Modelling of a power electricity mix supporting the demand in France in 2050

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January 2022

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Introduction

In 2015, during the COP21, the Paris agreements ([2]) were signed by 195 nations. Their main objective is to limit global warming at 1.5 degrees. Consequently, nations made a commitment to reduce their greenhouse gas emissions. The sectors producing gas emissions are numerous such as the electricity sector (17.5%), the transports sector (41.6%), and the building sector (23.8%) ([13]). Decarbonisation is essential in all these sectors but seems easier to set up in the electricity sector where renewables can be used instead of fossil fuels. According to Rogelj and al. (2018, [14]), renewables and CO_2 capture and storage could generate more electricity than nuclear power and fossil fuels.

However, the deployment of renewable energies generates economic, environmental and social costs. It includes investment and maintenance costs, raw materials costs, space required, inconvenience caused by visual pollution and nuisances, the preference of the residents concerning the renewable alternatives...(2019, [17]).

Using only renewable energies has been studied by numerous researchers, like Hansen and al. in Germany (2019, [9]) and Quirion and al. in France (2019, [18]). The main challenges are the uncertainty of the cost and the lack of robustness of renewable energies like solar panels or wind turbines.

In this report, we concentrate on the study of the French economist Philippe Quirion. He assumes that the transition to full renewable energies is possible in France in 2050. With a model, called EOLES, he estimates the cost of such a transition. He built more than 300 scenarios by varying the price assumptions of the various technologies based on available studies. His results show that the total cost of a 100% renewable system is not particularly sensitive to the power mix chosen in 2050.

In this report, we will focus on the EOLES model. Our goal is to build the model and analyze it following different scenarios. In Part 1 we describe the model and the equations. In Part 2 we focus on the data and the parameters used by the model. We then concentrate on analysing the simulation outputs of the model in Part 3. Finally, in Part 4, we study the robustness of the optimization of the model based on different scenarios.

1 Energy Optimization for Low Emission Systems (E.O.L.E.S) Model

1.1 Principle

The EOLES (Energy Optimization for Low Emission Systems) model is built by P.Quirion and his collaborators [18]. It is constituted by different technologies which produce or store electricity such as solar panels, wind turbines, batteries....We detail these technologies in part 1.2. The model aims to find an optimal power mix between these technologies, which support the hourly demand in France in 2050 with a price under-control. Thus, the EOLES model minimizes the cost of storage and production of different technologies respecting constraints. In addition to the demand constraint, a number of physical constraints have been created to make the model more realistic. The number of variables of the model is huge. They are all described in section 1.3. We note that the optimization is linear.

France is simulated as one node, so we do not consider regions or departements. This approximation means that all of the data are averaged on the whole French territory. Moreover, we do not take into account French overseas territories. Only the area of mainland France is considered. The model does not include the possibility to import electricity to meet the electricity demand (or export it). Finally, the model does not consider the flexibility of electricity demand. This means that the model must meet the electricity demand at each hour, without exception during off-peak hours for example.

In this report we focus on the first version of the EOLES model, a second version of this model exists which has more technologies and is more complex.

1.2 Technologies implemented in the model

The model includes six power generation technologies: offshore and onshore wind turbines, solar photovoltaics (PV), lake-generated, run-of-river and biogas. It includes three energy storage technologies: pump-hydro storage (PHS), batteries and methanation. These 9 technologies belong to sets defined in table 1.

Index of the set	Description	Technologies
tec	Technologies used for electricity generation and energy storage	offshore, onshore, PV, river, lake, biogas, PHS, battery, methanation
gen	Technologies used for electricity generation	offshore, onshore, PV, river, lake, biogas
str	Technologies used for energy storage	PHS, battery, methanation
vre	Renewable electricity generation technologies	onshore, offshore, PV
frr	Dispatchable technologies for secondary reserves	lake, battery, PHS, biogas

Table 1: Sets defined for the EOLES model

We describe below the nine technologies.

Offshore and onshore wind power and PV constitute the variable renewable energies, noted *vre*. These technologies are the most important contributors to electricity generation. The main disadvantage is the dependence on weather conditions. Offshore and onshore can not generate electricity without wind. Same for PV which can not generate electricity during nights and cloudy days.

Lake-generated electricity and run-of-river are two types of hydro-electricity. Lake-generated electricity comes from the potential energy of a volume of water held by a dam. The main disadvantages are the high cost of building such a structure and the ecological damage caused. The advantage is the constant rate of electricity generated (Bagher and al, 2015 [5]). Run-of-river consists of turbines in rivers with a minimum flow to generate electricity. It has the same disadvantage as *vre* technologies. It strongly depends on weather conditions and the upstream river flow.

Biogas electricity generation is a gas renewable technology. Biogas is a mixture of gasses produced by anaerobic biomass digestion (methanization). The renewable gas produced is then converted to electricity by gas power plants. The disadvantage of this technology is the high investment cost (Bagher and al. 2015, [4]).

Methanation storage consists of converting the electricity in hydrogen by electrolysis and then producing methane using CO_2. The advantage of this technology is the large volume available for storage.

PHS is another hydro-electricity technology. The disadvantage of this storage technology is its limited capacity. Figure 1 shows how a PHS works.

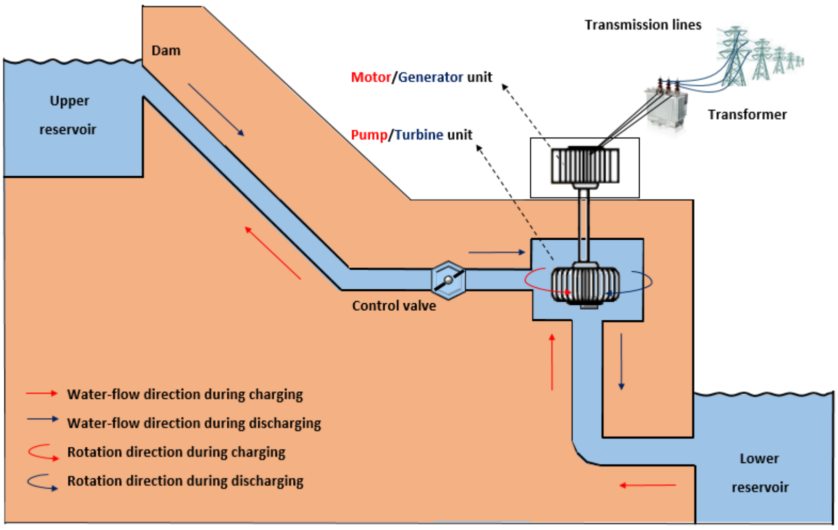

Figure 1: Diagram of the functioning of a PHS. Illustration taken from [11].

We consider here lithium-ion batteries. The advantages are the high charging and discharging flux and the low set-up costs (2019, [16]). The disadvantages are the short lifetime of a battery, the environmental impact caused by the supply of copper and aluminium for construction, and to a lesser extent the extraction of lithium (2010, [12]).

