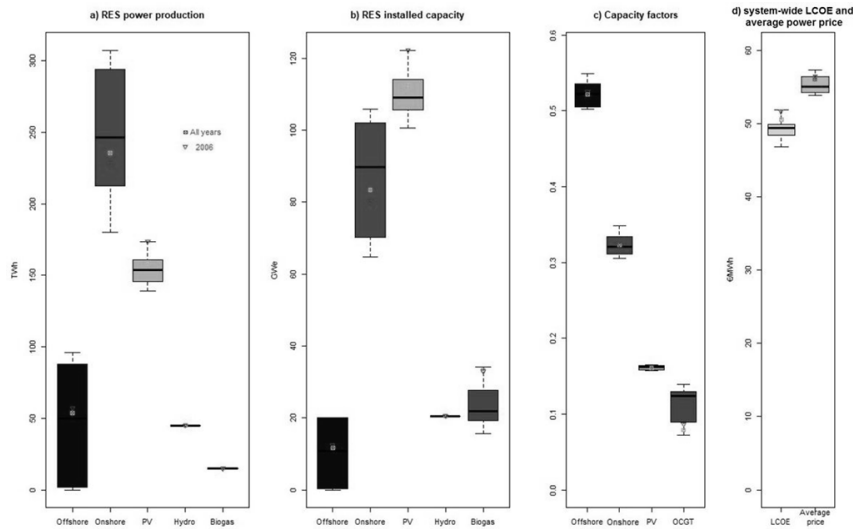


Figure 4. Optimization results for each weather-year from 2000 to 2017 and for the whole 18-year period. (a) power production; (b) installed capacity; (c) average capacity factor of each VRE and the gas power plant for biogas produced by anaerobic digestion and methane produced by methanation and (d) system-wide LCOE and average power price of electricity. The square-shaped light marks show the results of the optimization over the 18-year period and the triangle-shaped dark ones show the results for weather-year 2006. The box plots show the first and third quartiles and the median for each scenario.

Figure 5 shows the energy mix of the chosen representative year (2006) and the whole 18-year modelling. There is a very close match between the percentage of each energy source for the overall 18-year-long optimization and the representative year. Onshore wind power is clearly dominant with solar power and offshore wind power as the second- and third- biggest sources of energy respectively.

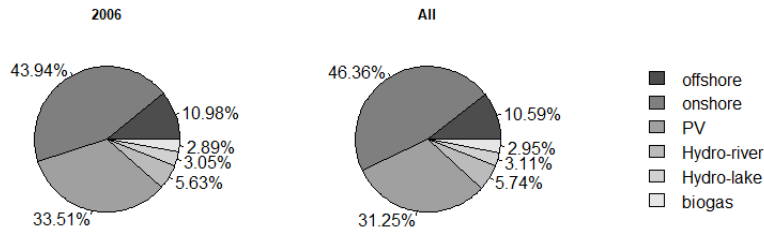


Figure 5: Energy mix for the chosen representative weather-year (2006, left) and for the 18-year optimization (right)

3.2 The optimal power mix is highly sensitive to technology cost assumptions

Our results indicate that the optimal energy mix is highly sensitive to cost uncertainty. Offshore wind often reaches either zero installed capacity or the maximum allowed value, while the range of onshore wind and PV capacities is approximately five-fold across the cost scenarios (Figure 6a). Storage technologies also demonstrate such high sensitivity except for 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 (Figure 6d1), and methanation ranges from 7 to 33.5 TWh , more than twice the capacity in the reference cost scenario (Figure 6d2).

This analysis also highlights some patterns of substitutability and complementarity between technologies. Obviously, each option is particularly influenced by its own cost, but also by the cost of other technologies. In particular, a higher cost of methanation entails much more offshore wind and vice-versa. Indeed, electricity from offshore wind suffers from a higher cost per MWh produced than other VREs but its production 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-wide LCOE¹ and the average power price are much more influenced by the cost of generation technologies than by that of storage technologies². Keeping the reference investment cost scenario for power production technologies, changing the investment cost of battery and

¹ The system-wide LCOE is calculated as the cost of the electricity system (including production and storage) divided by the electricity consumption.

² 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.

methanation storage options from the lowest storage investment cost scenario (both -50%) to the highest storage investment cost scenario (both +50%) changes the overall system-wide LCOE from €46/MWh to €51/MWh, while changing the investment cost of three VRE power production technologies from the lowest cost scenario to the highest cost one (keeping the storage options at the reference cost scenario), changes the overall system-wide LCOE from €37/MWh to 58€/MWh.

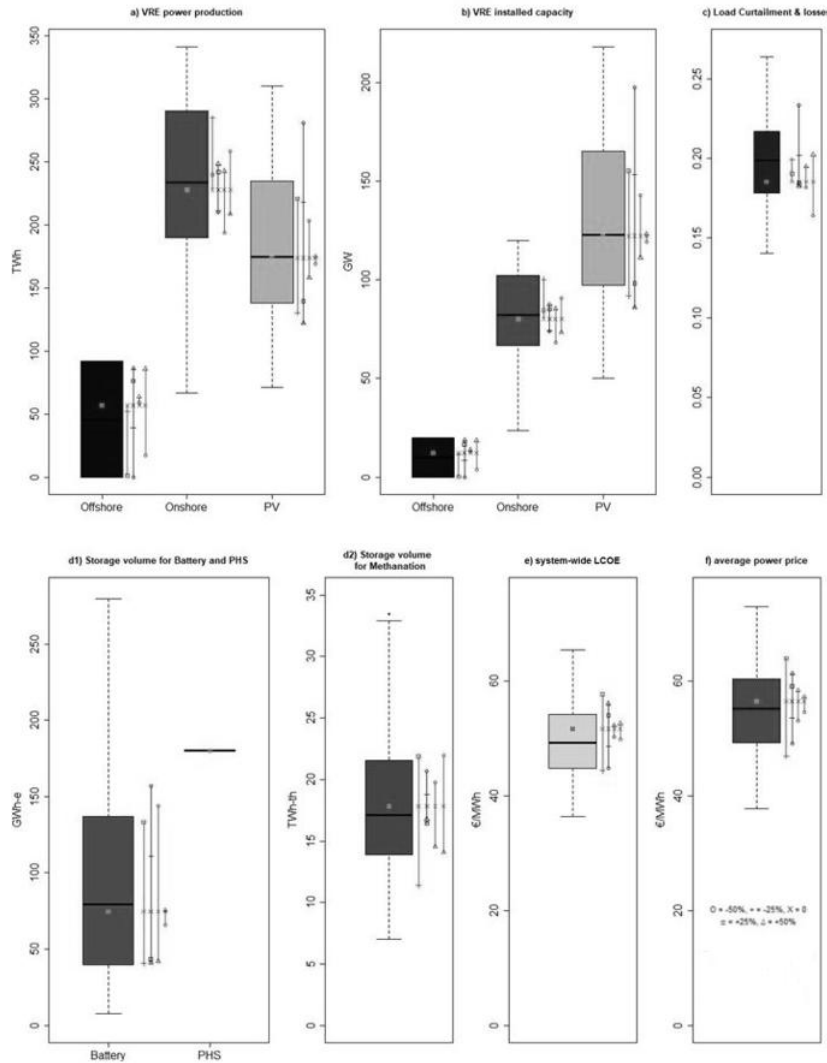


Figure 6 Optimization results for the representative year (2006) over the 315 future cost projection scenarios. (a) power production and (b) installed capacity of each VRE resource; (c) load curtailment and storage losses; (d) needed storage volume in GWh_e for batteries and pumped hydro storage (d1) and in TWh_e for methanation (d2); (e) system-wide LCOE in €/MWh_e; (f) average power price in €/MWh_e. The square-shaped points show the reference cost scenario. The lines beside whisker plots show the impact of varying separately the cost of one technology, keeping all other technologies at their reference cost, from left to right: variation of offshore and onshore wind power (by 25%), solar PV (by 50%), battery storage (by 50%) and methanation (by 50%).

3.3 However, optimizing the capacity mix based on wrong cost assumptions hardly increases costs

Globally, the previous cost sensitivity analysis confirms that the optimal power mix is highly sensitive to technology costs. Thus, a decision maker might be tempted to favor a flexible policy over a more rigid one, at the expense of visibility for investors. However, a high cost sensitivity of the optimal power mix does not imply a high cost for choosing a non-optimal mix. In the case of highly substitutable technologies, a small change in cost will lead to a strong shift in the optimal mix but choosing one mix or the other would not change total cost much.

The question we aim to answer in this subsection is the following: “If we decide now a trajectory of renewable capacities for the future based on current cost estimates, could it entail a high over-cost if our assumptions of technology costs are wrong”? To answer that question, we use the installed capacities of generation and storage technologies optimized for the reference cost scenario, and we calculate the system-wide LCOE for this “rigid capacity” across our 315 cost scenarios (Figure 7). The system-wide LCOE is necessarily equal to or higher than that of the “flexible capacity”, the difference being the “regret” from basing the optimization on the wrong cost assumptions.

In most cases the regret is remarkably low given the wide range of cost scenarios considered: for the cost scenarios considered, the average value is 4% i.e. $\text{€}2/\text{MWh}_e$, the third quartile is 6%, and the regret is below 9% in 95% of the scenarios. A close examination of the 14 cost scenarios with the largest regret (more than 2 billion $\text{€}/\text{year}$, i.e. around 10%) shows that all but one concern scenarios in which the cost of onshore or offshore wind, or both, is lower than expected. Hence the regret in this scenario stems from having installed too little windpower. The only exception is a scenario in which PV and batteries are 50% cheaper than in the reference scenario, onshore at the reference cost, offshore 25% cheaper and methanation 50% more expensive. In this case only, the regret stems from having not installed enough PV and batteries.

The average system-wide LCOE for the rigid capacity mix (black vertical line in Figure 7) equals the system-wide LCOE under the reference cost scenario (dark grey vertical dashed line). This result is due to the symmetric distribution of technology cost shocks and the linear nature of the model, and can be understood as follows: starting from the system optimized over the reference cost scenario, a +25% technology cost shock entails a change in system-wide LCOE by the same amount (in absolute value) as a -25% technology cost shock, so the average system-wide LCOE for the rigid capacity mix is the same as the system-wide LCOE without uncertainty, i.e. the system-wide LCOE in the reference cost scenario (dark grey dashed vertical line in Figure 7).

The average system-wide LCOE for the flexible capacity mix (dark grey vertical line in Figure 7) is obviously lower than the rigid one, since optimization is based on accurate information – thus it is also lower than the system-wide LCOE in the reference cost scenario. In this sense, uncertainty actually *reduces* the expected system-wide LCOE – because we allow optimizing the mix depending on uncertainty realizations.