These technologies are uniformly distributed through the French territory. The effects of a strategic distribution are not discussed in this report.

The figure 2 summarizes graphically the model EOLES.

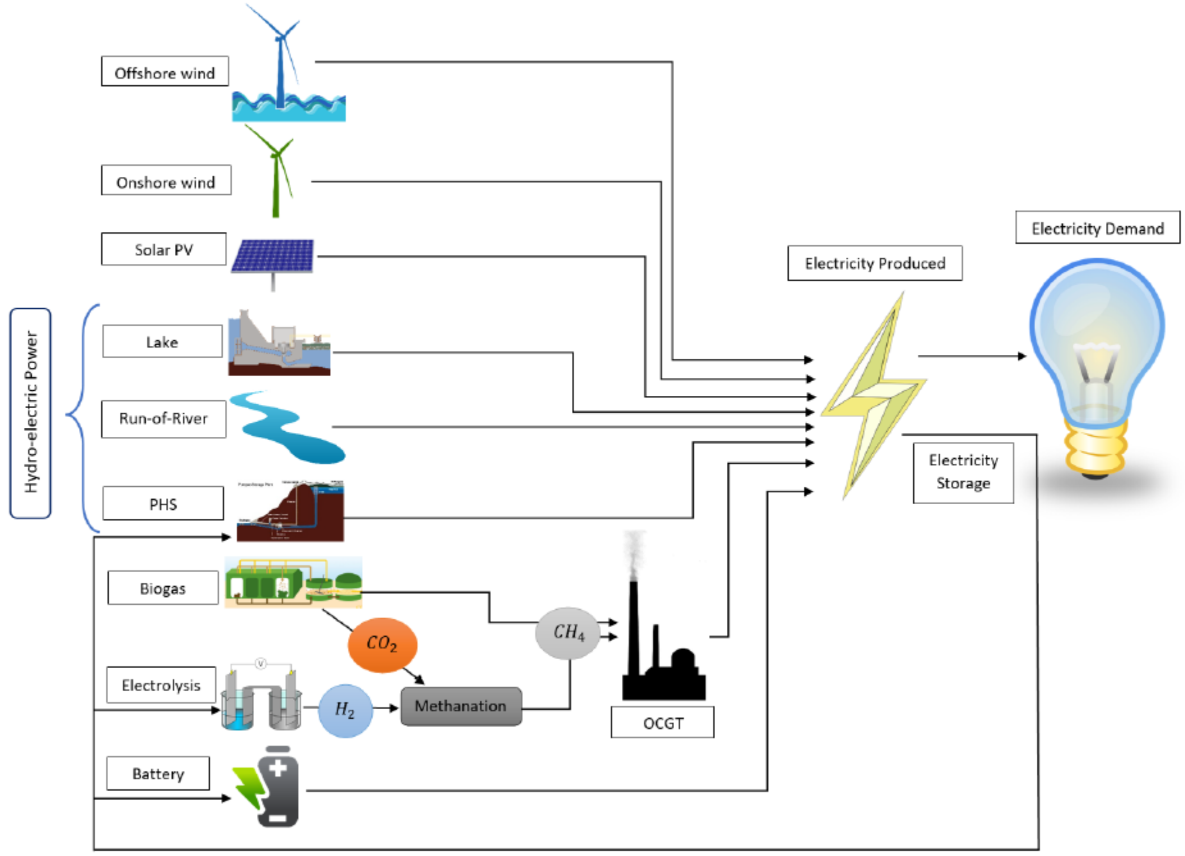

Figure 2: Model EOLES. Illustration taken from [18].

1.3 Variables to minimize

The EOLES model minimizes several variables. Table 2 defines the variables to minimize. We have two types of variables : annual variables and hourly variables.

The first type is constituted by Q, S and $VOLUME$. They are fixed at the beginning of the year. Concretely, the installed capacity Q, for a generated technology corresponds to what the technology could produce at its maximum. For a storage technology Q is the output flux and S the entrance flux. $VOLUME$ is the maximum energy of a storage technology that we can store.

G, $STORAGE$, $STORED$, RSV are hourly variables. They vary during the year and are optimized at each hour. G corresponds to what a technology generates at each hour. It has to be less than or equal to the installed capacity. $STORAGE$ corresponds to the surplus electricity generated that we put into a storage technology and $STORED$ the total of electricity stored for a given storage technology. RSV is the hourly reserve capacity required to deal with problems in the electrical network. These problems can be a forecast error of the wind or the sunshine which affects the electricity generated by vre. It also can be an error on the electricity demand. To fill this reserve, frr technologies are used.

There are 8759 hours in a year. Consequently, the optimization is made on more than 7 billion variables.

Finally, the $COST$ is the variable to minimize.

Variable	Description	Unit
$G_{tec,h}$	Electricity generation by a technology at hour h	GWh_e
Q_{tec}	Installed capacity of a technology	GW_e
$STORAGE_{str,h}$	Electricity entering in a storage technology at hour h	GWh
$STORED_{str,h}$	Stored electricity in a storage technology at hour h	GWh_e
S_{str}	Charging capacity of a storage technology	GW
$VOLUME_{str}$	Energy capacity of a storage technology	GWh
$RSV_{frr,h}$	Upward frequency restoration requirement at hour h	GWe
COST	Overall investment cost over the year	b€

Table 2: Variables

Units are expressed in electricity-equivalent units. This defines the amount of electricity that can be generated or stored by a given source of energy. For example, methane is a gas that can be transformed into electricity with 45% efficiency. Thus, if the stored methane is equal to $100MWh$, $45MWh_e$ can be generated.

1.4 Model equations and constraints

The cost function is defined in 1. It is the sum of all the costs of storage and generation over a year: investment costs, fixed and variable operation and maintenance (O&M) costs. The parameters of the model are detailed in section 2.1.

$$\begin{aligned} COST = \Big(&\sum_{tec}((Q_{tec} - q^{ex}_{tec}) \times annuity_{tec}) + \sum_{str}(VOLUME_{str} \times annuity^{en}_{str}) \\ &+ \sum_{tec}(Q_{tec} \times fO\&M_{tec}) + \sum_{str}(S_{str} \times (capex^{ch}_{str} + fO\&M^{ch}_{str})) \\ &+ \sum_{tec}\sum_{h}(G_{tec,h} \times vO\&M_{tec})\Big)/1000 \end{aligned} \tag{1}$$

We assume that the electricity demand has to be satisfied hour by hour (2), so for all the hour h, the electricity generated by all the technologies has to be greater than or equal to the demand plus what we store. This is the adequacy equation.