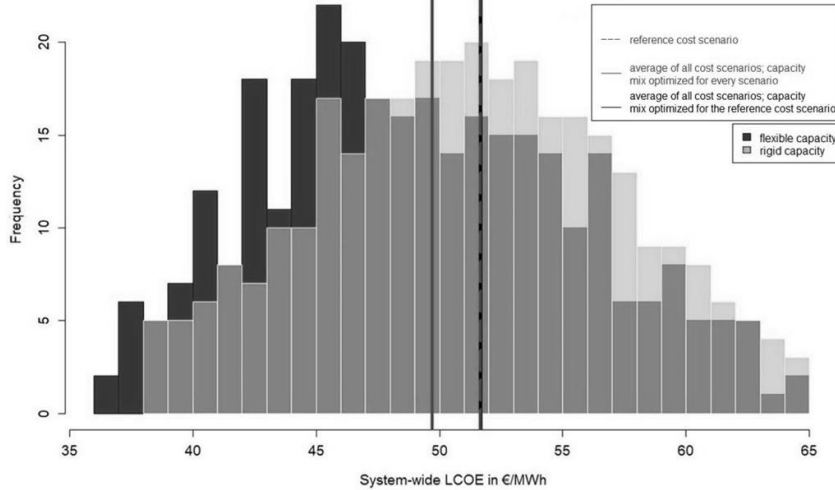


Figure 7 Distribution of system-wide LCOE across cost scenarios. The dark grey distribution represents optimal energy mixes; the light grey distribution is computed using the capacities of the reference scenario.

4 Discussion & Conclusion

4.1 Comparison with current cost and 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 (Appendix 6). Moreover, we have seen that the system-wide 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.

According to the latest quarterly report from the French energy regulator (CRE, 2019), 35% of a typical electricity bill (varying between 170€/MWh and 200€/MWh depending on the tariff chosen and consumption profile) represents electricity production, which thus costs between 59€/MWh and 70€/MWh. Thus, 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) 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 result in very high power import 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 technologies, which leads to a lower 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) 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, 2019). 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. 422 TWh_e).

Moreover, recent market observations make us think that our high-cost scenario for offshore wind is rather unlikely, since many recent calls for tenders have resulted in purchasing power agreements at a very low price, throughout Western Europe. This has led the IEA (2019) to project that by 2040 the global average offshore wind investment cost would fall to \$1 900/kW (€1 700/kW at the current market rate), slightly less than our low-cost scenario.

However, our results are based on simplifying assumptions. In the remainder of this section, we address several factors which could push our estimates up or down.

4.2 Model limitations

Factors which could push costs up

Cost of the transmission and distribution network

Our system-wide LCOE includes storage costs, as well as some network costs: the connection costs are included in the JRC cost estimates we use, as well as the French “quote-part”, which represents the network upgrade costs over the

next five to ten years. Dividing France into several nodes in order to account for transmission costs and internal congestion is numerically demanding (increasing the run-time of a single year model from 10 minutes to more than 40 hours for a 4-node model), therefore, we applied a single node model for weather-year selection, sensitivity analysis and robustness study. But to assess the importance of the internal congestion issue, we developed a 4-node version of EOLES_elecRES model, which leads to an increase by less than 7% in the system cost, slightly increasing the load curtailment with no significant change in the energy mix once both wind power generation technologies are aggregated. The results of a 4-node version of this study for year 2006 and the central cost scenario can be found in appendix 10.

Admittedly, a 100% power mix would require some additional upgrade costs, in particular in the distribution network, so it would be preferable to have a model that endogenously represents network costs. However, distribution costs are difficult to model, as they vary with each specific situation: is the installation far from an existing line? Is the power of the line enough or should it be increased?

Moreover, several recent studies indicate that the network cost differential across scenarios featuring more or less renewable energies would be limited:

- According to RTE (2018a), 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 and storage cost. However, the relationship is not linear and it cannot be easily extrapolated for higher proportions of renewables.
- Two studies by ADEME (2015, 2018) conclude that the cost of renovating the French network in any event, 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.
- EirGrid¹ (the Irish electricity network operator), estimates that for an electricity mix with nearly 90% of renewables, the reinforcement required to integrate VREs will cost no more than €1/MWh_e.

These studies justify why the distribution network cost is not modelled in long-term planning models, including ours.

Discount rate

Some studies use higher discount rates than ours, e.g. 7% in Villavicencio (2017), as mentioned above. This would increase the annualized cost, especially for capital-intensive technologies. While higher rates may well be used by private companies, 4.5% is already much higher than both the risk-free real

¹ <http://www.eirgridgroup.com/newsroom/record-renewable-energy-o/index.xml>

interest rate available on financial markets and expected GDP growth over the next few decades. Using a higher rate in a socioeconomic analysis means that future generations would be penalized when compared to current ones, which can hardly be defended on ethical grounds.

Table A.10 in Appendix 9 provides a sensitivity analysis in which the discount rate varies from 2% to 7%. Increasing the discount rate from 4.5% to 7% raises the total annual cost from €21.86 billion to €25.72 billion. The most affected technology is offshore wind, the decrease in which is offset by an increase in onshore wind. This higher impact of the discount rate on offshore wind can be explained by its longest lifespan, which makes it more sensitive to the discount rate than onshore wind or solar PV. To give an idea of the magnitude, increasing the discount rate from 4.5% to 7% would increase the total annual cost from €21.86 billion to €25.72 billion.

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.

Climate change

Climate change will impact both electricity demand and supply. The effect on demand is taken into account through an increase in demand for air conditioning and a decrease in demand for space heating (section 2.1 above).

Concerning supply, the production of wind farms and PV panels will be affected by climate change but based on our synthesis of the scientific literature these effects should be limited in France. Tobin et al. (2015) conclude, based on an ensemble of 15 regional climate projections, that for the period 2031–2060, the impact of climate change on the production of the French windfarms will be somewhere between -3% and +3%, (their Figure 3.b). The same conclusion stands for PV whose production will not be impacted by climate change by more than plus or minus 2% according to Jerez et al. (2015, Figure 3).

Factors which could bring costs down

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. We studied demand side management (DSM) in a previous version of the EOLES model. As a result, part of the battery capacity was replaced by DSM and system cost was slightly lower. We decided not to include DSM because its cost is difficult to estimate.

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 allows benefitting from the differences in climatic and weather conditions between the countries concerned.

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.

Neither vehicle-to-grid nor second-hand batteries

We have not considered 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 (2018a) 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-wide 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.

4.3 Conclusion

In this article, we have studied the sensitivity of optimal fully renewable power systems to technology cost. To that end, we have developed EOLES_elecRES, a model optimizing investment and dispatch in the power sector with a particular focus on the modelling of storage technologies and applied it to study fully renewable power systems in France. We have built 315 cost scenarios by combining assumptions about the long-term cost of the key power generation and storage technologies.

Our results indicate that even though the technologies involved in a fully renewable power system are very different, they will become by and large substitutable in the coming years. 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 wind power, with a very limited impact on the system-wide LCOE. On the contrary, if wind power 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.

Overall, the impact of storage cost should not be overestimated: even in a 100% renewable power system, 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 share of storage in overall cost would be even lower.

Across all cost scenarios, the system-wide LCOE, 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 is cheaper than today's value (€59-70). Moreover, setting a capacity target in advance for every technology would only increase the system-wide LCOE by €2/ MWh_e averaged over the 315 cost scenarios compared to the optimum mix, even if costs vary by +/-25% for wind and +/-50% for solar and storage.

Finally, 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.

Our results have the following policy implications. First, they indicate that a fully renewable power system in France can hardly be dismissed on economic grounds. Second, given the massive scale-up required for wind and PV capacities (cf. Appendix 8), investment should be boosted in both technologies.

Last, while the optimal mix is highly dependent on technologies costs assumptions, these investments should not be delayed because even if the energy mix is optimized based on cost assumptions which turn out to be wrong, the extra cost is low. This result calls for providing visibility to investors, even if it entails reducing flexibility in the policy design. It echoes the necessary “preservation of incentives for continued investment” highlighted by Yatchew (2016) in the context of renewable energies.

This work could be extended in many directions, for example including the other power generation technologies that entail low direct CO₂ emissions: CO₂ capture and storage and nuclear power. Their cost and the possibility of storing massive quantities of CO₂ 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. Additional coupling with the gas sector or with electric vehicles could also be considered. These would provide further flexibility options to the power system and would thus probably reinforce the conclusions of this study.

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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 (A.1) shows the main methodology used in the cost projection using the learning rate method:

$$Cost_t = Cost_0 \cdot \left(\frac{C_t}{C_0}\right)^\delta \quad (A.1)$$

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 (A.2);

$$LR = 1 - 2^\delta \quad (A.2)$$

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	
<i>Baseline</i>	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 GtCO ₂ .
<i>Diversified</i>	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 GtCO ₂ by 2050.
<i>ProRES</i>	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 CO ₂ emissions are about 4.5 GtCO ₂ 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. Weather-year sensitivity

The results for each weather-year can be seen in Tables A.2, A.3 and A.4.

Table A.2 installed capacity of each power production technology in GW_e and energy storage capacity of each storage technology during each optimization period

Year	Offshore	Onshore	PV	river	Lake	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.3 Yearly power production of each production technology (in TWh) and capacity factor of VRE resources

Year	Offshore	Onshore	PV	River	Lake	Biogas	Offshore	Onshore	PV	OCGT
2000	54.1	246.4	146.6	29.2	15.8	15	0.538	0.334	0.158	0.139
2001	1.8	307.3	143.6	29.2	15.8	15	0.537	0.335	0.162	0.089
2002	82.1	212.4	145.5	29.2	15.8	15	0.547	0.348	0.157	0.127
2003	45.0	245.3	153.5	29.2	15.8	15	0.503	0.311	0.164	0.088
2004	0.00	296.5	159.7	29.2	15.8	15	0.509	0.322	0.161	0.130
2005	0.00	290.2	160.0	29.2	15.8	15	0.507	0.312	0.165	0.102
2006	56.9	227.8	173.7	29.2	15.8	15	0.525	0.324	0.162	0.087
2007	0.00	294.7	170.2	29.2	15.8	15	0.532	0.341	0.164	0.100
2008	3.7	296.2	145.5	29.2	15.8	15	0.536	0.331	0.158	0.120
2009	51.4	246.9	153.7	29.2	15.8	15	0.504	0.315	0.162	0.130
2010	88.5	226.7	140.7	29.2	15.8	15	0.505	0.308	0.160	0.130
2011	91.5	179.8	165.8	29.2	15.8	15	0.522	0.311	0.165	0.085
2012	0.0	294.0	164.1	29.2	15.8	15	0.523	0.326	0.163	0.130
2013	48.2	259.7	138.9	29.2	15.8	15	0.533	0.320	0.157	0.128
2014	89.2	193.9	153.5	29.2	15.8	15	0.509	0.314	0.157	0.133
2015	96.3	190.9	148.6	29.2	15.8	15	0.549	0.335	0.163	0.072
2016	88.1	187.0	160.3	29.2	15.8	15	0.502	0.302	0.160	0.101
2017	23.4	272.5	160.6	29.2	15.8	15	0.504	0.309	0.164	0.135
Mean	45.6	248.2	154.7	29.2	15.8	15	0.522	0.323	0.161	0.113
All	53.8	235.5	158.8	29.2	15.8	15	0.522	0.323	0.161	0.079

Table A.3 shows the total cost, marginal cost and the system-wide LCOE¹ for each yearly optimization and for the whole 18-year optimization.