$$\sum_{tec} G_{tec,h} \geq demand_h + \sum_{str} STORAGE_{str,h} \tag{2}$$

To have a more realistic model, we add physical constraints. First, we have constraints on the generation. The equation 3 gives the relationship between the installed capacity and the electricity generated at each hour for a given technology.

$$G_{tec,h} \leq Q_{tec} \tag{3}$$

The installed capacity of all the technologies is limited (see equation 4). This equation illustrates the fact that we cannot add an infinite amount of a technology like wind turbines. q^{max}_{tec} represents the maximum installed capacity possible for each technology.

$$Q_{tec} \leq q_{tec}^{max} \tag{4}$$

For variable renewable energy, the electricity generated depends on an hourly capacity factor profile (see equation 5). The run-of-river electricity generated depends also on an hourly capacity factor (see equation 6). These hourly capacity factors are linked to the weather conditions. The closer to 1 the factor is, the better the weather conditions are, so the higher the amount of electricity generated is.

$$G_{vre,h} = Q_{vre} \times cf_{vre,h} \tag{5}$$

$$G_{river,h} = Q_{river} \times river_h \tag{6}$$

The electricity generated by lakes and by biogas have a maximum fixed by natural and technical constraints. The constraint on lakes is monthly and for biogas yearly. We can see these constraints in equations 7 and 8.

$$lake_m \geq \sum_{h \in m} G_{lake,h} \tag{7}$$

$$e_{biogas}^{max} \geq \sum_{h=0}^{8759} G_{biogas,h} \tag{8}$$

We have a constraint on the frr technologies. The equation 9 shows how to fill the reserve. This reserve implies a supplementary constraint on the capacity of the frr. It has to be greater than the electricity generated plus the electricity used for the reserve (see equation 10).

$$\sum_{frr} RSV_{frr,h} = \sum_{vre} (\epsilon_{vre} \times Q_{vre}) + demand_h \times (1 + \delta_{variation}^{load}) \times \delta_{uncertainty}^{load} \tag{9}$$

$$Q_{frr} \geq G_{frr,h} + RSV_{frr,h} \tag{10}$$

We also have constraints on the storage. The equation 11 shows how the stored electricity for a technology is defined. At time $h+1$, it is equal to the stored electricity at time h plus the storage that we add with a charging efficiency minus the electricity that we use with a discharging efficiency.

$$STORED_{str,h+1} = STORED_{str,h} + STORAGE_{str,h} \times \eta_{str}^{in} - \frac{G_{str,h}}{\eta_{str}^{out}} \tag{11}$$

We define equation 12 which limits the electricity stored by a technology under a volume.

$$STORED_{str,h} \leq VOLUME_{str} \tag{12}$$

We add a constraint to ensure the replacement of the consumed stored electricity in every storage technology (13).

$$STORED_{str,h=0} \leq STORED_{str,h=8759} \tag{13}$$

The equation 14 limits the storage flux which has to be lower than the charging capacity for each storage option and cannot exceed the discharging capacity.

$$STORAGE_{str,h} \leq S_{str} \leq Q_{str} \tag{14}$$

2 Input Data

2.1 Parameters of the model

EOLES needs a lot of parameters to be fixed prior to the execution of the model. Some parameters are fixed over the year, others are fixed each hour h or each month m. The table 3 shows the exhaustive list of the parameters with a short description and their unit (if they have one).

Parameter	Description	Unit
$demand_h$	Hourly electricity demand profile	GW_e
$\delta^{load}_{uncertainty}$, $\delta^{load}_{variation}$	Uncertainty coefficient for electricity demand / Load variation factor	
$cf_{vre,h}$	Hourly capacity factor profile of variable renewable energies	
ϵ_{vre}	Additional frequency restoration requirement for renewables	
$river_h$	Hourly capacity factor profile for run-of-river	
$lake_m$	Producible energy of a lake during a month	GWh_e
q^{ex}_{tec}	Existing capacity for a technology	GW_e
η^{in}_{str} , η^{out}_{str}	Charging and discharging efficiency for a storage technology	
q^{pump}	Pumping capacity of PHS	GW_e
e^{max}_{PHS}	Maximum energy volume of a PHS	GWh_e
e^{max}_{biogas}	Maximum energy generation by biogas over a year	TWh_e
$annuity_{tec}$, $annuity^{en}_{str}$	Capital cost of each technology / energy volume storage	$M€/GW_e/year$, $M€/GWh/year$
$capex^{ch}_{str}$	Capital cost of charging power for storage technology	$M€/GW/year$
$fO\&M^{ch}_{str}$, $fO\&M_{tec}$	Fixed Operation and Maintenance cost of charging power for storage technologies / for a technology	$M€/GW/year$, $M€/GW_e/year$
$vO\&M_{tec}$	Variable Operation and Maintenance cost for a technology	$M€/GWh_e$

Table 3: Description of the EOLES model parameters

2.2 Sources of input data

In this section we present the sources used for the parameters defined in table 3.

Cost data

The economic parameters are *capex*, *annuity*, $fO\&M$ and $vO\&M$. For power generation technologies, they are fixed according to the European Commission Joint Research Center (2017 [6]). They present a study of cost trajectories to 2050.

Remark: we consider wind turbines at 30km-60km from the shore for offshore and wind turbines with medium specific capacity (0.3kW/m2) and medium hub height (100m) for onshore. We take an average of the costs of utility use, commercial use and residential use for PV costs. We take the mean between low-cost and high-cost power plants for lakes and PHS.

Three different sources have been used to set these cost parameters for storage technology. Parameters for PHS have been fixed according to the "Commercialization of Energy Storage in Europe" report (2015, [8]). A study on the power-to-gas realised by ENEA Consulting (2016, [7]) has been used for the values of methanation parameters. Finally, the battery cost parameters are based on the study on the cost projections of storage technologies from O. Schmidt (2019, [16]).

VRE hourly profiles

The hourly capacity factors for onshore wind power and solar power have been extracted from renewable.ninja website ([19]). The data used by the website come from global reanalysis models and satellite observations. Offshore wind turbines are not yet implemented in France. To have hourly capacity factors, offshore projects around France have first been identified using the 4C offshore website ([1]). Then, the average of the hourly capacity factors of the most notable projects is taken as the hourly capacity factor of offshore wind power used for the EOLES model.

Electricity hourly demand scenarios

For the electricity hourly demand we use 3 sources:

1 - ADEME

We use mostly the hourly central electricity demand scenario for 2050 from ADEME (2015, [20] [3]). It supposes that the electricity demand decreases by 12% from 2010 to reach 422 TWh. The mean hourly demand is 48 GWh. The demand decreases slowly because of the use of electric cars and heat pumps which need electricity.

2 - Negawatt

The Negawatt electricity demand (2021, [10]) is the most optimistic. It predicts a demand of about 272 TWh with a mean of 31 GWh per hour. To achieve such a low electricity demand, Negawatt relies on a societal transition with total energy consumption which is halved.