¹ System-wide 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.

Table A.4 Total cost, average marginal cost (average spot price), levelized cost of electricity, load curtailment and storage related losses of each year

year	Total Cost (b€)	System-wide 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
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

Table A.5 shows the ranking of each weather-year in correlation with overall 18-year period.

Table A.5 Closest years to the overall 18-year period in term of 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			
- with mean absolute error	2006 (value 0.015)	2012 (value 0.0236)	2004 (value 0.028)
- with mean squared error	2006 (value $3.667e^{-6}$)	2012 (value $4.667e^{-6}$)	2013 (value $5.667e^{-6}$)

According to our simulations, 2006 is the best proxy for the whole 18-year period in terms of capacity factor, both using the mean absolute error and the mean squared error. It is the best match for onshore wind, the second best for solar PV and the third best for offshore wind.

The installed capacity of solar power for the year 2006 is 122 GW, while it is 112 GW for the whole 18-year period, an 8% difference. This value seems high from the graph, but it remains low in comparison with the offshore and onshore

wind power installed capacity variations. Comparatively, for offshore wind power the variation ranges from 0 to 20 GW of installed capacity, while the overall 18-year period optimization results in 11.8 GW of installed capacity. Similarly, the installed capacity of onshore wind power varies from 65 GW to 106 GW while the overall 18-year optimization results in 83 GW of installed capacity. Our main conclusion from these results is the following: the inter-annual variation of solar power is of minor importance in comparison with the high inter-annual variation of wind power (in particular the relative share of offshore to onshore wind).

Appendix 4: the EOLES_elecRES model

Sets and parameters

Table A.6 presents the sets and indices of the EOLES_elecRES model, Table A.7 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 A.6 Sets and indices of the EOLES_elecRES model

Index	Set	Description
h	$\in H$	Hour: the number of hours in a year, from 0 to 7659
m	$\in M$	Month: the twelve months, from January to December
tec	$\in TEC$	Technologies: The set of all electricity generation and energy storage technologies (offshore, onshore, PV, river, lake, biogas, gas, PHS, battery, methanation)
gen	$\in GEN \subseteq TEC$	Generation: Electricity generation technologies (offshore, onshore, PV, river, lake, biogas, gas)
vre	$\in VRE \subseteq TEC$	VRE: Variable renewable electricity generation technologies (offshore, onshore, PV)
str	$\in STR \subseteq TEC$	Storage: Energy storage technologies (PHS, battery, methanation)
$ncomb$	$\in NCOMB \subseteq TEC$	Non-combustible generation technologies (offshore, onshore, PV, river, lake, PHS, battery)
$comb$	$\in COMB \subseteq TEC$	Combustible generation technologies (biogas, methanation)
frr	$\in FRR \subseteq TEC$	Frequency restoration reserves: Technologies contributing to secondary reserves requirements (lake, PHS, battery, gas)

Table A.7 Parameters of the EOLES_elecRES model

Parameter	Unit	Value ¹	Description
$month_h$	[-]		A parameter to show which month each hour is in

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

$cf_{vre,h}$	[-]		Hourly production profiles of variable renewable energies
$demand_h$	[GW_e]		Hourly electricity demand profile
$lake_m$	[GW_h_e]		Monthly extractable energy from lakes
$river_h$	[-]		Hourly run-of-river capacity factor profile
ε_{vre}	[-]		Frequency restoration requirement because of forecast errors on the production of each variable renewable energy
q_{tec}^{ex}	[GW_e]		Existing capacity by technology
$annuity_{tec}$	[$M\text{€}/GW_e/\text{year}$]		Annualized capital cost of each technology
$annuity_{str}^{en}$	[$M\text{€}/GW_h/\text{year}$]		Annualized capital cost of energy volume for storage technologies
$capex_{str}^{ch}$	[$M\text{€}/GW/\text{year}$]		Annualized capital cost of storage technology charging power
$fO\&M_{str}^{ch}$	[$M\text{€}/GW/\text{year}$]		Fixed operation and maintenance cost of storage technology charging power
$fO\&M_{tec}$	[$M\text{€}/GW_e/\text{year}$]		Annualized fixed operation and maintenance cost
$vO\&M_{tec}$	[$M\text{€}/GW_h_e$]		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}	GW_h_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

Variables

The main variables resulting from the optimization are presented in Table A.8.

Table A.8 Variables of the EOLES_elecRES 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 (inflow)
$STORED_{str,h}$	GWh_e	Hourly energy stored in each technology (stock)
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 to manage the variability of renewable energies and demand uncertainties
$COST$	b€	Total power system cost, annualized (minus the fixed cost of already installed capacities). This is the objective function to be minimized.

Appendix 5: Transport cost of carbon dioxide for methanation

The cost of transporting carbon dioxide along a 200km onshore pipeline is €4/ tCO_2 , for 100km long pipeline, this transporting cost can be assumed around €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):

$$\frac{1 \text{ t } CO_2}{1000000 \text{ g } CO_2} \times \frac{44 \text{ g } CO_2}{1 \text{ mol } CO_2} \times \frac{1 \text{ mol } CO_2}{0.8 \text{ mol } CH_4} \times \frac{1 \text{ mol } CH_4}{802.3 \text{ kJ}} \times \frac{1 \text{ kJ th}}{0.0002227778 \text{ kWh th}} \times \frac{1 \text{ kWh th}}{0.45 \text{ kWh elec}} \times \frac{1000 \text{ kWh elec}}{1 \text{ MWh elec}} = 0.5486 \frac{tCO_2}{MWh elec}$$