3 - RTE

On the contrary, the RTE demand (2020, [15]) is the most pessimistic scenario with a demand of 580 TWh. The mean hourly electricity demand is about 66 GWh. In this scenario, the energetic consumption decreases but the electricity consumption increases to substitute fossil fuels. Moreover, electrification in turn increases electricity demand. Nevertheless, according to the RTE study, it is necessary to act on the consumption to reach climate goals.

3 Simulation of the EOLES model

3.1 Method and scenarios designing

In this part we focus on the simulation of the EOLES model. The objective is to make a first approach.

For a given year, we fix all the annual variables : Q_{tec}, $VOLUME_{str}$ and S_{str} and run the model. Hence the optimization is done only on hourly variables. To do that, we consider all the constraints except the equation 4 and the annual variables as input parameters.

We code the EOLES model in python and use the solver CBC (Coin-or branch and cut) to optimize the model.

We define six scenarios to make all the scenarios comparable, we fix all of the parameters. We always use the load factors for the *vre* and *river* from the year 2006. We only change Q, S and $VOLUME$, the inputs of the simulation, and the electricity demand profile.

We consider different scenarios of simulation :

- Scenario 0 : Outputs obtained by the optimisation of P.Quirion using Ademe demand. Among the outputs we have the optimal values of Q, S and $VOLUME$ that we sum up in table 4. The solver used by P. Qurion is CPLEX.
- Scenario 1 : We reproduce scenario 0 with another solver: CBC. Our inputs are the optimal values from P. Quirion found in 2006 and we use the Ademe demand.
- Scenario 2 : We consider a simpler model without methanation. It involves choosing $S_{methanation} = Q_{methanation} = VOLUME_{methanation} = 0$ and we use Ademe demand.
- Scenario 3 : In this scenario, we remove the offshore wind turbines from the technologies ($Q_{offshore} = 0$) and we increase the onshore wind turbines capacity from 80 to 120 GW to compensate for it.
- Scenario 4 : We test the robustness of the optimal values found by P. Quirion by replacing the Ademe electricity demand profile by the Negawatt electricity demand.
- Scenario 5 : This is the same as scenario 4 replacing the Negawatt demand by the RTE demand which is higher.
- Scenario 6 : We use the Ademe electricity demand profile that we perturb with a random Gaussian noise. We set the mean of the noise to 1, 2, 5 and 10. We keep the same values of Q, S and $VOLUME$ than the scenario 0. The objective is to test the robustness. Figure 3 represents 10 independent simulations of noisy electricity demand. Red curve represents the initial Ademe electricity demand on which the noisy demands are based. Only the electricity demand of the first week of the year is represented below.

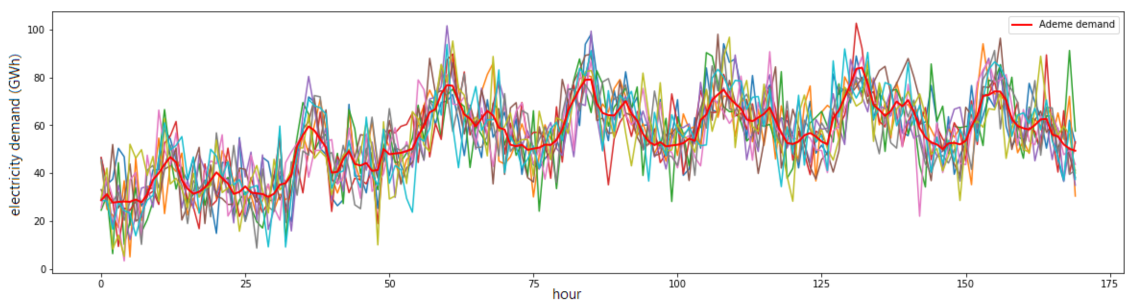

Figure 3: Simulations of noisy electricity demand

The table 4 shows the values of Q, S and $VOLUME$ obtained by P. Quirion in the scenario 0.

	Offshore	Onshore	PV	Lake	River	Biogas	PHS	Battery	Methanation
Q (GW)	12.64	79.73	121.98	7.5	13.0	32.93	9.3	20.08	32.93
S (GW)							9.3	20.08	7.66
$VOLUME$ (GWh)							180.0	74.14	124999.09

Table 4: Optimal values of variables found by P. Quirion

3.2 Results

In this section we focus on the results.

3.2.1 Visualization of the results

First, we visualize the electricity generation and storage on a profile graph. The figure 4 represents the profile of a summer week from scenario 1. The first graph shows the demand, the electricity generated to meet the demand and the volume of energy stored and the 3 others graphs the stocks of each stored technology.