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

Appendix 6: Cost decomposition

Figure A.1 shows the share of each technology in overall cost of power system (except distribution and transmission costs);

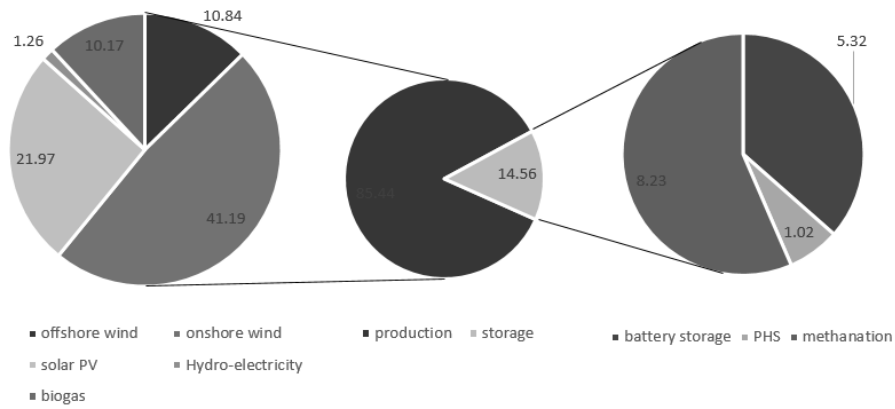


Figure A.1. Overall decomposition of the system cost in percentage for the reference cost scenario

Appendix 7: Insights on profitability by technology

In this article, we model an economic optimum, not a decentralized economy. However, in this appendix, we provide some insights on the decentralization of this optimum in the form of a market economy, assuming perfect competition and an energy-only market¹. In this aim, we consider that the Lagrange multiplier of the adequacy equation (eq. 3) represents the market price. Figure A.2 below adds to Figure 2 the electricity spot price, defined this way.

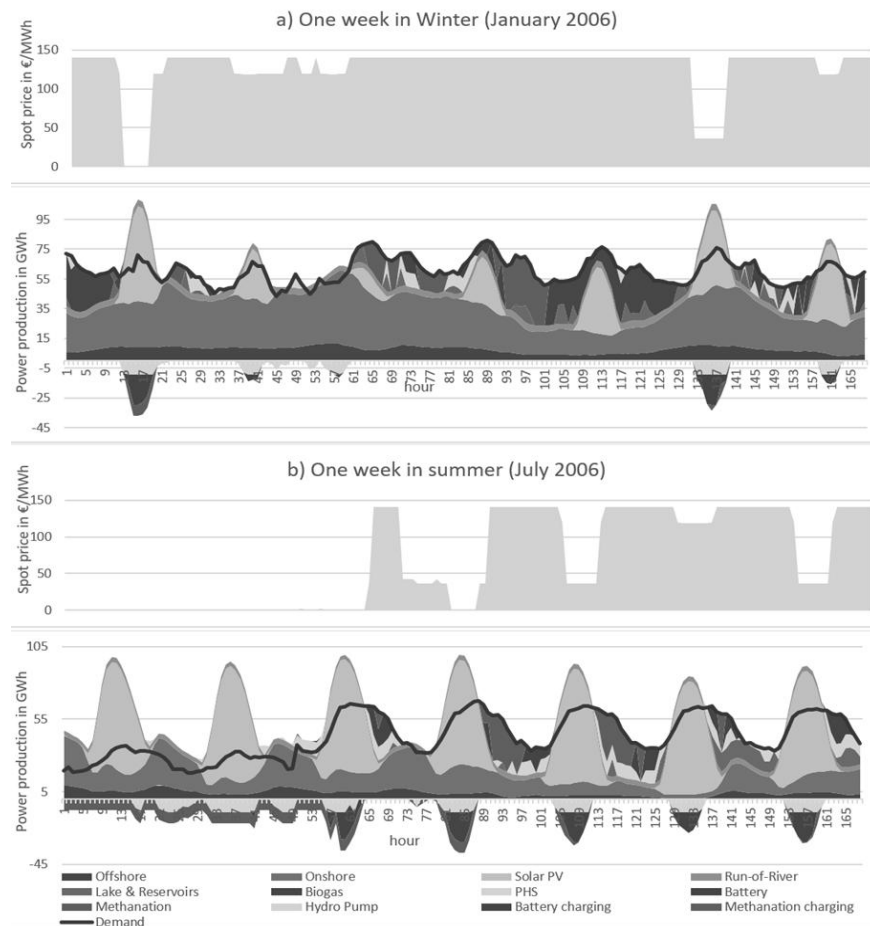


Figure A.2. Hourly power generation, electricity demand, storage charge and discharge profiles and power prices for (a) third week of January (Winter) and (b) third week of July (Summer) 2006

¹ We do not assess the relevance of supplementing the energy-only market with capacity remuneration mechanisms. On this point, cf. Riesz et al. (2016).

As we can see, the price is often either zero (when there is some excess power generation) or around €140/MWh. Figure A.3. below, which presents the price frequencies, confirms this result: over the year, the price is zero during ca. 3500 hours (out of 8760) and between €140/MWh and €160/MWh during ca. 2000 hours. These price ranges are similar to those calculated by Abrell et al. (2019) for Germany, when they assume a storage capacity similar to that resulting from our optimization.