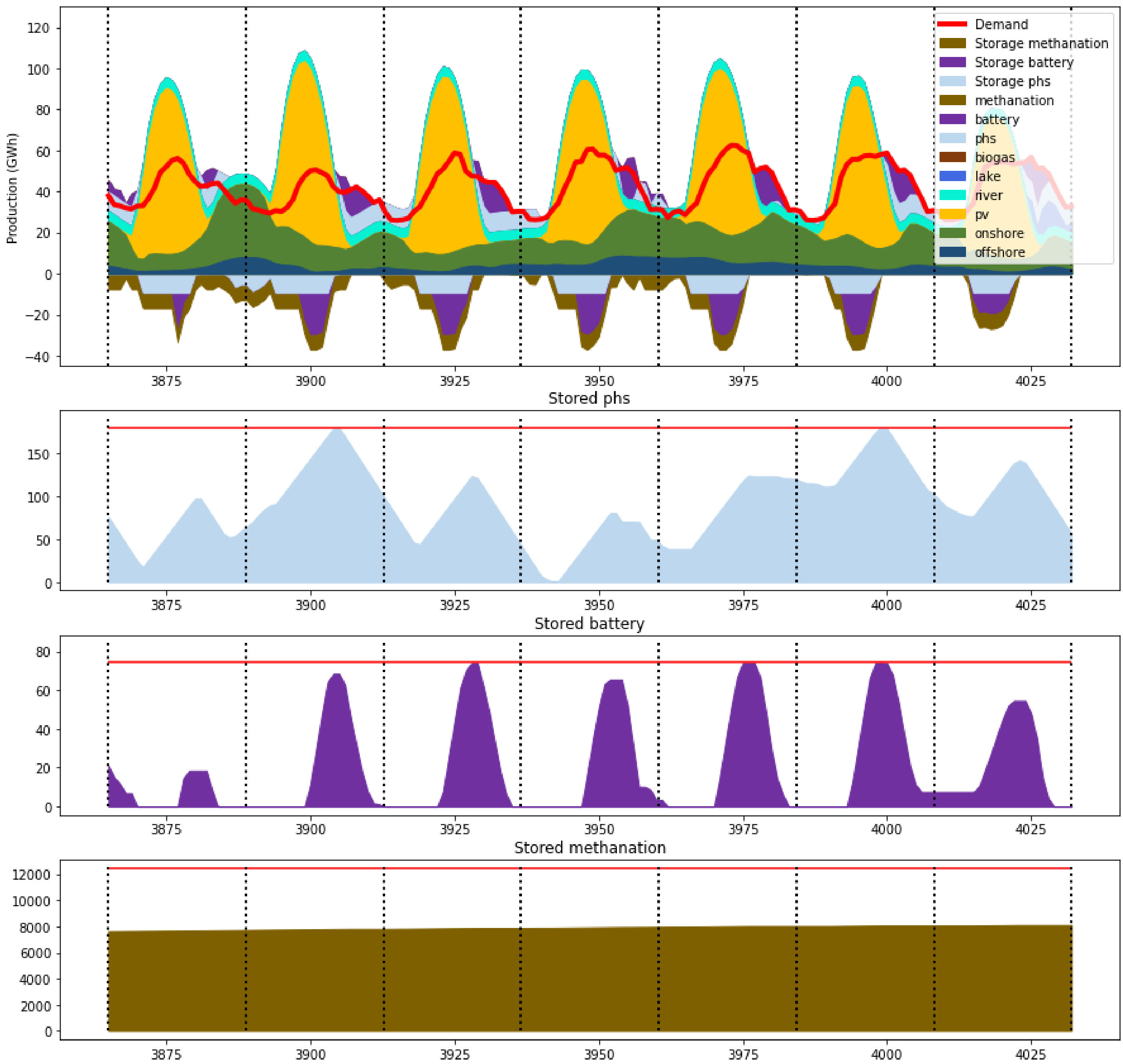

Figure 4: Electricity generation profiles for each technologies and stock levels for storage technologies during week 24

On the first graph, we can see the high production by solar panels during daytime. It is consistent with a summer week. So, the surplus electricity is stored. We remark that the maximal entrance flux of these technologies is reached. Indeed we observe that the area representing the storage is constant. During the night, the power generation technologies do not allow to meet the demand. Hence, we use electricity from PHS and batteries.

We observe that we use more electricity from batteries and PHS that we need to meet the demand at some moments and this surplus is used to fill methanation stocks. If we had not emptied the stocks so much, the maximal volume of PHS and battery would be reached and then during the next daytime these technologies could not be filled. So, surplus electricity would be lost. The model chose this optimisation because of the maximal entrance flux defined which limits the charge of a technology. This choice is made despite the charging and discharging efficiencies.

On the PHS graph, we can see linear increase and decrease of the stock. This linearity is due to the maximal entrance and output flux (S and Q). When we see that there is PHS storage on the first graph, the stock increases. On the contrary, when we use PHS electricity on the first graph, the stock decreases. We can make the same remarks for the battery stocks.

On the methanation graph, the scale does not precisely permit reading the stocks variation. The overall curve shape is increasing which is coherent with the first graph.

Now, we concentrate on the cost of using 100% of renewable energies. For all the scenarios using values found by P.Quirion the total cost does not vary too much. Indeed, in the cost function, when we fix the annual variables, only the last term of the sum changes (see equation 1). This term do not have a big importance on the sum. For this reason we only focus on the cost obtained in the first scenario.

The cost of scenario 1 is equal to €19.94 billion. The figure 5 shows the distribution of the cost according to the technologies. We observe that €16.16 billion of the cost is provided from the vre technologies. It is due to the cost of construction of solar panels and wind turbines. Then, we note that the cost of storage represents a small part of the total cost. The methanation and battery cost are 1.15, the PHS cost 0.22. The storage technologies represent 12.63% of the total cost. It is coherent with the values found by P. Quirion in his article. Finally, the cost linked to rivers and lakes are 0.11 and 0.16 respectively. This is explained by the fact that all the installations of these technologies are already constructed and their cost of maintenance is weak.

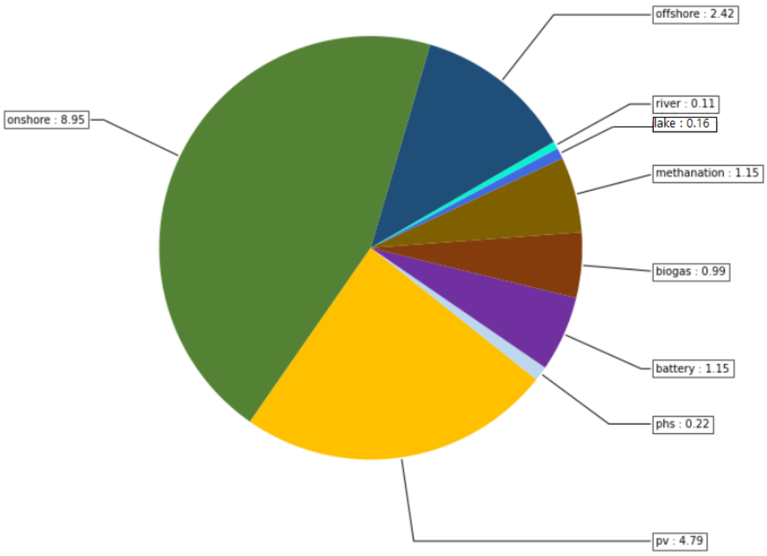

Figure 5: Distribution of the cost according to the technologies

3.2.2 Analysis of the scenarios

Then, we analyze scenario 2 to scenario 6 one by one.

The execution of the model according to scenario 2 results in the infeasibility of the simulation. It means that no solution is found by the solver respecting all the constraints and without the methanation. We could anticipate it with the analysis done on the first scenario. The methanation is indeed the main storage option.

In the third scenario we want to quantify the difference of cost between a model using offshore wind turbines (scenario 1) and a model not using this technology. Globally, the cost of an offshore wind turbine is higher than an onshore wind turbine. However, their yield is higher due to the better regularity and strength of the wind in the sea. To compensate for the absence of offshore wind turbines, it is necessary to significantly increase the capacity of onshore wind turbines by about 40 GW. This particularity makes the third scenario more expensive than the first of more than €1.50 billion, from a cost of €19.94 billion to €21.53 billion. The higher efficiency of offshore wind turbines is sufficient to compensate for their installation and operating costs.

We use the electricity demand scenario from Negawatt in scenario 4. The simulation works with the optimal values for the variables Q, S and $VOLUME$ provided from the scenario 0. The cost is €18.87 billion. It is a little bit lower than scenario 1. This can be explained by the Negawatt demand which is lower than the Ademe demand (see part 2.2).

In the fifth scenario, we repeat the change in the electricity demand scenario by taking the RTE scenario which is a more demanding scenario. As expected, the simulation of the model does not find a solution for such a high electricity demand.

For scenario 6, we create 10 electricity demand scenarios from Ademe adding to each of them a random normal noise with a mean of 1. The values of Q, S and $VOLUME$ from scenario 0 allow to find a solution which permits to meet the demand at each hour. The mean of the Ademe electricity demand scenario is about 40. We redo this experience with a mean of 2, 5 and then 10 and obtain the same result. We increase again the mean to 20 and this results in the infeasibility of the simulation. To conclude, the optimal values found by P. Quirion are robust to perturbations of the electricity demand up to a certain noise level.

4 Optimization of the EOLES model

4.1 Method and scenarios designing

In this section, we build the full EOLES model. For a given year, this model finds all the optimal variables to have the lowest price. We compute this model in python thanks to the Pyomo library and use the CBC solver.

First, we consider multiple scenarios. All these scenarios are based on the data from 2006. They consist of a modification of the following parameters: the hourly capacity factor profile of the onshore wind turbines, offshore wind turbines and solar panel and the run-of-river factor profile. These parameters are linked to the weather.

- Scenario 1 : We keep all the parameters according to the year 2006.
- Scenario 2 : We replace a sunny week to a week without sun. It means that we replace the hourly capacity factor profile of solar panels of week 28 (from hour 4536 to hour 4704) by the ones of week 48 (from hour 8064 to hour 8232), which is a cloudy week. We keep all the other parameters.
- Scenario 3 : We take scenario 2 and add 3 more cloudy weeks in place of week 29, week 30 and week 31, corresponding approximately to a cloudy month of July. We do not change all the other parameters.
- Scenario 4 : This scenario consists of a month without wind. We copy the week 29 and use it to replace from week 45 to week 48. So we create artificially a month without wind. We keep all the other parameters the same as scenario 1.
- Scenario 5 : This is the scenario of the drought. We put all the run-of-river factor profiles to 0 during summer weeks, corresponding from week 23 to week 36. We keep all the other parameters the same as scenario 1.

Then, we study the sensitivity of the total cost by adding noise to the electricity demand. We add a random Gaussian noise. We choose 3 different noise means (1, 10, 20) to control its importance and simulate 10 realizations of each. We consider here the Ademe electricity demand scenario for 2050. Its mean is about 40 GWh. Therefore, we add 2.5%, 25% and 50% random noise for each factor respectively.

Finally, we compare the 3 electricity demand scenarios given by Ademe, Negawatt and RTE.

4.2 Results

4.2.1 Weather sensitivity of the results

We first study the sensitivity of the results according to the different weather scenarios. Table 5 resumes the values of the annual variables found by the optimization for each scenario.

We notice some variables values remain the same after the optimization of each scenarios. This concerns $Q_{offshore}$, $Q_{methanation}$, S_{phs} and $VOLUME_{phs}$. All these variables also reach their maximum capacity, represent in bold in the table. This means that they are the most efficient technologies for Q, S and $VOLUME$.

Remark: 2 variables capacity are fixed i.e. $Q_{river} = 7.5$ GW and $Q_{lake} = 12.855$ GW.

Variables	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Q offshore	20.0	20.0	20.0	20.0	20.0
Q onshore	70.23	73.7	78.05	86.91	68.38
Q pv	113.03	109.68	106.06	119.46	123.15
Q phs	5.70	5.43	5.66	6.0	5.12
Q battery	13.34	12.56	11.43	13.13	15.94
Q methanation	100.0	100.0	100.0	100.0	100
S phs	6.2	6.2	6.2	6.2	6.2
S methanation	7.56	8.14	8.77	12.68	7.47
Volume phs	135.5	135.5	135.5	135.5	135.5
Volume battery	64.59	58.68	51.74	56.54	80.49
Volume methanation	7992.03	8786.84	9855.69	17104.68	7897.73

Table 5: Values for Q (GW), S (GW) and $VOLUME$ (GWh) depending on the scenario

We describe below the strategy of the EOLES model for dealing with changing weather conditions.

For the second scenario, the capacity of the PV is lower than scenario 1. On the contrary, the capacity of the onshore wind turbines is a bit higher. Stocks are being filled before the artificial cloudy week, particularly PHS and battery storage. To compensate for the loss of electricity generation by PV due to the cloudy week, we meet the demand using mostly methanation stored electricity, and also PHS and battery stored electricity to a lesser extent.

The maximum volume of electricity stored by methanation in scenario 3 is higher than in scenario 2, rising from 8786 to 9855 GWh. Moreover, the capacity of onshore increased again while the capacity of PV decreased again. At the beginning of week 28, the stocks of methanation are filled with almost 8000 GWh. The other stocks are almost at their maximum capacities of energy storage volume. This allows to meet the demand during the first 2 weeks of our artificial cloudy period which consumes almost all the electricity stored volume. For the next 2 weeks, high hourly capacity factors allows onshore and offshore wind turbines to generate enough electricity to refill the stocks and to meet the demand.

To meet the electricity demand of the fourth scenario, the energy volume of methanation drastically rises to reach 17104.68 GWh. We remark that the capacities of PV and onshore increased to fill the stocks before the month without wind. At the beginning of the artificial month without wind, the stored energy volume is almost full for each storage technology. This amount of energy stored allows to meet the demand for the first 2 weeks. Then, the electricity required is generated using mainly biogas.

The results of scenario 5 are similar with those of scenario 1 because of the low capacity of the run-of-river (7.5 GW). The capacity of PV rises from 113.03 to 123.15 to compensate for the loss of the run-of-river capacity. Indeed, the mean of the difference between the hourly electricity generated in scenario 1 and scenario 5 is near 0.

The figure 6 shows the cost according to the scenario. All the scenarios with "bad" weather conditions lead to a cost greater than the first scenario. The fourth scenario leads by far to the highest cost. This is due to the drastic rising of the volume of methanation and the adding of onshore wind turbines capacity.