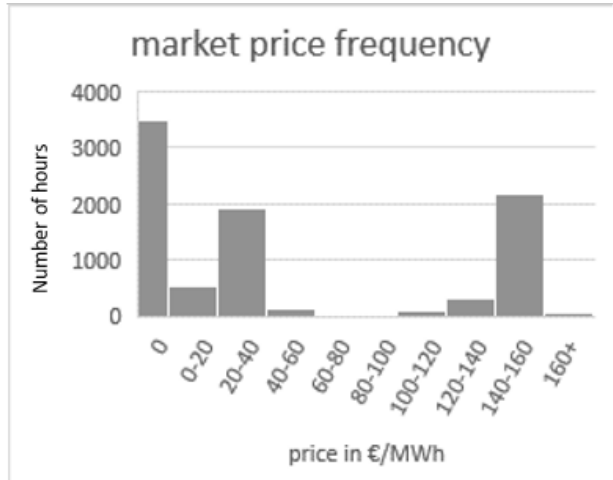


Figure A.3. Market price frequency.

On the basis of these “market prices”, we can calculate the average selling price for every technology, and the average buying price for storage technologies. These are presented in Table A.9 together with the LCOE (the levelized cost of electricity produced) the LCOS (levelized cost of storage; cf. Jülch et al., 2015) and the long-term profit, i.e. the difference between the market price and the LCOE.

Table A.9 LCOE/LCOS and average price of electricity sold and bought and unit profit for each technology, for weather-year 2006

Prices (€/MWh)	offshore	onshore	PV	lake	river	biogas*	OCGT*	battery	PHS	methanation*
LCOE/LCOS	41.6	39.4	27.6	98.8	40.8	82.0	67.1	87.5	16.3	116.1
Average selling price	41.7	39.6	28	143.7	55.2	141.6	209.0	99.5	86.1	142.5
Average buying price	-	-	-	-	-	-	141.9	21.5	23.0	26.4
Long-term profit	0.09	0.15	0.42	38.19	14.39	59.57	0	-9.54	46.83	0

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

For most technologies, the long-term profit is close to zero. A large positive profit occurs for biogas and the three hydro technologies. 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.

Conversely, the reserve requirements generate a negative profit for batteries operators and a (slightly) positive one for PV and wind operators. To fulfil the reserve requirements, the optimization leads to a larger capacity of batteries and lower capacities of PV and wind, compared to a cost-minimization without these requirements. To decentralize the modelled optimum, additional revenue should be paid to battery operators for them to invest on this capacity, e.g. in the form of a capacity market, but we have not modelled such a market to keep the model simple.

Appendix 8: Renewable capacities compared to potential and other scenarios

Table A.10 Renewable capacities in our study, capacities currently installed, capacities in other scenarios and available potential

	Optimum in our reference cost scenario	Current capacity, mid-2019 (RTE, 2019)	Other scenarios for 2050			Renewable potential			
			ADE ME (2015)	négaWatt (2017)	ADE ME (2018)	ADE ME (2018)	Enevoldsen et al. (2019)	FEE (2019)	Cerema (2017)
Offshore wind	12GW	0GW	10GW	28GW	8GW	66GW	-	220GW	-
Onshore wind	80GW	16GW	96.5GW	50GW	77GW	174GW	300GW	-	-
Solar PV	110GW	9GW	63GW	136GW	85GW	459GW	-	-	776GW+ for south of France

For our reference cost scenario, the optimal mix features 12 GW of offshore wind (vs. 2 MW as of mid-2019), 80 GW of onshore wind (vs. 16 GW, i.e. 5 times more) and 110 GW of solar PV (vs. 9 GW, i.e. 13 times more). This yields two related questions: are such surges in installed capacities feasible? How different are they from the other 100% renewable scenarios for France?

To address the first question, we show in the last four columns of Table A.10 the renewable potential identified by several studies. For each of the three technologies at stake, the capacity resulting from our optimization is much lower than those identified by these studies. 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 80 GW in 2050 means an increase of 2 GW/yr. on average, from 2018 onwards, a bit less than WindEurope's (2017) "high" 2030 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. 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.

To address the second question, we show in Table A.9 (columns 3-6) the capacities installed in the other 100% renewable scenarios for France, i.e. négaWatt (2017), and Ademe (2015, 2018). The négaWatt scenario does not result from an explicit economic optimization while the Ademe scenarios do, but based on different assumptions and models than our study. Our optimal mix is in-between the other scenarios for the three VRE. Moreover, the VRE capacities in these three scenarios are in the range of optimum values presented in Figure 6 based on our 315 cost scenarios, except for offshore wind in the négaWatt scenario because it slightly exceeds our prescribed potential (28 GW vs. 20). To sum up, our results do not cast doubts on the technological choices made by the authors of these scenarios.

Appendix 9: Sensitivity to the discount rate

Table A.11 below shows, for a discount rate ranging from 2 to 7% per year, the installed capacities and the yearly cost. The latter increases almost linearly with the discount rate. The installed capacity by technology is almost unaffected, the main exception being wind energy. A higher discount rate reduces the share of offshore wind because of its longer lifetime (30 years vs. 25 for onshore wind and PV). As a result, when the discount rate rises, offshore wind is partly replaced by onshore wind.

Table A.11 Capacities installed for various discount rates and annual system cost

Discount rate (%)	Installed capacity (GW)						
	2	3	4	4.5	5	6	7
Offshore	20	20	20	12.78	0	0	0
Onshore	67.93	67.59	67.8	80.16	101.4	101.17	100.95
PV	122.73	122.67	121.39	121.42	122.49	122.15	122.29
Gas	33.55	33.51	33.53	33.07	32.38	32.27	32.19
Battery	20.11	20.16	20.08	20.05	19.92	20.03	20.13
Methanation	6.91	7.12	7.33	7.36	7.86	7.93	7.97
Lake	13	13	13	13	13	13	13
River	7.5	7.5	7.5	7.5	7.5	7.5	7.5
PHS	9.3	9.3	9.3	9.3	9.3	9.3	9.3
Cost (bn. €/yr.)	18.248	19.62	21.08	21.86	22.58	24.42	25.72

Appendix 10: Impact of the inter-regional transmission network

We developed a 4-node version of the EOLES_elecRES model, dividing France into 4 geographical divisions: North-East, North-West, South-East and South-West. We added the existing interconnections and the possibility of new investments in overhead transmission lines from each division to the other three divisions, considering an average distance of 400km between each division. The new transmission line costs are taken from the JRC 2014 study mentioned in the text (investment cost of 450,000€/km for a 500MW overhead transmission line, and 1.5% of the investment cost as fixed operation and maintenance cost per year). Adding the regional hourly electricity demand (keeping the overall demand for 2050 but using the 2018 repartition of electricity demand for different regions of France from RTE – the French transmission network operator) and hourly VRE profiles from renewable.ninja, keeping the same sources for all the input data, we ran the model for the weather-year 2006.

The preparation of variable renewable energies' capacity factor profiles is as follows: having the hourly profiles for each county (*département*) in France for each year, we took a weighted average proportional to the existing installed capacity in each county for each region, and we prepared aggregated hourly VRE profiles for each of the four geographic divisions. The technical potential of each renewable energy resource, as well as pumped hydro storage is presented in ADEME's 100% renewable electricity study (ADEME, 2015) for each of the 12 regions of continental France. By summing them, we defined maximal installable capacity of each renewable technology in each of the four divisions.

The installed capacities and yearly power production of each power generation technology for both the 4-node version and the single-node version of EOLES_elecRES for year 2006 are presented in tables A.12 and A.13 below. The codes can be found on GitHub¹.

Table A.12 Installed capacity of each electricity production technology (in GW) and volume capacity of each storage technology for the single node and the 4-node versions of EOLES_elecRES

Technology	Region NE	Region NW	Region SE	Region SW	All regions summed	Single node version
Offshore wind	0	0	0	0	0	12.36
Onshore wind	16.12	55	4.1	30.86	106.08	80.08
Wind	16.12	55	4.1	30.86	106.08	92.44

¹

https://github.com/BehrangShirizadeh/EOLES_elecRES/blob/master/model/EOLES_RE_4regions.gms

Solar PV	15.83	0	77.5	35.49	128.82	122.17
Lake	0.62	0.22	8	4.6	13	13
Run-of-river	1.5	0.2	4.1	1.7	7.5	7.5
Biogas	18.16	7.73	3.95	0.91	30.75	32.89
Battery	3.56	10.43	62.59	28.71	105.29	74.62
PHS	29.34	0	113.48	37.17	180	180
Methanation (TWh)	0	4.49	7.05	2.01	13.55	12.90

Table A.13 Yearly electricity produced by each technology (in TWh), imports and exports, for the single node and the 4-node versions of EOLES_elecRES

The technology	Region NE	Region NW	Region SE	Region SW	All regions summed	Single node version
Offshore wind	0	0	0	0	0	56.90
Onshore wind	43.87	181.67	9.86	80.92	316.32	227.80
Wind	43.87	181.67	9.86	80.92	316.32	284.70
Solar PV	19.59	0	116.37	52.26	188.22	173.72
Lake	0.74	0.27	9.40	5.41	15.82	15.82
Run-of-river	5.84	0.97	15.96	6.62	29.19	29.19
Biogas	15	0	0	0	15	15
Imports	106.71	27.64	43.01	15.82	193.18	-
Exports	10.74	85.44	46.62	52.25	195.05	-

The cost, average system-wide levelized cost of electricity, load curtailment and losses for both versions of EOLES_elecRES model are presented in table A.14.

Table A.14 Main outputs from the single-node and the 4-node EOLES_elecRES models for year 2006

The variable	4-node model	single-node model	Difference in %
Cost (b€/year)	23.36	21.82	6.6
System-wide average LCOE (€/MWh _e)	55.31	51.65	6.6
Load curtailment (%)	14.13	11.99	15
Storage loss (%)	6.08	6.53	7.3
Interconnection loss (%)	0.9	-	-

Table A.15 provides the interconnection capacity between each of the 4 divisions, and table A.16 the energy flow between each pair of divisions.

Table A.15 Interconnection capacity among the four divisions considered for France

Pair of divisions	Interconnection capacity (GW)	Of which existing (GW)
NE <-> NW	9.3	2
NE <-> SE	7	7
NE <-> SW	3.73	0
NW <-> SE	7.88	0
NW <-> SW	5	5
SE <-> SW	5	5

Table A.16 Annual electricity flow between each pair of divisions

Annual power flow (TWh)	to NE	to NW	to SE	to SW
From NE	-	3.13	5.89	1.72
From NW	55.55	-	23.39	9.60
From SE	28.51	13.19	-	4.91
From SW	25.39	12.03	14.84	-

What we can observe from the results is the fact that the impact of internal congestion is of minor importance and the electricity mix stays very close to the single-node model once the two wind power technologies are aggregated. The reason for the replacement of offshore by onshore wind power is the additional flexibility gain thanks to spatial optimization, where more variable but cheap onshore wind replaces more stable but also more expensive offshore wind. The difference in cost is less than 7% (in line with RTE's 5% of order of magnitude for a 71% renewable power system). On the other hand, interconnection inefficiencies lead to 0.9% of additional loss, and a 15% increase in load curtailment (from 11.99% to 14.13%), but thanks to the additional flexibility coming from spatial optimization, battery usage – and therefore loss from storage inefficiencies – decreases by 7.3%.