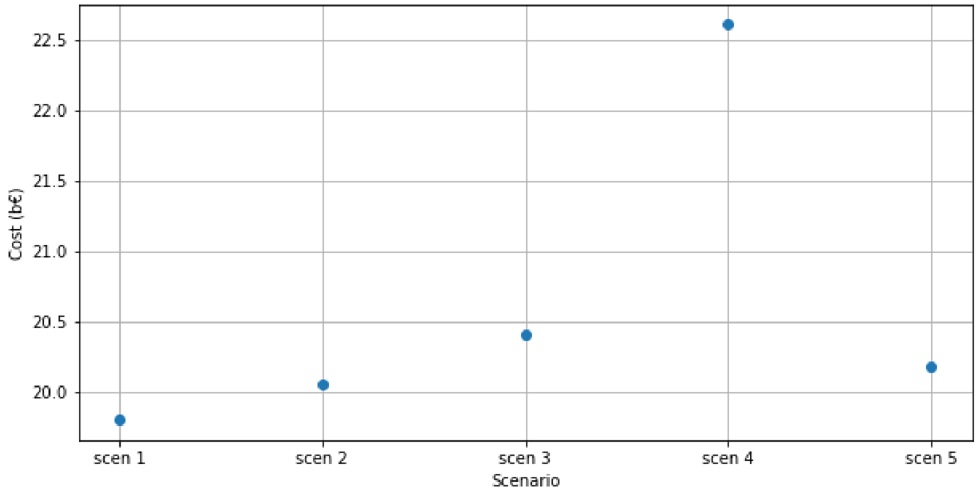

Figure 6: Cost according to the scenario

4.2.2 Electricity demand sensitivity of the results

First, we study the results obtained with different noisy demands. The objective is to test the sensitivity of the cost. The figure 7 shows the boxplots of the cost according to the mean of the noise added to the Ademe demand. The boxplots are computed on the 10 simulations made for each noisy demand. We observe that the higher the mean of the noise added, the larger the range of the boxplot and the higher its mean. Without noise, the cost is €19.801 billion. The mean of the noise equal to 1 leads to a boxplot very tightened close to €19.8 billion. Thus, the solution is robust for a small perturbation. When the mean of the noise is 10 (respectively 20), the average of the cost is €20.15 billion (respectively €21 billion). To conclude, the robustness of the solution decreases significantly as the mean of the noise added rises.

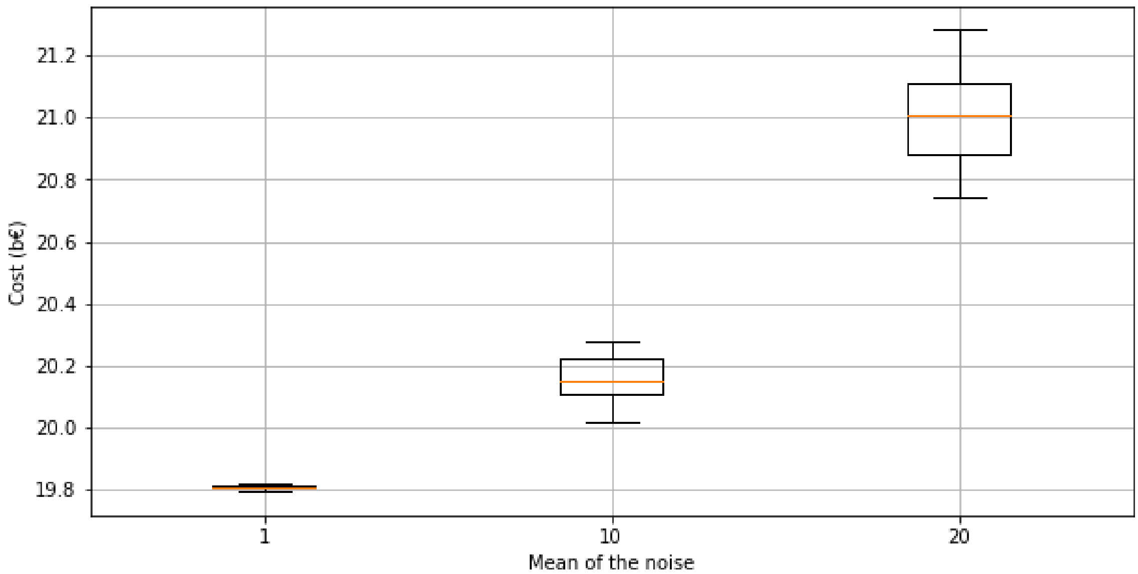

Figure 7: Boxplots of the cost according to the mean of the noise added to the Ademe demand

The figure 8 represents the mean variation of the cost of each technology according to the mean of the noise added to the Ademe electricity demand.

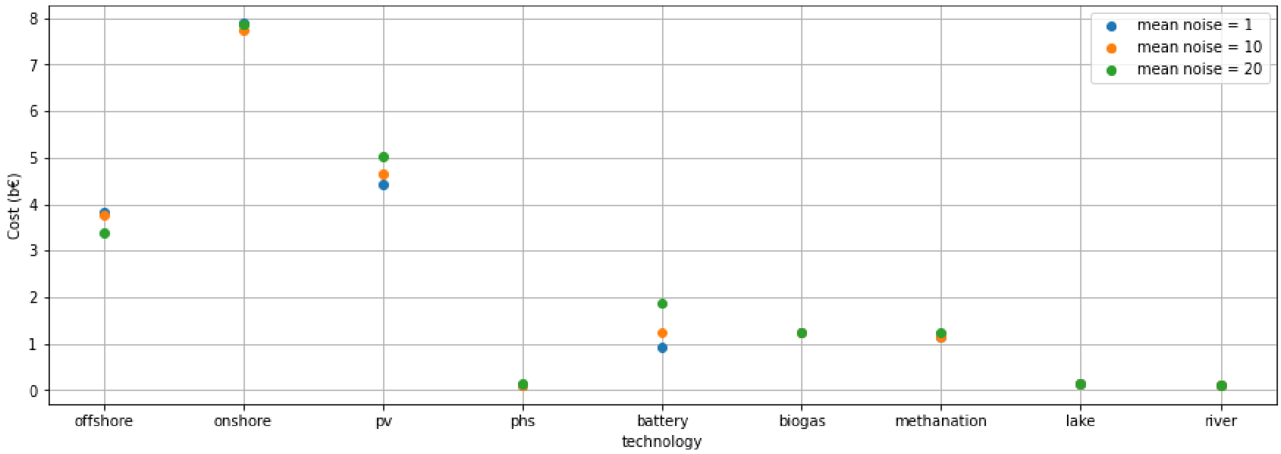

Figure 8: Cost of the technologies according to the mean of the noise added to the Ademe demand

Lake and river capacities are fixed so the variation is null and the cost is constant. PHS reaches its maximum capacity because it is the most profitable technology. This explains its constant cost. Technologies whose cost vary the most are offshore, PV and battery. For PV and battery, the maximum cost is reached for a mean noise of 20 which is coherent with the previous figure. However, we observe the contrary for offshore technology which is interesting.

Second, we study the sensitivity of the results according to different electricity demand scenarios: Ademe, Negawatt and RTE scenarios.

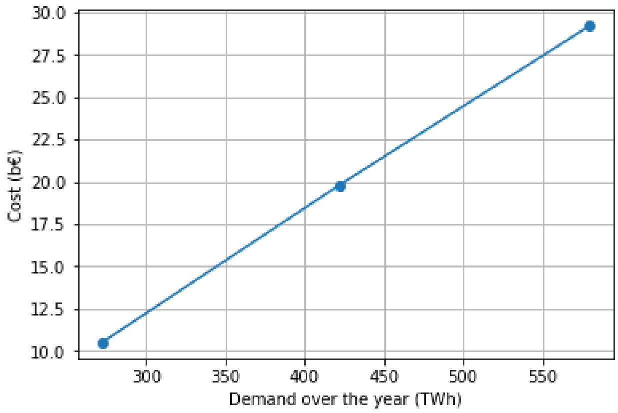

Figure 9: Linearity of the cost according to the annual demand

The figure 9 represents the cost as a function of the total electricity demand over the year. We observe that it is linear.

Conclusion

This project was a first approach to a larger project. We coded the EOLES model in python in two different ways : simulation and optimization. We analyzed multiple scenarios. The scenarios are: using a model with less technology, changing the weather conditions playing on the load factors and modifying the hourly electricity demand.

In the simulation section, we concluded that methanation storage technology is essential and that the input parameters are robust when the electricity demand is little disturbed. The optimal values of P.Quirion are based on the Ademe demand. They cannot satisfy the RTE demand which is higher than the Ademe demand.

In the optimization section, we highlighted the capacities, the volume and the charging capacity of the technologies sensitivity according to the weather conditions. Moreover, the cost increases as the weather conditions deteriorate. The results are also sensitive to a noisy electricity demand. The robustness of the solution given by the EOLES model decreases as the noise increases.

However, we have noticed some limitations of the EOLES model. First, the model has to exactly know the demand and the load factors hour by hour over the year to compute the optimization (or the simulation). It is not realistic to consider such a hypothesis. We cannot build a production model for 2050 using this hypothesis. Second, France is considered as one node. We do not take into account the specificities of the regions of the territory. For example, in reality, the sunshine and the wind are not uniformly distributed around the territory. Third, the demand is not flexible and has to be satisfied at each hour. This involves the model to anticipate filling stocks.

Finally, several perspectives could be studied in more detail.

The EOLES model built in this report is simplified. For example, we take the mean capacities of the different types of solar panels. The idea would be to differentiate the technologies. Indeed, for example, several types of batteries exist, solar panels can be placed in residential areas or in the field and so their capacities are different.

In the cost function we remove the cost of capacities already installed but we do not remove the cost of the volume already installed. To have a better estimation of the cost, removing this cost can be an idea.

As we said in the limitations of the model, France is considered as one node, so, we could separate France in different areas. Therefore, we could consider optimizing the location of the technologies to choose the areas with the best weather conditions, bearing in mind all the economic, environmental and social constraints.

Then, we could add hazard on the load factors because we do not know exactly these parameters in 2050. We can analyze the sensitivity of the simulation with perturbed load factors over the year.

The optimisation is done over the year knowing exactly the hourly electricity demand and the load factors. We could create a model doing the optimization day by day. This model would not use the data of future days or maybe forecasts of the future week but not exactly all the data.

A further study on the environmental impact of the installation of the technologies could be interesting: mineral extraction, electricity required for transports and installation... Also, we could study the environmental impact in the countries where the minerals are extracted: is the electricity used by this country non-carbon? What is the impact of the rise of the minerals demand in the energy sector ? Does the country import energy from other countries ?

Moreover, we could add flexibility in the demand. The model would not have to satisfy it hour by hour. For example, we could consider some hours where the population does not have access to electricity.

We can study the possibility of recovering old car batteries to store electricity.

Some studies highlight the difficulty to use only renewable energies in France without using nuclear power plants. So, we could add nuclear in the model.

Finally, the last perspective we thought about is the integration of new generation or storage technologies that could be developed in the future.

References

[1] https://www.4coffshore.com/.

[2] Paris Agreement. Paris agreement. In *Report of the Conference of the Parties to the United Nations Framework Convention on Climate Change (21st Session, 2015: Paris). Retrived December*, volume 4, page 2017. HeinOnline, 2015.

[3] Gissela Landa Paul Malliet Aurélien Saussay, Fredéric Reynes. Mix électrique 100% renouvelable ? analyses et optimisations, 2015.

[4] Askari Mohammad Bagher, G Fatemeh, M Saman, and MM Leili. Advantages and disadvantages of biogas energy. *Bulletin of Advanced Scientific Research*, 1(5):132–135, 2015.

[5] Askari Mohammad Bagher, Mirzaei Vahid, Mirhabibi Mohsen, and Dehghani Parvin. Hydroelectric energy advantages and disadvantages. *American Journal of Energy Science*, 2(2):17–20, 2015.

[6] European Commission, Joint Research Centre, D Tarvydas, A Zucker, and I Tsiropoulos. *Cost development of low carbon energy technologies : scenario-based cost trajectories to 2050, 2017 edition.* Publications Office, 2018.

[7] ENEA Consulting. The potential of power-to-gas. *Technology review and economic potential assessment*, 2016.

[8] JU FCH. Commercialisation of energy storage in europe. final report. 2015.

[9] Kenneth Hansen, Brian Vad Mathiesen, and Iva Ridjan Skov. Full energy system transition towards 100% renewable energy in germany in 2050. *Renewable and Sustainable Energy Reviews*, 102:1–13, 2019.

[10] Negawatt. La transition énergétique au cœur d'une transition sociétale, 2021.

[11] Pavlos Nikolaidis and Andreas Poullikkas. A comparative review of electrical energy storage systems for better sustainability. *Journal of power technologies*, 2017.

[12] Dominic A Notter, Marcel Gauch, Rolf Widmer, Patrick Wager, Anna Stamp, Rainer Zah, and Hans-Jorg Althaus. Contribution of li-ion batteries to the environmental impact of electric vehicles, 2010.

[13] Hannah Ritchie and Max Roser. Co and greenhouse gas emissions. *Our world in data*, 2020.

[14] Joeri Rogelj, Drew Shindell, Kejun Jiang, Solomone Fifita, Piers Forster, Veronika Ginzburg, Collins Handa, Haroon Kheshgi, Shigeki Kobayashi, Elmar Kriegler, et al. Mitigation pathways compatible with 1.5 c in the context of sustainable development. In *Global warming of 1.5° C*, pages 93–174. Intergovernmental Panel on Climate Change, 2018.

[15] RTE. Futurs énergétiques 2050 : les scénarios de mix de production à l'étude permettant d'atteindre la neutralité carbone à l'horizon 2050, 2020.

[16] Oliver Schmidt, Sylvain Melchior, Adam Hawkes, and Iain Staffell. Projecting the future levelized cost of electricity storage technologies. *Joule*, 3(1):81–100, 2019.

[17] Mohammed Seddiki and Amar Bennadji. Multi-criteria evaluation of renewable energy alternatives for electricity generation in a residential building. *Renewable and sustainable energy reviews*, 110:101–117, 2019.

[18] Behrang Shirizadeh, Quentin Perrier, and Philippe Quirion. How sensitive are optimal fully renewable power systems to technology cost uncertainty? *The Energy Journal*, 43(1), 2019.

[19] Iain Staffell Stefan Pfenningern. https://www.renewables.ninja/.

[20] Meunier L. Vidalenc, E. and Topper B. Ademe's visions 2030-2050; visions ademe 2030-2050, Mar 2013.